KNOWLEDGE SPILLOVERS, THE TECHNOLOGY FRONTIER AND HIGH-TECH FDI – EVIDENCE FROM FINLAND*

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Abstract

The link between foreign direct investment (FDI) and the technology frontier is strong in the theoretical and empirical literature, particularly for high-tech multinational corporations. Policymakers aiming to harness local high-tech clusters therefore tend to cherish high-tech inward FDI. It is not clear whether they should. With an unbalanced panel of Finnish ICT manufacturing firms for 1993–2003, I identify the direction of knowledge spillovers by comparing the technical efficiencies of foreign and indigenous firms with DEA and order-m methodology. When knowledge spillovers flow predominantly to foreign firms, innovation policy seeking to accelerate them may accelerate the net loss of strategic assets. (JEL: O47, O33, O52, L63)

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1. Introduction

Foreign ownership is common in high-tech industries, and positively associated with proximity with the technology frontier, and TFP growth and innovation (Griffith *et al.* 2002, Criscuolo *et al* 2015). High-tech foreign owners are often multinational entreprises (MNEs), which carry out a large share of global private R&D and produce, possess, and control most of the world's cutting-edge production methods and technologies (Blomström and Kokko 2003; Nordås *et al.* 2006). Along with trade, foreign direct investment is one of the main vehicles of technology diffusion, which in turn is a major source of productivity growth. Most productivity growth originates from abroad, 90% in fact, according to Keller (2004, p. 752), the more so the smaller and more open the economy. Andrews *et al.* (2015), among others underscore policies related to knowledge diffusion to promote catching up with the global frontier. Most FDI tends to be associated with positive net spillovers to the host country, and high-tech FDI with its technology spillovers would appear most attractive in this regard. Spillovers on knowledge of more advanced technologies, or better organisational and managerial practices can raise productivity in local firms (Saia *et al*. 2015; Guadalupe *et al.* 2012, Criscuolo *et al.* 2015).

Yet, the evidence is not clearcut. Aitken et al. (1999) found negative impacts from foreign investment on the productivity of local Venezuelan plants. More importantly, it is also known that knowledge acquisition is one key motive for FDI. Firms seek to obtain access to strategic assets, such as technologies and workers with technological expertise. "Firms locate in leading edge countries close to the technology frontier, in order to benefit from the diffusion of advanced technologies" (Criscuolo et al 2015, p. 9). It is not therefore clear whether innovation policy should always support high-tech inward FDI, or when it should not. The purpose of this paper is to further examine this issue by analysing the relative efficiency of foreign vs. indigenous firms in the Finnish ICT sector.

At the theoretical level, Dunning (1981), Markusen (1995) and Helpman (1984) refer to firm-specific advantages that parent firms share with their subsidiaries and/or plants. Hymer (1960) originally categorized as owner- or firm-specific advantages access to raw materials, economies of scale, intangible assets, superior management etc. In Dunning's OLI theory (ownership-specific, location-specific and internalization advantages), firm-specific advantages refer particularly to assets such as knowledge capital, which can be easily replicated and transferred within the firm across countries, without incurring high transaction costs or knowledge leakages. Firm-specific advantages explain MNC activity in R&D-intensive innovative sectors involving complex technologies and intangible capital (know-how, patents) such as the ICT industry.

Technologically less advanced firms seek knowledge and other spillovers by locating close to the headquarters and production facilities of their more advanced competitors. Bjorvatn and Eckel (2006) define such investment as technology acquisition or technology sourcing FDI. Griffith *et al.* (2006) found that local R&D establishments may facilitate knowledge sourcing by UK firms in the US. Carrying out R&D in the US was associated with accelerated productivity growth for UK firms, particularly if the local industry's overall R&D stock grew. Nachum and Zaheer (2005) argue that knowledge and efficiency-seeking are the most prominent reasons for transnational operations in information-intensive industries to harness intangible capital. Innovation in high-tech sectors is vital to a small number of rapidly growing "superstars" (Coad and Rekha 2008). Even at the technology frontier, innovation may be highly clustered into a few firms, and foreign firms may be seeking to absorb their superior technology.

Knowledge spillovers are geographically localized, which motivates firms seeking them to establish themselves in the vicinity of potentially valuable new knowledge (Jaffe *et al.* 1993). Innovation hubs have frequently emerged close to a university and been reinforced in a 'triple-helix' partnership between the municipality, university and local entrepreneurs (Etzkowitz and Leydesdorff 1999). According to Porter (1990,

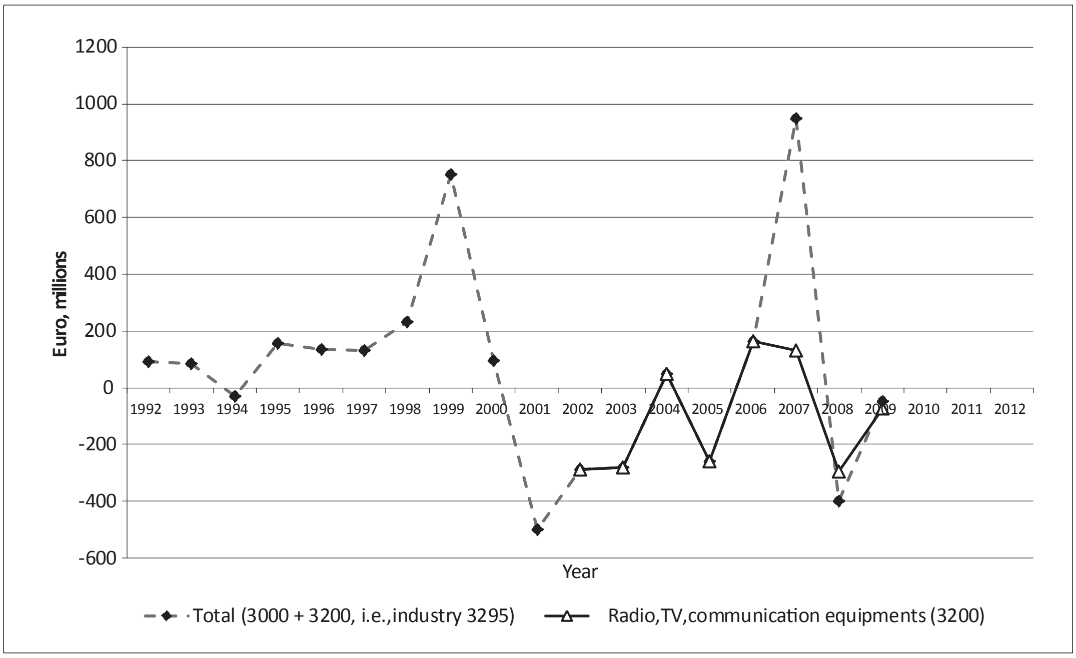

Figure 1. FDI Inflows into the Finnish ICT Industry, 1992–2009 in millions of euro.
Source: OECD Statistics.[2]

1998) important microeconomic foundations of competitiveness and productivity growth which drive the direction and pace of innovation in advanced economies are often cluster specific. Policies to build competitive and innovative clusters have therefore been intertwined to harnessing national innovation systems, with local knowledge sourcing often explicitly aided through R&D platforms and R&D establishments.

The issue of social returns such as knowledge spillovers is at the heart of innovation policy, since government R&D support can be justified by large expected social, but inadequate private, returns on R&D, provided that public R&D agencies are able to identify such projects (Klette *et al.* 2000). But spillovers are notoriously difficult to quantify. One means of encouraging spill-overs, is to condition public support of R&D explicitly on collaboration, as in Finland, where firms are eligible to R&D support irrespective of whether a firm is indigenous or foreign-owned.[1] Such policy appears to generate spillovers. Van Beers et al. (2008) showed that compared to Dutch firms, Finnish firms were more willing to share proprietary knowledge with public R&D institutes, while incoming spillovers from such R&D institutes were the major reason for foreign-owned firms to cooperate with them.

The literature is not clear on whether it is worthwhile to encourage high-tech FDI seeking knowledge spillovers. Pajarinen and Ylä-Anttila (2001) conducted a survey of 300 foreign-owned firms in Finland in June 2000 following significant inflows to the ICT industry, and found indications of stronger technology flows and knowledge spillovers to the parent companies and their networks of affiliates abroad than inwards. Actual inflows into the ICT industry are presented in Figure 1. This suggests that policies to encourage spillovers may accelerate the loss of technological advantage.

1 EU regulations demand equal treatment of foreign and domestic firms in the provision of public R&D support for research in Finland. One key condition for approval is cooperation with a Finnish firm.

2 The 2007 peak in FDI inflows may represent foreign portfolio acquisitions of e.g. Nokia Corporation associated with the stock market boom. Inflated global cross-border capital inflows broke a worldwide record in 2007 ($12.4 tn US), including acquisitions ($4.2 tn US).

The issue is an empirical question. Criscuolo et al. (2016) find that faster productivity growth in frontier firms is not due to capital investment, but rather productive efficiency. This in turn is related to market power, i.e., "the winner takes all" phenomenon is prevalent in many new high technologies, as well as the intensity of competition. I therefore identify the predominant direction of spillovers by comparing the relative efficiencies of foreign and domestic firms in the industry.

With data from the Finnish ICT industry for 1990–2003, i.e. when mobile phones revolutionized the world, I estimate the evolution of technical efficiencies of Finnish and foreign firms with data envelopment analysis (DEA). I carry out various robustness checks, including with order-*m* efficiency estimation methodology and EU KLEMS industry data.

Results show indigenous firms, if anything, more efficient than foreign firms during the sample period, and confirm the finding of Pajarinen and Ylä-Anttila. When the gap is to the benefit of indigenous firms and other motives are unlikely, an efficiency comparison of foreign and domestic firms can help reveal the direction of knowledge leakages and a technology-seeking motive. A technology-seeking motive and ample inward FDI flows can reveal inside information on the proximity of indigenous firms to the world technology frontier (WTF). I contribute to the literature with a counter example displaying the downside risks associated with attracting high-tech FDI to a small open economy with a high-tech cluster, but few other strengths beyond indigenous innovations.

The next section presents the data and variables and the third section summarizes the methodology. The results are presented in the fourth section and their implications are discussed and conclusions drawn in the final fifth section.

2. Data and variables

2.1 Finnish ICT firm-level data

The unbalanced panel of ICT manufacturing firms was constructed from several databases from Statistics Finland for 1990–2003. Firm-level data on capital and labour was obtained by summing up plant-level data to avoid the division of R&D capital plant-wise. In the estimation of efficiency, output (Y) is measured by real value-added measures, while the inputs are non-R&D labour (L), the physical capital stock (K) and the R&D stock (R). Labour input is proxied by total firm personnel due to data shortages on hours worked.[3] As R&D was included as an input, R&D employees were deducted from the total number of labour input to avoid double-counting (see e.g. Hall and Mairesse, 1995).

Proxies for physical capital, constructed from longitudinal panels of machine and equipment investments[4], using the perpetual inventory method with a 10% depreciation rate[5], i.e., $K_t=(1-\delta)K_{t-1}+I_t$, where δ is the depreciation rate, were available from Statistics Finland. Similarly, R&D capital stocks were constructed from total intramural R&D investments, available in the R&D panel, based on the perpetual inventory method. The initial R&D stock was based on data for 1985–1989 to the extent available, and estimated with a 30% depreciation rate, in line with rapid technological development (confirmed by the results) and a prior finding for electrical products (Bernstein and Mamuneas, 2006).

Due to data shortages, as well as to improve the homogeneity of the sample, the analysis was restricted to innovative (with R&D activities), exporting (firms with at least some exports) and minimum 20-employee firms. Since efficiency increases with firm size (Berghäll 2012), the exclusions increase average efficien-

3 At least for blue-collar workers, hours worked are likely to differ little by employee due to labour regulation in Finland restricting the number of hours worked.

4 The initial capital stock was retrieved from book value. The length of the underlying panel reduced the potential bias it may have introduced to the current economic value of machinery and equipment stocks.

5 The data description http://www.tilastokeskus.fi/tup/mikroaineistot/me_ldpm.pdf does not specify any reference to the standard practice of assuming a 10% depreciation rate, but it falls within the band of empirical results surveyed e.g. by Nadiri and Prucha (1996). Small differences in the depreciation rate may influence the distribution of efficiency over time, but is not expected to influence results with respect to the origin of the firm.

cy due to firm size and smaller sample size[6]. Since entry conditions into the industry may differ for foreign and indigenous firms, the size cut-off places foreign and indigenous companies on a more equal footing for average efficiency comparison than a comparison based on the averages of all indigenous vs. foreign firms. Large firms with over 500 employees dominate the industry in terms of sales and R&D, covering over 90% of the private R&D carried out in the industry, which in turn represents over half of total corporate R&D in Finland.

The sample was restricted to exporting firms for reasons of homogeneity as well as to allow conclusions at the global level. Exporting firms are subject to global competition and are therefore more likely to adopt frontier technology or innovate it. In contrast, non-exporting firms may be on the frontier at the local level, but nothing can be concluded on their global position. This removed a further 12% from the sample, leaving a total of 813 observations (Figure 2). Since non-exporting firms were generally few and small, their exclusion does not prevent the generalizability of the results to the industry level.

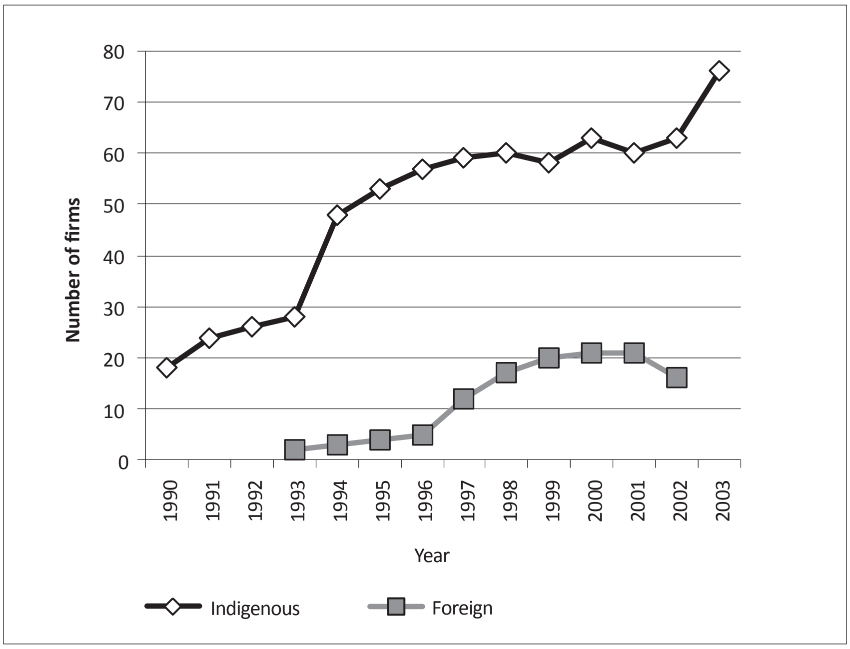

Figure 2. Number of indigenous and foreign firms in the sample 1990–2003. Data source: Statistics Finland.

Table 1a. Summary statistics for indigenous, i.e., Finnish firms, total pooled observations for 1990–2003.

	N	Min.	Max.	Mean	Std. dev.
Value added (€), (Y)	693	91 531	6 474 956 360	47 552 133.3	338 510 536.4
Capital (€), (K)	693	218	541 878 095	14 300 036.6	46 231 941.1
No of personnel excluding R&D personnel, (L) [7]	693	1	7 839	294.7	769.7
R&D capital stock (€), (R)	693	826	695 930 103	10 617 776.3	49 544 214.0

Table 1b. Summary statistics for foreign firms, total pooled observations for 1993–2002.

	N	Min.	Max.	Mean	Std. dev.
Value added (€), (Y)	121	119 267	176 033 413	23 475 238.4	31 533 415.5
Capital (€), (K)	121	25 998	66 150 378	11 479 143.0	13 403 853.3
No of personnel excluding R&D personnel, (L)	121	13	1 094	312.7	310.9
R&D capital stock (€), (R)	121	16 776	70 539 293	5 520 402.5	10 328 705.1

Data source for both tables: Statistics Finland.

6 Average efficiencies are of interest only with respect to their differences between indigenous and foreign firms.

7 Personnel following the exclusion of R&D personnel for over 20 employee firms.

Nominal variables were deflated with sectoral producer price indices at the 2- and 3-digit levels (1995=100), with the exception of the R&D stock, which prior to 1995 was deflated with the general earnings-level index. Following these cuts and modifications, the panel firms can be assumed to be subject to similar (minimal) regulation and demonstrate comparable behaviour. Summary statistics for indigenous and foreign firms are presented in Tables 1a and 1b, respectively.

Data on foreign firms from the same sources is available for 1993–2002, following the removal of remaining entry barriers in 1993. The foreign firms are on average only slightly larger than the indigenous firms, not enough to expect them to gain an advantage in terms of efficiency. Only one foreign firm was excluded from the sample due to it having no exports. Due to their export-orientation, inward investment has scarcely been market size-seeking. In Dunning's (1993) taxonomy, the other principal motives for FDI are resource-seeking, efficiency-seeking and strategic asset-seeking. Helpman *et al.* (2004) have established that it is the most productive firms in advanced economies that establish subsidiaries in other countries, while less productive ones settle for exporting, and the least productive ones do not serve foreign markets at all. Since only the most productive firms serve global markets, the export orientation of investors suggests that the investors seek resources, efficiency or strategic assets to improve their productivity or competitiveness on global markets. Due to the narrow focus of the local industry base on mobile phones, all remaining firms are expected to operate in the same technology niche. Even though similar technologies are not assumed by the methodology, foreign and local firms present a rather homogeneous sample, which is pooled to compare efficiencies with respect to the same frontier for a varying number of observations.

2.2. Robustness check on best readily available (KLEMS) data

The data period selected, 1990–2003, covers a period when the global mobile handset industry took off. Towards the end of it, offshoring e.g. to China got underway. That is to say, the time period represents an era when Finnish ICT firms were most likely to be close to the WTF. For further support, I examine best available harmonized international data, i.e. the EU KLEMS and its linked databases (Inklaar and Timmer 2008). The data available on the related electronics industry is far from global coverage, being limited to similar advanced medium-sized developed open economies. The final sample consisted of 11 countries and 215 observations over a longer period of 1980–2003 for industry category 30 to 33 based on European NACE rev. 1 industrial classification (Table 2), i.e. a broader electronics category than used in the firm-level inspection.

Table 2. Availability of KLEMS data by country

Country	Frequency/ Years	Percent	Time period
Austria (AUS)	24	11.2	1980–2003
Czech (CZE)	5	2.3	1999–2003
Denmark (DNK)	24	11.2	1980–2003
Spain (ESP)	18	8.4	1986–2003
Finland (FIN)	24	11.2	1980–2003
Germany (GER)	13	6.0	1991–2003
Italy (ITA)	24	11.2	1980–2003
Japan (JPN)	24	11.2	1980–2003
Netherlands (NLD)	24	11.2	1980–2003
Sweden (SWE)	11	5.1	1993–2003
United Kindgdom (UK)	24	11.2	1980–2003
Total	215	100.0	

The estimated variables included value-added (Y), R&D stock (R), capital stock (K), hours worked (H_EMP/L) (Table 3). These were deflated with the price indices available in the dataset and converted into US dollars for comparability. However, since KLEMS linked database R&D stocks were estimated significantly differ-

Table 3. Descriptive Statistics for KLEMS electronics industry data (European NACE Rev. 1 industrial classification 30 to 33).

Variable	Mean	Std.Dev.	Minimum	Maximum	No. Of Obs.
Value Added	25558.8	49804.2	767.5	286420.0	215
Hours Employed	933.6	1401.3	59.0	5428.3	215
Capital Stock	43113.4	92128.7	963.5	532507.0	215
R&D Stock	31340.5	64347.6	201.0	377190.0	215

ently from the firm level analysis, the results are not directly comparable. In particular, the data does not specify the share of R&D labour input. Hence R&D labour is "double-counted". Moreover, the depreciation rate applied to the R&D stocks available was 12 %, i.e. much lower than the 30% applied at the firm level. While the 30% was drawn from empirical evidence of rapid depreciation in the electrical and electronic products industry, the 12% R&D stock depreciation rate was applied uniformly to all industries in the database. While the reallocation effect may be stronger for firms than industries, the large difference between the R&D depreciation rates applied at the firm and industry levels estimates suggests that it may affect results. In particular, a lower depreciation rate in industry R&D increases the R&D stock, but reduces the technical efficiency estimates. In addition, the labour input variables, hours worked and number of employees, differ.

3. Methodology

Data constraints frequently confine frontier comparisons to limited labour or multifactor productivity estimates that tend to rely on strong assumptions of perfectly functioning markets[8]. Yet varying production functions, variable returns to scale, imperfect competition, and technical and allocative inefficiency are also present in mature market economies. Standard neoclassical assumptions rarely hold (Balk 2010). The mere existence of cross-border foreign direct investment (FDI) proves the assumption of perfect competition to be unrealistic, since the internalization of firm-specific (monopolistic) advantages is one of the key reasons why FDI is preferred over exporting (Markusen 1995). Recent literature has also recognized the hypothetical nature of a frictionless frontier (Caselli and Coleman 2006). Moreover, since the global technology frontier by definition responds to innovation, as opposed to technological diffusion, standard assumptions of perfect competition and decreasing returns to scale are inappropriate if not contradictory. Issues such as R&D, innovation, imperfect competition, increasing returns, technological progress, knowledge diffusions, etc. are of particular relevance to the WTF. As Aghion *et al.* (2005) have postulated, new technological breakthroughs can establish significant leads in competition and increasing returns for a while, until laggards copy and catch up with innovators.

Bloom *et al.* (2012) have found multinational firms to be well- managed in low and high income countries. In contrast to local small firms, the inefficiency of multinationals cannot therefore be assumed to be due to bad management, but rather technological differences. Efficiencies may also reflect differences in market power, but in the case of high-tech, market power is likely to be related to technological advantages protected by patent rights. The presence of inefficient foreign investors in a knowledge intensive industry in itself suggests a technology-seeking motive. A simple efficiency test can reveal it.

3.1 Data Envelopment Analysis (DEA)

Non-parametric efficiencies are estimated to establish technical efficiency gaps between for-

8 Index based measures of TFP are an exception, which allow for imperfect competition or non-profit maximization.

eign and domestic firms. Farrell's (1957) original insight was to extract information from extreme observations of data to determine the best practice production frontier. In theory this production possibility frontier emerges from the long-term equilibrium of perfectly competitive markets, when average costs are minimized on the average cost curve. This technical (productive or x-efficiency) efficiency refers to the ability to obtain maximum output on the production possibility frontier from a given set of inputs (given their optimal ratios) or expenditure. Technical inefficiency captures the production unit's shortfall in productivity from the most efficient units in the sample. In practice the most efficient units receive a score of one, and less efficient a score somewhere below one, but above zero.

Non-parametric DEA is a straightforward application of this principle. The method seeks the points that maximize output given the inputs (output-oriented measure) or minimize inputs given the output (input-oriented measure). Again, the most efficient firms receive a score of one, and less efficient firms a score somewhere below one, but above zero. It applies linear programming to compare relative performance when the production process involves multiple inputs and outputs. Several programs are available to carry it out. Its complexity in terms of the number of inputs and outputs causes no constraint.

One alternative, the meta-frontier approach developed by Battese *et al.* (2004) allows the estimation of comparable firm efficiencies while allowing for different technologies. For example, Lee *et al.* (2014) estimate the efficiencies of Android and iOS platform users as a group relative to the meta-frontier. Since the sample firms cannot be categorized based on clear technological differences beyond efficiency differences, the objective of foreign and domestic firms was to compete on or for the same technology, and different group sizes could bias the results (de Witte and Marques 2009) without obtaining significant additional advantages, the meta-frontier approach was not selected. Instead, the firms were pooled and comparable efficiencies estimated.

The original constant returns DEA methodology was developed by Charnes *et al*. (1978), and further developed by Banker et al. (1984) to a variable returns to scale (VRS) version, relaxing the scale efficiency assumption. Since prior tests have proved returns to scale in the industry to be highly variable (Berghäll 2012), there is no pitfall in applying the VRS model warned against by Dyson *et al.* (2001). When input-based efficiency is less than output-based efficiency, returns to scale are decreasing and vice versa for increasing returns to scale (Coelli 1996).

There is no clear rule as to whether one should select the input or the output-based efficiency measure, other than the type of industry studied. The output measure may be more appropriate, since it is reasonable to assume that during "normal/good" times, competitive firms in open market-based economies maximize value-added rather than minimize costs. Moreover, the R&D-intensity of the ICT industry suggests that firms would maximize output since R&D imposes no additional size-related marginal cost and there are significant benefits to size. Nevertheless, both were estimated to confirm the presence of scale efficiencies.

Coelli et al. (1999) present an output-oriented variable returns to scale DEA model in the following way:

$$\max_{\Phi,\lambda}\Phi, \tag{1}$$

$$\text{so that } -\Phi y_i + Y\lambda \geq 0, \tag{2}$$

$$x_i - X\lambda \geq 0, \tag{3}$$

$$N1'\lambda = 1, \tag{4}$$

$$\lambda \geq 0, \tag{5}$$

where Φ is a scalar, λ is a $Nx1$ vector of constants, $1 \leq \Phi < \infty$, and $\Phi - 1$ is the proportional increase in output that could be achieved by the *i*-th firm, with input quantities held constant. That is to say, *i* indicates the unit of analysis and N the number of decision-making unit (DMU, i.e., the production unit). $1/\Phi$ defines a technical efficiency score between 0 and 1. y_i and x_i are values of output and input, respectively, at point i, and X represents the input matrix and Y the output vector that include all the data in the DMUs. The linear programming problem is optimized for each DMU in the sample.

Sabirianova *et al.* (2005) approximated the technology gap with the world technology frontier as the average efficiency of the top third of foreign firms in a given two-digit industry. In applying this proxy DEA has the advantages of not adding to the approximation, nor confusing differences in efficiency with other differences between local and foreign firms. One of the major advantages of DEA and order-m (see below) is that beyond convexity, no distorting assumptions are imposed with respect to the technology[9]. Since the target was to compare technologies, an initial assumption on the technology would have been inappropriate. Stochastic frontier methodology, in contrast, assumes a functional form and distribution of the error term. If the motivation of foreign firms is technology-sourcing, it would be incorrect to assume similar technologies for foreign and indigenous firms. The shortcoming of the method is that it cannot separate random variation from actual productivity effects. There is no adjustment for outliers (Coelli *et al.* 1999). I therefore carry out robustness checks with a semi-parametric method, as well as on aggregated data.

3.2 Sample size and robustness check with order-m methodology

DEA efficiency declines with sample size, because the probability of encountering more efficient firms rises with the sample, as the estimated frontier asymptotically approaches the true production frontier (Banker 1989) – the so-called curse of dimensionality. Since efficiency is estimated from a pooled sample of foreign and indigenous firms, their different sample sizes do not bias their efficiencies with respect to one another. Similarly, the technology frontier is estimated from the top third of indigenous and foreign firms of the pooled estimation results. While the approach avoids biases caused by the different sample sizes of indigenous and foreign firms, the overall sample size may affect the results. As a first robustness check, the first years of foreign inflows, 1993–1995, were removed from the comparison due to the low number of foreign firms. While pooling may result in comparing a DMU to its future observation, the results for indigenous and foreign firms are compared over the time period (Figures 3 and 4). Hence only the relative values are of interest.

As another robustness check, so-called order-*m* methodology was applied to control for the impact of sample size and outliers on the estimates. Zhang and Bartels (1998) have proposed adjusting obtained DEA efficiency results to the sample size based on random draws of n_f firms from the larger sample of indigenous firms. These random draws are repeated several times without replacement. The final mean efficiency estimate is the average of these draws. In their example, the mean efficiency of the larger sample rose more than that of smaller samples. This method resembles the popular and more state-of-the-art method called order-*m* proposed by Cazals *et al*. (2002), with the exception that in order-*m* the random draws are repeated with replacements. Instead of benchmarking a DMU against the best-performing peer in the sample, as in DEA, in order-*m* the DMU is benchmarked against the expected best performance of an *m* sample of peers. This varying coverage of observations excludes and includes outliers in the sample on which efficiency is estimated.

In more formal terms, let $Y_1,...,Y_m$ be *m* random observations drawn from the distribution of Y given $X \leq x_0$, i.e. only firms with equal or less inputs than firm (x_0, y_0) are considered. The output-oriented order-*m* efficiency measure $\tilde{\gamma}_m$ (x_0, y_0) is defined for firm (x_0, y_0) as $\tilde{\gamma}_m (x_0, y_0) = \max(i=1,...,m)\ \{\min(j,...,q)\ (Y_i^j / y_0^j)\}$[10] with Y_i^j (y_0^j) being the j^{th} component of Y_i (of y_0 respec-

9 *DEA also rests on standard assumptions of homogeneity (firms can share the same technology), accuracy of data, monotonicity (disposability of inputs), ability to expand/contract activity (firms face no production limits), in addition to convexity (firms can combine their product).*

tively). It compares the relation between an observation's output to the best practice found among observations with equal or less inputs. In the context of the paper, it indicates by how much a firm's value-added has to increase in order for the firm to become best practice (efficient) given its level of capital, labour and R&D.

Here $\tilde{\gamma}_m(x_0, y_0)$ is a random variable because the firms against which (x_0, y_0) is compared are randomly drawn.

$$\hat{\gamma}_m(x_0, y_0) = \mathrm{E}[\tilde{\gamma}_m(x_0, y_0)|\mathrm{X} \leq \mathrm{x}_0] \approx \frac{1}{\mathrm{B}}\sum \tilde{\gamma}^b_m(x_0, y_0). \quad (6)$$

Daraio and Simar (2007, p. 72, 83) simplify the computation to a four-step procedure:

1. m peer DMUs are randomly drawn from the sample with replacements.

2. Pseudo *FDH*[11] efficiencies are calculated using this artificial reference sample.

3. Steps 1 and 2 are repeated *B* times[12], with *B* defining the accuracy of the computation. With contemporary ample computing power, B can be raised to e.g. 200, and the approximation in equation (6) can be replaced with an equality sign.

4. The final order-*m* inefficiency estimate $\hat{\gamma}_m(x_0, y_0)$ of country (x_0, y_0) is computed from the arithmetic mean of the pseudo *FDH* scores $\tilde{\gamma}_m(x_0, y_0)$.

Values of $\hat{\gamma}_m$ smaller or equal to one indicate efficiency and larger values represent inefficiency, since the final efficiency score is obtained from its inverse. Super-efficiencies, in which the final efficiency score exceeds one, arise because, in contrast to DEA, in each replication a DMU may be unavailable as its own peer. If at least equally efficient DMUs are absent from the draw, the comparison of the DMU against inefficient points shows super-efficiency. That is to say, an inefficient point appears more efficient than it is in reality. The true production frontier may lie above the estimated order-m frontier since the sample is not all-inclusive. It is therefore important to find an appropriate *B* and *m* to minimize the impact of super-efficient points. In practice, a relatively large *m* reduces the number of super-efficiencies and the impact of outliers on the results, while not merging with the FDH result.

4. Results

4.1 Firm-level results

The results show that on average indigenous firms were more efficient during the period. Foreign firms proved less efficient relative to the sample average of indigenous firms, with 0.83 relative to 0.85 average output-oriented DEA efficiency, respectively. The WTF benchmark applied by Sabirianova *et al*. (2005), i.e. the average efficiency of the top third of firms, gave an average efficiency score of 0.88 to foreign firms relative to a higher score of 0.92 for indigenous firms for output-oriented DEA.

Input-based DEA measures give indigenous firms a stronger lead: 0.77 vs. 0.82 respectively for foreign and domestic firms. The indigenous top third of firms beat their foreign counterparts by an even larger margin, i.e. 0.92 against 0.82, respectively. Foreign firms appear less able to minimize inputs given output (*ceteris paribus*). Differences between input- and output-based DEA prove that returns to scale are not constant, but are increasing in this case. Declining average efficiency over time can be explained by successful innovation and growth in leading firms, as lagging firms fall further behind the rapidly progressing frontier. This result also emerges as a result of scale economies, but even among small firms average efficiency declined over time.

10 In a one output case, this simplifies to $\tilde{\gamma}_m(\mathrm{x}_0, \mathrm{y}_0) = \max_{(i=1,\dots,m)}(\mathrm{Y}_i/y_0)$.

11 See Daraio and Simar (2007) for an explanation of the Free Disposal Hull (FDH).

12 Cazals et al. (2002) proposed a Monte-Carlo algorithm.

Table 4a. Input and output-based DEA and order-m[13] efficiency estimates for total sample ICT firms for 1990–2003.

		N	DEA min.	DEA max.	DEA mean
Finnish	Input-based	689	0.62	1	0.82
	Output-based	689	0.63	1	0.85
Foreign	Input-based	121	0.65	0.91	0.77
	Output-based	121	0.69	0.93	0.83
	Total	810			
			Order-m (200) min.	**Order-m (200) max.**	**Order-m (200) mean**
Finnish	Input-based	693	0.36	1.55	1.16
	Output-based	693	0.49	1.06	0.89
Foreign	Input-based	121	0.54	1.55	1.15
	Output-based	121	0.62	1.04	0.88
	Total	814			

Note 1: Efficiency greater than one equals full efficiency. Data source: Statistics Finland.

Table 4b. Input and output-based DEA and order-m efficiency estimates for top third of Finnish and foreign ICT firms for 1990–2003.

		N	DEA min.	DEA max.	DEA mean
Finnish	Input-based	222	0.86	1.00	0.92
	Output-based	210	0.87	1.00	0.92
Foreign	Input-based	46	0.78	0.91	0.82
	Output-based	38	0.86	0.93	0.88
			Order-m (200) min.	**Order-m (200) max.**	**Order-m (200) mean**
Finnish	Input-based	232	1.31	1.55	1.40
	Output-based	229	0.93	1.06	1.00
Foreign	Input-based	40	1.28	1.55	1.39
	Output-based	41	0.91	1.04	0.97

Note 1: Efficiency greater than one equals full efficiency. Data source: Statistics Finland.

13 Only results for m=200 are shown, but the relative results were fairly consistent regardless of the size of m. A relatively large m reduces the number of super-efficiencies and the impact of outliers on the results, while not merging with the FDH result.

Figure 3 below shows that in 1994–2000 the average technical efficiency of indigenous firms was above that of foreign firms, while Figure 4 shows it for the top third for 1994–2002. The absence of data on foreign firms prior to 1993 can be explained by the removal of the final barriers to foreign direct investment in that year. Inflows subsequently rose rapidly, being highest in 1997–2003. Judging by average output-based DEA efficiencies (Figure 3), foreign firms caught up with the indigenous industry in 2000. Figure 4 confirms the outcome for the top third of firms, except that indigenous firms kept their lead a little longer until 2002.

An important drawback of DEA methodology is that efficiency estimates are sensitive to sample size. Yet, the decline in DEA efficiencies in Figure 3 is not due to this curse of dimensionality, since the sample was pooled. As a robustness check, the first years of foreign inflows, 1993–1995, were removed from the comparison, but the average results were little affected.

As a second robustness check, robust order-*m* estimates following Cazals *et al*. (2002) were derived (lower sections of Tables 4a and 4b). Only results for regressions with *m*=200 are shown, but regardless of the size of *m*, the

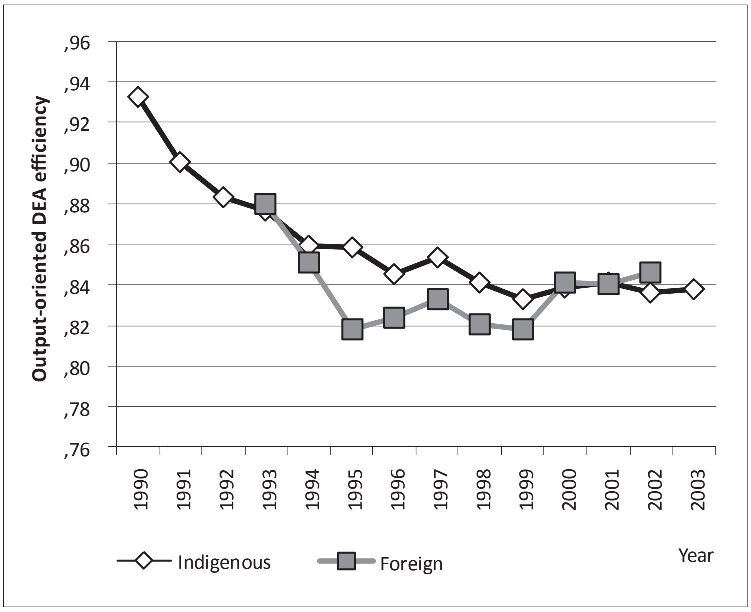

Figure 3. Average output based DEA technical efficiency in foreign and indigenous ICT firms in Finland, during 1990–2003.

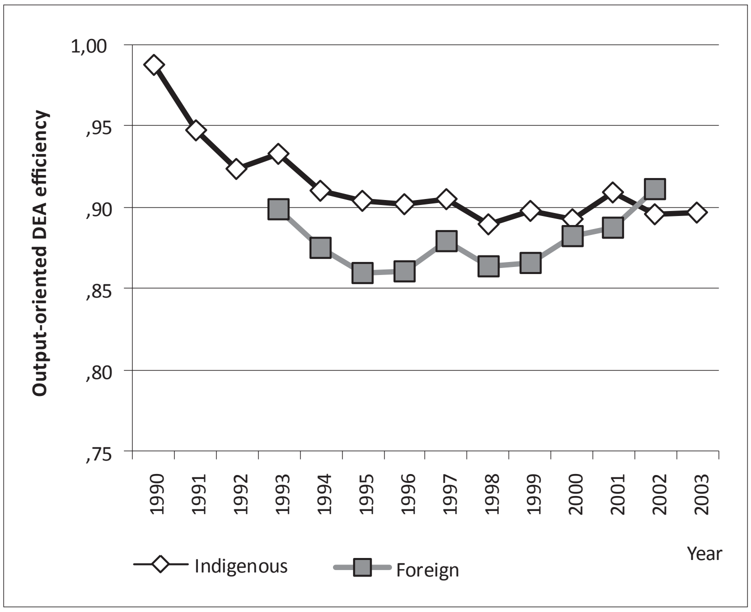

Figure 4. Average output based DEA technical efficiency of the top third of foreign and indigenous ICT firms in Finland, during 1990–2003

results were fairly consistent in showing indigenous firms to be equally or more efficient compared to foreign firms. The top-third input-oriented order-*m* results confirmed full efficiency, while the output-oriented results showed a small difference in favour of indigenous firms. These efficiency results turned out to be significantly higher, many showing full efficiency. Since foreign and indigenous firms also proved almost as efficient, one cannot conclude that indigenous firms lagged behind the global frontier. Rather the contrary: leading Finnish firms easily met the threshold set by foreign firms. Again, once observations preceding 1996 were removed, the average results remained almost the same. The slight difference between foreign and indigenous firms that remained was in favour of indigenous firms.

The difference between foreign and domestic firms was significant only for input-oriented DEA. The order-*m* methodology, however, mitigates standard deviations due to its robustness, i.e., exclusion of outliers in estimating efficiency. Nevertheless, it showed slightly larger average efficiency for domestic firms. The insignificance of t-statistics[14] is also a reflection of small size of the inflow of foreign firms in statistical terms, even if it was exceptionally large and significant for a small, gradually opened economy with a limited history in inward FDI. Considering in addition that the relative DEA results for foreign firms are not biased by the curse of dimensionality, and that being slightly larger on average, foreign firms were in a better position to benefit from scale efficiency, results suggest that if there was any difference in efficiency, it was in favour of indigenous firms.

4.2 Internationally harmonized data comparison results

As another robustness check, technical efficiencies were compared with EU KLEMS data to map average technology gaps in the electronics industry[15] between countries with DEA methodology. The results (Table 5) show relatively high efficiencies for both output- and input-based estimates suggesting that firms in different countries competed on fairly even ground. The Finnish industry was relatively close to the global frontier, even though one cannot conclude that it was on it.

Table 5. Average input- and output-oriented DEA efficiency (incl. R&D) estimates for KLEMS electronics industry.

	Input oriented DEA	Output oriented DEA
Austria (AUS)	0.9692	0.9593
Czech (CZE)	0.9980	0.9963
Denmark (DNK)	0.9950	0.9929
Spain (ESP)	0.9682	0.9779
Finland (FIN)	0.9907	0.9858
Germany (GER)	0.9705	0.9777
Italy (ITA)	0.9635	0.9717
Japan (JPN)	0.9614	0.9712
Netherlands (NLD)	0.8981	0.9013
Sweden (SWE)	0.9574	0.9578
United Kindgdom (UK)	0.9787	0.9827

This result does not contradict with the firm level results, as the firm level analysis focused on a small niche in a large electronics industry. Results may also be influenced by the extension of the dataset to 1980, i.e., far prior to the commercial launch of mobile phone innovations. Moreover, the KLEMS data cannot be adjusted to avoid double-counting of R&D, which may therefore bias the results in favour of countries carrying out little R&D.

5. Discussion and conclusions

Many scholars (Andrews *et al.* 2015, Criscuolo *et al.* 2015, Guadalupe *et al.* 2012, Saia *et al.* 2015) underscore the benefits of FDI to productivity growth and/or advocate policies related to knowledge diffusion to promote catching

14 Nonparametric models do not carry out statistical tests per se. Nevertheless, t-statistics could be calculated by hand from standard deviations.

15 European NACE rev. 1 industrial classification 30 to 33.

up with the global frontier. Yet, the evidence is not clearcut. In addition to negative impacts for indigenous industries in lagging countries (e.g., Aitken et al. 1999, Sabirianova *et al.* 2005), particularly high-tech firms are known to source leading edge firms in countries close to the world technology frontier, for cutting edge technologies (e.g., Criscuolo et al 2015, Nachum and Zaheer 2005, Griffith *et al.* 2006).

To explore whether policies to encourage spillovers can accelerate the loss of technological advantage, I seek to identify the predominant direction of spillovers in the Finnish ICT industry for 1993–2003 by comparing the relative efficiencies of foreign and domestic firms. Since the time period appears to have been rather exceptional related to the removal of final barriers to FDI in 1993, as well as the rise of Nokia Corporation to global market leadership, a repetition of the exercise today, or for some other time period, should produce different results. Nokia's revolutionary technology is likely to have been a major factor attracting technology-seeking FDI into Finland, but due to data secrecy requirements, it is not possible to separate its impact on overall results. In any case, control over such important and exceptional strategic assets may be rapidly lost.

Results show indigenous firms, if anything, more efficient than foreign firms during the sample period. Considering the lack of other motives, findings confirm the strategic asset seeking motive suggested by Pajarinen and Ylä-Anttila (2001) and van Beers *et al.* (2008). If there had been other motives, foreign investors might have been less footloose. In the 2000s, inward FDI began to fade and the sample of foreign firms with it (Figures 1 and 2), while offshoring became increasingly commonplace in the Finnish ICT industry. As mobile phone technology diffused in the 2000's, Nokia competed with production efficiency until Apple Inc. introduced its radical innovations.

I contribute to the literature by confirming the presence of the technology sourcing motive in cutting edge industries. In addition to indigenous firms in technologically lagging countries, my results show that frontier industries in leading countries may be equally hurt from FDI liberalization, although due to different reasons. Furthermore, I contribute to the literature by showing that superior foreign technology cannot be assumed *a priori* as Sabirianova *et al.* (2005) do for transition economies. Ample FDI inflows and superior efficiency offer an indicator of domestic firms' proximity to the WTF.

The policy implication is that innovation policy seeking to generate productivity growth by means of knowledge diffusion may, unless carefully designed, generate a net loss of strategic assets. Appropriate design of innovation policy, while considering the constraints of a small, open, locationally disadvantaged economy, is left for further research.

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