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Has Finland advanced from an investment to an innovation-driven stage?[1]

ABSTRACT

A widely entertained hypothesis states that as countries catch up with the global technology frontier, they need to adjust their strategies and public policies from investment to innovation. It has been claimed that low aggregate investment in Finland reflects such a structural change. The purpose of this paper is to explore whether this is true with more harmonized industry-level data and recent methodological advances. I estimate the technology gap for 1986 – 2003 with robust order-m frontier methodology, and thereafter regress innovation, investment and other variables on it by applying fixed-effects panel data methodology. Results show Finnish industries lagging far from the frontier, providing evidence against an innovation regime. Moreover, R&D intensity impacts on efficiency are industry related. R&D intensity increases does not therefore offer a universal remedy to catch-up. Other so-called determinants of efficiency suggest that improved absorption capacities (education) and new ICT technologies aid catch-up.

Key words: *investment, innovation, R&D, ICT, human capital, efficiency, technology gap, Finland.*
JEL codes: *F43, H25, O38, O47, E22.*

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1 INTRODUCTION

A widely entertained hypothesis states that as countries catch up with the global technology frontier, they need to adjust their strategies and public policies from investment to innovation promotion by means of R&D, new technologies and education. A technologically lagging country invests in capital embodied new technologies in order to catch up, in which case physical investment dominates innovation. Once the frontier has been reached, it is necessary to shift to innovation strategies to maintain technological progress, simply because frontier countries/ industries/ firms already apply best-practice technology and methods, and productivity cannot be improved by adapting existing technologies. Extensive growth arises from additional factor inputs, while quality-oriented intensive growth necessitates productivity growth arising from innovation and new technologies. This policy shift represents what Acemoglu et al. (2006) identify as the shift from (a) adaptation of existing technologies to (b) innovation to create new technologies. Porter (1990) calls it a shift from an *Investment-Driven Stage* (reliant on efficient manufacturing and outsourced service exports)2 to the *Innovation-Driven Stage*. At this stage nations compete on their "ability to produce innovative products and services at the global technology frontier using the most advanced methods" (Porter & Schwab 2008, p.51). To generate innovations, countries/ industries/ firms shift their investment focus from physical capital to R&D.

It has been claimed that Finland's reduced investment level reflects such a shift. As Figure 1 illustrates, ever since the early 1990s Finland's investment levels relative to GDP have lingered far behind the 1980s levels. Meanwhile, innovation inputs in terms of R&D expenditure have exceeded 3% of GDP ever since 1999, being among the highest in the world in relative terms[3]. Finland has been called an "information society". Sorjonen has argued that low investment reflects a shift from a resource-based economy to the information age, i.e. structural change from physical capital-intensive to R&D-intensive sectors in the economy (ETLA, 2006). According to the official evaluation of the Finnish national innovation system carried out in 2008, Finland is close to the global technology frontier, and this necessitates increasingly innovation-based strategies, in which context it is only natural for investment in physical capital to decline. "Since the late 1980s Finland has been moving from an investment-driven catching-up country towards an innovation-driven and knowledge-based economy." (TEM 2009, p. 130).

Now such claims seem premature. Even at the time, the evidence that Finland was indeed competing on innovation at the technology frontier was rather scarce and rested on shaky evidence, such as high R&D and education inputs, (past) success of the ICT industry and labor

2 Prior to this, Porter (1990) identifies the Factor or Resource Driven Stage (labour and natural resource endowment based competition).
3 Source: OECD, Main Science and Technology Indicators.

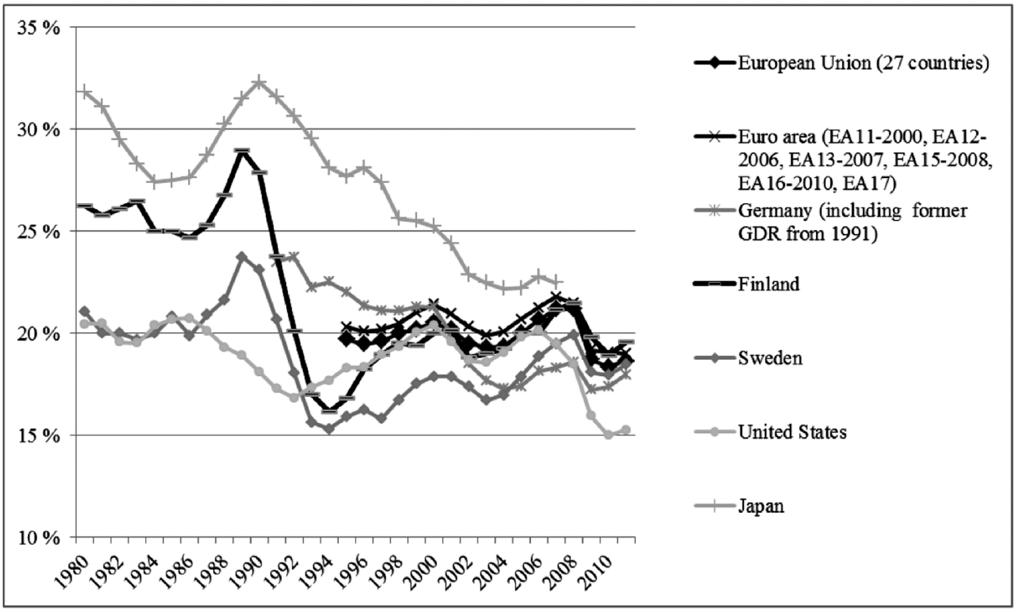

FIGURE 1: ***Gross fixed capital formation per gross domestic product, 1980–2011.***
Source: Annual national accounts, Eurostat (database).

productivity comparisons. The above evaluation of the national innovation system referred to labour and multifactor productivities (MFP) as evidence of Finland's frontier status (see TEM 2009, pages 106–107). Labor and MFP comparisons based on growth accounting typically suffer from stringent and often unrealistic assumptions, such as perfect competition4. According to Romer (1990), increasing returns to scale and imperfect competition are common characteristics of R&D activity at the technology frontier. Moreover, a labor productivity comparison does not take into account capital inefficiencies, which at least according to Pohjola (1996) were significant in Finland in the past.

In economics, the distance to the production possibilities frontier is measured by the technology gap, i.e. efficiency (see e.g. Coelli *et al.* 1997). Relevant empirical literature on technology gaps includes Kneller and Stevens (2006), who applied stochastic frontier analysis (SFA) to test human capital and R&D impacts on 9 manufacturing industries in 12 OECD countries between 1973–1991. They found inefficiency to be dependent on the level of human capital in the coun-

4 Particularly prior to the establishment of the competition authority in 1993, the assumption of perfect competition is misplaced in Finland.

try's workforce, while R&D effects were less robust. With a Malmquist index and DEA applied to a distance function, Färe *et al*. (2006) found that the efficiency-enhancing effects of capital accumulation in OECD industries between 1965–1998 plunge once human capital accumulation is included. Disregarding human capital, Bos *et al*., (2010), in contrast, found that R&D facilitates the absorption of existing technologies in 6 OECD countries over the period 1980–1997. Such state-of-the-art efficiency comparisons are the most appropriate methodologies for estimating the gap to the global technology frontier, as well as for exploring what factors contribute to it. Apart from a few niches e.g. in ICT (see e.g. Berghäll 2009), there is little Finnish evidence of a technology frontier status in the first place, nor of catching up with it.

The purpose of this paper is to fill this gap by applying harmonized international data and state-of-the-art methodology to estimate the technology gap and its determinants. Using empirical evidence, I therefore contribute to the debate on whether Finland has indeed advanced to compete on innovation at the technology frontier. While it is not possible to obtain exact technology gap measures due to the lack of globally harmonized data, it is nevertheless possible to establish a minimum technology gap for sample countries. If there is a gap in the sample, the true gap to the world technology frontier is likely to be wider still. I shall thereafter explore whether innovation or investment have reduced the gap during the sample period.

The data sample is drawn from the harmonized industry-level EU KLEMS database[5], which includes measures of the quality of physical capital services (ICT and other) and human capital (level of education). I apply order-*m* methodology in the estimation of actual competitive advantage of Finnish industries as defined by their relative distance to the technology frontier. Robust nonparametric order-*m* methodology mitigates the impact of outliers and errors, while avoiding simplifying assumptions with respect to the error term, the nature of competition or economies of scale etc, which plague growth accounting and earlier non-parametric and parametric efficiency estimation methods. In the second stage, I explore the effects of the most likely determinants, such as R&D, human capital, ICT capital, and the physical capital intensities of the technology gap, using fixed-effects panel data methodology, to explore whether innovation or investment have been significant in closing the gap.

The results show Finland lagging far behind the frontier. Nevertheless, Finland does not appear to be in an investment regime, although investment in new ICT technologies seems to narrow the technology gap. Improved absorption capacities, in terms of R&D and education, also aid catch-up. The results are presented and discussed in more detail in section 4. Prior to them, the methodology is presented in section 2 and the data in section 3. The conclusions and policy implications are summarized in the final section, 5.

5 Available at www.euklems.net. See Inklaar and Timmer (2008) for a description.

2 METHODOLOGY

Ever since Farrell (1957) pointed out that the production possibility frontier can be identified from extreme observations in the data, efficiency estimation methodologies have been developed. Microeconomic productive efficiency comes from the long-term equilibrium in perfectly competitive markets, when average costs are minimized on the average cost curve, (true production frontier in Figure 2). An individual firm's or production unit's relative shortfall from the theoretical frontier, due to various market imperfections and other causes, equals its technical (productive or x-efficiency) inefficiency, i.e. the technology gap. Data Envelopment Analysis (DEA) is a straightforward application of Farrell's insight that simply seeks the points that maximize output given inputs (output-oriented measure) or minimize inputs given output (input-oriented measure). The most efficient firms receive a score of one, and less efficient firms a score somewhere below one, but above zero. The standard assumptions that DEA imposes include convexity of the production set and strong disposability of inputs and outputs. A related methodology, the Free Disposal Hull (FDH), introduced by Deprins, Simar and Tulkens (1984), removes the convexity assumption, and is therefore more applicable and consistent with situations involving indivisibility of inputs and outputs, and economies of scale and specialization. The major drawback of both nonparametric efficiency estimators is the absence of an adjustment for outliers6, noise or simple mistakes in the data. Both impose assumptions on the production function or technology, and frequently require large datasets to reach meaningful estimates.

$$\textit{Output} = f(\textit{inputs}) + \textit{efficiency} + \textit{random error} \qquad (1)$$

In parametric efficiency estimation, similar to equation (1), the error term is divided into a random error part and a systematic inefficiency part. Hence strict exogeneity of the random error term and the variables is assured. The systematic part of the error term, i.e. inefficiency, can be tackled subsequently by analyzing its determinants. Parametric methods, such as stochastic frontier analysis, are less sensitive to outliers than nonparametric methods, but are sensitive to the underlying assumptions and number of observations. Meanwhile, growth accounting by index methods, such as Divisia, Malmqvist, Solow and Kendrick indexes, typically require price data and assume constant returns to scale, confusing technical efficiency with scale efficiencies.

2.1 Order-*m* estimation of the technology gap

I apply the robust order-*m* method, introduced by Cazals *et al*. (2002), to estimate the distance to the technology frontier in the first stage of the analysis. This represents significant progress in overcoming the problems related to traditional nonparametric estimators, such as the mitigation

6 Coelli, Rao and Battese (1997).

of outlier impacts, without imposing stringent assumptions on convexity, structural form, or technology across firms, industries and countries. Instead of benchmarking a decision-making unit (DMU) against the best-performing peer in the sample, as e.g. in DEA, order-*m* benchmarks DMUs with respect to the expected best performance of a sample of *m* peers. While order-*m* does not remove measurement error, this varying coverage of observations excludes and includes outliers in the sample on which efficiency is estimated, thus mitigating their impact as the exercise is repeated numerous times. The larger the number of random draws, the more robust the estimate. However, parameter *m* should not be too high as not to merge with the FDH result and lose the advantages of the partial frontier approach.

Formally, let $Y_1,\ldots,Y_m$ be *m* random observations drawn from the distribution of *Y* given $X \leq x_0$, where y represents output and x inputs. Hence, only countries with equal or less inputs than country (x_0, y_0) are considered. The output-oriented order-*m* efficiency measure $\tilde{\lambda}_m(x_0,y_0)$ is defined for country (x_0,y_0) as $\tilde{\lambda}_m(x_0,y_0) = \max(i=1,\ldots,m)\ \{\min(j,\ldots,q)\ (Y_i^j / y_0^j)\}$ with Y_i^j (y_0^j) being the j^{th} component of Y_i (of y_0 respectively). It compares the relation between an observation's outputs to the best practice found among observations with equal or less inputs. In the context of the paper, it indicates by how much a country's value-added has to increase in order for this country to become best practice (efficient) given its level of factor inputs. Here $\tilde{\lambda}_m(x_0, y_0)$ is a random variable because the countries against which (x_0, y_0) is compared are randomly drawn. 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 replacement.
2. Pseudo FDH efficiencies are calculated using this artificial reference sample.
3. Steps 1 and 2 are repeated *B* times, with *B* defining the accuracy of the computation.
4. The final order-*m* inefficiency estimate $\tilde{\lambda}_m(x_0, y_0)$ of country (x_0, y_0) is computed from the arithmetic mean of the pseudo FDH scores $\tilde{\lambda}_m(x_0, y_0)$:
5. $$\hat{\lambda}_m(x_0,y_0) = E[\tilde{\lambda}_m(x_0,y_0) \mid Y \leq y_0] \approx \frac{1}{B}\sum_{b=1}^{B}\tilde{\lambda}_m^b(x_0,y_0). \quad (2)$$

Values of smaller or equal to one indicate efficiency and larger values represent inefficiency, since the final efficiency score is obtained from its inverse. A distinctive feature of order-*m* analysis is the so-called super-efficiencies, in which the final efficiency score can exceed one. Point A in Figure 2 is a super-efficient point. These arise because, in contrast to FDH and DEA, in each replication a DMU may be unavailable as its own peer. Hence a point on the order-*m* frontier maximizing output relative to inputs may be compared against inefficient points (such as B). As Figure 2 shows, the true production frontier lies above the estimated order-*m* frontier since the sample is not all-inclusive. In reality, for the same inputs output cannot be expanded to A, but it

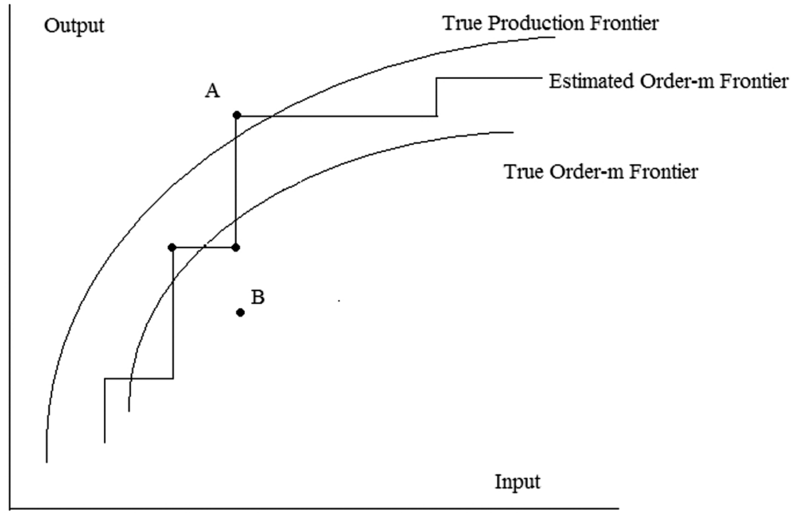

FIGURE 2. ***Output oriented order-m efficiency.***

can be expanded to points on the true production frontier. Figure 2 is a simplified one-input and output illustration, which does not attempt to cover all potential variations. Super-efficient points may also lie below the true production frontier, and true production and estimated or true order-*m* frontiers can be close to each other.

The output-based efficiency measure was selected, since it is reasonable to assume that competitive firms in open market-based economies maximize value-added rather than minimize costs. To ensure the appropriateness of the approach, industries at risk of being dominated by cost-minimization, such as the public sector and services in general, as well as heavily regulated industries, were excluded from the sample.

2.2 Fixed effects estimation of determinants of efficiency

Following the estimation of efficiency levels with order-*m* methodology, the obtained efficiency scores can be further explored to define the so-called determinants of efficiency. In the second stage, efficiency scores served as dependent variables in regression on potential determinants of efficiency (Z):

$$1/\hat{\lambda}_{it} = Z_{it}\beta + e_{it} \quad (3)$$

where $1/\hat{\lambda}_{it}$ indicates the estimated *m*-order efficiencies of the i^{th} industry observed in period *t*, the β's denote the parameter estimates of the regression function, and the *Z*'s the determinants of efficiency and *e* is the error term. The regression is estimated with OLS, as well as fixed-effects panel methodology[7]. The initial choice for fixed effects was carried out after running the Hausman specification test, which rejected a random-effects formulation[8]. The fixed-effects formulation of the above equation includes dummies to control for industry (φ_i) fixed effects and time-specific (γ_t) effects, such as economic cycles. The distribution of the error term e_{it} is assumed to be i.i.d. $N(0,\sigma^2_e)$.

$$1/\hat{\lambda}_{it} = \alpha + Z_{it}\beta + \varphi_i + \gamma_t + e_{it} \qquad (4)$$

3 THE DATA

3.1 The EU KLEMS Data

Distances to the technology frontier are computed from industry-level EU KLEMS and its linked databases (Inklaar and Timmer 2008) for the period 1986-2003[9]. The EU KLEMS2003[10] project was a sizable effort to construct a harmonized database to estimate economic growth, productivity, employment creation, capital formation and technological change at the industry level. The database was specifically designed to generate high-quality comparative assessments of productivity growth and divergence, skill formation, technological progress and innovation.

The resulting 63-industry breakdown for the EU's 25 Member States as well as for the US, Japan and Canada, from 1970 onwards (1990 for the recently acceded Member States) is in practice much more limited in data availability. Due to various mismatches in data availability and lack of initial purchasing power parities (PPPs)[11] for the base year (1997) and the base country (Germany), the availability of R&D and education-level data, data checks, and the exclusion of regulated industries, the initial dataset for efficiency estimation dwindled to an unbalanced panel of 11 countries and 13 (2-digit European NACE revision 1 classification) industries for the period 1986 – 2003 (Table 1). The total number of observations in the final Finnish sample declined to 227.

7 See e.g. Greene, 2007 for a detailed presentation of fixed effects estimation.
8 See e.g. Greene, 2007 for a detailed presentation.
9 It can be found at www.euklems.net.
10 Source: Productivity in the European Union: A Comparative Industry Approach (EUKLEMS2003) , Project Description http://www.euklems.net/project_site.html.
11 PPPs represent the price ratio of a product or bundle of products between two countries.

TABLE 1. ***Industries* and countries available in the data sample for 1986–2003. Data source: EU KLEMS database.***

	AUS	DNK	ESP	FIN	ITA	JPN	NLD	UK	Total
15t16	17	18	18	18	18	18	18	18	143
17t19	17	18	18	18	18	18	18	18	143
20	17	18	18	18	18	18	17	18	143
21t22	17	18	18	18	18	18	18	18	142
23	17	0	18	11	18	18	17	18	143
24	17	18	18	18	18	18	17	18	117
25	18	18	18	18	18	18	16	18	142
26	18	17	18	18	18	18	18	18	142
27t28	18	18	18	18	18	18	18	18	143
29	18	18	17	18	18	18	18	18	144
30t33	18	18	18	18	18	18	17	18	143
34t35	18	18	18	18	18	18	18	18	143
36t37	18	18	18	18	18	18	17	18	144
Total	228	215	233	227	234	234	227	234	1832

Industry notations: 15t16 Food, beverages and tobacco, 17t19 Textiles and leather products, 20 Wood, 21t22 Pulp, paper, printing and publishing, 23 Coke, refined p1etroleum and nuclear fuel, 24 Chemicals and chemical products, 25 Rubber and plastics, 26 Other non-metallic mineral, 27t28 Basic metals and fabricated metals, 29 Machinery, nec., 30t33 Electrical and optical equipment, 34t35 Transport equipment, 36t37 Manufacturing nec; recycling.

** Country notations: AUS Australia, DNK Denmark, ESP Spain, FIN Finland, ITA Italy, JPN Japan, NLD Netherlands and UK United Kingdom. The industries are classified according to the European NACE revision 1 classification, which is very close the International Standard Industrial Classification (ISIC) revision 3.*

For maximum homogeneity, all countries and industries lacking R&D data were removed, and the sample was restricted to industry only[12]. All public and regulated industries were excluded from the sample, because they are more likely to be cost-minimizing industries, thus necessitating a different input-oriented approach. These include agriculture and fishing, mining, electricity, social services, public administration, education, health, and other social services. In contrast, market-based industries can be assumed to maximize output or revenue, requiring a similar output-oriented estimation approach.

12 This results in the exclusion of only construction from the final panel.

Since the sample countries are all developed countries, one can assume that they are reasonably close to the world technology frontier (WTF). The data set excluded the largest developed country and R&D investor, the US[13], which, combined with the exclusion of some other countries from the sample due to a lack of harmonized data, may cause underestimates of the technology gaps to the frontier.

To obtain PPPs, the EU KLEMS website provides initial levels for the benchmark year 1997 for all 25 countries and industry levels. PPPs were computed from the available data following Timmer *et al.* (2007, p.49-50). Industry-specific PPPs for gross output are available for all countries c and industries j for 1997 ($PPP_{c,j,1997}$). Country aggregations (TOT), however, were unavailable for purchasing power parity (PPP) comparisons. The base country for the PPPs is Germany (G). The PPPs were back- and updated to cover the data period (t), using gross output, value-added or input price deflators (P^{Y}, P^{VA} or P^{II}) for each country c relative to Germany (G) at a detailed industry level". Based on the available data, I computed PPPs from equation (7) provided by Timmer *et al.* (2007, p. 49–50) below.

$$PPP_{c,j,1997} = \frac{P^{Y}_{c,j,t} / P^{Y}_{c,j,1997}}{P^{Y}_{G,j,t} / P^{Y}_{G,j,1997}} * PPP_{c,j,t} \quad (7)$$

A major advantage of the EU KLEMS data is the availability of ICT capital services in addition to traditional physical capital services, i.e. flows derived from the stock of physical assets and software, estimated as a capital income-weighted average of the growth rates of each asset. Short-lived assets such as inventories, equipment and software provide more services per unit of stock than long-lived assets such as structures and land. Hence capital services are not sensitive to depreciation assumptions. Moreover, the disaggregation of capital into non-ICT and ICT, and labor by the level of education allows their influence to be considered already in the estimation of efficiency. Kneller and Stevens (2006), for instance, found that human capital has a direct impact on the production technology, and not just on the efficiency, in which it is applied[14].

The capital variables are calculated separately for ICT and non-ICT capital based on capital services per hour worked (CAPIT_QPH) in purchasing power parities and hours worked (H_EMP). The labor variable is hours worked by high, medium, and low-skilled employees, thus adjusted for human capital.[15] The data is deflated to 1995 prices with the price indexes available (i.e the gross output, value-added and intermediate input price indices). The descriptive statistics applied

13 This is not necessarily a drawback, since the mere size of the US makes it an outlier.
14 There has been some controversy on this point, with Benhabib and Spiegel (1994), Pritchett (1996), Islam (1995) opposing, and Mankiw, Romer and Weil (1992), Miller and Upadhyay (2000) and Bloom, Canning and Sevilla (2002) supporting.
15 R&D was excluded from the order-*m* efficiency estimation to avoid double counting, which arises because over half of R&D expenditure is typically used to employ highly educated researchers and engineers (Hall, 2002).

to the order-*m* efficiency analysis are presented in Table 2. Figure 3 shows their average evolution over the sample period.

TABLE 2. ***Descriptive statistics for order-m efficiency analysis, including all countries for the period 1986–2003. Data source: EU KLEMS database.***

Production function variables	N	Min.	Max.	Mean	Std. Dev.
Value-added	1832	26.2	266975.6	13262.9	22105.2
Non-ICT capital	1832	47.0	77143.0	4386.8	8130.4
ICT capital	1832	1.1	17955.4	453.9	1130.3
Hours worked by high. educated	1832	.12	986.4	56.5	131.4
Hours worked by med. educated	1832	2.2	3395.4	343.2	537.0
Hours worked by least educated	1832	.45	1792.3	139.0	226.2

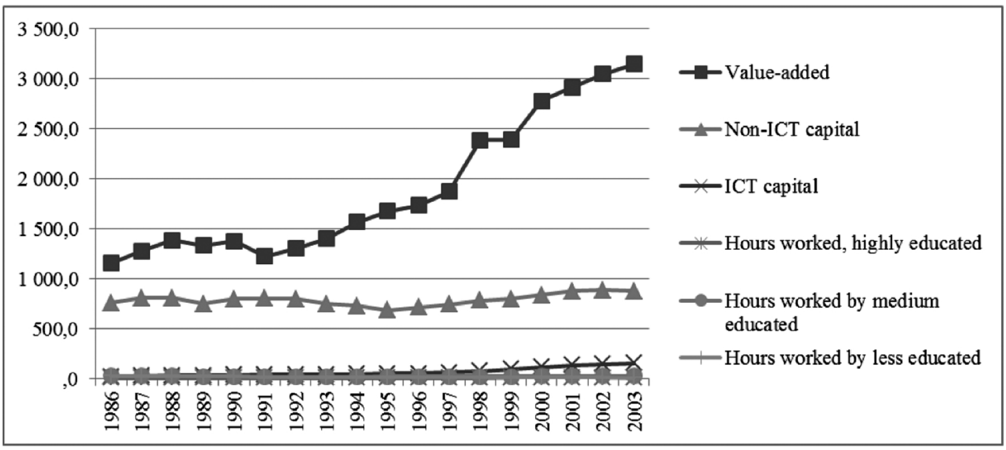

FIGURE 3. ***Average evolution of factor inputs and value-added, 1986–2003.***

The period 1986–2003 represents an era of profound transformation, during which Finland moved from a reliance on Soviet barter trade to become one of the world's leading high-tech exporters.[16] The 1980s represents an era of financial deregulation and liberalization, which led to a severe recession in Finland in the early 1990s and floatation of the exchange rate in 1992. Policywise, the recession marked a decisive shift from the prior capital accumulation, energy and material-

16 In particular, Nokia became a leading global mobile handset brand.

intensive model to a knowledge-based growth strategy combined with reliance on R&D and human capital[17] (see e.g. Kiander et al., 2006). As discussed, the investment level dropped markedly in the early 90s economic crisis (Figure 1), and innovation policy gained increasing clout thereafter. The post-recession period witnessed a rapid ICT manufacturing-led recovery, and accession to the EU (in 1995) and subsequently to the euro towards the end of the millennium. After 2003 the growth trend continued for several years before the financial meltdown on Wall Street resonated to northern Europe, and competition intensified with technological breakthroughs, such as the iPad.

3.2 Determinants of efficiency

The potential determinants of efficiency motivated by economic theory are limited by the availability of data. Major advances in economic theory with respect to innovation and frontier technology have included the advent of the new growth theory (Abramovitz 1986, Romer 1990, etc.) and a revival of Schumpeterian theories, which led, in the 1990s, to a widespread replacement of prior investment promotion by innovation-based growth models. The original Romer (1990, p.98) model emphasized human capital, but was subsequently complemented (e.g. Lucas 2002, Aghion and Howitt 1998, Grossman and Helpman, 1991) with a broadened focus including R&D and other knowledge-generating or diffusing efforts, including national science and technology policies. With the accumulation of empirical research, the R&D intensity and innovativeness of the technology frontier (Griffith, Redding, and Van Reenen (2004) has been well established. According to theory, if Finland is indeed close to the estimated frontier, it can also be close to the true frontier, and innovation, rather than investment, would increasingly be needed to maintain technological progress.

If there is a gap with the estimated frontier, one can then estimate what factors have been most significant in influencing it. If the gap is small, innovation should be conducive to efficiency. The R&D stock influences own innovation, as well as technology absorption, i.e. the two faces of R&D discussed by Griffith et al. (2004). Along with R&D, human capital helps absorb new technologies and knowledge produced by others, not only by adding to the technology stock, but also by influencing the efficiency with which the technology is applied in production. Countries are well known to differ in their ability to adopt foreign technologies[18], i.e. their absorptive capac-

17 Finland does not enjoy natural endowments that would give it a comparative advantage in energy or capital-intensive production. In contrast, it enjoys a relative abundance of highly educated employees.

18 In small countries, foreign technologies can be more important than their own R&D. A seminal reference is Eaton and Kortum (1999), who found that positive R&D externalities from abroad account for 40% of productivity growth in the US in 1988.

ity (Arrow 1969), but investing in human capital (Abramovitz 1986, Cohen & Levinthal 1989) or R&D (Fagerberg 1988, Verspagen 1991) is believed to enhance this capacity. Griffith et al. (2004) and Kneller (2005) have also obtained supportive evidence for this. Fagerberg (1994) has emphasized a minimum threshold in the efficiency with which human capital can effectively mediate technology transfer.

Human capital influences the distance from the technology frontier because different countries, industries and firms are likely to employ human capital with differing efficiencies. ICT technologies, which are frequently capital-embodied, have also been found to accelerate productivity (e.g. Brynjolfsson 1993 and Stiroh 2002), although the evidence is less convincing in Europe than in the US (see e.g. Vijselaar and Albers 2004 or Koszerek *et al.* 2007). As with human capital, it is plausible to assume that they influence both the technologies applied in production, i.e. movements of the technology frontier, as well as the efficiency with which technology is applied, i.e. the distance from the frontier. With some modifications, physical, ICT and human capital are therefore included among the determinants of efficiency, in addition to the efficiency-level analysis.

According to Huovari and Jalava (2007, p. 17), the expansion of trade in intermediate inputs reflects imported embodied technical progress in practice. Material intensity may therefore, along with services intensity, signal outsourcing and off-shoring in a fragmented globalized economy. These intensities were computed from intermediate services and material inputs related to gross output. Energy intensity was computed similarly. Energy intensity is related to the type of industry, as well as production methods.

Taxes and subsidies are the most direct form of public sector involvement. The TXSP variable in the KLEMS data, which measures (other) taxes minus subsidies to production, was used to construct the net tax intensity variable (net taxes per value-added). The direction of its impact on efficiency is not clear *a priori*. While high net tax intensity may drain resources from investment in the private sector, it may also make the remaining investments more productive relative to what they would have been if all potential investments had been undertaken. There are also indirect effects from public spending on infrastructure, education and health, which may generate returns in terms of improved private sector productivity relative to the opportunity cost of taxes.

Market size was computed by summing gross output by country. As a determinant of efficiency it indicates returns to scale and market size expansion by means of economic integration. Market size is expected to raise efficiency, since large size allows firms to enjoy economies of scale and scope. Due to the size of the variable, logarithms were taken to obtain comparable measures.

Competition is also related to market size, but was based on profit margins due to trade liberalization. The Lerner index (Lerner 1934) is a measure of the lack of competition based on profit margins[19] estimated from gross operating surplus divided by value-added.

The potential determinants of value-added efficiency available in the data include R&D intensity[20], ICT capital intensity, physical or non-ICT capital intensity, human capital intensity, but also material input intensity, energy intensity, services intensity, net tax intensity, market size, and competition. The intensities of ICT services, traditional physical capital services, and human capital (share of highly educated persons) were estimated relative to total hours worked. R&D intensity was also computed by relating the R&D stock[21]similarly to the number of hours worked. Material and services intensities were computed from intermediate services and material inputs related to gross output. Energy intensity was computed similarly. The descriptive statistics are presented in Table 3.[22]

TABLE 3. ***Descriptive statistics for determinants of efficiency for Finnish market-based industries, 1986 – 2003. Data source: EU KLEMS database.***

	N	*Minimum*	*Maximum*	*Mean*	*Std. Dev.*
Technical efficiency	**244**	**.07**	**1.01**	**.42**	**.31**
Non-ICT capital intensity (phw)	**244**	**.15**	**36.25**	**11.3**	**9.74**
ICT capital intensity (phw)	**244**	**.02**	**6.91**	**.93**	**.97**
Human capital intensity (highly ed. phw)	**244**	**9.95**	**33.75**	**21.48**	**5.17**
Energy intensity (per GO)	**244**	**.00**	**.83**	**.06**	**.14**
Material intensity (per GO)	**244**	**.02**	**.65**	**.45**	**.12**
Services intensity (per GO)	**244**	**.05**	**.24**	**.13**	**.03**
Log market size (sum of GO)	**244**	**12.00**	**12.51**	**12.30**	**.13**
Lack of competition (Lerner)	**244**	**.01**	**.27**	**.13**	**.05**
Net tax intensity	**244**	**-.11**	**.00**	**-.01**	**.01**
R&D intensity (phw)	**244**	**.10**	**97.15**	**11.41**	**16.46**

Note: phw = per hours worked. ; GO= gross output.

19 In microeconomic theory profits decline to zero when competition becomes perfect.

20 R&D intensity may leave the global technology frontier unaffected if innovation fails. Some prefer patents as these measuresinnovation output. However, in both cases productivity and consequently the global technology frontier may be unaffected.

21 The R&D stock data available in the EU KLEMS linked database is compiled from annual R&D expenditures from the "OECD Research and Development in Industry Database" (ANBERD). The years 1987-2004 are classified according to ISIC3. The perpetual inventory method was applied to calculate the stock with a 12% rate of depreciation as in Nadiri & Prucha (1996).

22 The initial estimations also included the exchange rate and total factor productivity (TFP) as control variables, but were subsequently removed. As a robustness check, TFP correlated with efficiency effects, while exchange rate impacts merit a separate detailed inspection.

In addition to the stability of R&D personnel and the resulting high serial correlation of R&D relative to other investment (Hall, 2002)[23], shocks to R&D inputs are moderated by the use of R&D stocks instead of flows. Because of these stabilizing effects, past shocks to efficiency are unlikely to have significant impacts on current R&D stock intensities. The use of stocks is also motivated by the significant lags in the productivity effects of R&D. According to Rouvinen (2002), R&D influences productivity with a lag of up to four years.

4 RESULTS

4.1 Relative Efficiency

The results reveal that Finland falls well short of the sample technology frontier. In fact, Finland was on average the least efficient country in the sample (Figure 4). Moreover, the distance to the frontier showed no shift over the period, rather a gradual decline.

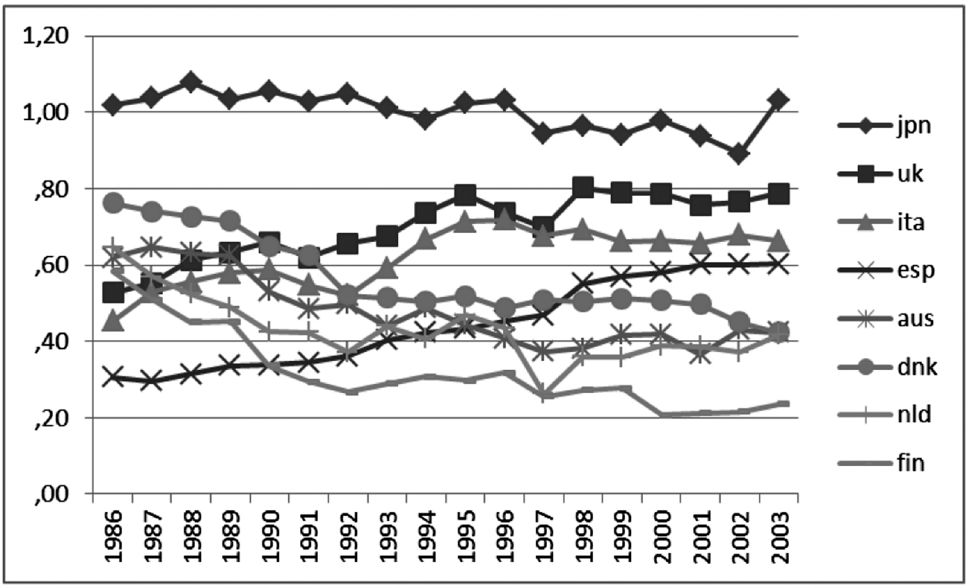

FIGURE 4. ***Average country* order-m efficiencies over time, 1986–2003.***

** Country notations: AUS Australia, DNK Denmark, ESP Spain, FIN Finland, ITA Italy, JPN Japan, NLD Netherlands and UK United Kingdom.*

23 According to Hall (2002), the high serial correlation of R&D relative to other investment is a well known fact. Research personnel and engineers to a large extent embed the firm's knowledge capital, which can therefore easily leak to competitors if the key researchers leave. Hence, firms are likely to be reluctant to let such employees go during downturns.

TABLE 4. ***Average order-m (m=200) output-based efficiency estimate[1] of value-added by country in purchasing power parity (PPP)*, for 1986–2003.***

Land	N	Minimum	Maximum	Mean	Std. Deviation
Average of all	1832	.04	2.78	0.57	.37
Australia (AUS)	228	0.11	1.07	0.48	0.27
Denmark (DNK)	215	0.06	1.01	0.57	0.39
Spain (ESP)	233	0.06	1	0.44	0.2
Finland (FIN)	227	0.07	1	0.32	0.27
Italy (ITA)	234	0.16	1.27	0.62	0.3
Japan (JPN)	234	0.06	2.78	1.00	0.43
Netherlands (NLD)	227	0.09	1.01	0.43	0.30
United Kingdom UK)	234	0.04	1.24	0.70	0.25

** PPP represents the price ratio of a product or bundle of products between two countries.*
[1] The FEAR program described in Wilson (2008) was applied to obtain the estimates.

Table 4 below shows large variation in country efficiencies. Several countries appear super-efficient. Since the sample may not include global technology leaders, Finland's gap with the world technology frontier is likely to be wider still.

4.2 Determinants of Efficiency

The determinants of efficiency estimation results for the OLS and fixed effects estimations are reported in Table 5. The model estimated (Model 1) is a standard OLS regression with no controls. The Baltagi-Li form of the Lagrange Multiplier (LM) test rejected the null hypothesis that the variances across industries were zero. Hence there were panel effects and OLS is inappropriate. In addition, the initial Hausman test results consistently favored fixed over random effects. Since the risk of omitted variable bias with random effects estimation is significant, random effects do not appear to be a correct model choice in any case.

The second model (Model 2) therefore includes industry fixed effects to control for fixed industry-specific differences. The third model (Model3) includes controls for time only. Model 3 has the virtue of controlling for cyclical (time) effects, i.e. economic cycles only, while it does not account for permanent industry-specific differences, in e.g. energy, capital or R&D intensity, as Model 2 does. The fourth model (Model 4) includes both time and industry fixed effects.

Controlling for economic cycles, model 3 attributes positive efficiency-enhancing effects for ICT and R&D intensities and competition, but negative effects for physical capital, human capital, and material intensities. R&D and ICT-intensive industries, as well as those with low profit mar-

TABLE 5. *Determinants of order-m efficiency for Finnish market-based industries, 1986–2003 panel.*

Variable	Model 1	Model 2	Model 3	Model 4
Constant	3.498* (1.372)	2.795* (1.291)	1.257** (.284)	-4.567* (2.204)
Capital int.	-.010** (.002)	-.009 (.009)	-.009** (.002)	.011 (.010)
ICT int.	.032 (.024)	.120** (.032)	.046* (.026)	.145** (.037)
Human cap. int.	-.020** (.003)	-.050** (.007)	-.015** (.004)	.027* (.016)
Energy int.	.123 (.271)	2.214* (.906)	.190 (.286)	1.076 (.995)
Material int.	-1.100** (.312)	1.848* (.753)	-1.049** (.328)	1.193 (.794)
Services int.	-.104 (.639)	3.111** (.791)	.090 (.635)	2.265** (.787)
Log market size	-.159 (.107)	-.220* (.093)		.269* (.161)
Lack of competition / Profitability	-1.625** (.524)	.623 (.653)	-1.932** (.564)	.125 (.750)
Net tax int.	.301 (1.049)	3.711** (1.063)	-.411 (1.114)	3.385** (1.103)
R&D intensity	.003** (.001)	.000 (.003)	.003* (.001)	-.004 (.003)
R2	.507	.676	.573	.742
No. obs.	227	227	227	227
Industry FE	No	Yes	No	Yes
Time FE	No	No	Yes	Yes
Industry*Time	No	No	No	No

***Significant at the 1% level; **Significant at the 10% level. Data source: EU KLEMS.*

gins, tend to be more efficient than capital, human capital and material-intensive industries. The positive R&D and negative capital investment effects are industry-specific.

If both industry and time fixed effects are controlled for, ICT, human capital, services and net tax intensities, as well as market size, have a significant positive impact on efficiency. Thus, regardless of the economic cycle and industry, high education and ICT investment have been among the best means for public policy to turn the trend from falling behind towards catch-up in Finnish industry. The positive impact of human capital in the final model is in line with theories of absorptive capacity (Arrow 1969, Eaton & Kortum 1996) and human capital (Abramovitz 1986, Cohen & Levinthal 1989), and the empirical findings of Kneller & Stevens (2006), Griffith et al. (2004), and Kneller (2005).

Across all models, net tax, competition, services, energy, ICT and R&D intensities have either an insignificant or significantly positive impacts on efficiency. In contrast, capital intensity has either a negative or insignificant impact on efficiency, depending on the model's controls. Material and human capital intensity, as well as market size effects, depend on the model.

The official evaluation of the Finnish national innovation system carried out in 2008 was not altogether wrong in its analysis. At least, “the high level of education and increasing technology inputs” (TEM 2009, p. 130) indeed reduced the technology gap. One cannot, however, truly speak of an innovation regime since the technology gap was wide, and it could be more effective to imitate technology leaders where possible, rather than engage in risky innovation. Higher R&D intensity levels may therefore be more related to structural change towards R&D-intensive (high-tech) industries, as the official evaluation of the Finnish national innovation system suggests (TEM 2009, p. 130). R&D intensity does not, however, raise industries automatically towards the technology frontier. Industries frequently invest in R&D to absorb foreign technologies, although statistically such imitation is typically categorized as innovation[24]. In any case, there is little evidence to support a shift since the late 1980s from “an investment-driven catching-up country towards an innovation-driven and knowledge-based economy” as claimed by TEM (2009, p. 130).

Efficiency only measures relative change with respect to the sample frontier, and the average sample efficiency change is zero, while underlying productivity growth can be negative or positive. Productivity growth in leading countries in the sample period has not, in all evidence, been negative. Spillovers from positive global technological progress can raise productivity growth. It is therefore possible that the global technology frontier advanced more rapidly elsewhere, resulting in a widening technology gap with Finland despite local technical change. The shortage is therefore not of innovation, but of absorption of foreign technologies. The evidence is in favor of a technology absorption regime/ stage, rather than of an innovation regime.

4.3 Correlations by industry

Average effects are likely to have varied widely across industries. Correlations in Table 6 gives an idea of the directions and magnitudes. The fact that efficiency correlates negatively or insignificantly with capital intensity in all industries shows the absence of an investment regime during the sample period.

R&D intensity correlates with efficiency in only two export-intensive industries: paper and pulp (21t22), and electrical and optical equipment (30t33) (Table 6). The negative correlation of efficiency with R&D intensity in other industries may result e.g. from their maturity with respect to the industry life cycle. Hence, only two industries appear to have been anywhere near an innovation regime. In consequence, the exodus of the ICT manufacturing industry, the flagship of Finnish innovation, is all the more disconcerting. This industry was the key high-tech engine that revived growth after the early 90s depression and raised R&D intensity to leading global levels. Off-shoring of production began already well before the recent adverse economic downturn in 2008.

24 For instance, the R&D survey of Statistics Finland categorizes products or processes new to the firm or the local market as innovation, even if they are not new on the global market.

TABLE 6. ***Order-m Efficiency Pearson Correlations with Determinants of Efficiency[1] by Industry[2].***

	Capital int.	ICT cap. int.	Human cap. int.	Energy int.	Material int.	Services int.	Size	Lack of comp.	Tax int.	R&D int.
Average N=227	-.223**	-.227**	-.317**	.510**	-.482**	-.067	-.067	-.252**	.035	-.089
15t16, N=18	-.850**	-.707**	-.853**	-.706**	.774**	-.568*	-.054	-.424	.317	-.869**
17t19, N=18	-.021	-.819**	-.765**	-.737**	-.731**	.067	-.091	-.399	-.731**	-.738**
20, N= 18	-.530*	-.649**	-.570*	.105	.059	-.383	-.290	-.318	-.244	-.627**
21t22, N=18	.434	.957**	.897**	.354	-.809**	.381	.229	.697**	.931**	.752**
23, N=11	-.135	.195	.158	.029	-.336	-.317	.158	.334	.514	-.193
24, N=18	-.601**	-.771**	-.836**	-.722**	-.179	-.252	-.261	.411	-.184	-.745**
25, N=18	-.474*	-.635**	-.661**	.613**	-.330	.499*	-.275	-.364	.099	-.574*
26, N=18	-.347	-.533*	-.518*	.577*	-.340	.145	-.315	.172	.223	-.531*
27t28, N= 18	-.782**	-.573*	-.730**	.602**	-.564*	.403	-.080	-.189	-.044	-.827**
29, N= 18	-.907**	.332	.559*	-.237	.705**	.572*	.241	-.514*	.881**	-.139
30t33, N=18	.374	.741**	.888**	.005	-.185	.887**	.237	.579*	.650**	.774**
34t35, N=18	-.371	-.720**	-.702**	.708**	-.106	.436	-.163	-.262	.193	-.806**
36t37, N=18	-.433	-.662**	-.681**	-.184	-.614**	.370	-.102	.559*	.421	-.573*

**. Correlation is significant at the 0.05 level (2-tailed). **. Correlation is significant at the 0.01 level (2-tailed).*

[1] Capital intensity; R&D intensity; Human capital intensity; Tax intensity; Subsidy intensity; ICT intensity; Services intensity; Energy intensity; Material intensity; Market Size; and Competition, respectively.

[2] Industry notations: 15t16 Food, beverages and tobacco, 17t19 Textiles and leather products, 20 Wood, 21t22 Pulp, paper, printing and publishing, 23 Coke, refined petroleum and nuclear fuel, 24 Chemicals and chemical products, 25 Rubber and plastics, 26 Other non-metallic mineral, 27t28 Basic metals and fabricated metals, 29 Machinery, nec., 30t33 Electrical and optical equipment, 34t35 Transport equipment, 36t37 Manufacturing nec; recycling.

In addition, services intensity, market size and net tax intensity proved positively associated with efficiency. Public sector intervention in terms of net tax intensity (taxes minus subsidies to production) seems on average to have been efficiency-raising. This can be explained by the fact that taxes are high for profitable enterprises, hence successful industries tend to pay taxes and net tax intensity is associated with efficiency. In key export industries, such as pulp, paper, printing and publishing (21t22), machinery, nec. (29), electrical and optical equipment (30t33), the correlation was positive. While it is natural that efficient firms pay more taxes, less expected is the finding in the data that net taxes have burdened the private sector only to the extent that subsidies may have distorted competition.

On average, services intensity seems to have contributed to efficiency over the entire period studied, rarely endangering efficiency. At the industry level, the average correlation was negative only in the wood-processing (20) industry. The positive effect of services intensity is in line with the rapid growth of outsourcing in Finnish high-growth sectors, found by Huovari and Jalava (2007, p. 17). In addition, the significant positive market size effects suggest that economic integration and globalization contribute to efficiency, as one would expect particularly with respect to scale and scope efficiency.

5 CONCLUSIONS

A widely entertained hypothesis holds that as countries catch up with the global technology frontier, they need to shift from investment (capital-embodied technology adaption) to innovation-based growth models. It has been argued that low aggregate investment in Finland reflects such a structural change. To explore whether this is true, I estimated the distance to the frontier using order-*m* frontier methodology on harmonized industry-level data for the period 1986 – 2003.

The results show that on average Finnish industries lie far from the frontier, with plenty of catch-up potential.[25] However, disregarding positive ICT capital intensity effects, there was no indication of an investment regime either. Past overinvestment in capital may continue to burden efficiency long into the future, but low aggregate investment may also reflect stuctural change from capital-intensive to R&D-intensive industries in the economy. Instead, improved absorption capacities (R&D and education) and absorption of new ICT technologies apparently aided catch-up, although the R&D intensity impacts turn insignificant once industry fixed effects are controlled for. Their positive impacts are therefore industry related, and raising R&D intensity does not present a universal remedy to industrial inefficiency. Moreover, the declines of the only two industries anywhere near an innovation regime, paper and pulp (21t22) and electrical and optical equipment (30t33), do not suggest a merry outlook to the Finnish innovation regime.

25 Though the sample ends in 2003, the fall in the share of high-tech in total exports from over 23% in 2000 to 7.5% in 2012 supports the conclusion. Source: Finnish Customs, 2014.

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