Innovation, Competition and Technical Efficiency

Elina Berghäll

VATT WORKING PAPERS

77

Innovation, Competition and Technical Efficiency

Elina Berghäll

Senior Researcher, VATT Institute for Economic Research, P.O.Box 1279,
FI-00101 Helsinki, Finland, Telephone + 358 40 304 5511, E-mail
elina.berghall@vatt.fi

Innovation, Competition and Technical Efficiency

VATT Institute for Economic Research
VATT Working Papers 77/2016

Elina Berghäll

Abstract

Contradictory empirical and theoretical evidence on the relationship between innovation and competition has been reconciled in a model that yields an inverted U-shaped curve. I test whether the predictions of the model are supported by the data with an unbalanced panel of firms for 1990-2003 in a high productivity growth, high-tech industry, Finnish ICT manufacturing. In particular, I investigate how well alternative, yet rigorous measures of innovation and the technology gap, such as R&D intensity, R&D elasticity, technical change, technical efficiency and total factor productivity fare with respect to competition measured by the Lerner index. The results prove sensitive to the choice of variable. Overall, the model is not supported by the empirical evidence of the industry.

1.   Introduction

By definition, fully efficient firms form the global technology frontier. Since the frontier represents the state of the art in technology, it responds to innovation only. Meanwhile neoclassical theory postulates competition to reduce productive inefficiency. Yet, the Schumpeterian paradigm (Schumpeter, 1934) recognised monopoly rent prospects of the innovator as the central innovation incentive. Hence firms at the frontier are frequently sheltered from intense competition. The theoretical model of Aghion *et al.* (2005), postulating an inverted U-curve shaped relationship between innovation and competition, has proposed a way to reconcile controversial empirical findings between innovation and growth and the contradictions of industrial organisation (e.g. Dixit and Stiglitz 1977) and endogenous growth models (e.g. Romer 1990, Aghion and Howitt 1992, and Grossman and Helpman 1991). The purpose of this paper is to explore the robustness of the predictions of the model on empirical evidence from an innovative industry subject to intense competition from abroad.

According to the model, new technological breakthroughs can establish significant leads in competition and increasing returns for a while, until laggards copy and catch up with the innovators. Innovation increases at low levels of competition, reaches an optimum, and thereafter declines as competition intensifies and begins to discourage innovations as monopoly rents from innovation decline. The inverted U-shaped interrelationship emerges from the escape competition effect at low levels of competition, which turns into a Schumpeterian effect as higher levels of competition begin to discourage R&D investment. As empirical predictions of the inverted U-model, Aghion and Griffith (2005, page 57) list that

1) additional product market competition (PMC) in frontier industries increases innovation;

2) *Vice versa*, additional PMC in lagging industries reduces or increases innovation only weakly;'

3) An increase in PMC in the economy on average reduces the share of frontier industries and raises the average technological gap. "The average fraction of frontier sectors decreases – namely, the average technological gap between incumbent firms and the frontier in their respective sectors increases – when competition increases";

4) As a result, the general effect of additional PMC on the economy follows an inverted U-shape. Additional PMC encourages innovation at low levels of competition, but discourages it at high levels of PMC.

In efficiency terms, this means that additional PMC in efficient industries increases innovation, and *vice versa* additional PMC in inefficient industries reduces or increases innovation less, and that additional PMC in the economy on average reduces the share of frontier firms or raises average inefficiency. In other words, there is a positive relationship between inefficiency and (additional)

competition at the industry or economy-wide level. The more efficient the economy on average, the more inefficiency increases as a result of competition.

Aghion and Griffith (2005) refer to productivity in the context of the innovation – competition dichotomy. They (page 49) state that *"while competition appears to be effective at improving productivity levels in satisficing firms (those plagued with agency and managerial slack problems), this does not automatically translate into higher rates of productivity growth in such firms relative to more profit-maximizing ones."* In other words, competition can be effective in raising productivity in inefficient firms relative to more efficient firms, but not its growth rate. Innovation has been proxied by the level and growth rate of TFP also by Nickel (1996), who found evidence that more intense PMC is reflected in more rapid TFP growth. In practice, while innovation may raise productivity, high innovation input or output does not automatically translate into TFP growth. In addition, the use of productivity for innovation confuses the relationship of innovation with the frontier, also referred to in the Aghion et al. model. In economic theory, inefficiency is a relative term that measures the gap between the production possibilities frontier and the realized output. Productivity improvements, in contrast, reduce inefficiency in lagging firms, but increase it if the improver is a frontier firm. If firms are inefficient, competition is more likely to raise efficiency. Moreover, although all may be pushed to seek ways to improve their efficiency, the gap between successful firms and the rest may widen and average inefficiency increases.

In addition to productivity, Aghion et al. (2005) applied patents as a measure of innovation and the Lerner index as a measure of competition. Subsequent literature, surveyed in the next section, has applied further measures of innovation and technology gaps. Tingvall and Poldahl (2006) test the predictions of the model on firm-level data, and find that the inverted U-shaped relation is supported by a Herfindahl index measure of competition, but not by a price cost margin.

I contribute to the literature by testing whether results correspond to the theory if more rigorous determinants of innovation and technology gaps are applied, such as R&D intensity and technical efficiency. In particular, I apply frontier methodology to estimate the technology gap, and R&D intensity, R&D elasticity and technical change as proxies for innovation. The dataset is from an innovative and competitive industry, the Finnish ICT manufacturing industry during a period of rapid technological change, 1990-2003. At the time, the industry attracted technology adopters from abroad in the form of FDI. Hence, one can assume it to have been close to the frontier, while being open to intense competition from abroad.

According to the predictions of the theory, if the industry was indeed at the frontier at the time, average technical efficiency in Finnish ICT manufacturing should be high, competition neck-and-neck on the upward sloping part of the inverted U-curve. That is, additional competition should increase innovation. I seek answers to questions, such as is average technical efficiency high in the industry? Has competition increased technical inefficiency or innovation? Does technical inefficiency or total factor productivity (TFP) provide a good measure of innovation? The results prove sensitive to the choice of variable. Overall, the model is not supported by the empirical evidence of the industry.

The next section reviews empirical applications of the theory. I present the data and variables in the third section, and methodology in the fourth section. The fifth section summarises the results and their implications are briefly discussed in section 6.

2. Related Theories and Empirical Findings

The literature on firm performance, competition, sources of innovation and industrial organisation extends beyond the Schumpeterian paradigm (Schumpeter, 1934), which recognised monopoly rent prospects of the innovator as the driving force of innovation. Arrow (1962) identified the profit appropriation opportunity of the new comer to arise from the public good properties of knowledge (spillovers). Bain (1951) found that rates of return of firms in relatively more concentrated industries were significantly higher than those in un-concentrated ones, interpreting it as evidence in favour of the now so-called structure conduct performance paradigm in industrial organization theory.

Demsetz (1973 and 1974) challenged this view by arguing that abnormal profits reflect higher efficiency levels rather than monopoly profits, and that researchers need to distinguish between the impacts of efficiency on performance from those of market power. To test the cause, if collusion is present, then smaller firms should earn similar (if not higher) rates of return than large firms. If in contrast, efficiency is driving the rates of returns, then a positive correlation with the industry rate of return should only emerge for large firms. Similarly Carlsson (1972) found productive efficiency to increase with producer concentration, and explained it by the small size of the Swedish market relative to economies of scale in manufacturing. Caves (2007) has argued that efficiency rents and monopolistic profits (due to the dominance of one large buyer firm over many suppliers), may also coexist. The resource-based view (RBV) of the firm holds that if short-run competitive advantages are heterogeneous in nature and not perfectly mobile, they can be transformed into a sustained competitive advantage generating abnormal returns (Peteraf 1993, p180).

Most traditional models of product market competition and innovation predicted a detrimental impact from competition on innovation and growth. These include e.g. the Hotelling linear model and the monopolistic competition model by Dixit and Stiglitz (1977). Dasgupta and Stiglitz (1980) propose that the anticipation of future competition deter entry and hence competition today. In the mid-1990's, empirical findings began to contradict these theories, but the models applied so far suffered from linearity. The only exception was Scherer (1965), who showed how patenting activity increases with firm size, but with diminishing patenting relative to size. He questioned the role of large monopolistic conglomerates in technological progress, i.e., the Schumpeterian (Mark II) model of competition, innovation and growth. His view received support from subsequent empirical research. (Aghion & Griffith, 2005).

Empirical findings of a positive relationship between product market competition and productivity growth have generated new models and theories on gradual technological progress that evolves step by step. That is first, lagging firms need to catch-up with market/technology frontier leaders by means of imitation, before they attempt to escape competition by means of innovation. (See e.g., Aghion, *et al.* 1997, or Aghion *et al.* 2001). Also in line with the theory, Aghion, Bloom, Blundell,

Griffith and Howitt (2005) evaluate the predictions listed above with patent data on UK firms, and find that the inverted U-curve is steeper in more neck and neck (efficient) industries. E.g., the curve is steeper in the food and beverages sector, than in electronics and electrical products. Other positive evidence for the inverted U-curve has been found by Kilponen and Santavirta (2007), who found that R&D subsidies to have adverse effects on competition in only extreme cases, but generally positive influences on innovation.

In contrast, Gorodnichenko, Svenjar and Terrell (2010) claim to find no evidence on an inverted U-curve for emerging markets firms, although what they find is in accordance with the downward sloping part of the inverted u-curve. That is, competition has a negative effect on innovation, especially for firms further from the frontier, but they do not rule out an inverted U relationship in more pro-business environments.

Bos et al. (2013) proxy innovation with input-based (cost minimization) technical efficiency, and estimate the presence of an inverted u-curve between competition and technology gaps in the U.S. banking industry. They find consolidation to have reduced innovation. Similarly, Badunenko *et al.* (2006) consider efficiency as an overall measure of innovativeness, resulting from high productivity in production and the sale of highly priced innovative goods and services. It is unexpected that the technology gap has been used to proxy innovation, since it is a rather common presumption that efficiency and innovativeness are contradictory, because innovation requires some degree of slack. Particularly, industrial organization theories typically expect innovation to decline with efficiency enhancing competition (Aghion *et al.* 2005).

Well before them, research by Hanusch and Hierl (1992) suggests that the relationship between profit margins and technical efficiency is not linear. Hanusch and Hierl analyzed the relationship between profitability and technical efficiency in German electronics and machinery industries and found it to be convex, i.e., enterprises enjoy increasing returns to their attempts to raise efficiency. They concluded suggestively that leading enterprises may be subject to strong efficiency pressures to maintain profitability relative to competition. Their data on R&D expenditures was sufficient only for the machinery industry. Since deviations from the production frontier were small, they concluded that the sample firms' best strategy is innovation as opposed to imitation, in order to ensure technological leadership and above average profitability.

3.   The Data and Variables

Empirical evidence is sought from a fairly homogenous innovative high-tech industry in the small country that is subject to intense competition from abroad. Asset seeking FDI into the industry during the sample period suggests it to have been close to a technology frontier, characterized by intense and rapidly evolving innovation and competition (Berghäll 2015). It therefore offers potential to test the predictions of the model in a concise setting with few disrupting unknowns. While external validity requires more extensive evidence on other industries and countries, the empirical research needs to be carried out separately by industry to avoid unrealistic production function assumptions with respect to underlying technologies. The present exercise therefore

contributes to the literature with an example of an innovative industry, which may have counterparts in other countries and high-tech industries.

3.1 The ICT industry data

The unbalanced panel of ICT manufacturing firms was constructed from the Longitudinal Database on Plants in Finnish Manufacturing [1]1974-2002, Financial Statements Statistics[2] 1986–2003, and R&D Surveys 1985–2003 at Statistics Finland. R&D, capital, labour and value-added data were available for 988 observations of 164 firms and 1282–1357 observations of plants over the period 1990–2003. Altogether 3–4% of observations were removed due to negative or missing value-added when logarithms were taken, extreme annual variation or impossible value-added figures. Summary statistics of the final 928 observations are presented in Table 1.

Table 1.   Firm level summary statistics for key variables

	N	Mean	Std. Deviation	Minimum	Maximum
Value added (€), (Y)	928	15.63	1.56	11.42	22.59
Capital (€), (K)	928	14.68	1.98	5.38	20.11
No of personnel minus R&D personnel , (L)	928	4.64	1.38	.00	8.97
R&D capital stock (€), (R)	928	13.69	2.34	6.72	20.36
Lerner	928	.17	.0012	.17	.18
R&D intensity	928	8.88	1.99	.35	13.75
R&D elasticity	928	.047	.1	-.35	.31
Technical change	928	.013	.044	-.14	.17

In the production function, real value-added measures output *(Y)*, the dependent variable. There are three main independent variables: 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. 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). The LDPM database provides proxies for physical capital, built from machine and equipment investments using the perpetual inventory method with a ten percent depreciation rate, i.e., $K_t = (1-\delta)K_{t-1} + I_t$ where δ is the depreciation rate. Similarly, R&D capital stocks were built 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 from 1985–1989 when 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)[3].

---

[1] LDPM/ Teollisuustilasto.
[2] Tilinpäätöspaneeli.
[3] The depreciation of the R&D stock (δ) is most often fixed arbitrarily at 15% (Hall, 2010). Pakes and Schankerman (1984) have estimated an average rate of 25% also from patent renewal data, and recently Bernstein and Mamuneas (2006) have estimated industry-specific rates that range from 18% for chemicals to 29% for electrical products.

Firm level data on capital and labour was obtained by summing up plant levels in the LDPM database by firm. Analysis at the firm level avoids the questionable division of R&D capital plant-wise, as well as the comparison of units within the same firm as if they competed.

Due to data shortages, as well as for homogeneity of the sample, the analysis concerns only innovative firms with at least 20 employees. Large firms dominate the industry in terms of sales and R&D. Though small and microfirms are large in number, 89% in 1993 and 86% in 2004, their share of total employees was only 12% and 7% respectively, and even less of total turnover 6% and 2%, or total wage costs 9% and 5% respectively for 1993 and 2003. Their exclusion therefore cuts out only about 10% of total economic activity in the industry. In 2003, the true number of firms operating in the industry rose to almost 1700, and 233 if only firms with over 20 employees are considered. Larger firms cover 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 exclusion of smaller firms does not confuse the analysis because estimation results showed most results to be (strictly) increasing in size, and consequently, the potential direction of microfirms' impact is rather obvious.

To avoid selectivity bias caused by the exclusion of loss-making and indebted firms when logarithms are taken, Lerner values and debt ratios were adjusted by adding the maximum loss or maximum debt to all observations plus one, as is recommended in the literature. About 3–4% of observations were removed due to negative or missing values when logarithms were taken, extreme annual variation or impossible value-added figures. Due to data secrecy requirements, there was no other basis for the exclusion of outliers other than their extremeness in value. In frontier analysis, such a cause is even more suspect than usual, as it could lead to the removal of frontier firms defeating the purpose of the exercise. Nominal variables were deflated with sectoral producer price indices at the 2 and 3 digit levels (1995=100), with the exception of R&D prior to 1995, for which the general earnings level index was used (due to the unavailability of alternatives).

In consequence, panel firms can be assumed to be subject to similar (minimal) regulation, demonstrate similar behaviour, i.e., profit or revenue maximizing, allowing me to apply an output distance function, i.e., an output oriented efficiency measure. In addition, firms can be assumed to fit into the same functional form of the production function for their relative efficiencies to be comparable.

3.2 Innovation variables

Aghion *et al.* use patents, i.e., an innovation output measure for innovation. Innovation ouput can also be approximated by technical change and R&D elasticity. Innovation, however, may refer to the innovation inputs, for which R&D provides more accurate estimates. Innovation input is measured by R&D intensity (R&D Capital/ No. of Personnel), which does not vary by the model applied, though it is not constant over time and firm size (Figure 1). In contrast, innovation output measures (implemented innovative activity), which is measured by R&D elasticity and technical change were estimated.

Figure 1.   *Log R&D intensity over 1990-2003 for different firm size groups*
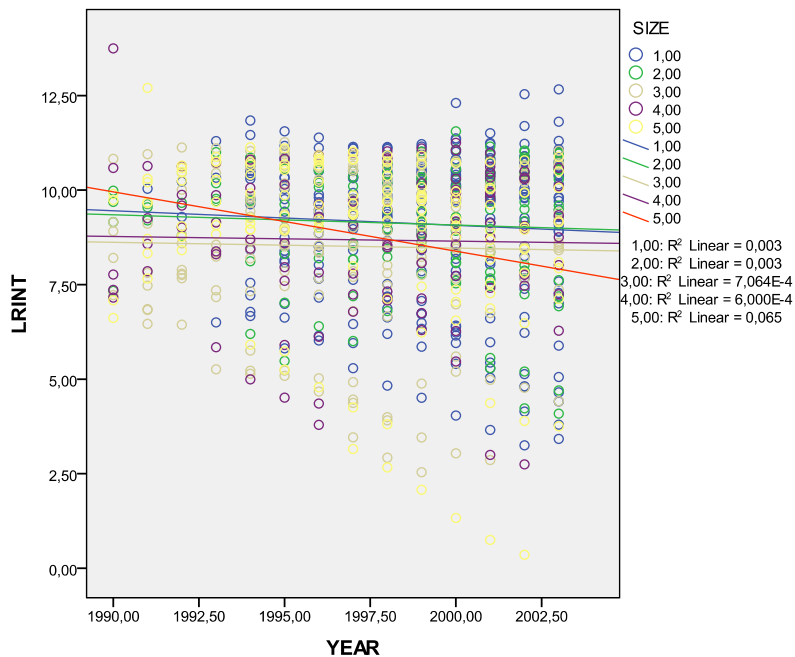
Various other firm characteristics are listed in Table 2 such as firm size (number of employees, 6 categories), firm age (4 categories), and the firm leverage (debt ratio). Aghion et al. (2005) have argued firm leverage to be positively related with innovation to escape the risk of bankruptcy. Also firm size and age are expected to have a significant impact on innovation, the direction varying by technological regime. The Schumpeterian hypothesis deems firm size to be conducive to R&D, while the so-called Schumpeterian Mark I regime characterises situation in which technological progress emerges from new technology-based firms through a process of creative destruction (see e.g. Nelson and Winter, 1982). Although most formal R&D is concentrated in large corporations, Acs and Audretsch (1991) argue that small firms account for a disproportionate share of new product innovation, given their low formal R&D expenditures. Audretsch (1995) confirms that the empirical evidence on their role as engines of innovative activity in certain industries is robust, and yet the link between R&D and innovation disappears as the unit of observation is reduced to the firm level, particularly with small firms. Small is typically new, but since it proved impossible to establish an exact age for each firm, firms were merely grouped into 4 age categories.

Table 2.   *Frequency Distribution of Firms by Debt Ratio, Age and Number of Personnel*

Debt ratio	Freq. (%)	Age in years	Freq. (%)	Size by number of personnel	Freq. (%)	Exports	Freq. (%)
< 50%	594 (60%)	years ≤2	244 (25%)	20 ≤ labour <50	347 (35%)	No	130 (13%)
50-100%	151 (15%)	2<years ≤4	144 (15%)	50 ≤ labour <100	167 (17%)	Yes	858 (87%)
>100%	243 (25%)	4<years ≤7	135 (14%)	100 ≤labour <250	195 (20%)		
		7<years	465 (47%)	250 ≤labour <500	119 (12%)		
				labour ≥ 500	160 (16%)		
Total	988		988		988		988

3.3 Competition variables

The primary competition measure was specified as a firm specific Lerner index based on firm operating profit divided by the value of gross output (turnover), i.e., profit margin. Operating profit was derived from firm value added minus factor input costs, i.e., expenses including payroll taxes and social security payments incurred by the firm, as well as capital costs as indicated by financing expenses in firm profit and loss statements. The Lerner Index is common to the literature due to its significant advantages in measurement (Aghion & Griffith, 2005, page 22) and is in accordance with the microeconomic principle that high profit margins equal imperfect competition. For example, domestic market shares are rather irrelevant since the share of international trade in the industry is high.The Lerner index overcomes the difficulties inherent in input and output price measurement, and quality change, since the measure of competition is defined by the profits of firms. Since all firms operate in the same country, general price level and foreign exchange conditions are the same for all firms. In accordance with the microeconomic principle that high profit margins equal imperfect competition, increased competition is expected to reduce profit margins. Rates of returns are indicated similarly to Aghion et al. (2005) with a firm specific Lerner index, which is common to the literature due to its significant advantages in measurement (Aghion and Griffith 2005, page 22). Here, the Lerner index is based on firm operating profit divided by the value of gross output (turnover), i.e., profit margin, price cost margin or mark-up.

In contrast, domestic market shares, such as the Herfindahl index, are rather deceptive measures of competition when most of it originates from abroad. Moreover, according to survey results by Gilbert (2006), empirical research based on market concentration to proxy competition has not reached definite conclusions on the relationship between market structure and R&D, once industry characteristics, technological opportunities and appropriability were controlled for.

In 1990-1993, the economy plunged into a deep recession. Yet, profitability was rapidly regained in the industry (Figure 2) with radical innovation. Net entry into the industry was high until mid 1990's, falling subsequently to exit levels by the end of the decade. Entry-based competition

revived only after 2005. Thereafter profitability gradually declined and competition intensified. While average competition (1-Log Lerner) has intensified very gradually, competition actually declined for the largest firms as Figure 3 above shows over the sample period. On average, production growth (gy) correlates significantly (0.30) with the Lerner index, showing boom times to raise profitability. In contrast, recessions intensify competition, as one would expect. Low profitability is expected to signal intense competition.

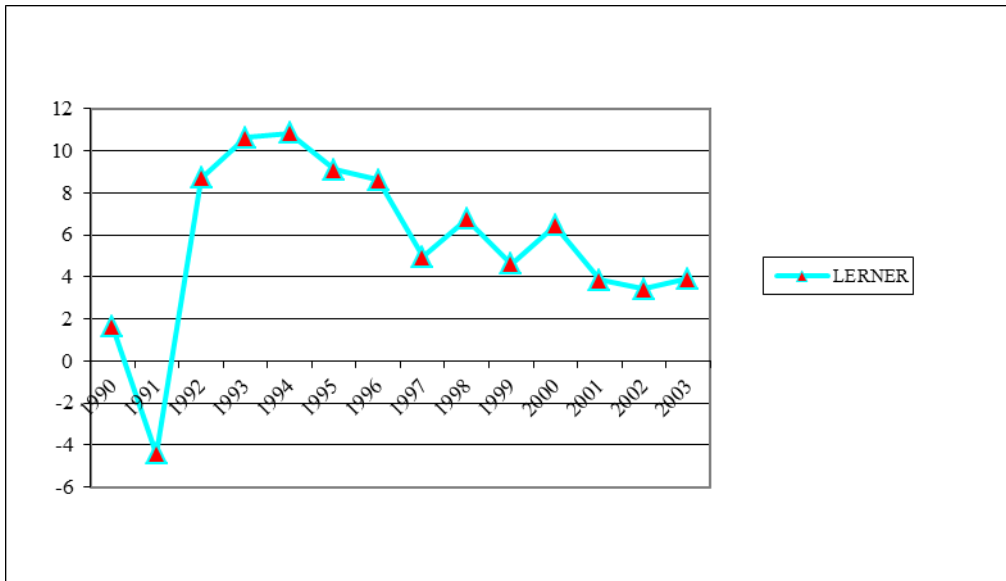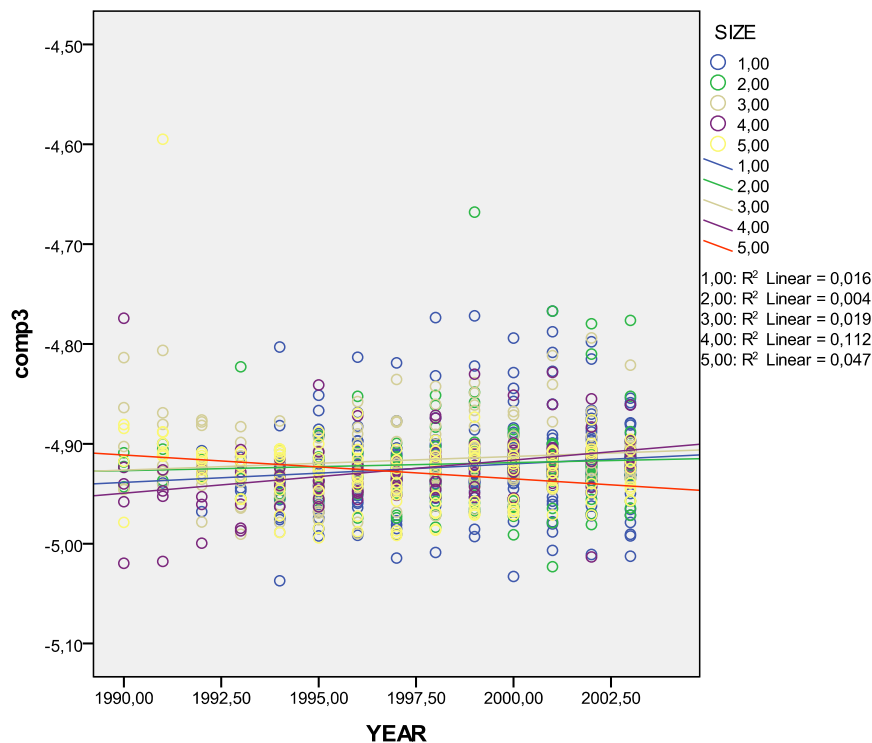*Figure 2. Evolution of the Lerner Index over the sample period*

Figure 3.   *Evolution of competition (1-Log Lerner) over the sample period for different firm sizes[4]*

Another determinant of inefficiency related to global competition is foreign ownership. Data on foreign firms is available for 1993-2002, with an emphasis observable for 1997-2002, but since the entire industry is subject to global competition, foreign ownership is of little relevance. Related research has found inward FDI into the industry to have been most likely asset-seeking (see Berghäll 2015).

3.4 Determinants of the technology gap

Technological gaps between leaders and followers are measured by Battese-Coelli (1995) technical inefficiencies following the inverted u-curve shaped theoretical predictions of the relationship between innovation and competition. Thus technical inefficiency also estimates innovation impacts. Technical efficiency results were compared with other reasonable indicators of innovation, such as technical change (implemented innovative activity), R&D intensity, an input measure and R&D elasticity, an innovation output measure.

The analysis concerns only innovative firms. Since the industry is highly R&D intensive, the R&D requirement does not introduce a selectivity bias. It has the beneficial corollary that panel firms can be assumed to be subject to similar (minimal) regulation, demonstrate similar behavior. In addition, I can assume the firms to fit into the same functional form of the production function for their relative efficiencies to be comparable.

---

[4] Size 1: 20 – 50; Size 2: 50 – 100; Size 3: 100 – 250 ;Size 4: 250 – 500; Size 5: over 500.

4.   Methodology

The inverted u-curve model does not argue causality. I am therefore only interested in correlations of competition and innovation in this context. Technology gaps, in contrast, are estimated with parametric and non-parametric methodologies. Otherwise estimation methods depend on the estimator. Technical change and R&D elasticity are estimated with maximum likelihood. The impact of competition on the technology gap is estimated with true fixed and Battese-Coelli efficiency.

4.1 Firm level estimates

The key insight Farrell (1957) proposed was to extract information from extreme observations of the data to determine the best practice production frontier, rather than having to rely on some hypothetical production possibilities curve. A flexible translog functional form was assumed to approximate the production technology, following Heshmati *et al.* (1995):

$$Y_{it} = f(K_{it}, L_{it}, R_{it}; \theta) \exp(\varepsilon_{it}), \tag{1}$$

where Y_{it} is the output of the *i*-th firm observed in period *t*, *f(.)* represents the production technology, *K* is physical capital, *L* is non-R&D labour, *R* is R&D capital input and θ is a vector of parameters to be estimated. The following flexible translog (transcendental) production function was assumed to approximate production technology:

$$\ln Y_{it} = \beta_0 + \sum_j \beta_j \ln X_{jit} + \tfrac{1}{2} \sum_j \beta_{jj} (\ln X_{jit})^2 + \sum_{j \neq h} \sum_h \beta_{jh} \ln X_{jit} \ln X_{hit}$$
$$+ \beta_t t_i + \tfrac{1}{2} \beta_{tt} t^2 + \sum_j \beta_{jt} \ln X_{jit} t + v_{it} - u_{it}, \tag{2}$$

where the β's denote parameter estimates of the production function, *i* the company, *j* and *h* denote inputs (i.e., logarithms of physical capital *(k)*, non-R&D labour *(l)* and R&D capital *(r))*, and *t* the time period (i.e., the year concerned). Also Cobb-Douglas forms of the model were tested and found to apply only for the international data comparison.

R&D elasticity, i.e., the percentage change of output divided by the percentage change of R&D, was obtained from the first derivative of the production function with respect to R&D:

$$E_{ijt} = \frac{\partial \ln Y_{it}}{\partial \ln X_{ijt}} = \beta_j + \beta_{jj} \ln X_{jit} + \sum_h \beta_{jh} \ln X_{hit} + \beta_{jt} t \ . \tag{3}$$

where E_{ijt} is firm, input and time varying, respectively.

The rate of exogenous technical change was obtained as:

$$TC_{it} = \frac{\partial \ln Y_{it}}{\partial t} = \beta_t + \beta_{tt} t + \sum_j \beta_{jt} \ln X_{ijt} \ . \tag{4}$$

where TC_{it} is neutral if $\beta_{jt} = 0$ for all inputs j. In other words, technical change merely represents the change in the production function with respect to time.

4.2 Data Envelopment Analysis for technical efficiency measures

Several estimation methods were used to confirm and check results. State of the art true fixed and random effects estimates of technical efficiency proved unreasonable. Instead, for consistency and comparability of results, as well as to abstain from potentially distorting assumptions, non-parametric Data Envelopment Analysis (DEA) was applied to estimate technical efficiency. DEA applies linear programming to compare relative performance when the production process involves multiple inputs and outputs. In contrast to stochastic frontier modeling, there is no need to specify a mathematical form for the production function beforehand, since the method simply seeks the points that maximize output given inputs (output-oriented measure) or minimize inputs given output (input-oriented measure). Hence DEA efficiency results do not depend on the above formulation of the production function. Several programs are available to carry out the linear programming problem. Hence its complexity in terms of the number of inputs and outputs causes no constraint. Most efficient firms receive a score of one, and less efficient a score somewhere below one, but above zero. At the same time, the major drawback of the method is the fact that there is no adjustment for outliers. Yet, it is simple to check visually how the efficiency estimates are distributed and how "unreasonable" outliers are.

The original constant returns DEA methodology was developed by Charnes, Cooper and Rhodes (1978). In 1984, Banker, Charnes and Cooper developed it further into a variable returns to scale (VRS) version. The differences in the input and output-oriented measures reveal whether returns to scale are not constant, decreasing or increasing. When input-based efficiency is smaller than the output-based, returns to scale are decreasing[5]. If returns to scale appear to be increasing, output-based efficiency measures are generally higher, but there is no clear rule on which measure should be selected.

As a robustness check, so-called order-m efficiencies were also estimated. The methodologies are described in more detail for instance in Daraio and Simar (2007).

5.   Results

According to the predictions of the model, if the industry is indeed at the frontier, average technical efficiency should be high, competition neck-and-neck and firms located on the upward sloping part of the inverted U-curve. That is, additional competition should increase innovation. Whether this is the case, is inspected by seeking answers to the following questions: Is average technical efficiency high in the industry? Has competition increased technical inefficiency or innovation? Does technical inefficiency or total factor productivity (TFP) provide a good measure of innovation?

---

[5] See e.g. Coelli (1996) pages 6-7.

5.1 Is average technical efficiency high in the industry?

Parametric efficiency estimates vary greatly by the methodology chosen. Hence the assumptions underlying them appear to influence results significantly. Therefore, after checking for outliers, results for non-parametric data envelopment analysis (DEA) measures are presented (Figure 4). Both input and output based DEA measures are high. The input-based measure showed smallest firms as most efficient, while the output measure showed the largest firms to huddle closest to the frontier. Since their difference suggests increasing returns to scale, and firm size clearly contributes to efficiency, the largest firms appear to be the most efficient, and the output-based measure more reliable.

Figure 4.   Scatter plot of input-based and output-based DEA technical efficiency
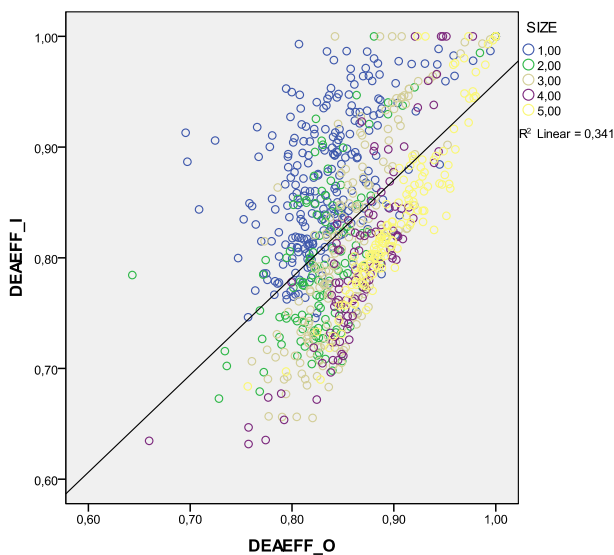
5.2 Has competition increased technical inefficiency on average?

Determinants of inefficiency show competition to contribute significantly to inefficiency in the Battese-Coelli inefficiency model estimated with maximum likelihood. Efficiency is an increasing function of profit margins. In contrast, foreign ownership and exporter status did not prove to be significant determinants of inefficiency (Table 3). Exposure to global competition does not seem to affect technical efficiency. Moreover, the correlation between competition and technical efficiency was significant and negative: Input-based DEA -0.15 and output-based DEA -0.40 (Table 4). Competition increases technical inefficiency, but the relationship is not linear, as Hanusch and Hierl (1992) have suggested. These results run counter to the neoclassical assumption that efficiency increases with competition, but are in line with the inverted u-curve (Aghion and Griffith, 2005, page 71-72), i.e., increasing the threat of competition advances innovation in the more efficient firms, but dampens it in inefficient firms. Yet, Figures 5 – 7 provide a better fit than inverted U-curves.

Table 3.   Maximum likelihood estimates on panel data and determinants of Battese-Coelli and DEA technical inefficiency[6] (δ=30% R&D depreciation rates)

Variable		Average
δ_0	Intercept for efficiency	25.46**
δ_1	Log Lerner index (profits/turnover)	-4.23***
δ_2	Log debt ratio	0.75
δ_3	Log capital intensity	0.05
δ_4	Log R&D intensity	-0.08***
δ_5	Type 2 (Foreign-owned)	0.16
δ_6	Exp2 (Exporter)	0.16
δ_7	Size 2	-0.26***
δ_8	Size 3	-0.64***
δ_9	Size 4	-0.82***
δ_{10}	Size 5	-1.18***
δ_{11}	Age 2	-0.12
δ_{12}	Age 3	-0.24*
δ_{13}	Age 4	-0.16
δ_{14}	Localisation 2	0.04
δ_{15}	Localisation 3	0.16
δ_{16}	Urbanisation 2	-0.11
δ_{17}	Urbanisation 3	-0.26
λ	Lambda	0.65***
γ	Gamma	
σu	Sigma(u)	0.31***
σ^2		
DEA (output)	Mean efficiency	0.85
RTS	Mean scale elasticity	0.65
Elast	Mean technical change	0.01
Elask	Mean capital elasticity	0.12
Elasl	Mean labor elasticity	0.49
Elasr	Mean R&D elasticity	0.05

---

[6] Since true fixed effects results were similar to Battese-Coelli results and true random effects varied off limits, only Battese-Coelli results are reported above for comparison.

Figure 5.   *Scatter plot of technical efficiency (output-based DEA) and competition (1-unadjusted Lerner)*
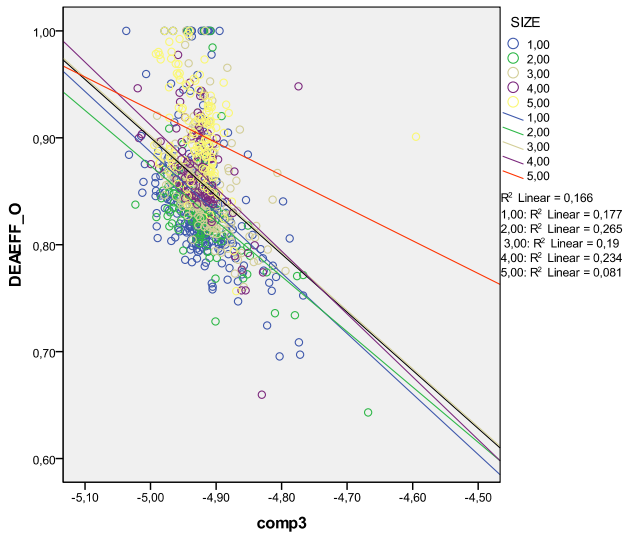

Figure 6.   *Scatter plot of technical efficiency (output-based DEA) and the Lerner index (profit margins adjusted to loss-making firms)*
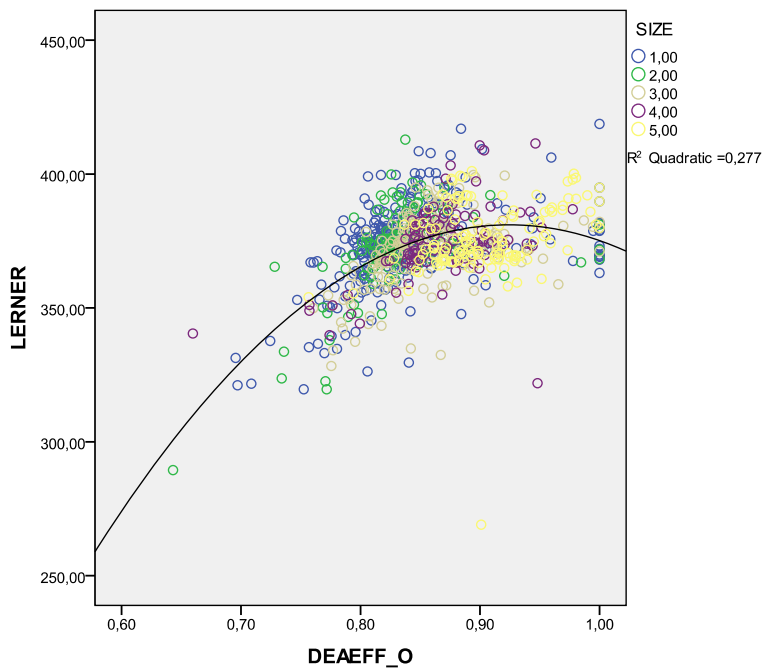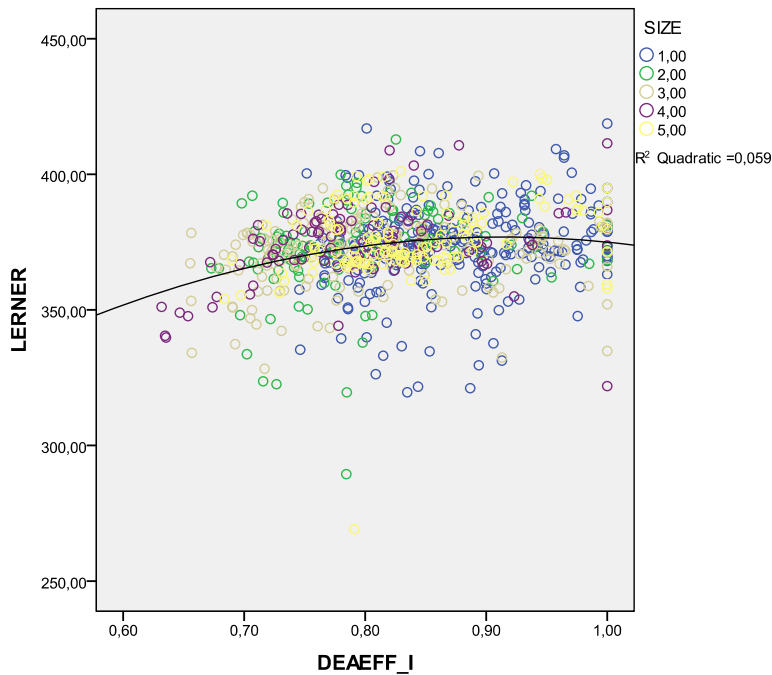
Figure 7.   *Scatter plot of technical efficiency (input-based DEA) and the Lerner index*
               (profit margins adjusted to loss-making firms)

5.3 Can inverted u-curves be found between competition and innovation?

Results with respect to innovation are somewhat contradictory. As Table 4 shows, the correlation is contradictory with respect to innovation and competition. While competition is associated with significantly increased R&D intensity (1% level), and R&D elasticity (at the 5% significance level), competition is associated with significantly decelerated technical change (1% level). It may be that product related innovation is conducive to intense competition, but when it comes to process innovation (technical change), competition decelerates it. Yet, as Figures 8-10 below show, an inverted u-curve relationship between innovation and competition could only be found for technical change and competition. For R&D intensity and elasticity, the relationship was more of a u-curve. In all cases, however, the fit was not convincing.

Figure 8.   Scatter Plot of Innovation (technical change) on Competition (1-Lerner). Correlation
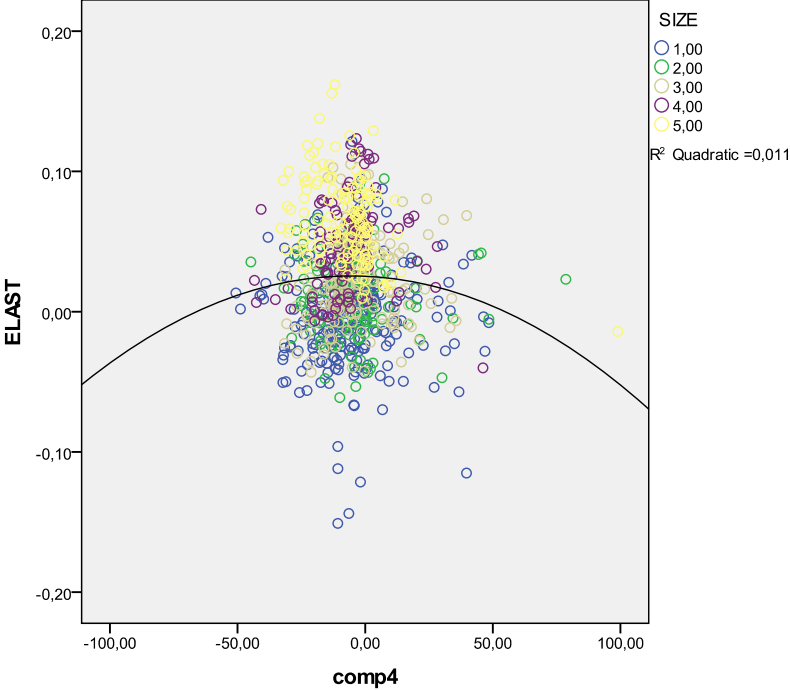

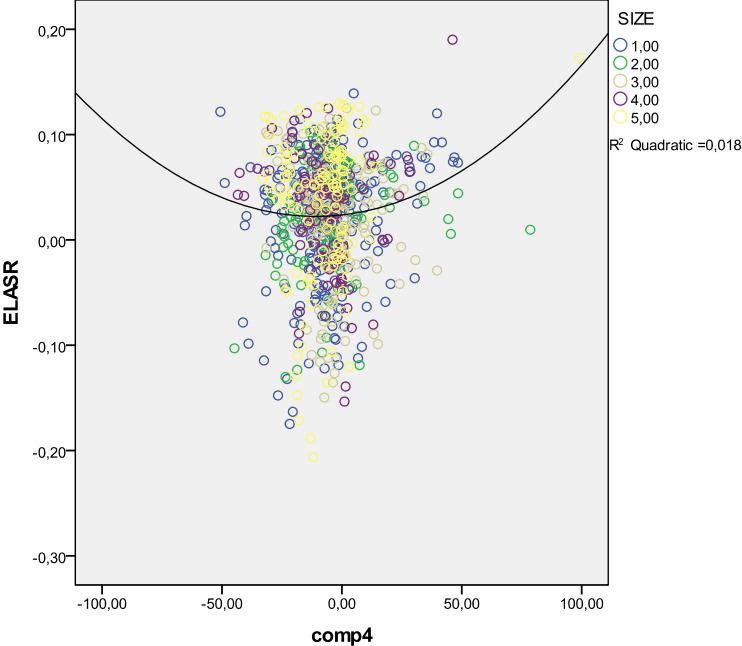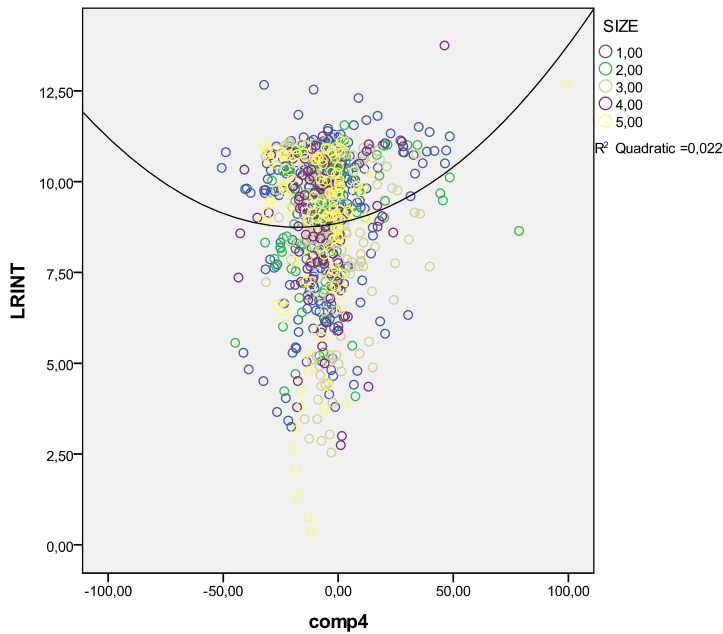*Figure 9.   Scatter Plot of Innovation (R&D elasticity) on Competition (1-Lerner)*

Figure 10.   Scatter Plot of Innovation (R&D Intensity) on Competition (1-Lerner)

5.4 Does technical inefficiency provide a good measure of innovation? The relationship between technical efficiency and technical change

Results do not support technical efficiency as an appropriate measure of innovation. As Table 4 shows, input-based DEA correlates significantly at the 1 % level, but negatively with R&D elasticity (-0.14) and technical change (-0.28). Its correlation with R&D intensity is insignificant and almost zero. Hence, input-based DEA technical efficiency is not a proxy to innovation. As for output-based DEA, it correlates positively and significantly at the 1 % level with technical change (0.22), and positively and significantly at the 5 % level with R&D intensity (0.08). Its correlations with R&D elasticity is insignificant and almost zero. Hence, output-based DEA may proxy technical change and perhaps R&D intensity, but the correlations are fairly small.

Table 4.   *Pearson Correlation, Sig. (2-tailed), N=928, total sample*

	Competi-tion (4)	R&D intensity (rdint)	Elasticity of R&D (elasr)	Technical change (elast)	Input-based DEA efficiency	Output-based DEA efficiency	Scale elasticity (rts)	Growth of output (gy)	Output based TFP growth	Labour produc-tivity
Competition (4)	1	0.15**	0.07*	-0.11**	-0.15**	-0.4**	-0.07*	-0.39**	0.32**	-0.19**
		0	0.031	0.001	0	0	0.03	0	0	0
	928	928	928	928	925	925	928	769	769	928
R&D intensity (rdint)	0.15**	1	0.46**	-0.30**	0.01	0.08*	-0.06	-0.03	-0.07	0.36**
	0		0	0	0.733	0.017	0.06	0.356	0.058	0
	928	928	928	928	925	925	928	769	769	928
Elasticity of R&D (elasr)	0.07*	0.46**	1	-0.56**	-0.14**	0.02	-0.03	-0.07	-0.05	0.17**
	0.031	0		0	0	0.493	0.439	0.056	0.139	0
	928	928	928	928	925	925	928	769	769	928
Technical change (elast)	-0.11**	-0.30**	-0.56**	1	-0.28**	0.22**	0.83**	0.13**	0.20**	-0.07*
	0.001	0	0		0	0	0	0	0	0.027
	928	928	928	928	925	925	928	769	769	928
Input-based DEA efficiency	-0.15**	0.01	-0.14**	-0.28**	1	0.53**	-0.48**	0.13**	-0.09*	0.24**
	0	0.733	0	0		0	0	0	0.017	0
	925	925	925	925	925	925	925	767	767	925
Output-based DEA efficiency	-0.4**	0.08*	0.02	0.22**	0.53**	1	0.24**	0.38**	-0.17**	0.42**
	0	0.017	0.493	0	0		0	0	0	0
	925	925	925	925	925	925	925	767	767	925
Scale elasticity (rts)	-0.07*	-0.06	-0.03	0.83**	-0.48**	0.24**	1	0.11**	0.20**	0.03
	0.03	0.06	0.439	0	0	0		0.002	0	0.453
	928	928	928	928	925	925	928	769	769	928
Growth of output (gy)	-0.39**	-0.03	-0.07	0.13**	0.13**	0.38**	0.11**	1	-0.81**	0.14**
	0	0.356	0.056	0	0	0	0.002		0	0
	769	769	769	769	767	767	769	769	769	769
Output based TFP growth	0.32**	-0.07	-0.05	0.20**	-0.09*	-0.17**	0.20**	-0.81**	1	-0.08*
	0	0.058	0.139	0	0.017	0	0	0		0.029
	769	769	769	769	767	767	769	769	769	769
Labour produc-tivity	-0.19**	0.36**	.017**	-0.07*	0.24**	0.42**	0.03	0.14**	-0.08*	1
	0	0	0	0.027	0	0	0.453	0	0.029	
	928	928	928	928	925	925	928	769	769	928

The finding that technical efficiency is not a good measure of innovation questions the external validity of estimations of Bos *et al.* (2013), which used input-based (cost minimization) technical efficiency to proxy innovation to estimate the presence of an inverted u-curve between competition and technology gaps. Even in this respect, the relationship resembles that of a (non-inverted) u-curve. As Figure 11 shows, competition is minimized at a higher efficiency level[7]. In other words, most efficient firms have indeed escaped competition. Even if technical efficiency could proxy

---

[7] The figure applies an output-based measure, since the input-based measure did not fit a u-curve.

innovation, the relationship between technical efficiency and competition is far from a robust inverted u-curve. An important factor that distinguishes efficiencies is firm size. As Figure 12 shows, the most (output-based DEA) efficient largest and smallest firms enjoy actually the most rapid technical change. This is the result also on average for the sample. The positive relationship is pronounced only for the largest firms with respect to input-based DEA. Even with a quadratic function the relationship is straightforward, more efficiency is good for innovation (Figure 13).

Figure 11. *Scatter plot of technical efficiency (input-based DEA) and competition (1-unadjusted Lerner)*
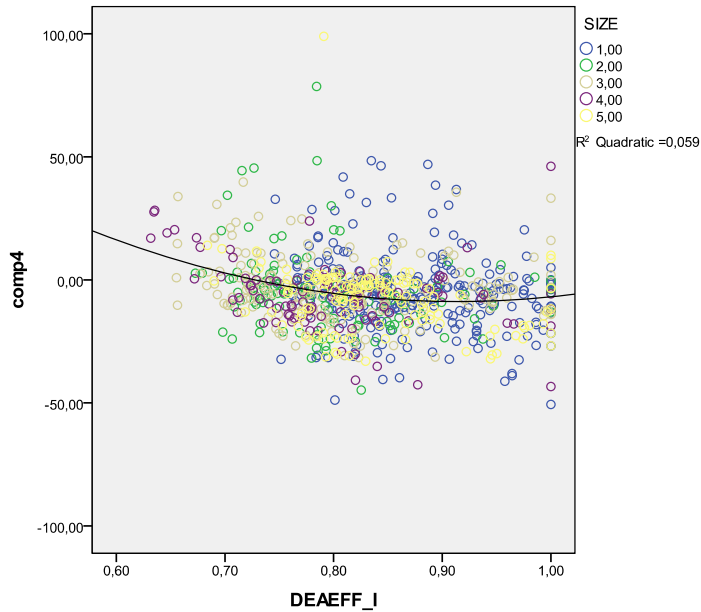
Figure 12.   *Scatter plot of innovation (technical change) on technical efficiency (output-based DEA) on firm size*
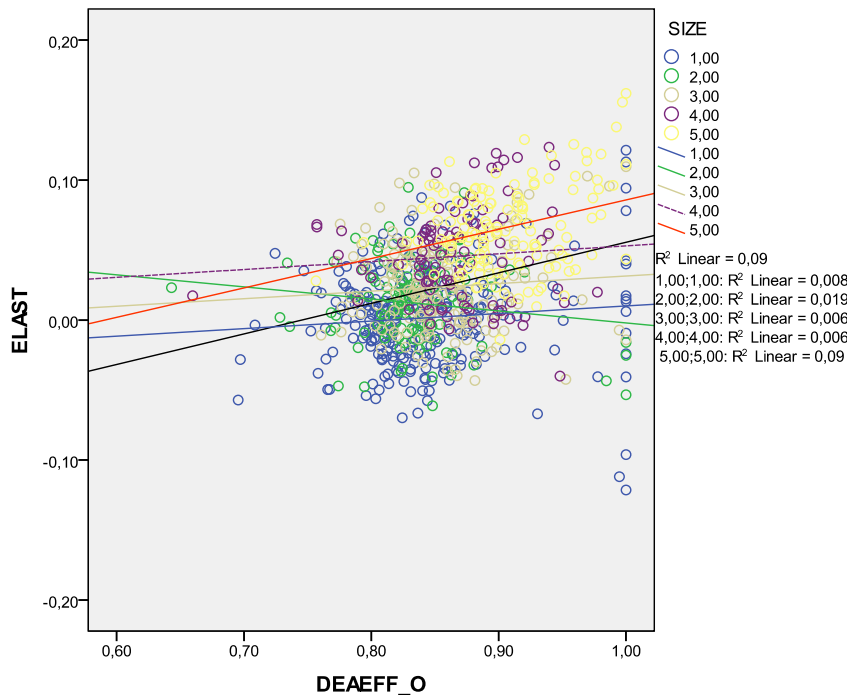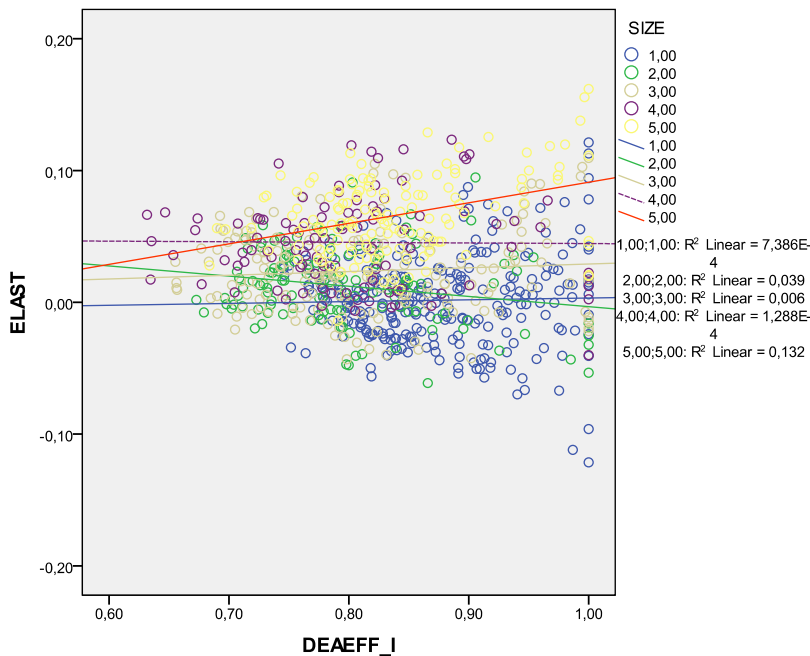

Figure 13.   *Scatter plot of innovation (technical change) on technical efficiency (input-based DEA) on firm size*

For R&D elasticity, a vaguely inverted U-curve could be traced only for input-based DEA (Figure 14). there seems to be an efficiency optimum that maximizes innovation below full efficiency. Output-based DEA shows inefficient firms as typically small. Input-based DEA, however, showed smallest firms as most efficient. Profit margins increased with efficiency across the board regardless

of firm size, and small firms have been more R&D intensive on average. Thus, contrary to the predictions of the inverted u-curve theory, small firms that have on average been furthest from the frontier have also been most keen to escape competition by means of innovation.

Figure 14.   Scatter plot of innovation (R&D elasticity) on technical efficiency (input-based DEA)
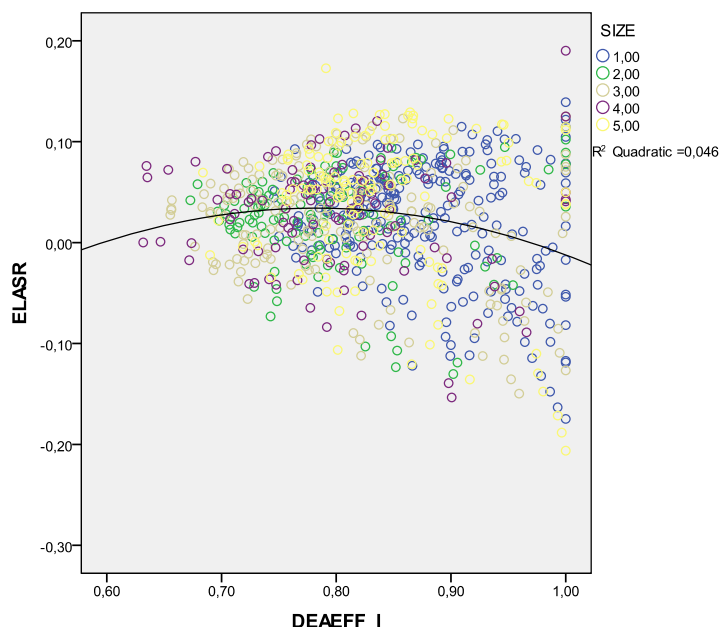
In sum, the predictions of the inverted u-curve theory are controversial in relating innovation and the concept of efficiency. TFP and technical efficiency do not appear to provide adequate proxies of innovation. Output-based DEA may proxy technical change, and perhaps R&D intensity, but the correlations are small though significant. Output-based TFP correlates significantly (at the 1 % level) and positively with technical change (0.20), but not with R&D intensity or R&D elasticity. TFP may proxy technical change, but the correlation is rather small.

5.5 Does total factor productivity (TFP) provide a good measure of innovation?

Innovation has also been proxied by the level and growth rate of TFP. E.g. Nickel (1996) found evidence in line with the neoclassical postulation that more intense product market competition (PMC) is reflected in more rapid TFP growth. In my sample, in contrast, there is little correlation between TFP and innovation. Output-based TFP correlates positively significantly at the 1 % level and with technical change (0.20), but not with R&D intensity or R&D elasticity (Table 4). As Figures 15 – 18 below show, a slight positive correlation could be detected only for technical change. In conclusion, TFP would not appear to provide a good measure of innovation.

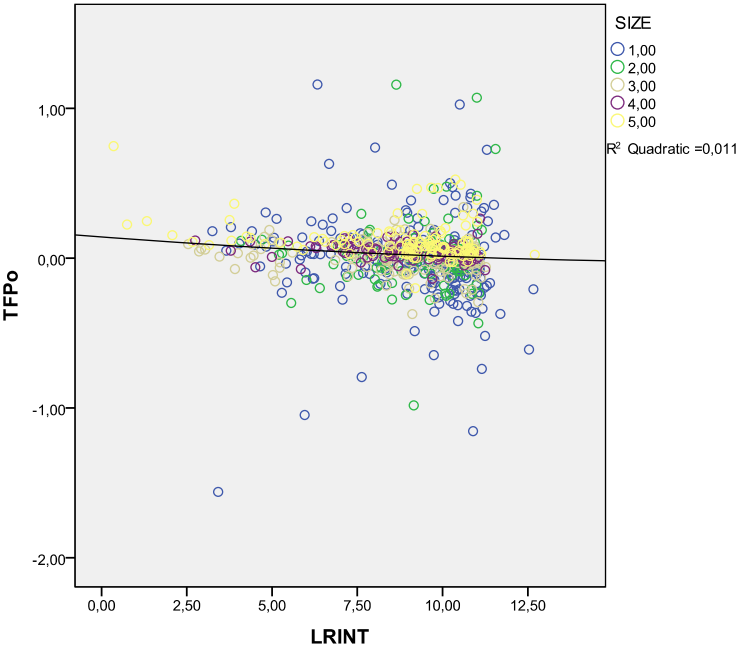*Figure 15.*   *Scatter plot of productivity (output-based TFP) on innovation (log R&D intensity)*

Figure 16.   *Scatter plot of productivity (output-based TFP) on innovation (R&D elasticity)*
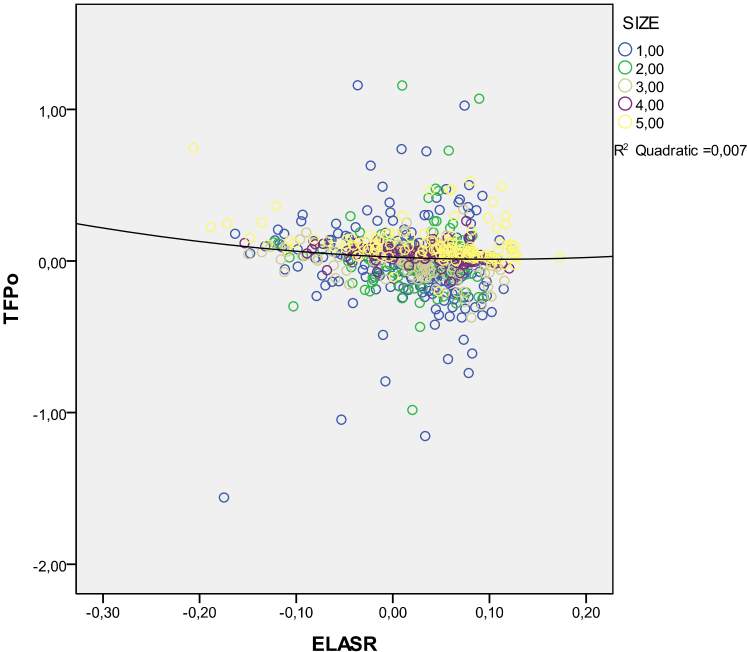
Figure 17.   Scatter plot of productivity (output-based TFP) on innovation (technical change)
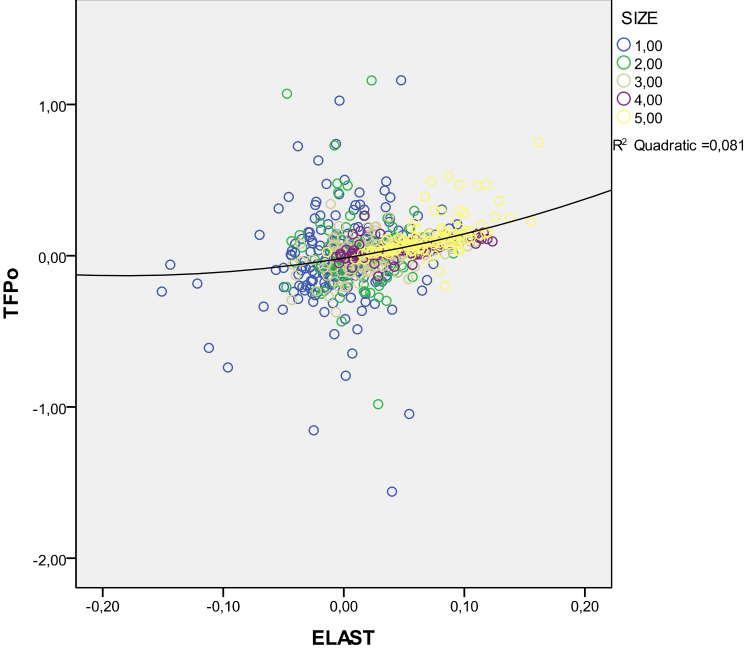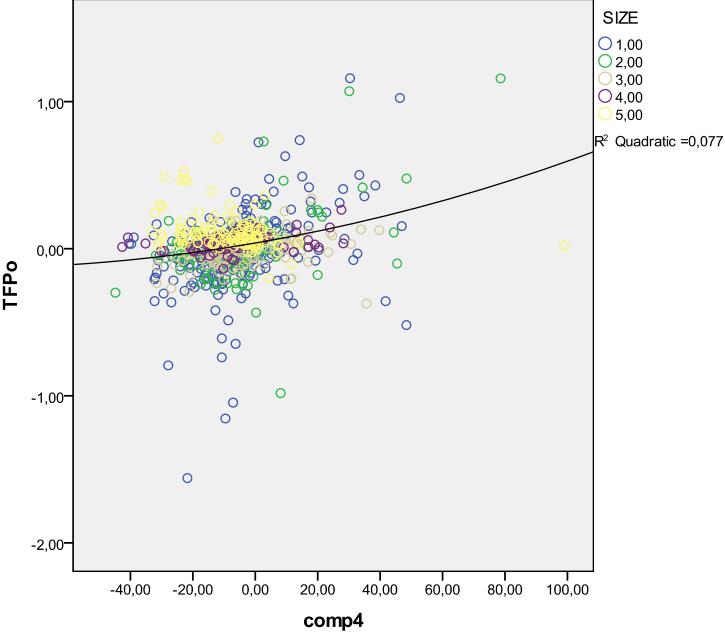

Figure 18.   Scatter plot of productivity (output-based TFP) on competition (1-unadjusted Lerner)

6. Discussion and conclusions

Average technical efficiency is high in the industry. Competition increases technical inefficiency on average. In these respects, the evidence with respect to the industry being on the technology frontier is clear, but overall, the evidence in support of the inverted U-curve relationship is weak and contradictory. Results are sensitive to the proxies and methodologies applied. In conclusion, I contribute to the literature by showing that model predictions cannot be generalized into stylized facts of the relationship between competition and innovation.

In addition to Schumpeterian models and the inverted u-curve, the finding that the most profitable firms and plants are also to be the most efficient, combined with the finding that profit margins increased with efficiency across the board regardless of firm size, are in line with so-called resource-based views of the firm, in contrast to traditional structure conduct performance or contemporary industrial organization views. Efficient small firms are also profitable, although large firms are generally the most efficient. Hence, the causality may run from efficiency (and innovativeness) to profit margins and firm growth, i.e., there are efficiency rents that firms may be able to transform into long term competitive advantages that generate abnormal returns. Overall, the industry seems to reflect the Schumpeterian Mark II hypothesis of creative accumulation, rather than creative destruction.

Competitive and innovation conditions can, at least to some extent, be tampered with, by e.g. generous R&D support to bridge the disincentive gap between private and social returns – hence their appeal. This evidence suggests, however, that tampering with competitive conditions to raise innovation is futile. Innovation within smaller firms is already relatively high in terms of R&D intensity, while technical change is R&D saving and the two correlate negatively.

One should not confuse productivity with efficiency when discussing the beneficial effects of competition. Competition may e.g. increase productivity, but not necessarily average efficiency. Second, when there are large differences in technical efficiencies that are due to other factors than innovation and competition, such as simple scale efficiencies, technological gaps may provide insufficient guidance on the impact of competition on innovation. Efficiency measures distance from the technology frontier, while it is technological progress that expands the production possibilities frontier through innovation. The most efficient firms are likely to be highly innovative, but for the rest, efficiency change merely measures imitation based catch-up with frontier firms. Some level of slack may even be necessary in highly innovative industries. Efficiency-raising may be counterproductive to innovation.

References

Àcs, Z. J. – Audretsch, D.B. (1991): 'Innovation and Size at the Firm Level', The Southern Economic Journal 57(3), 739–744.

Aghion, P. – Howitt, P. (1992): A Model of Growth Through Creative Destruction. Econometrica, 60(2), 323–351. http://doi.org/10.2307/2951599

Aghion, P. – Harris, C. – Vickers, J. (1997): Competition and Growth with Step-by-Step Innovation: An Example. European Economic Review, Papers and Proceedings, 771–782.

Aghion, P. – Harris, C. – Howitt, P. – Vickers J. (2001): Competition, Imitation and Growth with Step-by-Step Innovation. Review of Economic Studies, vol. 68, No. 3, 467–492.

Aghion, P. – Bloom, N. – Blundell, R. – Griffith, R. – Howitt, P. (2005): Competition and Innovation: An Inverted-U Relationship. Quarterly Journal of Economics 120(2), 701–728.

Aghion, P. – Griffith, R. (2005): Competition and Growth, Reconciling Theory and Evidence. The MIT Press, Cambridge, MA.

Arrow, K. J. (1962): The Economic Implications of Learning by Doing. Review of Economic Studies, 29, 155–173.

Audretsch, D. B. (1995): Innovation and Industry Evolution, The MIT Press, Cambridge, MA.

Badunenko, O. – Fritsch, M. – Stephan, A. (2006): What Determines the Technical Efficiency of a Firm? The Importance of Industry, Location and Size. Jenaer Schriften zur Wirtschaftswissenschaft 33/2006, Friedrich-Schiller-Universität Jena, Wirtschaftswissenschaftliche Fakultät, Germany.

Bain, J.S. (1951): Relation of Profit to Industry Concentration: American Manufacturing 1936–1940. Quarterly Journal of Economics, 65 (August), 293–324.

Battese, G. E. – Coelli, T. J. (1995): "A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data." Empirical Economics 20, 325–332.

Berghäll, E. (2015): Foreign Firms and the Technology Frontier, in Essays on the Technology Frontier and Finnish Innovation Policy. Aalto University publication series Doctoral Dissertations, 155/2015, Aalto University, Helsinki.

Bernstein, J.I. – Mamuneas, T.P. (2006): "R&D Depreciation, Stocks, User Costs and Productivity Growth for US R&D Intensive Industries." Structural Change and Economic Dynamics 17, 70–98.

Bos, J.W.B. – Kolari, J.W. – van Lamoen, R.C.R. (2013): Competition and Innovation: Evidence from Financial Services, Journal of Banking & Finance 37, 1590–1601.

Carlsson, B. (1972): The measurement of efficiency in production: an application to Swedish manufacturing industries, 1968. Swedish Journal of Economics 74, 468–485.

Caves, R. E. (2007): In praise of the Old I.O. International Journal of the Industrial Organization 25(2007), 1–12.

Charnes, A. – Cooper, W. – Rhodes, E. (1978): Measuring The Efficiency of Decision Making Units. European Journal of Operational Research 2, 429–444.

Coelli, T. (1996): A Guide to DEAP Version 2.1: A Data Envelopment Analysis (Computer) Program. CEPA Working Paper 96/08, Centre for Efficiency and Productivity Analysis, Armidale. Australia.

Coelli, T. – Prasada, D.S. R. – Battese, G.E. (1999): An Introduction to Efficiency and Productivity Analysis. Boston/ Dordrecht/London: Kluwer Academic Publishers.

Daraio, C. – Simar, L. (2007): Advanced Robust and Nonparametric Methods in Efficiency Analysis. Methodology and Applications. Springer, New York

Dasgupta, P. – Stiglitz, J. (1980): Industrial Structure and the Nature of Innovative Activity. The Economic Journal 90, no. 358 (June): 266–293.

Demsetz, H. (1973): Industrial Structure, market rivalry and public policy, Journal of Law and Economics 16, 1–9.

Demsetz, H. (1974): Two systems of belief about monopoly. In: Goldschmid, H. – Mann, H. –Weston, J. (Eds.), Industrial Concentration: The New Learning. Little Brown, Boston, 164–184.

Dixit, A. – Stiglitz, J. (1977): Monopolistic Competition and Optimum Product Diversity. The American Economic Review 67(3), 297–308.

Farrell, M.J. (1957): The Measurement of Productive Efficiency, Journal of the Royal Statistical Society 120(3), 253–82.

Gilbert, R. (2006): Looking for Mr. Schumpeter: Where Are We in the Competition-Innovation Debate? In: Innovation Policy and the Economy, Eds.: Adam B. Jaffe, – Josh Lerner – Scott Stern, The MIT Press, Cambridge, MA. URL: http://www.nber.org/chapters/c0208

Gorodnichenko, Y. – Svenjar, J. – Terrell, K. (2010): Globalisation and Innovation in Emerging Markets, American Economic Journal: Macroeconomics 2 (2), 194–226.

Grossman, G. M. – Helpman, E. (1991): Quality Ladders in the Theory of Growth. The Review of Economic Studies, Vol. 58, No. 1. (Jan., 1991), pp. 43–61.

Hall, B. H. – Mairesse J. (1995): Exploring the relationship between R&D and productivity in French manufacturing firms. Journal of Econometrics 65, 263–293.

Hall, B. (2010): Measuring the Returns to R&D: The Depreciation Problem. Chapter in NBER book Contributions in Memory of Zvi Griliches (2010), Jacques Mairesse and Manuel Trajtenberg (eds.) (pp. 341–381), NBER, Cambridge, MA.

Hanusch, H. – Hierl, M. (1992): Productivity, Profitability and Innovative Behavior in West German Industries. Chapter in Entrepreneurship, Technological Innovation, and Economic Growth. Studies in the Schumpeterian Tradition. F.M. Scherer and M. Perlman (eds.). Ann Arbor. The University of Michigan Press.

Heshmati, A. – Kumbhakar, S. C. – Hjalmarsson, L. (1995): "Efficiency of the Swedish pork industry: A farm level study using rotating panel data 1976-1988." European Journal of Operational Research 80, 519–533.

Kilponen, J. – Santavirta, T. (2007): When do R&D subsidies boost innovation? Revisiting the inverted U-shape. Bank of Finland Research. Discussion Papers 10.

Nelson, R. – Winter, S. (1982): An Evolutionary Theory of Economic Change, Cambridge, M.A., Harvard University Press.

Nickel, S. (1996): Competition and corporate performance. Journal of Political Economy 104, no. 4: 724–746.

Pakes, A. – Schankerman, M. (1984): "Rates of Obsolescence of Knowledge, Research Gestation Lags, and the Private Rate of Research Resources." In Griliches, Z., (Ed.). R&D, Patents and Productivity, 209–232. University of Chicago Press, Chicago.

Peteraf, M.A. (1993): The Cornerstones of Competitive Advantage: A Resource-Based View, Strategic Management Journal 14 (3), 179–191.

Romer, P. (1990): Endogenous Technological Change, Journal of Political Economy 98 (5), 71–102.

Scherer, F. (1965): Corporate Inventive Output, Profits and Growth. Journal of Political Economy 73, no. 3: 290–297.

Schumpeter, J. (1934): The Theory of Economic Development. Harward University Press, Cambridge.

Tingvall, P. – Poldahl, A. (2006): Is there really an inverted U-shaped relation between competition and R&D? Economics of Innovation and New Technology, 15(2):101–118.