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Unraveling the Origins of EU Countries Productivity Growth

Evidence on R&D and Competition from Cross-Country Industry Analysis

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Abstract

Over the last two decades EU countries experienced diverging productivity growth developments. By examining the sources of EU countries growth drivers on the sectoral level, the paper takes a new look on the influence of innovations. While standard neo-classical Non-ICT capital deepening turns out the major contributor to EU productivity growth, detail industry analysis reveals that growth in innovation stocks via increased R&D in specialized and science-based industries spurred productivity growth as well. But those effects are only found for Nordic and Western Continental EU countries, while others are lacking such effects. Moreover, these specialized and science-based industries experienced strong innovation and productivity growth by decreases in competition, thereby favoring Schumpeterian growth arguments for highly dynamic sectors.

JEL Code: L10, L60, O30, O40, O52.
Keywords: Productivity growth, market structure, competition, innovation, R&D, panel data, industry analysis.

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1. Introduction

Productivity trend growth of EU countries and the US is characterized by a strong divergence over the last two decades. But not only EU countries as a whole experienced diverging productivity developments. Moreover, strong differences in productivity growth rates among EU members are disclosed as well (Van Ark et al., 2007; Eicher and Strobel, 2009). Since examining the sources of country productivity growth by aggregate data often disguises underlying sectoral trends, in this paper I will dwell down to the industry origins of EU countries' diverging productivity growth developments.

The novelty of this paper is in analyzing the impact of research and development (R&D) and competition on sectoral goods-producing productivity growth across selected EU countries, besides the impact of neo-classical Solow factors. The decisive contribution will be in determining the relationship between productivity growth and the sectoral innovation stock, which is determined by industries' R&D stock and their existing market structure. Thereby, heterogeneity among industries with respect to different innovation activities will be taken into account.

Modeling the effect of competition and innovation on productivity growth is a complex undertaking. According to Schumpeter (1934) the relationship between firm innovation and competition is determined by the rents a firm is expecting to generate *ex ante* on early stages of the production chain. Those rents provide the firm incentives to engage in R&D and to become ahead of their competitors; hence, reduced profit prospects due to intensive competition leads to less R&D, a lower rate of innovation and lower economic growth.

This rather strong prediction has triggered a number of theoretical papers that in contrast to Schumpeter's view have shown that increased competition can also stimulate innovations and R&D, and hence economic growth. Fellner (1951) and Arrow (1962), for example, have shown that a firm benefits more from innovations if competition is strong. Furthermore, Scherer (1967) argues that lack of competition leads to bureaucratic inertia that discourages innovation, while Porter (1990) states that competition is good for growth as it forces firms to innovate in order to stay in business.

Empirical result of the relationship between competition and innovation are manifold. In an early study Horowitz (1962) found a positive linear relationship between firm size and R&D undertaken by firms suggesting that mainly larger firms characterized by large market shares, stability and internally generated funds can afford to invest in risky R&D; hence, the lower the competition and the higher the market power of the firm, the higher the engagement in R&D.[1] On the contrary, studies revealing a negative correlation between competition and R&D are Hamberg (1964), Mansfield (1968), Kraft (1989), Crépon et al. (1998), and Pavitt et al. (1987). Because of these contradicting results one may expect an underlying non-linear relationship between competition and innovation that captures both contradictory effects.[2]

Determining the relationship between innovation, competition and productivity growth inevitably needs to refer to those various findings on the interdependency of competition and innovation. Hence, productivity growth induced by changes in the sectoral innovation stock will be modelled by the impact of R&D stocks and different functional forms of competition. Particularly in case of competition, it will be tested for the first time whether the empirically identified non-linearity between innovation and competition translates into a cogeneric relationship between competition and productivity growth as well.

The results of this paper show that post–1991 productivity growth of EU countries was mainly driven by standard factors as Non-ICT capital deepening. Nordic (Sweden & Finland) and Western Continental (Germany & France) countries, moreover, disclose strong growth contributions from increased innovation stocks in SGS & SBI (Specialized Goods Suppliers and Science-Based Innovators) sectors via increases in R&D stocks. Instead, other EU countries were lacking those effects. Growth in innovation stocks and productivity of Nordic and Western Continental SGS & SBI industries also went along with considerable decreases in competition, thereby favoring Schumpeterian growth arguments for these highly dynamic sectors. The empirical results also provide evidence that certain industries generated highest productivity growth under monopolistic competition; however, growth effects under such markets conditions were estimated significantly smaller.

The paper is organized as follows. Section 2 provides the theoretical underpinning of productivity growth derived from standard neo-classical inputs, R&D and competition. Section 3 describes the construction of the variables and the accounting of heterogeneity among industries via industry innovation taxonomy. In Section 4, I implement the empirical estimation strategy and present estimation results for different estimators, while Section 5 concludes.

[1] Other studies that find a positive correlation between competition and R&D are Mukhopadhyay (1985), Geroski (1990), Blundell et al. (1995, 1999), and Nickell (1996).

[2] Evidence for an inverted U-shaped relationship between competition and R&D was found by Scherer (1967), Scott (1984), Levin et al. (1985), and Aghion et al. (2005).

2. Theoretical Underpinning

Testing the sources of EU productivity growth, I implement a production function framework with output being generated from a production function F using capital and labor inputs, and Hicks neutral technology progress, A,

$$Y = A\,F(K, L, Q) \ . \qquad (1)$$

Thereby, Y reflects industry output, K capital input, L labor input. Additionally, a quality index of innovations, Q, is introduced. The first two input variables (K, L) are specified as ingredients of a standard neo-classical production function, while the quality index captures technology improvements that are not explicitly accounted for in capital goods and labor input, and that are not of disembodied nature reflected by the efficiency parameter A.[3] The functional form of the production function F(.) is Cobb-Douglas with

$$F(K, L, Q) = K^{\alpha} L^{\beta} Q^{\beta} \quad \text{and} \quad \alpha + \beta = 1 \ . \qquad (2)$$

The input elasticities exhibit constant returns to scale, while quality innovations are purely labor augmenting in the long-run. The incorporation of labor-augmenting technological progress follows the prominent steady-state growth theorem of Uzawa (1961) that postulates if an economy under a neoclassical growth model possesses an asymptotic path with constant growth of output, capital and consumption, and non-zero factor shares, then asymptotically technological progress can be represented as purely labor-augmenting (or *Harrod* neutral).[4]

Modeling technological progress follows the kind of Schumpeterian quality-ladder models that account for quality-adjusted intermediate goods with new technologies incorporated. Therefore the quality index, Q, is defined under the assumption that the innovation process is cumulative in the sense that new technologies build on existing ones. Technologies within sectors thus generate a stock of innovations that keeps growing as long as new innovation projects are undertaken, but that diminishes when existing technologies become obsolete and are not renewed.

As I am interested in labor productivity equation (1) is transformed into output and input per labor

[3] This approach follows the quality-ladder models representation in growth accounting exercises outlined by Barro & Sala-i-Martin (2004).

[4] The incorporation of labor-augmenting technological progress distinguishes from the concept of disembodied technological progress, captured by the efficiency parameter A (*Hicks* neutral). Thus the functional form of the output generating process allows for different specifications of technological progress.

$$\frac{Y}{L} = A\,F\left(\frac{K}{L}, 1, Q\right) . \tag{3}$$

Defining lower-case letters as per-labor variables, equation (1) and (2) can be simplified to

$$y = A\,F(k, Q) \tag{4}$$

with y specifying labor productivity and k capital deepening. In equilibrium, aggregate industry labor productivity is represented as

$$y = A\,k^{\alpha} Q^{1-\alpha} . \tag{5}$$

Log-linearizing the model and taking first differences transforms the model into exponential growth rates

$$\Delta \ln y = \Delta \ln A + \alpha \Delta \ln k + \beta \Delta \ln Q . \tag{6}$$

For the growth rate of the quality index of innovations, I assume that it is determined by two distinct factors. The first factor intends to capture the stock of existing technologies by implementing R&D stocks (denoted by RND) that directly translates into growth of innovations stocks.[5] Secondly, since the stock of innovations further depends on industry market structure (e.g. Aghion et al., 2005), I additionally introduce competition as a crucial driver. Thereby competition is measured by a Herfindahl index measure (denoted by H). Hence, growth in innovations quality is defined as

$$\Delta \ln Q = f(\Delta \ln RND, H) . \tag{7}$$

According to the seminal paper of Dasgupta and Stiglitz (1980) R&D and market structure are determined simultaneously, why the two factors driving the innovation quality index are assumed to be subject to endogeneity.[6] Inserting (7) into (6) and allowing capital deepening to differ by capital types (ICT and Non-ICT) renders labor productivity growth

$$\Delta \ln y = \Delta \ln A + \alpha_1 \Delta \ln k^{ICT} + \alpha_2 \Delta \ln k^{NICT} + \beta_1 \Delta \ln RND + \beta_2 H . \tag{8}$$

To start with, I assume a linear relationship between productivity growth and market structure, but I will also test non-linearity (quadratic and non-parametric) between productivity growth and market structure. Motivated by the empirically determined non-linearity between competition and innovation, I will test whether such a relationship for competition and innova-

[5] A similar modeling is outlined in Barro & Sala-i-Martin (2004).

[6] For an empirical investigation of the simultaneity between R&D and market structure, see e.g. Levin and Reiss (1984, 1988) and Loury (1979).

tion translates into a non-linear relationship between competition and productivity growth via the innovation stock as well.

Furthermore, Schumpeterian growth models differ from other endogenous growth theories by assuming that firms/industries are heterogeneous and that sectoral competition plays an important role in the growth process. Reaping benefits from R&D activities under specific intensities of sectoral competition is supposed to significantly impact the emergence of innovations and thus ultimately turns into higher firm/industry productivity growth. Accounting for heterogeneous firms, I will test the impact of competition and R&D on productivity growth by sectors of different innovation activities.

Investigating theoretically the relationship between technological change and what is typically considered as *total factor productivity* (denoted by TFP) shows that the organically derived TFP residual in this model can be decomposed according to

$$\begin{aligned}\Delta \ln \mathrm{TFP} = \Delta \ln y - \alpha_1 \Delta \ln k^{\mathrm{ICT}} - \alpha_2 \Delta \ln k^{\mathrm{NICT}} &= \Delta \ln A + \beta \Delta \ln Q \\ &= \Delta \ln A + \beta_1 \Delta \ln \mathrm{RND} + \beta_2 H\end{aligned} \tag{9}$$

Due to the equation (7) the TFP residual (output less inputs) is determined by a) an exogenous part, A, that reflects disembodied technological change and which is not determined by the model itself, and b) two further parts: R&D stock growth and sectoral market structure. For competition it is assume that productivity growth rates is conditional on its *level*.

Since R&D and market structure are determined simultaneously (Dasgupta and Stiglitz, 1980) this will induce potential endogeneity problems. Simultaneity may stem from competition-induced firm R&D that accelerates productivity growth. But as competition speeds up creative destruction as well, production factors are allocated from low- to high-productivity firms enabling more productivity firms to engage in new R&D activities. Accounting for these potential endogeneity issues is described in the econometric specifications section.

3. Data and Industry Innovation Taxonomy

3.1 Data

The data covers the period 1992–2005 for nine selected European countries, which are Germany, France, Sweden, Finland, Denmark, the Netherlands, Italy, Spain, and the United Kingdom. As the data is given on sectoral level, 13 goods-producing industries can be identified. For a list of the industries according to their ISIC classification see Table 1.

In the first step, I employing a standard neoclassical production function with output and input factors motivated by the Solow (1956) growth model. The input factors are capital and labor, where capital is measured as capital services and labor as total hours worked by persons engaged, while output is value-added. Output and input factors for Germany are provided by the *Ifo Industry Growth Accounting Database* (henceforth IIGAD)[7], which comprises unique growth accounts for Germany.[8] To derive comparable data for other European countries international output and inputs are obtained from the *EUKLEMS Growth and Productivity Accounts* (henceforth EUKLEMS).[9]

Since the period of analysis coincides with the launching phase of the New Economy during the second half of the 1990s, the data accounts for productivity enhancing effects from information and communication technology (ICT). Rapid changes in IT and communication technology are reflected in terms of embodied technological change in ICT capital services. After advances in the productivity measurement allowed for such an effective accounting of ICT in national statistics (Schreyer, 2001), it became obvious that part of the post–1995 productivity increases across countries originated with ICT investments.

Going beyond the standard neo-classical assumptions of factor accumulation as main source of country growth differentials and incorporating innovations into the production function (Romer, 1990; Aghion and Howitt, 1992; Grossman and Helpman, 1991), I employ R&D data as provided by the *OECD STAN R&D Database* (henceforth OECD). The key insight of the "New Growth Theory" was that sustained growth requires ever more efficient use of available resources, and that this increase in efficiency is ultimately driven by firm R&D. Implementing innovations, I account for the scale-effects critique by Jones (1995) and construct industry-level R&D stocks by industry and country using the OECD methodology outlined in Guellec and Pottelsberghe (2001).[10]

My measure of competition is the Herfindahl index, H, provided by the *EUKLEMS Company Database* (EUKLEMS, 2008b).[11] It indicates increased competition the closer the index is to 0. Since the Herfindahl index is constructed from firm data a normalised version as provided in O'Mahony et al. (2008) is used. Varying number of firms within an industry, especially in

[7] For a detailed description of the data, see Roehn et al. (2007).

[8] The IIGAD provides growth accounts on the highest detailed disaggregation level of different asset types and marginal productivities (measured as user costs) for Germany that allows construction of the most accurate measures of ICT and Non-ICT capital services.

[9] For a detailed description of the data, see Timmer et al. (2007a, b).

[10] For a detailed description of the construction of R&D stocks, see A1 in the Appendix.

[11] For a detailed description of the data and the index, see O'Mahony et al. (2008).

case of low firm coverage, will render the standard and the normalized Herfindahl index to differ. In particular, the normalization accounts for reporting bias in firm datasets to some extent, where some industries have a low number of firms reporting financial information.[12]

As I am interested in the effects on productivity growth all output and input variables, as well as the R&D stocks are employed in growth rates. In case of competition productivity growth is assumed to be conditional on the *level* of sectoral market structure.[13]

3.2 Industry Innovation Taxonomy

Considering the composition of R&D expenditures aggregate R&D figures are sometimes hard to interpret as they often include a heterogeneous mixture of different research activities. Hence, to answer important analytical and policy questions, R&D expenditures actually needed to be disentangled at the most detailed level. To overcome this data shortage, I employ an industry classification explicitly developed to take into account certain patterns of industry R&D activities.

Since heterogeneity among industries may drive productivity growth and lead industries to engage in different R&D projects, I seek to account for such industry differences by introducing an industry taxonomy originated by Pavitt (1984) and extensively applied by O'Mahony and Van Ark (2003) and Eicher and Strobel (2009). This industry classification separates goods-producing industries into four categories reflecting the diversity of R&D types (as product and process R&D), market structures (price and performance sensitivity), and means of appropriation (patents, licensing, etc). The four categories comprise: Scale-Intensive Industries (SII), Supplier-Dominated Goods-Producing Industries (SDG), Specialized Goods Suppliers (SGS), and Science-Based Innovators (SBI).[14]

The first classification group refers to SII sectors that use large-scale assembly production processes. R&D in these industries focuses mainly on process innovations facilitating capital-labor substitution and reducing production costs. The nature of SII industries is in process innovations located in in-house R&D departments (e.g. process engineering specialist groups) or in R&D that is delivered by upstream suppliers. Typical SII industries are Vehicles or Metal Production.

[12] A detailed description of the standard and the normalized Herfindahl index is available under A2 in the Appendix.
[13] For detailed descriptive statistics of the variables, see Table 2.
[14] A detailed list of goods-producing industries as classified in accordance with the innovation taxonomy is provided in Table 1.

SDG sectors are traditional manufacturing sectors whose main focus is on cost-cutting and less on technological innovations. Cost-cutting innovations are usually transmitted via upstream suppliers, why R&D expenditures on process and product innovation are less significant characteristics of those sectors. These industries rely greatly on industry-specific professional skills or trademarks, and usually comprise Textile and Printing, but also Furniture and Manufacturing n.e.c.

SGS are production-intensive sectors with a stronger focus on product innovations, which are often smaller, technologically specialized, and function as complementary sectors for SII industries. Those industries usually hold close relationships with their larger customers and provide them with specialized expertise. SGS sectors are often located in production processes of vertical disintegration in which various firms/industries of different economies of scale/scope split a production process into separate production unities, each performing a limited subset of activities required to create a final product. Machinery or Radio, TV and Communication Equipment are characteristic SGS sectors.

Finally, R&D in SBI sectors focuses on product and process innovations based on best available science. SBI industries' upstream R&D suppliers are universities and other organizations of high academic standards. These industries appropriate their innovations through patenting, specialized skills, and dynamic learning economies. In most cases, those industries differentiate by rapid growth potentials and strong market positions. Sectors that match the SBI characteristics are Chemicals and Electrical Apparatus n.e.c., as well as Office Machinery and Computers.

Due to the high aggregation level of industries, I need to merge the SGS and SBI sectors into one group. Grouping both sectors seems to be a viable compromise as both groups' R&D activities are characterized by high technology specialization.

4. Empirical Strategy

4.1 Econometric Specifications

For econometric strategy, I implement the following cross-country panel regression as benchmark according to equation (8)

$$\Delta \ln y_{i,j,t} = c + \beta_1 \Delta \ln k^{ICT}_{i,j,t} + \beta_2 \Delta \ln k^{NICT}_{i,j,t} + \beta_3 \Delta \ln R_{i,j,t} + \beta_4 H_{i,j,t} + \Delta \ln e_{i,j,t} \qquad (10)$$

with $y_{i,j,t}$ representing labor productivity (measured as value-added per hour worked) of industry i in country j at time t, $k_{i,j,t}$ is capital deepening (measured as capital services per hour worked) separated by ICT and Non-ICT, while $R_{i,j,t}$ is R&D stock. $H_{i,j,t}$ reflects the normalized Herfindahl index. The error term, $e_{i,j,t}$, is assumed to be

$$\Delta \ln e_{i,j,t} = \Delta \ln a_{i,t} + \Delta \ln b_{j,t} + \Delta \ln d_t + \Delta \ln \varepsilon_{i,j,t} \qquad (11)$$

with time-variant unobserved industry and country effects, $a_{i,t}$ and $b_{j,t}$ respectively, common time effects, d_t , and a stochastic i.i.d. component, $\varepsilon_{i,j,t}$.

Additionally to equation (10), I further introduce non-linearity between competition and labor productivity growth

$$\Delta \ln y_{i,j,t} = c + \beta_1 \Delta \ln k^{ICT}_{i,j,t} + \beta_2 \Delta \ln k^{NICT}_{i,j,t} + \beta_3 \Delta \ln R_{i,j,t} + \beta_4 H_{i,j,t} + \beta_5 H^2_{i,j,t} + \Delta \ln e_{i,j,t} \qquad (12)$$

with $e_{i,j,t}$ representing the same structural form as in equation (11). To test the non-linearity and the validity of the quadratic form between competition and labor productivity, I also estimate a semi-parametric specification according to

$$\Delta \ln y_{i,j,t} = c + \beta_1 \Delta \ln k^{ICT}_{i,j,t} + \beta_2 \Delta \ln k^{NICT}_{i,j,t} + \beta_3 \Delta \ln R_{i,j,t} + f\left(H_{i,j,t}\right) + \Delta \ln e_{i,j,t} \qquad (13)$$

in which the competition effect is modeled non-parametrically. The error term structure, once again, is assumed as given in equation (11). For the non-linearity part, I apply a difference-based semi-parametric estimation approach of partial linear regression models originated by Yatchew (2003) and computationally implemented by Lokshin (2006). Employing non-parametric methods is most appropriate in assessing the validity of the used model specification as well as in case of small sample size. Latter will become evident for the country sub-samples regressions.[15]

As the specter of endogeneity looms large due to the simultaneity of R&D, market structure and productivity growth postulated in the theoretical section, I employ the system GMM estimator (Arellano and Bover, 1995; Blundell and Bond, 1998; Roodman, 2005) to derive consistently estimated coefficients of equation (10) and (12). This estimator is preferred to the first-difference GMM as proposed by Arellano und Bond (1991) due to its increased efficiency in short panels.

According to the autocorrelation tests in dynamic panel settings, three to four lags of the dependent variable are employed in equations (10) and (12). Moreover, due to the fact that

[15] When the dataset is large it often makes little sense to use non-parametric statistics at all, because sample means as well as estimated coefficients will usually follow the normal distribution even if the respective variable is not normally distributed in the population. Thus, parametric methods, which are usually much more sensitive in terms of having more statistical power, are in most cases appropriate for large samples. However, testing the functional form of the competition effect is at the forefront of the non-parametric estimation application.

most of the regressors as well as the dependent variable are given in growth rates, lags t-4 and deeper are employed for valid instruments.

4.2 Productivity Growth and Competition By Sectoral Innovation Activities

A first exploration of the relationship between productivity growth and competition across countries shows an incremental dispersion of productivity growth rates for increased market concentration. In particular, this holds for a Herfindahl index ranging between .2 and .4 (Figure 1). However, productivity dispersion reduces for high market concentration, i.e. beyond a Herfindahl threshold of around .6, sectoral productivity growth decreases significantly.

Tracing productivity growth and competition to its industry origins by splitting the sample by innovation types of industries discloses different patterns (Figure 2). The SII sectors represent a blueprint of the total sample showing an increased dispersion of productivity growth for higher Herfindahl values up to a threshold of around .2. On contrary, SDG sectors' productivity growth varies less markedly by market competition. However, for very high Herfindahl values SDG sectors exhibit very low productivity growth rates. Differently from SII and SDG are the SGS & SBI sectors. Those high-specialized innovative sectors are characterized by an overall low market concentration of below .45, but show strongly increased productivity growth for lower market competition.

Analyzing these relationships via kernel-weighted local polynomial smoothing techniques for three different bandwidths (Figure 3) depicts similar relationships between productivity growth and competition for SII and SDG industries. While competition is rather not affecting productivity growth for a wide range of Herfindahl values in both sectors, SDG sectors exhibit a sharp drop in productivity growth for Herfindahl values beyond .75. On contrary, the relationship between productivity growth and competition is much more pronounced for SGS & SBI industries. It shows a positive relationship between higher levels of market concentration and productivity growth, providing strong support of the dominance of the Schumpeterian effect in those industries.

These distinguishing results indicate that treating productivity growth and competition separated by sectoral innovation activities is recommendable. Relying on aggregate average effects across all sectors instead will most likely induce coefficient biases.

4.3 Estimation Results

4.3.1 Panel Time Series Analysis

Examining panel time series behavior, I conduct non-parametric Fisher-type panel unit-root tests for augmented Dickey-Fuller (1979) and Phillips-Perron (1988) specifications, henceforth ADF and PP. Those tests were chosen as they allow for balanced as well as unbalanced datasets (see Table A1 in the Appendix).

Since both unit-root tests ADF and PP reject the hypothesis of panel non-stationarity for inputs and output in growth rates on the highest level of significance throughout all lag specifications, employment of those variables is unproblematic. As the existence of trends in sectoral growth rates can be precluded, no further differencing of variables is required. Fisher-type tests are based on combinations of tests conducted for individual time series, and are built under more general assumptions than conventional panel unit-root tests. Moreover, having stationary and non-stationary series in the panel and potential cross-sectional correlation Fisher-type tests have the highest power (Maddala and Wu, 1999).[16]

Regarding the competition variable it presumably exhibits strong unit roots that may spillover into the regression residuals, thus affecting statistical inference. Due to this, I conduct unit-root tests on the residuals of the least-square dummy-variable (LSDV) estimates as well. As provided in the subsequent section those tests reject the hypothesis of non-stationarity in the residuals, indicating that the regressions are well specified.

4.3.2 LSDV Estimations

Regarding the estimation results of equation (10) for all selected EU countries without competition but allowing R&D to differ by sectoral innovation type, it turns out that aggregate EU productivity growth is driven by ICT and Non-ICT capital deepening (Table 3a, column Ia) during the 1992–2005 period. Nonetheless, Non-ICT is stronger in magnitude than ICT. R&D only shows significant growth effects for the SGS & SBI sectors, with growth effects half the size of Non-ICT. Including competition separated by sectoral innovation types (column Ib) reveals a positive effect from decreased competition on productivity growth for SGS & SBI industries,

[16] Fisher-type tests combine significance levels of single time series and relax the assumption of having homogeneous autoregressive coefficients under the H_1. They combine significance levels from N independent unit-root tests (Maddala and Wu, 1999) and assume that all series are non-stationary under the H_0. Under H_1, at least some of the individual series in the panel may be non-stationary.

similar in magnitude to R&D. However, competition shows no significant effect for other sectors on the aggregate EU level.

Allowing for non-linearity in competition and productivity growth separated by sectoral innovations type shows a weakly significant inverted U-shape for productivity growth and competition in SII sectors (column Ic). Those results indicate that SII sectors' innovation and productivity growth is highest under monopolistic competition, whereas the impact is still relatively small. Other sectors do not exhibit a statistically significant non-linear relationship.

Disaggregating the EU sample by country groupings reveals strong heterogeneity in growth drivers by sectors and countries. Those country groupings are: Germany and France (Western Continental), Sweden and Finland (Nordic), Denmark and Netherlands (Northern Continental), Italy and Spain (Southern Continental), and United Kingdom (Anglo-Saxon), and were chosen according to *ex ante* assumptions on similarities of institutions, geographic location and productivity growth trends.

While Western Continentals' productivity growth was mainly driven by Non-ICT capital deepening (column IIa-c), Nordic countries experienced productivity growth primarily from increased R&D (column IIIa-c). Positive effects from decreasing competition that increased the innovation stock are disclosed for SGS & SBI sectors in Western Continentals (column IIb) and for SII sectors in Nordic countries (column IIIb), but these effects are relatively small. Moreover, non-linearity between competition and productivity growth is estimated as highly statistically significant in Western Continental and Nordic SII industries (column IIc and IIIc) with a considerable magnitude. Those findings indicate that SII industries' productivity growth in these countries profited from increased innovations via monopolistic competition.

Interestingly, Nordic countries SGS & SBI sectors (column IIIc) exhibit highly significantly productivity growth from decreased competition, disclosing very strong growth effects from innovations triggered by increased market concentration. Those findings suggest that competition in highly dynamic sectors is organized according to the principle that firms suddenly may come up with new technologies, enabling them to rapidly increase market shares, while non-successful firms drop out of the market. Hence, Schumpeterian growth arguments are crucial incentives for increased productivity growth in such dynamic sectors, at least in the Nordic countries.

Considering the other EU country groupings (Table 3b), it seems as if none of the standard driving factor as ICT and Non-ICT capital deepening has played a statistically robust role in Northern and Southern Continentals' productivity growth. Only in the Anglo-Saxon country both factors turn out to be productivity enhancing (column VIb, c). Nevertheless, the impact of Non-ICT is estimated substantially higher than ICT.

Besides some weakly statistically significant Non-ICT effect in Northern Continental countries, Northern Continental SGS & SBI sectors seem to have increased productivity growth by higher innovations and R&D (column IVa) as well. However, this R&D effect disappears when controlling for competition (column IVb, c). When competition is not controlled for, productivity enhancing R&D effects are also disclosed in Anglo-Saxon's SII and SDG industries (column VIa). But only in UK SII sectors R&D effects reveal a considerable magnitude. For Southern Continentals R&D effects are estimated insignificant throughout, which could be one of the reasons why those countries' productivity growth performed so badly since the mid–1990s.

Besides R&D growth and increases in the innovation stock, decreased competition generated increases in innovation and productivity growth in Northern Continental SII (column IVb) and Southern Continental SGS & SBI sectors (column Vb). Those findings support Schumpeterian arguments; even so, the effects are estimated with a low magnitude. On the other hand, increased competition favors innovation and productivity growth in Northern Continental SDG sectors (column IVb) as well as in Southern Continental and Anglo-Saxon SII sectors (column Vb and VIb). Those latter findings indicate that escape-competition arguments induce relevant incentives for innovation growth in those countries' sectors. Especially in Southern Continentals' SII sectors increased competition triggered highest productivity growth via increases in innovation stocks.

Non-linearity in competition and productivity growth shows a strong relationship between decreased competition and productivity growth in Northern Continental SDG industries (column IVc) that is similar to the findings for Nordic SGS & SBI sectors. However, these estimated effects are substantially lower for Northern Continental sectors. As in case of Nordic SGS & SBI sectors, Northern Continental SDG sectors managed to exploit strong growth effects from Schumpeterian arguments that contributed considerably to those countries aggregate productivity growth via increased innovation stocks.

As mentioned in the previous section, the panel unit-root tests of the LSDV residuals reject the hypothesis of non-stationarity throughout both test approaches (ADF, PP) and all lag specifications (see Table A2 in the Appendix for different country groupings). The rejection of the hypothesis of non-stationarity in the residuals verifies the appropriateness of the model specifications and ensures that the Herfindahl levels included do not cause serious problems in the estimated standard errors.

4.3.3 System-GMM and Semi-parametric Estimations

Controlling for endogeneity the system-GMM results disclose Non-ICT capital deepening as single key driver of EU productivity growth. ICT capital deepening turns statistically insignificant (Table 4a, column Ia–c). R&D in SGS & SBI industries is estimated insignificant in the specification without competition (column Ia), but turns significant as soon as competition is included (column Ib, c). The system-GMM estimates confirm the productivity growth effects from decreased competition in SGS & SBI sectors (column Ib), and moreover show positive effects from decreased competition in SII sectors as well. Non-linearity between competition and productivity growth is not confirmed on the aggregate EU level.

Disaggregating the EU sample by country groupings and controlling for endogeneity mainly confirms the LSDV effects for the standard neo-classical variables. Especially Non-ICT capital deepening for Western Continentals (column IIa–c) is estimated strongly significant, exerting a high impact on those countries' productivity growth. The new results also provide positive Non-ICT effects for Nordic countries when competition is included (column IIIb, c). The previously found strong R&D effects in SGS & SBI industries are once again estimated as highly statistically significant in both Western Continental and Nordic countries, thereby emphasizing the crucial role of introducing new technologies for productivity growth. The other countries do not reveal such statistically robust strong R&D effects.

Considering competition, previously determined LSDV results for Western Continentals cannot be confirmed univocally (column IIb, c), but the system-GMM results indicate increased SGS & SBI sector productivity growth from lower competition. However, for Nordic countries the new results support the inverted U-shape of productivity growth and competition in SII sectors as well as strong positive effects from reduced competition in SGS &SBI sectors (column IIIc). Once again, Nordic SGS & SBI sectors experienced stronger growth from decreased competition than Western Continentals.

For Northern and Southern Continental countries the system-GMM results are mixed compared to those of the LSDV approach (Table 4b). ICT capital deepening appears to be the only statistically significant productivity driver in Northern Continentals (column IVa, b), while Southern Continentals' Non-ICT capital deepening now is estimated as highly statistically significant (column Va–c). However, Non-ICT capital deepening exerts higher impacts on productivity growth than ICT. R&D effects show no or at least a negative impact for both country groupings. Negative growth from increased R&D may serve as an indication of severe structural problems within those countries to transform R&D into productivity gains, and may explain the secular decline in productivity growth of those countries.

Controlling for endogeneity in both country groupings, Northern and Southern Continentals, only reveals productivity growth effects from decreased competition in Southern Continentals' SDG sector. Non-linearity between productivity growth and competition appears to be insignificant and hence does not support the LSDV results (Table 3b).

Regarding the system-GMM results for the UK, the previously determined productivity effects from ICT and Non-ICT capital deepening are maintained. SGS & SBI sectors only experienced productivity gains from R&D when competition is not accounted for. Instead, including competition SGS & SBI sectors generate highest productivity growth from monopolistic competition (column VIc). This is different to Western Continentals and Nordic countries' SGS & SBI sectors that exhibit higher productivity growth from decreasing competition. Introducing competition renders R&D in SII sectors statistically significant, thereby confirm the LDSV results. Also, under the linear competition specification SDG sectors disclose weakly significant growth effects from increased competitions (column VIb), supporting escape-competition augments for this specific type of industries; however, the effects are very small in magnitude.

Next, I test the validity of non-linearity between competition and productivity growth as derived from the system-GMM approach by employing Lokshin's (2006) semi-parametric estimation algorithm. Figures 4a–e graph the non-linear effects estimated by system-GMM juxtaposed to semi-parametric estimates by country samples. In most of the cases the non-parametric estimation of the competition effect is close to the approximations generated by the quadric terms in the parametric regressions. Hence, the employed regressions indicate no severe specification error with regard to the competition effect. However, the results strikingly demonstrate country and sector heterogeneity in the relationship between competition and productivity growth.

5. Conclusion

EU countries and the US experienced different productivity growth trends during the last two decades. This study traces the driving forces of selected EU countries' productivity growth on the sectoral level. Beyond standard growth factors, the analysis for the first time implements growth effects from R&D and competition affecting productivity growth via the total factor productivity residual.

Examining EU productivity growth, it turns out that Non-ICT capital deepening is the standard growth driver. Disaggregation into country groupings reveals that those effects are apparent in most of the countries: Western Continentals (Germany and France), Nordic (Sweden and Finland), Southern Continentals (Italy and Spain) and the UK generate strong productivity growth from Non-ICT investments. On contrary, Northern Continentals (Netherlands and Denmark) are primarily driven by increased ICT capital deepening, although ICT effects are significantly lower. This is also the case for the UK, which provides strong evidence of productivity enhancing effects from ICT capital deepening.

Besides the standard neo-classical growth effects, the regression analyses reveal that there had been strong productivity growth effects from an increase in the innovation stock as well. Regarding the R&D determinant of the innovation stock, increases in R&D stocks significantly enhanced productivity growth in SGS & SBI industries. However, these effects are in particular generated in Western Continentals and Nordic countries. Isolated growth effects from R&D can also be stated in Western Continentals and Anglo-Saxon SII sectors as well as in Nordic SDG sectors, but those are significantly lower in magnitude. Interestingly, countries like the Northern and Southern Continentals experienced productivity drags from increased R&D in certain industries, thereby indicating severe structural problems in reaping benefit from R&D efforts.

Besides R&D, sectoral innovation stocks and productivity growth are significantly affected by competition within industries. Western Continentals and Nordic countries show strong productivity effects from decreased competition in SGS & SBI industries, indicating the dominance of Schumpeterian effects in these highly dynamic sectors. Noteworthy, Nordic countries growth effects from decreased competition are significantly stronger. Interestingly, Nordic SII industries also disclose evidence for an inverted U-shape relationship between competition and productivity growth. Similar to the relationship between innovation and competition (Aghion et al., 2005), highest productivity growth in these sectors is generated under monopolistic competition, however, productivity growth effects from these sectors are lower compared to SGS & SBI. The UK reveals a related inverted U-shape relationship in SGS & SBI sectors, indicating that different mechanisms underlie these highly dynamic sectors in this country, and that growth effects generated under monopolistic competition are lower.

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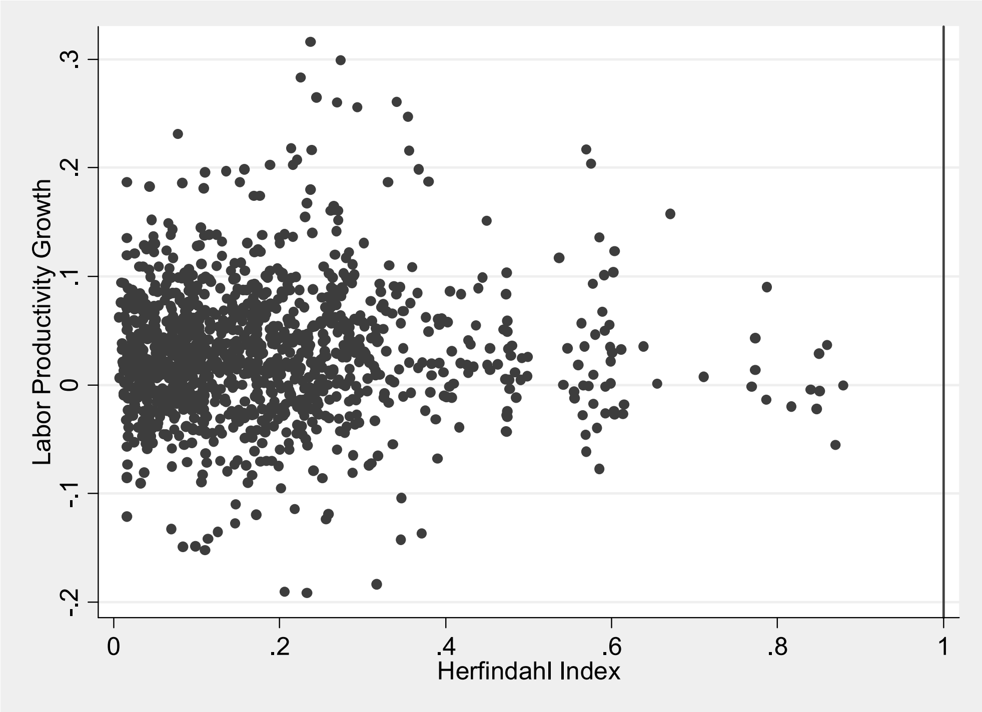
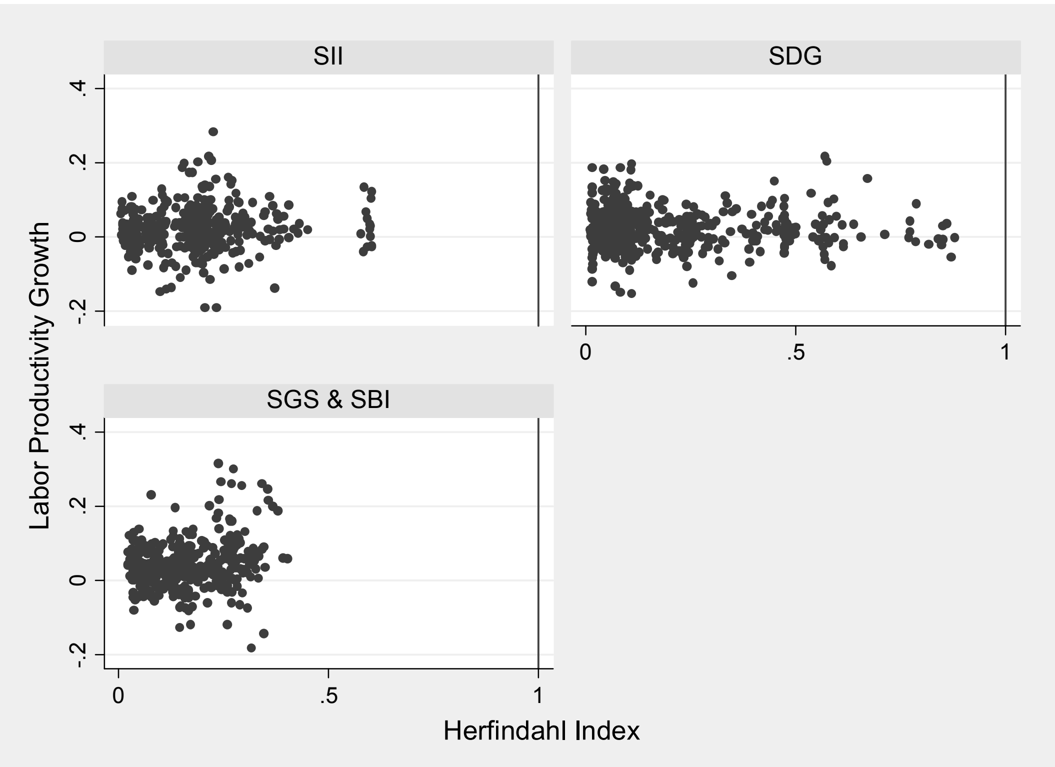
Figure 1:
Productivity Growth and Competition



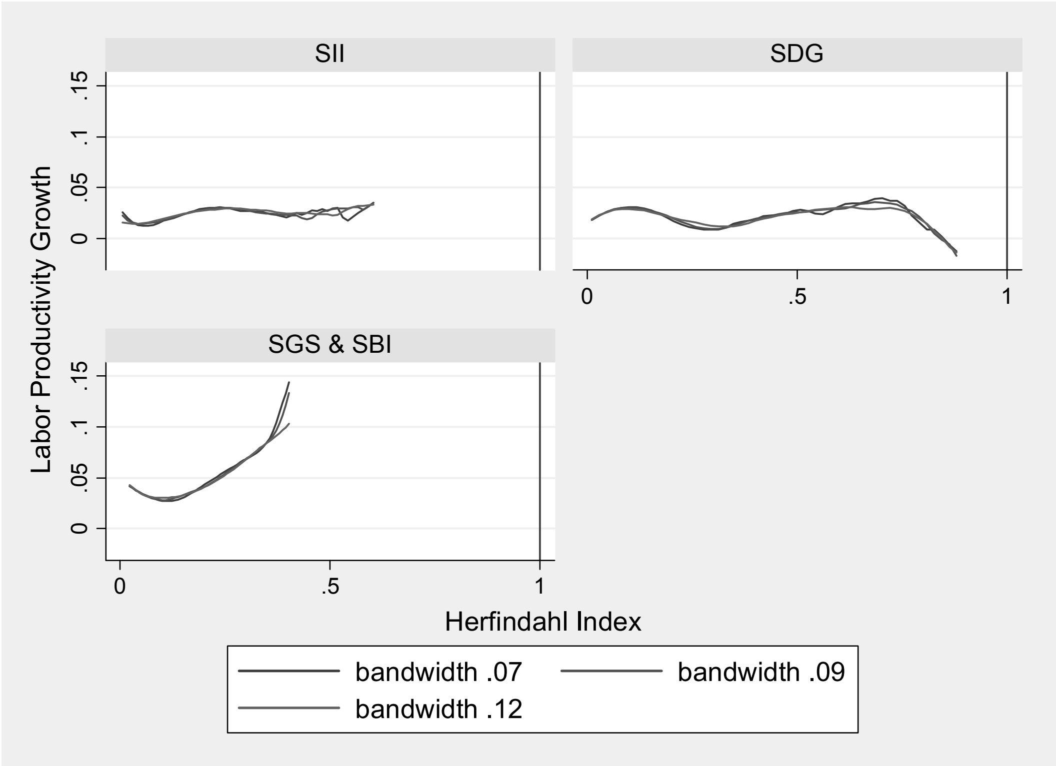
Notes: Pooled countries, 1992–2005. Herfindahl index ranges from 0 to 1 (from lowest to highest market concentration). Outliers excluded. *Sources:* EUKLEMS (2008b) and IIAGD (2008).

Figure 2:
Productivity Growth and Competition, by Sectoral Innovation Type



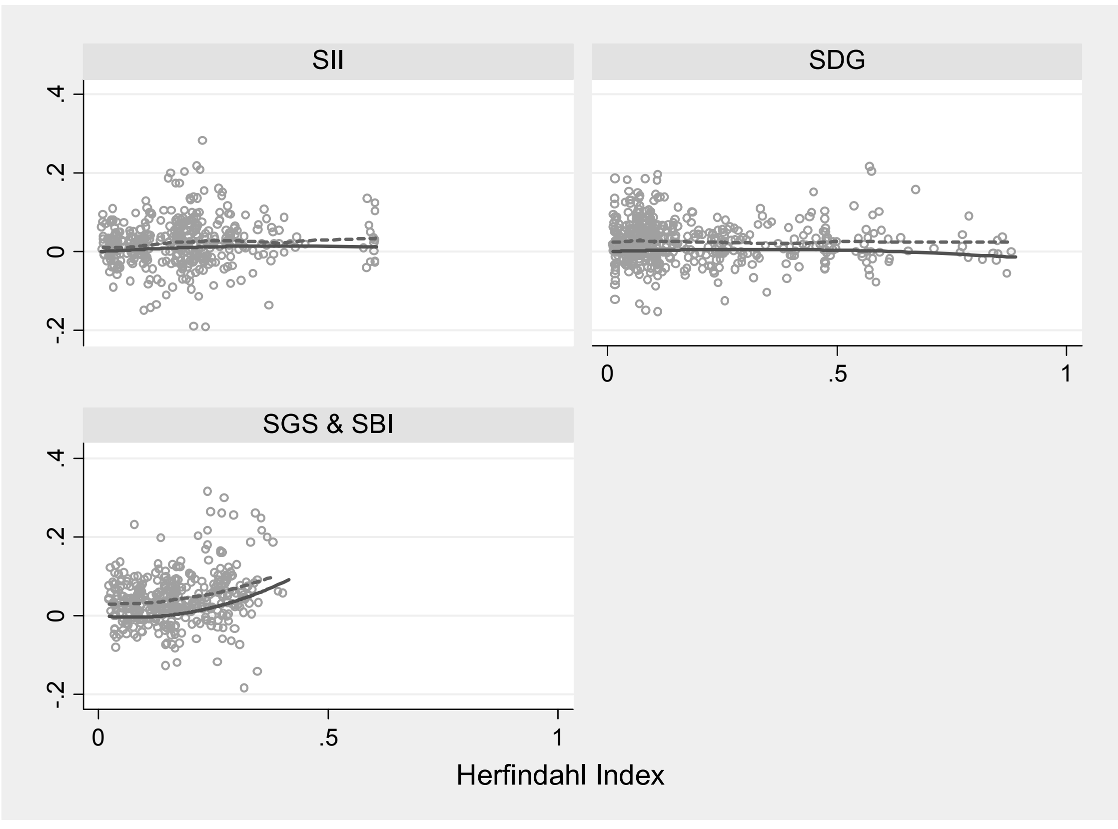
Notes: Pooled countries, 1992–2005. Herfindahl index ranges from 0 to 1 (from lowest to highest market concentration). Outliers excluded. SII = Scale-Intensive Industries; SDG = Supplier-Dominated Goods-Producers; SGS = Specialized Goods-Suppliers; SBI = Science-Based Innovators. *Sources:* EUKLEMS (2008b), IIAGD (2008).

Figure 3: Productivity Growth and Competition, by Sectoral Innovation Type Kernel-weighted Local Polynomial Smoothing



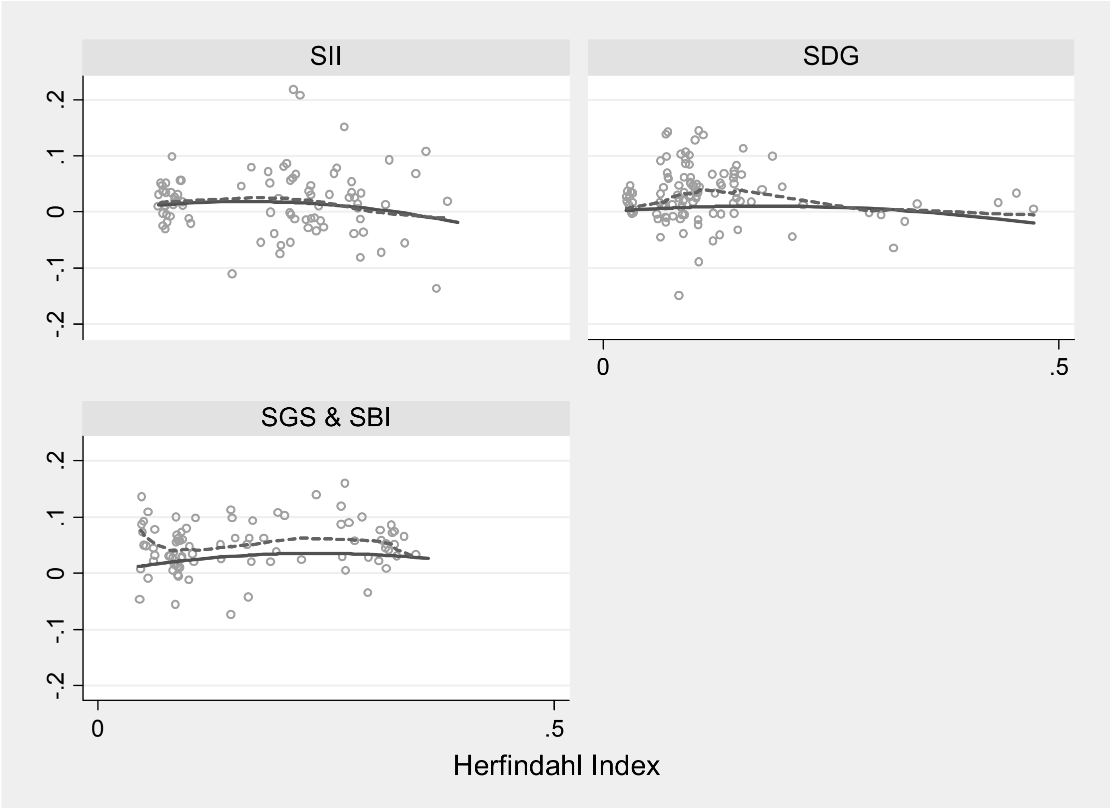
Notes: Pooled countries, 1992–2005. Herfindahl index ranges from 0 to 1 (from lowest to highest market concentration). Outliers excluded. SII = Scale-Intensive Industries; SDG = Supplier-Dominated Goods-Producers; SGS = Specialized Goods-Suppliers; SBI = Science-Based Innovators. *Sources:* EUKLEMS (2008b), IIAGD (2008).

Figure 4a: Productivity Growth and Competition, All Countries (Table 4a)



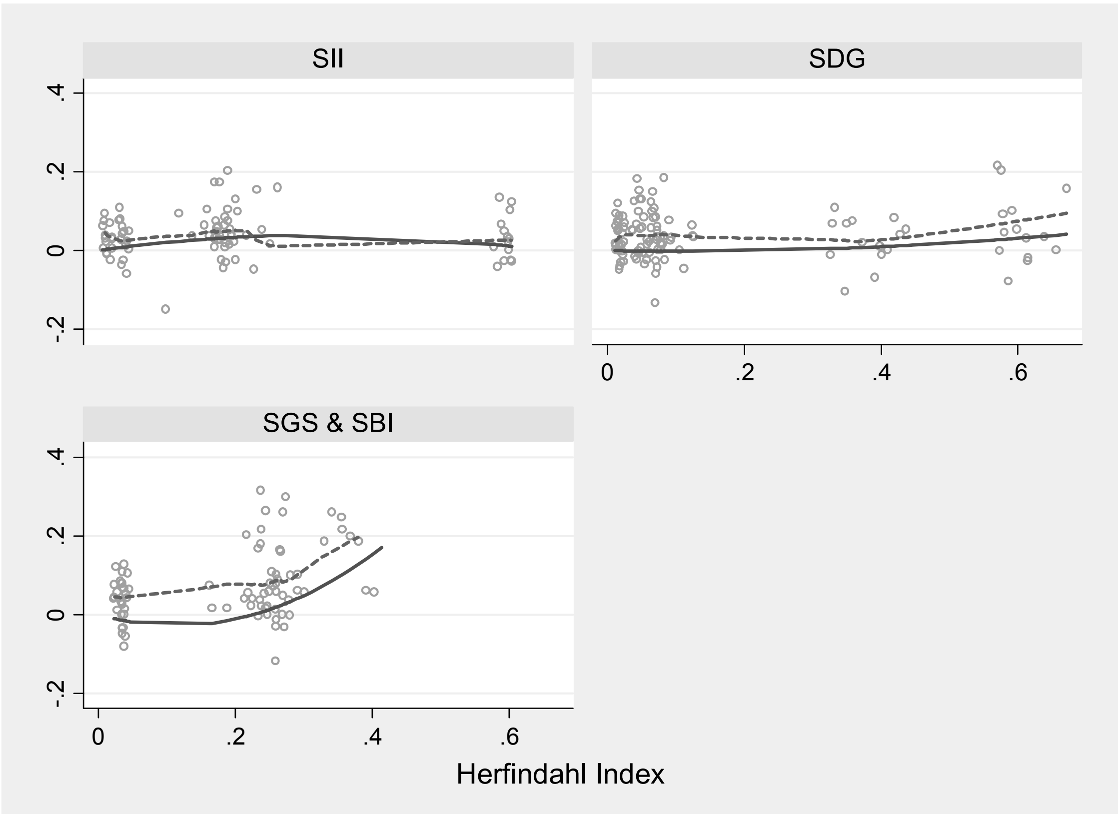
Notes: Pooled countries, 1992–2005. Red lines: non-linear effects provided by Table 4a. Green dashed lines: non-linear effects via difference-based semi-parametric estimations. Outliers excluded. SII = Scale-Intensive Industries; SDG = Supplier-Dominated Goods-Producers; SGS = Specialized Goods-Suppliers; SBI = Science-Based Innovators.

Figure 4b: Productivity Growth and Competition, Germany & France (Table 4a)



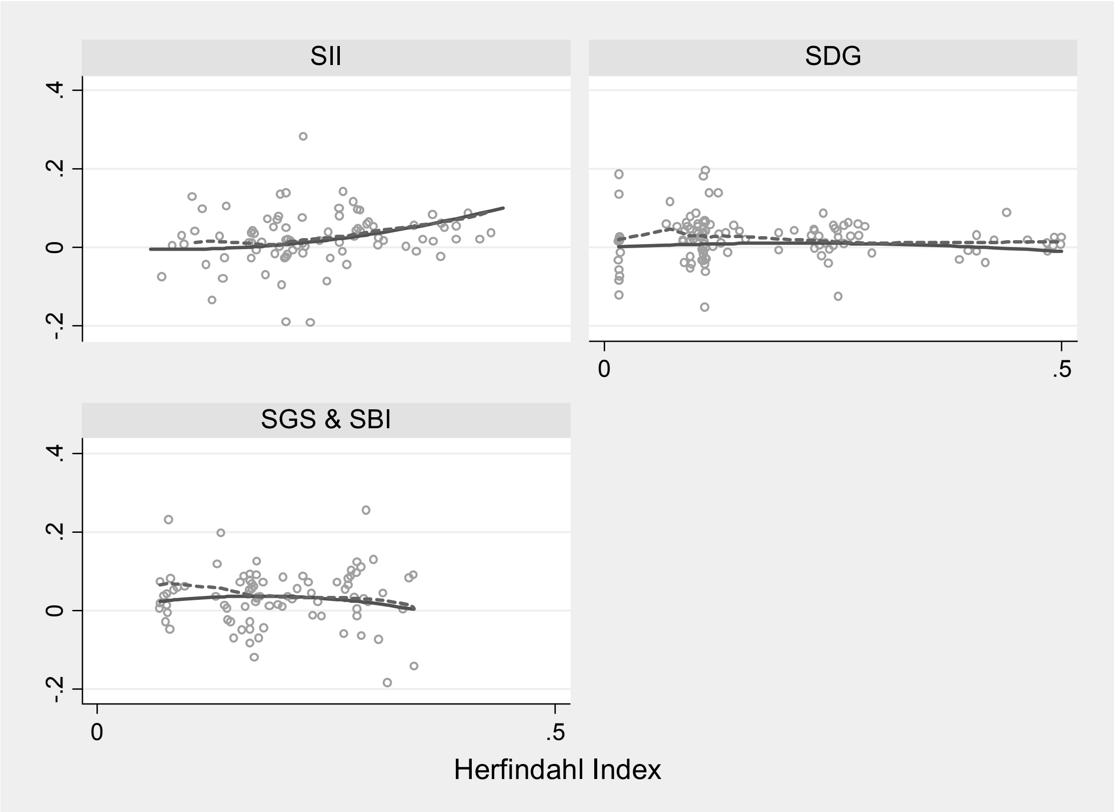
Notes: Sub-sample coverage, 1992–2005. Red lines: non-linear effects provided by Table 4a. Green dashed lines: non-linear effects via difference-based semi-parametric estimations. Outliers excluded. SII = Scale-Intensive Industries; SDG = Supplier-Dominated Goods-Producers; SGS = Specialized Goods-Suppliers; SBI = Science-Based Innovators.

Figure 4c: Productivity Growth and Competition, Sweden & Finland (Table 4a)



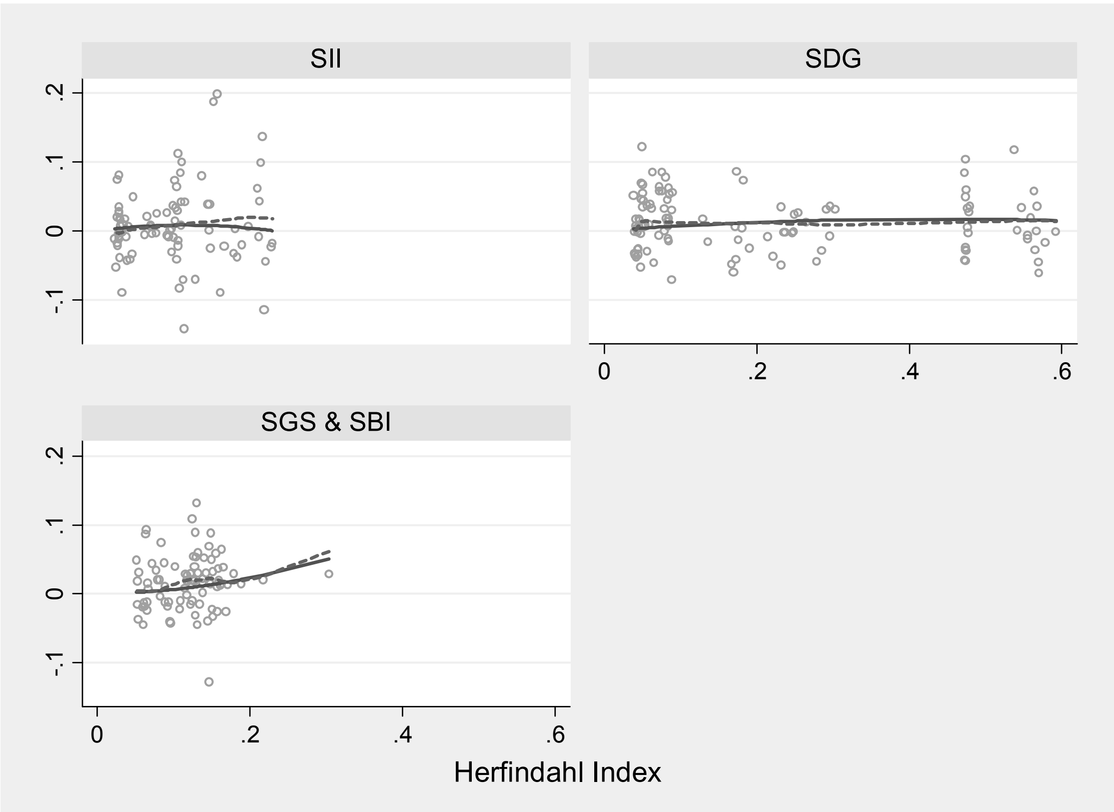
Notes: Sub-sample coverage, 1992–2005. Red lines: non-linear effects provided by Table 4a. Green dashed lines: non-linear effects via difference-based semi-parametric estimations. Outliers excluded. SII = Scale-Intensive Industries; SDG = Supplier-Dominated Goods-Producers; SGS = Specialized Goods-Suppliers; SBI = Science-Based Innovators.

Figure 4d: Productivity Growth and Competition, Netherlands &Denmark (Table 4b)



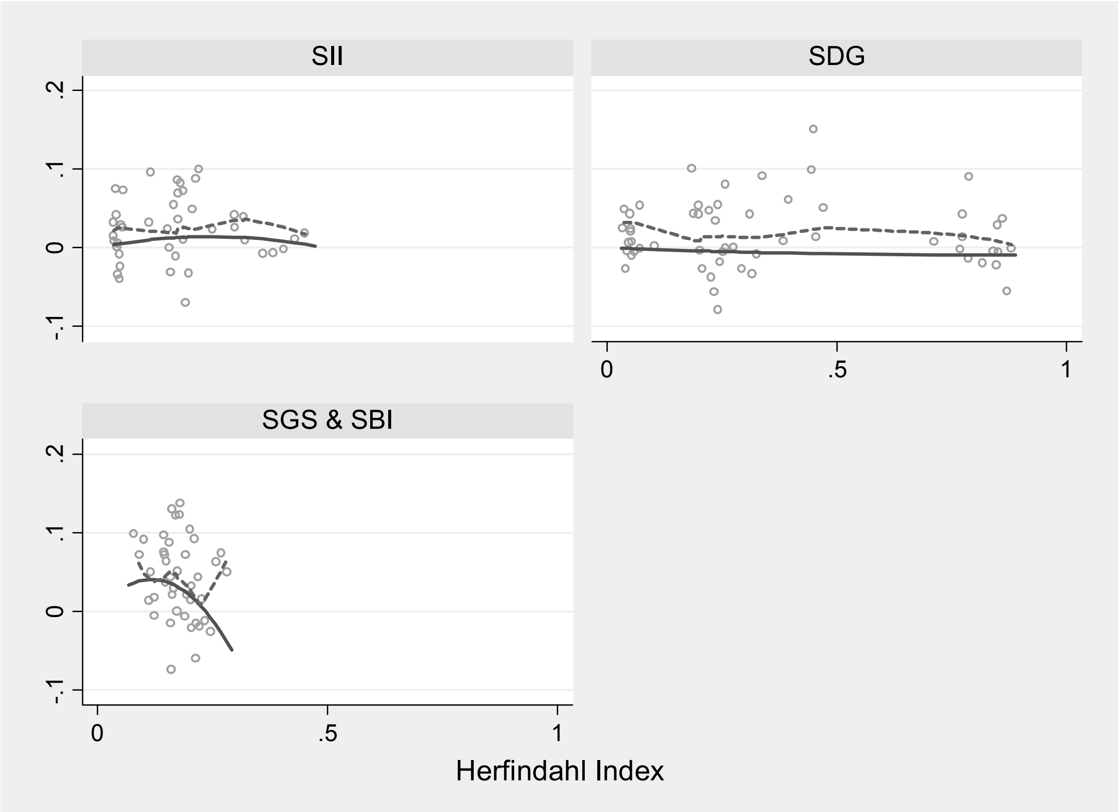
Notes: Sub-sample coverage, 1992–2005. Red lines: non-linear effects provided by Table 4b. Green dashed lines: non-linear effects via difference-based semi-parametric estimations. Outliers excluded. SII = Scale-Intensive Industries; SDG = Supplier-Dominated Goods-Producers; SGS = Specialized Goods-Suppliers; SBI = Science-Based Innovators.

Figure 4e: Productivity Growth and Competition, Italy &Spain (Table 4b)



Notes: Sub-sample coverage, 1992–2005. Red lines: non-linear effects provided by Table 4b. Green dashed lines: non-linear effects via difference-based semi-parametric estimations. Outliers excluded. SII = Scale-Intensive Industries; SDG = Supplier-Dominated Goods-Producers; SGS = Specialized Goods-Suppliers; SBI = Science-Based Innovators.

Figure 4f: Productivity Growth and Competition, United Kingdom (Table 4b)



Notes: Sub-sample coverage, 1992–2005. Red lines: non-linear effects provided by Table 4b. Green dashed lines: non-linear effects via difference-based semi-parametric estimations. Outliers excluded. SII = Scale-Intensive Industries; SDG = Supplier-Dominated Goods-Producers; SGS = Specialized Goods-Suppliers; SBI = Science-Based Innovators.

Table 1:
Industry Innovation and ISIC Classification

		ISIC Classification Revision 3.0	Innovation Activity
1	Food and Tobacco	D: 15 to 16	SII
2	Textiles, Apparel, and Leather	D: 17 to 19	SDG
3	Wood Products	D: 20	SDG
4	Paper, Pulp, Publishing, Printing	D: 21 to 22	SDG
5	Coke, Petroleum, Nuclear Fuels	D: 23	SII
6	Chemicals and Chemical Products[a)]	D: 24 to 26	SGS & SBI
7	Basic and Fabricated Metals	D: 27 to 28	SII
8	Machinery	D: 29	SGS & SBI
9	Office Machinery and Electronic Equipment	D: 30 to 33	SGS & SBI
10	Motor Vehicles and Other Transport	D: 34 to 35	SII
11	Manufacturing n.e.c.[b)]	D: 36 to 37	SDG
12	Electricity, Gas & Water Supply	E: 40 to 41	SII
13	Construction	F: 45	SDG

Notes: a) comprises Rubber and Plastic, and Non-Metallic Mineral Products; b) consists of the sectors Furniture, Recycling, and Manufacturing n.e.c. SII = Scale-Intensive Industries; SDG = Supplier-Dominated Goods-Producers; SGS = Specialized Goods-Suppliers; SBI = Science-Based Innovators.

Table 2:
Descriptive Statistics of Output and Input, Innovations and Competition

Variable	Status	Mean	Std. Dev.	Min.	Max.	Obs.
Labor Productivity	Growth	0.0277	0.0578	-0.1918	0.3155	1509
ICT Capital Deepening	Growth	0.0963	0.0820	-0.2170	0.5341	1464
Non-ICT Capital Deepening	Growth	0.0293	0.0436	-0.3851	0.4103	1464
R&D Stock	Growth	0.0584	0.1216	-0.1541	0.8732	1387
Herfindahl	Levels	0.1803	0.1489	0.0054	0.8897	1350

Notes: Pooled OECD countries, 1991–2005 for Herfindahl and 1992–2005 for others. Herfindahl index ranges from 0 to 1 (from lowest to highest market concentration). Outliers excluded. *Sources:* EUKLEMS (2008a, b), OECD (2006) and IIAGD (2008).

Table 3a:
Cross-Country Productivity Growth: Innovations and Competition, LSDV

	ALL COUNTRIES			GER & FRA			SWE & FIN		
	Ia	**Ib**	**Ic**	**IIa**	**IIb**	**IIc**	**IIIa**	**IIIb**	**IIIc**
ICT	**0.0544***	**0.0673***	**0.0683***	-0.0043	-0.0256	0.0011	0.0345	0.0371	0.0298
	[0.0292]	[0.0349]	[0.0347]	[0.0462]	[0.0466]	[0.0533]	[0.0846]	[0.0947]	[0.1012]
Non-ICT	**0.2922*****	**0.2576*****	**0.2613*****	**0.5767*****	**0.6471*****	**0.6128*****	0.0965	0.0694	0.0835
	[0.0606]	[0.0616]	[0.0631]	[0.0993]	[0.0998]	[0.1038]	[0.1246]	[0.1171]	[0.1045]
R&D × SII	-0.0155	-0.0077	0.0017	-0.0438	-0.0932	**-0.1542****	**0.1113***	-0.0280	**0.2905*****
	[0.0323]	[0.0381]	[0.0366]	[0.0312]	[0.0569]	[0.0576]	[0.0614]	[0.0801]	[0.0956]
R&D × SDG	0.0216	0.0238	0.0216	0.0395	0.0755	0.0581	0.0610	**0.1342***	0.1505
	[0.0143]	[0.0170]	[0.0176]	[0.0479]	[0.0580]	[0.0497]	[0.0642]	[0.0737]	[0.0904]
R&D × SGS&SBI	**0.1329****	**0.1349*****	**0.1283*****	0.0332	0.0374	0.0245	-0.1006	-0.0774	-0.2488
	[0.0572]	[0.0498]	[0.0469]	[0.0585]	[0.0617]	[0.0906]	[0.1929]	[0.2272]	[0.2799]
H × SII		0.0196	**0.1158***		-0.0376	**1.5413*****		**0.0852****	**0.7277*****
		[0.0226]	[0.0608]		[0.0805]	[0.4408]		[0.0313]	[0.0837]
H × SDG		-0.0113	0.0059		0.0597	0.4190		0.0754	-0.1932
		[0.0145]	[0.0452]		[0.0564]	[0.3640]		[0.0463]	[0.2141]
H × SGS&SBI		**0.1157****	0.0100		**0.1251*****	0.2505		0.0282	**-0.6838*****
		[0.0574]	[0.2220]		[0.0392]	[0.4785]		[0.0515]	[0.1987]
H^2 × SII			**-0.1752***			**-2.9690*****			**-1.0736*****
			[0.0910]			[0.7524]			[0.1236]
H^2 × SDG			-0.0262			-0.7132			0.4382
			[0.0603]			[0.6635]			[0.3721]
H^2 × SGS&SBI			0.2991			-0.2957			**2.2020*****
			[0.7119]			[1.1723]			[0.5229]
Observations	1338	1118	1118	309	259	259	284	237	237
R^2	0.37	0.39	0.39	0.49	0.52	0.53	0.57	0.60	0.62

Notes: Sample coverage: 1992–2005. All regressions control for industry, country and time effects. Outliers excluded. Robust standard errors in brackets allow for intra-group correlation at the industry level. SII = Scale-Intensive Industries; SDG = Supplier-Dominated Goods-Producers; SGS = Specialized Goods-Suppliers; SBI = Science-Based Innovators. Significance levels: * at 10; ** at 5; *** at 1 percent. *Sources:* EUKLEMS (2008a, b), OECD (2006) and IIAGD (2008).

Table 3b:
Cross-Country Productivity Growth: Innovations and Competition, LSDV

	NLD & DNK			ITA & ESP			UK		
	IVa	**IVb**	**IVc**	**Va**	**Vb**	**Vc**	**VIa**	**VIb**	**VIc**
ICT	-0.0181	0.0155	0.0177	0.0504	0.0357	0.0344	0.0603	**0.0659***	**0.0679***
	[0.0578]	[0.0641]	[0.0667]	[0.0403]	[0.0811]	[0.0825]	[0.0459]	[0.0346]	[0.0343]
Non-ICT	**0.1846***	0.1467	0.1371	**0.2256***	0.1296	0.1300	**0.5190*****	**0.4310*****	**0.4222*****
	[0.1004]	[0.0910]	[0.0881]	[0.1172]	[0.1416]	[0.1420]	[0.1462]	[0.0966]	[0.1007]
R&D × SII	**-0.0841****	-0.0540	-0.0451	0.0194	0.0460	0.0503	**0.2772*****	0.2834	**0.3155***
	[0.0325]	[0.0395]	[0.0456]	[0.0382]	[0.0408]	[0.0448]	[0.0718]	[0.2042]	[0.1640]
R&D × SDG	0.0025	0.0144	0.0290	-0.0129	-0.0102	-0.0098	**0.0561****	0.0409	0.0650
	[0.0346]	[0.0419]	[0.0380]	[0.0228]	[0.0274]	[0.0274]	[0.0245]	[0.0416]	[0.0641]
R&D × SGS&SBI	**0.0993***	0.0616	0.1124	0.0552	0.0763	0.0827	0.3296	0.1305	0.1307
	[0.0565]	[0.0767]	[0.0865]	[0.0434]	[0.0493]	[0.0532]	[0.4717]	[0.5132]	[0.5363]
H × SII		**0.1295*****	0.2659		**-0.2733*****	-0.1590		**-0.0552****	0.2114
		[0.0406]	[0.2516]		[0.0884]	[1.0012]		[0.0225]	[0.2343]
H × SDG		**-0.0625****	**-0.5063*****		0.0040	0.0329		0.0029	0.2214
		[0.0259]	[0.1662]		[0.0121]	[0.0729]		[0.0847]	[0.2864]
H × SGS&SBI		-0.0829	0.8424		**0.2208*****	**0.4378***		-0.1606	0.2335
		[0.0668]	[0.9823]		[0.0612]	[0.2401]		[0.1417]	[0.7528]
H^2 × SII			-0.2822			-0.3873			-0.4838
			[0.4740]			[3.0835]			[0.3668]
H^2 × SDG			**0.9515****			-0.0429			-0.2162
			[0.3421]			[0.1160]			[0.2408]
H^2 × SGS&SBI			-2.2703			-0.7218			-1.0914
			[2.4375]			[0.6371]			[2.1478]
Observations	284	237	237	306	255	255	155	130	130
R^2	0.30	0.35	0.36	0.37	0.38	0.38	0.65	0.63	0.63

Notes: Sample coverage: 1992–2005. All regressions control for industry, country and time effects. Outliers excluded. Robust standard errors in brackets allow for intra-group correlation at the industry level. SII = Scale-Intensive Industries; SDG = Supplier-Dominated Goods-Producers; SGS = Specialized Goods-Suppliers; SBI = Science-Based Innovators. Significance levels: * at 10; ** at 5; *** at 1 percent. *Sources:* EUKLEMS (2008a, b), OECD (2006) and IIAGD (2008).

Table 4a:
Cross-Country Productivity Growth: Innovations and Competition, System GMM

	ALL COUNTRIES			GER & FRA			SWE & FIN		
	Ia	**Ib**	**Ic**	**IIa**	**IIb**	**IIc**	**IIIa**	**IIIb**	**IIIc**
ICT	0.0372	0.0645	0.0428	0.0364	0.0289	0.0325	-0.0044	-0.0346	-0.0143
	[0.0588]	[0.0544]	[0.0443]	[0.0656]	[0.0724]	[0.0768]	[0.0779]	[0.0806]	[0.0861]
Non-ICT	**0.2845****	**0.2577****	**0.2696*****	**0.4508*****	**0.5444*****	**0.5553*****	0.1622	**0.2656***	**0.2599***
	[0.1092]	[0.0982]	[0.0914]	[0.0802]	[0.1116]	[0.1191]	[0.1132]	[0.1330]	[0.1329]
R&D × SII	-0.0261	-0.0923	-0.0069	**0.1929***	0.0623	0.1059	0.0673	-0.0269	-0.0161
	[0.0570]	[0.0819]	[0.0661]	[0.0934]	[0.0659]	[0.0679]	[0.1292]	[0.1802]	[0.0913]
R&D × SDG	-0.0465	0.0332	0.0219	0.0291	0.1241	0.0984	0.0158	**0.1058***	**0.1505****
	[0.0391]	[0.0392]	[0.0329]	[0.0529]	[0.0783]	[0.0712]	[0.0626]	[0.0595]	[0.0587]
R&D × SGS&SBI	0.1644	**0.1876***	**0.2245****	**0.4237*****	**0.3506****	**0.3464****	**0.4217*****	**0.4194****	**0.4817****
	[0.1251]	[0.1065]	[0.0960]	[0.1466]	[0.1637]	[0.1434]	[0.1478]	[0.1925]	[0.1857]
H × SII		**0.0458***	0.0711		-0.0071	0.2281		0.0531	**0.2423***
		[0.0233]	[0.0521]		[0.0293]	[0.1345]		[0.0339]	[0.1222]
H × SDG		-0.0007	0.0379		-0.0563	0.1205		0.0424	-0.0303
		[0.0166]	[0.0375]		[0.0420]	[0.1893]		[0.0275]	[0.1224]
H × SGS&SBI		**0.1028****	-0.1223		0.0780	**0.2969***		0.0702	**-0.4991****
		[0.0467]	[0.1478]		[0.0486]	[0.1461]		[0.0904]	[0.2259]
H^2 × SII			-0.0853			**-0.6987***			**-0.3730***
			[0.0867]			[0.3565]			[0.2014]
H^2 × SDG			-0.0604			-0.3426			0.1368
			[0.0478]			[0.3646]			[0.1807]
H^2 × SGS&SBI			0.8253			-0.6211			**2.1989****
			[0.5658]			[0.4596]			[0.9590]
Observations	1074	894	894	240	200	200	212	176	176
AR1 (p-value)	0.0000	0.0000	0.0000	0.0007	0.0011	0.0011	0.0007	0.0021	0.0024
AR2 (p-value)	0.8379	0.4150	0.4298	0.1730	0.2327	0.2689	0.3713	0.8344	0.9286
Hansen (p-value)	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

Notes: Sample coverage: 1992–2005. All regressions control for industry, country and time effects. Outliers excluded. Robust standard errors in brackets allow for intra-group correlation at the industry level. SII = Scale-Intensive Industries; SDG = Supplier-Dominated Goods-Producers; SGS = Specialized Goods-Suppliers; SBI = Science-Based Innovators. Significance levels: * at 10; ** at 5; *** at 1 percent. *Sources:* EUKLEMS (2008a, b), OECD (2006) and IIAGD (2008).

Table 4b:
Cross-Country Productivity Growth: Innovations and Competition, System GMM

	NLD & DNK			ITA & ESP			UK		
	IVa	**IVb**	**IVc**	**Va**	**Vb**	**Vc**	**VIa**	**VIb**	**VIc**
ICT	**0.0699***	**0.0857***	0.0750	0.0313	0.0132	0.0114	0.0032	**0.0658****	**0.0864****
	[0.0391]	[0.0494]	[0.0581]	[0.0357]	[0.0511]	[0.0533]	[0.0676]	[0.0247]	[0.0315]
Non-ICT	0.1380	0.0649	0.1332	**0.4382*****	**0.3673*****	**0.3783*****	**0.7192*****	**0.4397*****	**0.4207*****
	[0.1390]	[0.1055]	[0.1110]	[0.0822]	[0.0742]	[0.0752]	[0.2199]	[0.0930]	[0.1111]
R&D × SII	-0.0090	**-0.1424***	**-0.2156*****	-0.0154	-0.0423	-0.0596	0.0930	**0.2749*****	**0.2134***
	[0.0398]	[0.0745]	[0.0587]	[0.0529]	[0.0369]	[0.0407]	[0.1405]	[0.0800]	[0.1045]
R&D × SDG	0.0210	0.0506	0.0438	**-0.0432*****	-0.0310	**-0.0367***	-0.0502	0.0265	-0.0572
	[0.0525]	[0.0518]	[0.0541]	[0.0149]	[0.0179]	[0.0206]	[0.0354]	[0.0642]	[0.0871]
R&D × SGS&SBI	0.0527	0.0565	-0.0099	-0.0334	-0.0400	-0.0276	**0.4926***	0.2367	0.0462
	[0.0782]	[0.0955]	[0.1121]	[0.0470]	[0.0460]	[0.0437]	[0.2516]	[0.3785]	[0.2766]
H × SII		0.0594	-0.1301		0.0311	0.1424		0.0413	0.1144
		[0.0519]	[0.2102]		[0.0554]	[0.1369]		[0.0236]	[0.1049]
H × SDG		-0.0164	0.1029		**0.0268****	0.0782		**-0.0153***	-0.0237
		[0.0362]	[0.2163]		[0.0119]	[0.0506]		[0.0075]	[0.0656]
H × SGS&SBI		0.0669	0.4165		0.0835	0.0147		0.0691	**0.6923***
		[0.0476]	[0.3341]		[0.0519]	[0.1236]		[0.0872]	[0.3158]
H^2 × SII			0.8053			-0.6197			-0.2336
			[0.5094]			[0.5601]			[0.2773]
H^2 × SDG			-0.2487			-0.0902			0.0146
			[0.3761]			[0.0827]			[0.0750]
H^2 × SGS&SBI			-1.1817			0.5028			**-2.9484***
			[0.9607]			[0.4444]			[1.4541]
Observations	238	198	198	216	180	180	155	130	130
AR1 (p-value)	0.0005	0.0013	0.0008	0.0009	0.0008	0.0011	0.0531	0.0536	0.0565
AR2 (p-value)	0.8887	0.6451	0.7552	0.5300	0.7838	0.8460	0.2670	0.1944	0.1286
Hansen (p-value)	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

Notes: Sample coverage: 1992–2005. All regressions control for industry, country and time effects. Outliers excluded. Robust standard errors in brackets allow for intra-group correlation at the industry level. SII = Scale-Intensive Industries; SDG = Supplier-Dominated Goods-Producers; SGS = Specialized Goods-Suppliers; SBI = Science-Based Innovators. Significance levels: * at 10; ** at 5; *** at 1 percent. *Sources:* EUKLEMS (2008a, b), OECD (2006) and IIAGD (2008).

Appendix

A1) Calculation of Aggregate R&D Stocks

The R&D stocks employed in this study are calculated using the perpetual inventory method (PIM) following the approach of Guellec and Pottelsberghe (2001). The stocks are derived from R&D expenditures in constant prices with reference year 2000. To obtain real R&D expenditures value-added price deflators are applied. According to PIM the stock at time *t* is equal to the new investments (expenditures) at time *t* and the depreciated stock at time *t*-1

$$R_t = r_t + (1-\delta)R_{t-1} \; , \tag{A1.1}$$

while substituting R_t for R_{t-1} and so forth generates:

$$R_t = r_t + (1-\delta)r_{t-1} + (1-\delta)^2 r_{t-2} + (1-\delta)^3 r_{t-3} + (1-\delta)^4 r_{t-4} + \dots \; . \tag{A1.2}$$

For construction of the initial stock past investments are assumed to grow at a constant annual rate, so that (A1.2) can be written as

$$R_t = r_t + (1-\delta)\lambda r_t + (1-\delta)^2 \lambda^2 r_t + (1-\delta)^3 \lambda^3 r_t + (1-\delta)^4 \lambda^4 r_t + \dots \; . \tag{A1.3}$$

Such a described infinitely geometric row (A1.3) convergences to

$$R_t = \frac{r_t}{1-(1-\delta)\lambda} \; , \tag{A1.4}$$

where R_t resembles the R&D stock at time t, r_t the R&D investment (expenditures) at time t, δ the depreciation rate (which is assumed to be constant over time), and λ a factor generating constant growth in R&D investments. This factor is defined as

$$\lambda = \frac{1}{1+\eta} \; , \tag{A1.5}$$

where η is the annual growth rate of r_t.

The depreciation rate δ is assumed to be .15 following the assumptions of Guellec and Pottelsberghe (2001). There are various studies on the deprecation rates of R&D investments like Pakes and Schankerman (1984), who found the average annual decay rate of R&D to be 25 percent. Nadiri and Prucha (1996) estimated the annual depreciation rate of industrial R&D stock to be 12 percent. Most recently Bernstein and Mamuneaus (2004) calculated a 25 percent depreciation rate for the manufacturing sector. Hence, implementing a deprecation rate as suggested by Guellec and Pottelsberghe (2001) seems to be an acceptable compromise. Initial stocks with negative values are set to zero.

A2) Herfindahl Index (O'Mahony et al., 2008)

The employed measure of competition in this study is the normalized Herfindahl index as provided by the *EUKLEMS Company Database*[17]. In comparison the standard Herfindahl index is defined as

$$H = \sum_{i=1}^{N} S_i^2 \; , \tag{A2.1}$$

[17] The *EUKLEMS Company Database* can be accessed via the company accounts of *EUKLEMS – Linked Data 2008 Releases* on the internet www.euklems.net/index.html.

where S represents the share of firm i in industry sales (measured as turnover). By construction H can range from 0 to 1 and indicates how an industry moves from a large number of very small firms to an industry completely dominated by a single monopolistic producer. The closer this index gets to 1, the more concentrated the industry. This concentration reflects a decrease in competition and an increase of market power.

The normalized Herfindahl index ranges from 0 to 1 similarly to the Herfindahl index and is computed as

$$H^N = \frac{H - 1/N}{1 - 1/N} , \tag{A2.2}$$

where N is the number of sectoral firms. H is the standard Herfindahl index as described in equation (A2.1). If the number of sectoral firms is relatively large both indexes the standard Herfindahl index and the normalized are approximately equal as 1/N converges to zero. While with fewer firms the difference between the two indexes increases. The normalization adjustment accounts for reporting bias in firm datasets to some extent, particularly in those industries that exhibit a low number of firms reporting financial information.

The intuition behind the Herfindahl index is when all sectoral firms have equal market shares H equals 1/N. The Herfindahl is correlated with the number of firms in an industry because its lower bound is 1/N when there are N firms. Thus, theoretically H can range from 0 to 1 if N approaches infinity, but actually it will range from 1/N to 1. The normalized Herfindahl, in contrast, will always range from 0 to 1. According to this restriction an industry consisting of 5 firms cannot have a lower H than an industry with 25 firms when all firms have the same market shares, i.e. $H_5 = .2$ greater than $H_{25} = .04$, respectively. In case of the normalized Herfindahl index the 5-firm as well as the 25-firm industry both have $H_5^N = H_{25}^N = 0$. But as market shares of the 25-firm industry diverge from equality, H_{25}^N can exceed H_5^N. For example, if one firm holds 76% of the market share and the remaining 24 firms have 1% of the market share each, $H_{25}^N = .56$ compared to $H_5^N = 0$. A higher H^N thus signifies a less competitive industry. For the standard Herfindahl index applies $H_{25} = .58$ and $H_5 = .2$.

Table A1:
Panel Unit-Root Tests of Output and Input Variables

	ADF			PP		
Labor Productivity						
	Lag	(0)	0.0000	Lag	(0)	0.0000
	Lag	(1)	0.0000	Lag	(1)	0.0000
ICT Capital Deepening						
	Lag	(0)	0.0000	Lag	(0)	0.0000
	Lag	(1)	0.0000	Lag	(1)	0.0000
Non-ICT Capital Deepening						
	Lag	(0)	0.0000	Lag	(0)	0.0000
	Lag	(1)	0.0000	Lag	(1)	0.0000
R&D Stock						
	Lag	(0)	0.0000	Lag	(0)	0.0000
	Lag	(1)	0.0000	Lag	(1)	0.0000

Notes: Sample coverage: 1992–2005. All variables are in exponential growth rates. Unit-root tests are performed without trends including constants. Outliers excluded. *Sources:* EUKLEMS (2008a), OECD (2006), and IIGAD (2008).

Table A2:
Panel Unit-Root Tests of Regression Residuals of Table 3a, b

		ADF	PP			ADF	PP
Specification	**Ia**	**Table 3a**		**Specification**	**IIa**	**Table 3a**	
Lag	(0)	0.0000	0.0000	Lag	(0)	0.0000	0.0000
Lag	(1)	0.0000	0.0000	Lag	(1)	0.0000	0.0000
	Ib				**IIb**		
Lag	(0)	0.0000	0.0000	Lag	(0)	0.0000	0.0000
Lag	(1)	0.0000	0.0000	Lag	(1)	0.0000	0.0000
	Ic				**IIc**		
Lag	(0)	0.0000	0.0000	Lag	(0)	0.0000	0.0000
Lag	(1)	0.0000	0.0000	Lag	(1)	0.0000	0.0000
Specification	**IIIa**	**Table 3a**		**Specification**	**IVa**	**Table 3b**	
Lag	(0)	0.0000	0.0000	Lag	(0)	0.0000	0.0000
Lag	(1)	0.0000	0.0000	Lag	(1)	0.0000	0.0000
	IIIb				**IVb**		
Lag	(0)	0.0000	0.0000	Lag	(0)	0.0000	0.0000
Lag	(1)	0.0000	0.0000	Lag	(1)	0.0000	0.0000
	IIIc				**IVc**		
Lag	(0)	0.0000	0.0000	Lag	(0)	0.0000	0.0000
Lag	(1)	0.0000	0.0000	Lag	(1)	0.0000	0.0000
Specification	**Va**	**Table 3b**		**Specification**	**VIa**	**Table 3b**	
Lag	(0)	0.0000	0.0000	Lag	(0)	0.0000	0.0000
Lag	(1)	0.0000	0.0000	Lag	(1)	0.0000	0.0000
	Vb				**VIb**		
Lag	(0)	0.0000	0.0000	Lag	(0)	0.0000	0.0000
Lag	(1)	0.0000	0.0000	Lag	(1)	0.0000	0.0000
	Vc				**VIc**		
Lag	(0)	0.0000	0.0000	Lag	(0)	0.0000	0.0000
Lag	(1)	0.0000	0.0000	Lag	(1)	0.0000	0.0000

Notes: Sample coverage: 1992–2005. All variables are in exponential growth rates. Unit-root tests are performed without trends including constants. Outliers excluded.

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