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Discussion Paper Series nr: 08-03

Technology Clubs and Growth Patterns: Evidence from EU Manufacturing

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March 2008

Abstract

This paper investigates the forces driving output change in a panel of EU manufacturing industries. A flexible modeling strategy is adopted that accounts for (i) inefficient use of resources, and (ii) differences in the production technology across industries. With our model we are able to identify technical, efficiency, and input growth for endogenously determined technology clubs. Both the technology clubs and the parameters within each club are modeled as a function of R&D intensity. This framework allows us to explore the components of output growth in each club, potential technology spillovers and catch-up issues across industries and countries.

Keywords: growth, efficiency, R&D, stochastic frontier analysis, latent class

JEL classification: C33, L60, O32, O47

Acknowledgements

We thank Rob Alessie, Bill Greene, Gary Koop, Subal Kumbhakar, Mark Sanders, Efthymios Tsionas, and seminar participants at Maastricht University (School of Governance), the University of Bergamo, the University of Groningen and the University of Piraeus for helpful comments. Michael Koetter gratefully acknowledges support by the Netherlands Organization for Scientific Research (NWO). The usual disclaimer applies.

1. Introduction

A large body of literature has tried to explain why some countries or industries produce more than others. Most studies have investigated the relative contribution of factors of production and unobserved total factor productivity (TFP) to output growth. The growth accounting literature typically relies, implicitly or explicitly, on a Cobb-Douglas production function where output depends on inputs such as labor and physical (and human) capital. Cross-country output variation is then attributed to the variation in production factors and the unexplained residual that reflects all output growth that cannot be ascribed to inputs (see Maddison, 1987, for a survey). The literature, however, is still divided as to whether input augmentation or TFP dominates in explaining output growth.[1] The cross-country growth regression literature typically bases its regressions on a production function specification (Mankiw, Romer, and Weil 1992; Islam 1995), which is often expanded to include various sets of additional variables in an attempt to explain economic growth.[2] However, there is considerable disagreement as to the explanatory variables included in the analyses (see Temple, 1999, for a comprehensive survey).

This paper investigates the sources of output growth for a panel of manufacturing industries. We propose a flexible modeling strategy that goes beyond the bipartite division of output growth applied in the conventional (growth accounting and cross-country growth regression) studies and the strong assumptions they typically rely upon (e.g. efficient use of resources, constant returns to scale, etc.). The aim of the paper is to provide more insight in key issues in the literature related to the use of technology, the sources of output growth, technology spillovers and catch-up, and to draw policy implications. To decrease the aggregation bias that may occur when these issues are considered at the country-level (Bernard and Jones, 1996a,b), we focus on manufacturing industries.

Traditionally, the growth accounting literature has referred to the unexplained part of output growth as the 'productivity residual' or 'technical change' (Solow, 1957). This interpretation, however, depends, among others, on the strong assumption that economic units (countries or industries) are always efficient. In reality, however, economic units may well use the best-practice (frontier) technology with varying degrees of efficiency. If this is the case, part of what is measured as technical change is in fact an improved use of the best-practice technology. Put differently, inefficient industries increase output by becoming more efficient in the use of the best-practice technology, whereas efficient industries increase output through technical change. In addition, not controlling for possible inefficient use of inputs, may also result in underestimating the productivity of outputs for the best-practce technology.

In this paper, we account for inefficiency and estimate a stochastic production frontier, which is the empirical analog of the theoretical production possibility frontier. This modeling strategy adds structure to the unexplained residual. Under reasonable assumptions, it disentangles the residual into inefficiency and measurement error. Techni-

[1] Numerous studies point to the role of inputs in generating growth (Baumol, 1986; Barro and Sala-i-Martin, 1991, 1992; Mankiw, Romer, and Weil, 1992; Islam, 1995), while more recent empirical evidence shows that differences in output growth are largely the result of differences in total factor productivity (Bernard and Jones, 1996a,b,c; Hall and Jones, 1999; Easterly and Levine, 2001; Caselli, 2005).

[2] See among others, Barro (1991), Levine and Renelt (1992), and Persson and Tabellini (1994).

cal change is modeled as a shift of the stochastic frontier, whereas efficiency change is a movement towards or away from the frontier. This framework allows us to decompose output changes into three types of change: technical, efficiency and input change.

A growing body of empirical literature carries out efficiency analyses along lines similar to this paper, although using different modeling approaches. In this literature, output change is also decomposed into technical, efficiency, and input change. So far, the attention has largely been at decomposing aggregate (country-level) output. [3] Recently, a number of studies investigate the role of efficiency in explaining growth differentials for a panel of manufacturing industries in the OECD countries. For instance, Koop (2001) explores the driving forces of output growth in six manufacturing industries during the 1970s and 1980s, while Kneller and Stevens (2006) investigate the sources of inefficiency in nine industries over the same period. With the exception of Koop (2001), who estimates six frontiers for six industries, these studies all benchmark industries (countries) against a common production frontier.

However, it may be the case that not all industries share a single common frontier. Recent theoretical and empirical contributions (Basu and Weil, 1998; Acemoglu and Zilibotti, 2001; Los and Timmer, 2005) have stressed the 'appropriateness' of technology as industries (countries) choose the best technology available to them, given their input mix. Industries are members of the same technology club if their marginal productivity of labor and capital (the technology parameters that characterize the efficient production frontier) are the same for a given level of inputs. In other words, their input/output combinations can be described by the same production frontier (Jones, 2005). With the exception of a handful of studies that accommodate these technology clubs, therefore, allowing for parameter heterogeneity when estimating frontier or conventional production functions, the empirical literature has largely ignored this issue. [4]

In this paper, we allow for different production technologies. We differ from past attempts, which mainly relied on *ex ante* divisions to classify industries into different technology clubs, by endogenizing the technology club allocation. To this end, we augment the stochastic frontier production model with a latent class structure. A logit model is used to condition group membership probabilities on technological effort as measured by R&D. As a result, technology parameters depend on the effect of technological effort on club membership probabilities. Production function parameters differ across clubs and are estimated simultaneously with membership probabilities. Based on club-specific production parameters, we identify technical, efficiency and input growth for endogenously determined technology clubs.

[3] For instance, Färe, Grosskopf, Norris, and Zhang (1994) use data envelopment analysis (DEA) while Koop, Osiewalski, and Steel (1999, 2000) and Limam and Miller (forthcoming) use stochastic frontier analysis (SFA) to examine country-specific inefficiency in a number of developed and developing countries.

[4] A problem with industry-specific frontiers, as in Koop (2001), is that is difficult to compare relative efficiency scores across frontiers. Dividing industries into technology clubs based on technology effort, measured e.g. by observed R&D expenditure (Hatzichronoglou, 1997; OECD, 2005), is also problematic since any *ex ante* division rule is to some degree arbitrary (Orea and Kumbhakar, 2004). Furthermore, R&D itself may simultaneously affect the technology parameters and the efficiency *within* each technology club. Durlauf and Johnson (1995) endogenize the division rule using a regression tree analysis to identify multiple technology clubs of cross-country growth behavior. In their approach, both the parameters and the number of clubs result from a sorting algorithm applied to the whole sample, incorporating a cost to sample splits to avoid overparameterization.

We introduce further flexibility to the model by permitting industries to switch between technology clubs over time. The efficiency of industries in different technology clubs is estimated simultaneously, but relative to each club's specific frontier. Thus, the latent class stochastic frontier model allows us to avoid the routinely imposed assumption of a common production function for all industries, while still yielding results that are comparable across industries at a given point in time.

Our empirical analysis is based on a sample that consists of manufacturing industries that are twice as disaggregated as those used in past related studies (Koop, 2001; Kneller and Stevens, 2006), while the time span is extended to cover recent developments in the industrial sector. We apply our modeling approach to 21 EU manufacturing industries in six countries over the period 1980-1997, with two key questions in mind: (i) do industries use different technologies?; (ii) eventually, what drives output growth?

The use of a latent class structure in the specification of the stochastic frontier model results in identifying two technology clubs (regimes). One technology club appears to be technologically more advanced, as industries in that club exhibit a high R&D spending and a high marginal productivity of labor. Although we do not impose constant returns to scale, we indeed find industries in that club exhibit constant returns to scale. In contrast, industries in the other, less technologically advanced club exhibit decreasing returns to scale. The driving forces of growth are also different across the two clubs. Technical change is a crucial component for growth for the technologically advanced club, while input (in particular capital) growth plays an important role in both technology clubs. Since we permit switching from one club to another and condition membership on the technological effort (R&D), we can investigate the existence of technological spillovers and catch-up behavior. Regarding the former, we find some support within the technologically advanced club. Regarding the latter, we find that the distance between the clubs has increased over time. Finally, within the advanced club, we also find some evidence of cross-country technological catch-up.

Overall, our model reveals significant heterogeneity in the growth behavior of the manufacturing industries in our sample. Many of our findings could not be obtained using traditional approaches (imposing constant returns to scale, ignoring inefficiency, assuming a common production function). We find that capital elasticities are, for most industries, lower than labor elasticities, which contrasts with some of the results of the conventional literature that reports a marginal product of capital as high as 0.82 (Mankiw, Romer, and Weil, 1992). Our findings are in line with other studies that have also adopted flexible modeling approaches. More specifically, some evidence of technological catch-up is also documented by Koop (2001), while the importance of input growth is also a main finding in Koop, Osiewalski, and Steel (1999), Koop (2001), Kumar and Russell (2002), and Limam and Miller (forthcoming).

Our findings shed light on important policy questions, in particular for the EU (Lisbon Strategy). For instance, does higher R&D spending result in better use of the existing best-practice technology and/or the invention of new technology? Our results corroborate that it matters which industries are 'targeted' by R&D investment tax credits/subsidies. For industries in the advanced technology club, higher R&D spending can both increase the efficiency with which industries absorb the best practice technology and lead to technological improvements Industries in the other, less advanced club can improve their chances of becoming a member of this club by spending more on R&D.

The remainder of the paper proceeds as follows. Section 2 presents the methodology and specification. Section 3 introduces the data. Section 4 reports the empirical results and seeks to explain some of the patterns present in the output change decomposition. Section 5 summarizes the findings and concludes.

2. Methodology

First, we introduce a production model which accounts for inefficiency. Next, we augment the model with a latent class structure to allow for more than one type of production technology. Finally, we decompose output changes for every technology club into technical, efficiency and input changes.

2.1. *A Stochastic Frontier Production Model*

We model the performance of our industries by means of a stochastic frontier production model.[5] A frontier production function defines the maximum output achievable, given the current production technology and available inputs.

If all industries produce on the boundary of a common production set that consists of an input vector with two arguments, physical capital (K) and labor (L), output can be described as:

$$Y^*_{ijt} = f(K_{ijt}, L_{ijt}, t; \beta) \exp\{\nu_{ijt}\} \tag{1}$$

where Y^*_{ijt} is the frontier (optimum) level of output in country i, in industry j, at time t; f and parameter vector β characterize the production technology; t is a time trend variable that captures neutral technical change (Solow, 1957); and ν_{ijt} is and i.i.d. error term distributed as $N(0, \sigma^2_\nu)$, which reflects the stochastic character of the frontier.

Two aspects of equation (1) are important. First, the frontier, as it is defined, represents a set of maximum outputs for a range of input vectors. Therefore, at any moment in time, it is defined by the observations from a number of industries, and not just from one. This differentiates our modeling approach from conventional approaches in the empirical growth literature where the leader industry, i.e., the industry with the highest level of productivity, constitutes the frontier (Scarpetta and Tressel, 2002; Griffith, Redding, and van Reenen, 2004; Cameron, Proudman, and Redding, 2005). An implicit, but non-trivial assumption in this literature is that the leading industry itself constitutes the frontier and is the single benchmark for all other industries. In the latter case, technical progress is described by the observations of this single industry over time. Second, our modeling approach treats the frontier as stochastic through the inclusion of the error term ν_{ijt}, which accommodates noise in the data and therefore allows for statistical inference. In this respect, it fundamentally differs from other (non-parametric) frontier industry-level analyses (Färe, Grosskopf, Norris, and Zhang, 1994; Gouyette and Perelman, 1997; Arcelus and Arocena, 2000; Boussemart, Briec, Cadoret, and Tavera, 2006) that do not allow for random shocks around the frontier.[6]

[5] Stochastic frontier analysis (SFA) was introduced by Aigner, Lovell, and Schmidt (1977), Battese and Corra (1977), and Meeusen and van den Broeck (1977).

[6] For comprehensive reviews of frontier methodologies, see Kumbhakar and Lovell (2000) and Coelli, Rao, and Battese (2005).

Some industries, however, may lack the ability to employ existing technologies efficiently (e.g. due to mismanagement, lack of knowledge, etc.) and therefore produce less than the frontier output. If the difference between optimum and actual (observable) output is represented by an exponential factor, $\exp\{-\upsilon_{ijt}\}$, then the actual output, Y_{ijt}, produced in each country i, in industry j, at time t can be expressed as a function of the stochastic frontier output, $Y_{ijt} = Y^*_{ijt}\exp\{-\upsilon_{ijt}\}$, or equivalently:

$$Y_{ijt} = f(K_{ijt}, L_{ijt}, t; \beta)\exp\{\nu_{ijt}\}\exp\{-\upsilon_{ijt}\}, \tag{2}$$

where $\upsilon_{ijt} \geq 0$ is assumed to be i.i.d., with a half-normal distribution truncated at zero $\mid N(0, \sigma_\upsilon^2) \mid$ and independent from the noise term, ν_{ijt}.[7] Efficiency, $\exp\{-\upsilon_{ijt}\}$, is measured as the ratio of actual over maximum output, $\exp\{-\upsilon_{ijt}\} = \frac{Y_{ijt}}{Y^*_{ijt}}$.[8]

An industry is inefficient if it fails to absorb the best-practice technology. In this respect, our approach is comparable to conventional, non-frontier studies (Bernard and Jones, 1996a,b,c; Scarpetta and Tressel, 2002; Griffith, Redding, and van Reenen, 2004; Cameron, Proudman, and Redding, 2005) that measure impediments to the absorptive capacity using TFP changes. However, in their framework TFP changes cannot be separated into technical change and efficiency change (Kumbhakar and Lovell, 2000).

To operationalize equation (2) one needs to specify the functional form of the production frontier. Specification tests favor a Cobb-Douglas production function.[9] Thus, the stochastic frontier production function specification is:

$$y_{ijt} = \beta_0 + \beta_k k_{ijt} + \beta_l l_{ijt} + \beta_t t_{ijt} + \nu_{ijt} - \upsilon_{ijt} \tag{3}$$

where lower case letters denote logarithms and a time trend captures neutral technical change.

Next, we turn to modeling different technology clubs.

2.2. *Technology Clubs (Regimes)*

The empirical literature discusses a range of ways to account for technology heterogeneity.[10] One approach to test whether innovation intensity explains output differentials is to include a proxy such as R&D expenditure, as an additional input. But that approach implicitly assumes that R&D expenditure in itself contributes to output. More likely, however, the former enhances the factor productivity of labor and capital (Gordon, Schankerman, and Spady, 1987; Hall and Mairesse, 1995; Griliches, 1998).[11] Implementing an instrumental variable type of analysis using R&D as an instrument for inputs, in turn, would not allow for distinctively different technology clubs, reflected by

[7] We decompose the residual in equation (2), $\exp\{\varepsilon_{ijt}\} = \exp\{\nu_{ijt}\}\exp\{-\upsilon_{ijt}\}$, and identify its components, $\exp\{\nu_{ijt}\}$ and $\exp\{-\upsilon_{ijt}\}$, by re-parameterizing λ (=σ_u/σ_v) in the likelihood maximization (for an overview, see Kumbhakar and Lovell, 2000).

[8] Such that $0 \leq \exp\{-\upsilon_{ijt}\} \leq 1$ and $\exp\{-\upsilon_{ijt}\} = 1$ implies full efficiency.

[9] See footnotes 14 and 15 in Section 4.

[10] See Bos, Koetter, Kolari, and Kool (forthcoming).

[11] Note that R&D expenditure and capital stock measures may be contemporaneously and endogenously related. Building a laboratory to 'produce' patents can also accrue as capital expenditure. We therefore also estimated our model with various lags of R&D as a determinant of group membership probabilities and found no qualitative change compared to results reported in this paper.

factor shares varying across industries and countries. Finally, one may cluster industries *a priori* on the basis of observed R&D expenditure and estimate best-practice frontiers for each cluster separately. This approach has been often used in industry classifications (Hatzichronoglou, 1997; OECD, 2005) as a means of dividing manufacturing industries into various technology clubs. However, such a division is to some degree arbitrary since the appropriate cut-off levels of R&D remain unclear.

To allow for different technology parameters when estimating productivity without strong priors regarding class membership, Orea and Kumbhakar (2004) advocate a latent class stochastic frontier model. [12] In line with Greene (2002, 2005), we also specify technology club allocation as a latent class problem. We do so by introducing a latent sorting of y_{ijt} into z classes, $z = 1, ..., Z$. Given that an observed y_{ijt} is a member of technology club z, it has a club-specific density $f(i, j, t|z) = f(y_{ijt}|x_{ijt}, z)$. Regime membership is *latent*, and the probability θ_z of belong to club z must be estimated. Greene (2002) formulates the following approximation: [13]

$$f(i, j, t) = f(y_{ijt}|\beta' x_{ijt} + \delta_z' x_{ijt}, \sigma_z)F_z = exp(\theta_z/\sigma_z exp(\theta_z)) \tag{4}$$

where the θ_zs add up to zero. Each technology club z has its own parameter vector. All clubs share the mean (β) of the variables x_{ijt}, but there is a club-specific δ_z. The probability θ_z of belonging to club z can be estimated with a multinomial logit model. In the logit specification, we condition club membership on technological effort, measured by R&D intensity (RD_{ijt}). Hence, for industry j in country i at time t, we can estimate:

$$\theta_{ijt} = \frac{\exp(RD_{ijt}\theta_z)}{\Sigma_{z=1}^{Z} \exp(RD_{ijt}\theta_z)} \tag{5}$$

Now, we can obtain technology parameters by maximizing a weighted log-likelihood function, considering each observation's contribution to its club-specific log-likelihood. This partial likelihood is shown by Greene (2005) to be:

$$P(i, j, t|z) = f\left(y_{ijt}|x_{ijt}, \beta_z, \sigma_z, \lambda_z\right) = \frac{\Phi\left(\lambda_z \varepsilon_{ijt|z}/\sigma_z\right)}{\Phi(0)} \frac{1}{\sigma_z} \phi\left(\frac{\varepsilon_{ijt|z}}{\sigma_z}\right), \tag{6}$$

where $\varepsilon_{ijt|z} = y_{ijt} - x_{ijt}'\beta_z$. To obtain estimates of group-specific technology parameters β_z in equation (4), predicted probabilities of technology club membership $\theta_{ijt|z}$ as well as parameters of R&D intensity θ_z in equation (5), we follow Greene (2005) and maximize iteratively back and forth between posterior group probabilities from (5) and the (weighted) log-likelihood function in (6). Importantly, the likelihood maximization in equation (6) does not only depend on inputs and outputs per industry, but also on efficiency (λ and σ). Therefore, in contrast to *a priori* clustering on the basis of some innovation proxy, in our latent class model, both our technology parameters β and efficiency v are determined endogenously through the latent sorting into z classes. Thus, conditional on class membership z, we eventually estimate:

$$y_{ijt} = \beta_{0,z} + \beta_{k,z}k_{ijt} + \beta_{l,z}l_{ijt} + \beta_{t,z}t_{ijt} + \nu_{ijt|z} - v_{ijt|z} \tag{7}$$

[12] Alternatively, Tsionas and Kumbhakar (2004) propose a stochastic frontier production function augmented with a Markov switching structure to account for different technology parameters across heterogenous countries. Technology group membership depends on priors in their Bayesian framework. Koop, Osiewalski, and Steel (2000) are critical of this formulation of technology club membership priors.

[13] See Greene (2002, section E24.6.4).

In sum, the latent class approach pursued here allows for (i) inefficient industry production, (ii) group-specific input factor parameters, and (iii) R&D expenditure as an additional determinant of technology club membership.

2.3. *Decomposing Output Growth*

A key aim of this paper is to relate our results to some of the major macroeconomic debates on why and how some industries (countries) grow faster than others. To investigate these issues, we decompose output growth, for each technology club, into three components: input growth, which represents movements along the frontier; technical growth, which reflects shifts of the production frontier; and efficiency growth, which captures movements towards (or away from) the production frontier as industries absorb and implement best practice technologies and reduce (or increase) technical inefficiencies.

In doing so, we take logs and totally differentiate the deterministic part of equation (2) with respect to time, which yields a convenient expression of output growth:

$$\frac{\dot{Y}}{Y} = \frac{\partial \ln f_{ijt}}{\partial t} - \frac{\partial v_{ijt}}{\partial t} + \epsilon_K \frac{\dot{K}}{K} + \epsilon_L \frac{\dot{L}}{L} \tag{8}$$

where ϵ_K and ϵ_L denote the partial elasticity of stochastic frontier output with respect to the inputs, physical capital and labor, respectively and dotted variables refer to time derivatives.

Equation (8) indicates that output growth can be broken down into three components. The first term, $\frac{\partial \ln f_{ijt}}{\partial t}$, corresponds to technical growth, where $\frac{\partial \ln f_{ijt}}{\partial t} > 0$, represents an upward shift of the production frontier (technical progress). The second term corresponds to efficiency growth, $-\frac{\partial v_{ijt}}{\partial t}$, where $-\frac{\partial v_{ijt}}{\partial t} > 0$ represents a reduction of inefficiency. Finally, the last two terms capture the scale changes, $\epsilon_K \frac{\dot{K}}{K}$ and $\epsilon_L \frac{\dot{L}}{L}$ due to input accumulation in capital ($\beta_{1,z} K_{ijt}$) and labor ($\beta_{2,z} L_{ijt}$), respectively.

3. Data

Our analysis covers 21 two-, three- and four-digit industries in manufacturing for six countries (Finland, France, Germany, Italy, Netherlands and Spain) over the period 1980-1997, where the time span is determined by the data availability for the preferred level of disaggregation. Annual raw data are retrieved from various sources. Data on industry output (value-added) and investment (for constructing capital stock) are retrieved from the OECD (2002) *Structural Analysis Database* (STAN). Data on labor are extracted from the Groningen Growth and Development Centre (GGDC) (2006) *60-Industry Database*. R&D data are obtained from the OECD (2002) *Business Enterprise Expenditure on Research and Development* (BERD). Finally, import and export flows are obtained from the OECD (2002) *Structural Analysis Database* (STAN). The same International System of Industries Classification Code (ISIC, ver. 3) is used for all data sources. Definitions of the variables are provided in the Appendix.

Table A.1 in the Appendix reports the manufacturing industries employed in our analysis as well as the growth rates of output, capital and labor in every industry. The statistics reveal a wide variety of behavior patterns. Some industries (e.g., chemicals, machinery) appear to grow fast while some others (e.g., food, wood) grow slowly or even decline (e.g., textile, petroleum). Similarly, some countries (e.g., Finland) exhibit fast growth in manufacturing output while others (e.g., France, Germany) do not. This confirms the need for a flexible modeling approach that allows for considerable heterogeneity among manufacturing industries. For most countries and industries labor is shrinking, while factor growth is driven by capital accumulation.

4. Results

In this section we present our results. First, we discuss whether industries use the same technology. Next, for different technology clubs, we decompose output growth into three different components namely input, technical and efficiency growth. Finally, we explore whether our results support a number of economic theories.

4.1. *Do industries use different technologies?*

We investigate whether there are different technologies across manufacturing industries by employing a latent class model, as specified in equation (7). In doing so, we need to first determine the number of classes, z. Theoretically, the maximum number of classes is only limited by the number of observations in our study. Empirically, due to over-specification problems, the maximum likelihood estimation may not converge for a much smaller number of classes.

We find strong evidence in favor of two classes (clubs). For a possible third class, parameters are jointly not significantly different from zero, and the number of observations in the additional class is very small. Accordingly, we classify the industries in our sample as belonging to club A or B, respectively (see Table A.2 in the Appendix). The prior class probabilities (at the data means) show that technology club A contains 82% of our sample, whereas technology club B contains 18%. The same industry can be classified as belonging to club A for some countries, but as belonging to club B for some others. However, in some countries (e.g., Finland and Germany) the majority of industries fall in one club (A, in this case). [14] The evidence in favor of two clubs confirms the role of technology effort. In club A, mean R&D intensity is on average 9.7%, whereas it is 7.7% in technology club B. Importantly, from the logit coefficient of 1.838 ("Conditional latent class" in Table 1) we find that a one percent increase in R&D intensity increases the probabilities of belonging to club A by a factor of 6.28 (= $exp(1.838)$).

[14] We follow Greene (2005) and use the following rules when choosing the optimal number of classes: (i) we compare log-likelihood values; (ii) we consider the joint significance of parameters in a class; (iii) we consider class size (i.e., the decrease in class size of existing classes if we add another class). In our sample, three is the maximum number of classes for which neither multicollinearity nor over-specification prohibit convergence of the maximum likelihood estimator. We follow Orea and Kumbhakar (2004) and test downward. The best specification has the lowest AIC (respectively the highest BIC) value. The log-likelihood value for a specification with three classes is -852.32, with 24 parameters (for our specification with two classes, we have a log-likelihood value of -582.429 and 16 parameters). Hence the AIC for two (three) classes is 19.27 (34.50), and we prefer the specification with two classes.

Next, we explore to what extent the technology parameters and efficiency levels differ between the two clubs. Table 1 reports our latent class results, where the technology parameters (the coefficients for k, l and t) and efficiency are conditional on club membership and thereby on R&D.[15] Industries in each of our two clubs (A and B) are benchmarked against their own frontier.

Table 1
Latent Class Results

	A		*B*	
	Frontier			
	coeff.	t-ratio	coeff.	t-ratio
Constant	-2.467	-47.694	-0.285	-0.004
k	0.344	51.035	0.331	23.518
l	0.636	76.012	0.294	8.591
t	0.014	10.336	-0.006	-1.272
σ $(= (\sigma_u^2 + \sigma_v^2)^{1/2})$	0.303	18.605	0.335	0.165
λ $(= \sigma_u / \sigma_v)$	1.172	4.806	0.034	0.000
	Efficiency scores			
	Mean	SD	Mean	SD
	0.913	0.037	0.992	0.000
	Conditional latent class			
Constant	1.352	10.915		
R&D	1.838	2.000		
	Prior class probabilities at data means			
	0.821		0.179	

Log-likelihood value = -582.429

As Table 1 reveals, the results are markedly different for our two clubs. We observe that the marginal product of capital is not significantly different for industries in clubs A and B. Our estimation of a marginal product of capital of approximately 0.3 is in line with existing empirical literature (Barro and Sala-i-Martin, 1995; Koop, 2001). It appears, however, that industries in club A benefit from the fact that the marginal productivity of a unit of their labor is twice as high as that of industries in club B. Importantly, both marginal products are estimated here conditional on R&D. Hence, we may interpret this finding as stating that industries in club B "pay" for their low innovation efforts with less productive labor. Industries in club A are technologically superior, as is reflected

[15] We start with a likelihood ratio test of a frontier Cobb-Douglas production function versus a non-frontier Cobb-Douglas production function. The latter is rejected with a t-value of 5.99. Subsequently, a likelihood ratio test of a latent class frontier Cobb-Douglas production function versus a non-latent class frontier Cobb-Douglas production function yields a t-value of 15.51, with which the former is clearly favored. Tests of Cobb-Douglas versus translog production function are ambiguous, depending on the specification (latent class or not, frontier or not), but results for the latent class frontier are qualitatively similar. Therefore, in line with the literature, we proceed with a Cobb-Douglas specification.

in their higher R&D effort and their higher marginal productivity of labor. This implies that, for given input levels, the production frontier of club A is superior to (higher than) the production frontier of club B.

Taken together, this implies two things. First, whereas industries in club A produce at constant returns to scale, as is often reported in the literature (Barro and Sala-i-Martin, 1995; Mankiw, Romer, and Weil, 1992), industries in club B produce at decreasing returns to scale. Second, the marginal rate of technical substitution ($MRTS$) is 0.630 (1.086) for industries in class A (B), demonstrating that the rate at which labor can be substituted for capital while holding output constant is much higher for industries in club B. Put differently, industries in club B may use relatively cheap capital. Indeed, in the next section, we find evidence of this when we compare capital accumulation across technology clubs and observe that fast growing industries in club B are rapid capital accumulators.

As stated above, each technology club is characterized by its own optimal production frontier, where the frontier of club A is superior to the frontier of club B. Including a time trend t for each club allows us to measure technical growth. Interestingly, for the industries that consider the frontier of technology club B their benchmark, we find that technical growth is not significantly different from zero. In contrast, for industries in club A, technical growth is positive and significant at approximately 1.4% per year.

The latter finding does not necessarily imply that all industries in club A *indeed* benefit from 1.4% technical growth. The technical growth is measured at the frontier. Hence, we also need to consider the efficiency of industries in both clubs. In fact, the average efficiency in technology club A is almost 8% lower than the efficiency in technology club B and it is quite dispersed. Industries in club B appear to be quite efficient and operate very close to their (club-specific) frontier. This is confirmed by the parameters σ and λ, which measure the total variance and the relative magnitude of variance that is attributed to inefficiency, respectively. For the industries in club B, both parameters are insignificant, as inefficiency does not play a role. However, for the industries in club A a positive and significant λ shows that much of this variance indeed consists of inefficiency. This is important, given that most industries in our sample turn out to belong to club A.

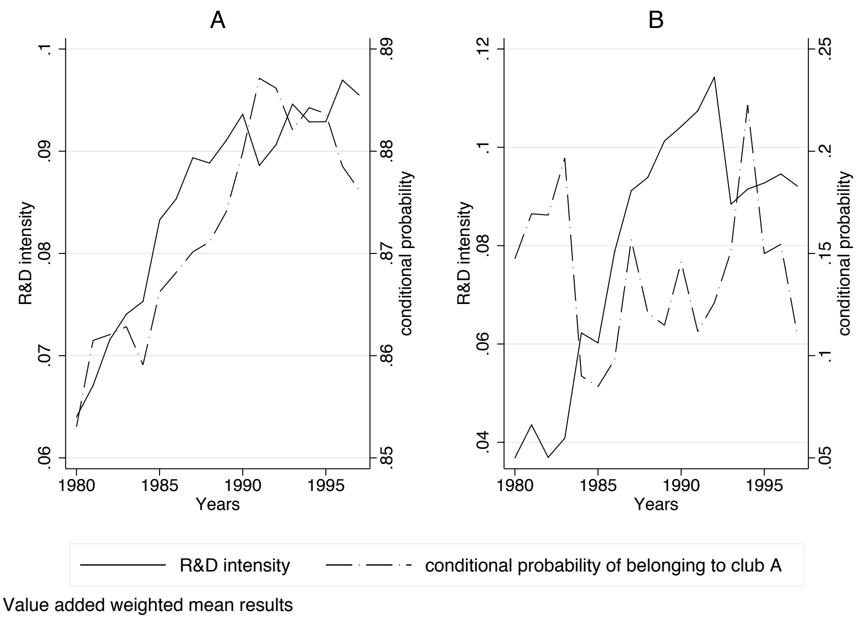
Do industries change technology club membership?

Industries are not restricted to one club. In principle, an industry in club B can develop to become a member of club A (and vice versa). One of the key assumptions in our modeling strategy is that our latent classes are conditional on the technology effort (R&D intensity). This implies that an important way in which an industry can try to become a member of club A is by engaging in more R&D. Put differently, we expect that the conditional probability of belonging to club A increases with R&D intensity.

In Figure 1, we explore this issue for both groups. We find large increases in the probability of being a member of club A during the 1980s. During the same period, we observe a sharp increase in R&D intensity. In the case of club A, the latter increase almost perfectly matches the former.

For the industries in club B, the story appears to be rather different. The link between the development of R&D intensity and the conditional probability of belonging to club

Figure 1. R&D intensity and conditional probability of belonging to club A



A is - on average - absent.[16] Therefore, only some industries in club B manage to successfully capitalize on their higher R&D intensity by becoming a member of club A.

In Table 2, we further investigate this issue by looking at the transition probabilities of industries switching technology clubs. As we saw, some industries in club B have been rather successful in increasing R&D. These industries may try to make the shift from club B to club A. In Table 2, we observe that over the sample period 8.37% of the industries in club B manage to shift to club A. This means that 19 industries that were before a member of club B, now joined club A. Average R&D intensity for this group is 17.1% in the year they shift, compared to an average of 7.1% for the industries in club B. We also find that 0.52% of the industries make the opposite move (a total of 10 industries, half of them in the Netherlands).[17]

Table 2
Transitions between Technology Clubs

	To	
From	A	B
A	99.48 %	0.52 %
B	8.37 %	91.63 %

Most of the industry transitions from club B to A take place in Spain (where 10.34% of the industries in club B become members of club A). The Netherlands and France are close followers with 9.3% and 8.3%, respectively. However, we find no pattern as to

[16] Correlation is 0.3 and insignificant.
[17] There is no overlap among the industries that transition (i.e., there is no switching back and forth).

when these transitions take place. Among the industries that became a member of club A, the office machinery industry stands out: over time, this industry became a member of club A in almost all countries. A remaining question, beyond the scope of this paper, is why some industries successfully use a strategy of high R&D growth, whereas others use the same strategy without much success.

Overall, our results confirm the high discriminatory power of our model. As Figure 1 indicates, for the industries in club B, the maximum (average) conditional probability of begin a member of club A is approximately 23% (Figure 1, right panel, right axis), whereas for the industries in club A, the minimum (average) conditional probability of being a member of club A is approximately 85% (Figure 1, left panel, right axis). Indeed, this explains the low number of club transitions over our sample period.

4.2. *How do industries grow?*

Now that we have identified two technology clubs, we want to find out how industries in each technology club grow. To this purpose, we decompose output growth into three components, using equation (8): input growth, technical growth and efficiency growth. In Section 3, we explained that output growth patterns are markedly different across industries. Hence, we analyze the output growth components in detail, by distinguishing different growth patterns *within* each technology club.

In Table 3, we break down the industries in each technology club according to their growth pattern. We identify high-, medium- and low-growth industries by using the 33rd and 66th percentile of the total growth distribution as cut-off points.

Table 3
Output growth decomposition of high-, medium- and low-growth industries

			output growth	input growth		technical growth	efficiency growth
				K	L		
Club	Growth	obs.					
A	High	680	0.094	0.077	0.000	0.014	0.004
			(0.323)	(0.325)	(0.012)	(0.001)	(0.016)
	Medium	681	0.016	0.004	-0.002	0.014	0.000
			(0.005)	(0.008)	(0.006)	(0.001)	(0.007)
	Low	563	-0.133	-0.138	-0.005	0.014	-0.004
			(0.721)	(0.721)	(0.017)	(0.001)	(0.017)
B	High	48	0.244	0.246	0.001	-0.006	0.004
			(0.648)	(0.649)	(0.005)	(0.005)	(0.010)
	Medium	26	0.015	0.020	-0.002	-0.006	0.003
			(0.004)	(0.010)	(0.003)	(0.005)	(0.010)
	Low	144	-0.089	-0.081	-0.002	-0.006	0.000
			(0.288)	(0.290)	(0.007)	(0.005)	(0.003)

Standard deviations in brackets (standard errors from frontier estimation for technical growth); high growth > 66th percentile of the total growth distribution; low growth < 33rd percentile of the total growth distribution.

From Table 3, we can draw the following conclusions. First, high growth industries in both technology clubs benefit from efficiency growth. Efficiency growth increases consistently with total output growth. Capital accumulation is important for high-growth industries, and in particular for industries in club *B*. This finding is not surprising, given the latter club's high marginal rate of technical substitution, which makes capital accumulation an attractive growth strategy. Second, medium growth industries in both technology clubs appear to substitute labor for capital. Once these industries start experiencing high growth, capital accumulation continues, but no longer at the expense of labor. Third, especially in technology club *B*, low (i.e., negative) growth is almost completely the result of capital depletion.

On the whole, there seems to be considerable heterogeneity in the growth patterns across technology clubs. Technical change is a crucial component for growth for the industries in club *A*, while input (capital, in particular) growth plays an important role in both technology clubs. These findings are consistent with Koop, Osiewalski, and Steel (1999), Koop (2001), Kumar and Russell (2002) and Limam and Miller (forthcoming). [18]

Next, we explore whether our results support a number of economic theories. Our discussion is mainly organized around the following three questions.

Is there any evidence of leader-follower behavior?

Our decomposition results, and in particular the differences we observe with respect to technical growth and efficiency, may shed some light on leader/follower models of technical growth. A body of research has examined whether technology spills over across countries, via R&D and trade. In these models, all countries have access to the same technology and the leader country, ie., the country with the highest TFP growth in an industry, develops a new technology while the rest of the countries (followers) can imitate the technology (Scarpetta and Tressel, 2002; Griffith, Redding, and van Reenen, 2004; Cameron, Proudman, and Redding, 2005).

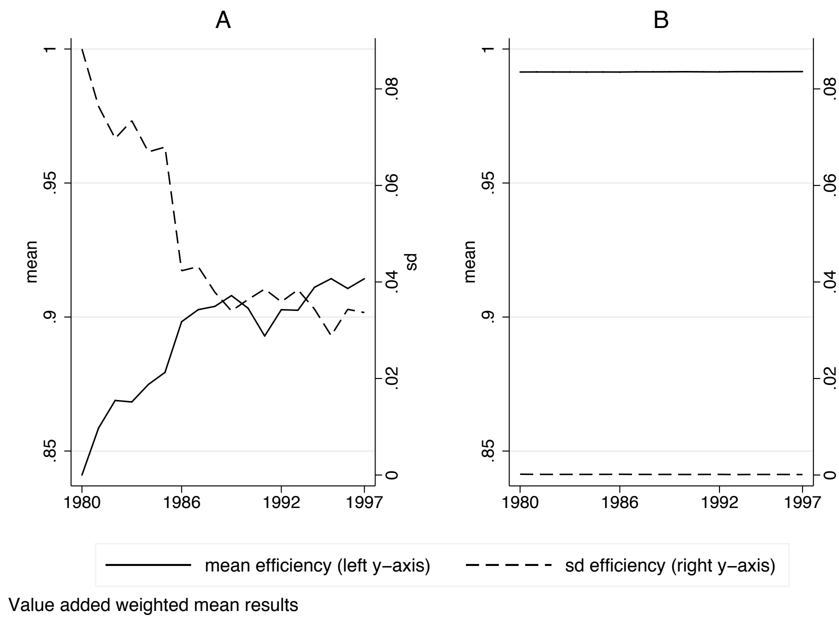
In our model, leaders in club *A* operate on, or close to the frontier, and they can try to push the frontier further outward through technical growth. Leaders in club *B* also operate on, or close to their own frontier, but they have an additional means of improving their technology: they can try to switch to club *A*. In both technology clubs, follower industries that do not immediately adopt new technologies may be left behind, unless they manage to increase efficiency and move closer to the output frontier. Therefore, support of the leader-follower model would imply in our case technical growth accompanied by improvements in efficiency.

For technology club *A*, our results provide clear evidence in favor of the leader-follower model. We find positive and significant technical growth of 1.4%. At the same time, Figure 2 shows that average efficiency in club *A* increases by approximately 7% (from 84% to 91%) while the spread (standard deviation) of efficiency decreases.

In club *B*, technical growth is not significantly different from zero. As a result, within club *B*, we do not find any support of leader-follower behavior as there is no evidence of technical growth accompanied by improvements in efficiency. However, as discussed above, leaders in club *B* may try to shift to club *A*. Our estimation results in Table 1

[18] Kumar and Russell (2002) use data envelopment analysis (DEA).

Figure 2. Efficiency patterns



(lower section) have shown that increasing R&D spending is a means of achieving this shift. In our discussion of the transition probabilities in Table 2, we indeed found that approximately 18% of the industries in club B manage to shift to club A. However, few industries in this club manage to follow the leaders of club A by switching to this more advanced technology club.

Does openness increase efficiency?

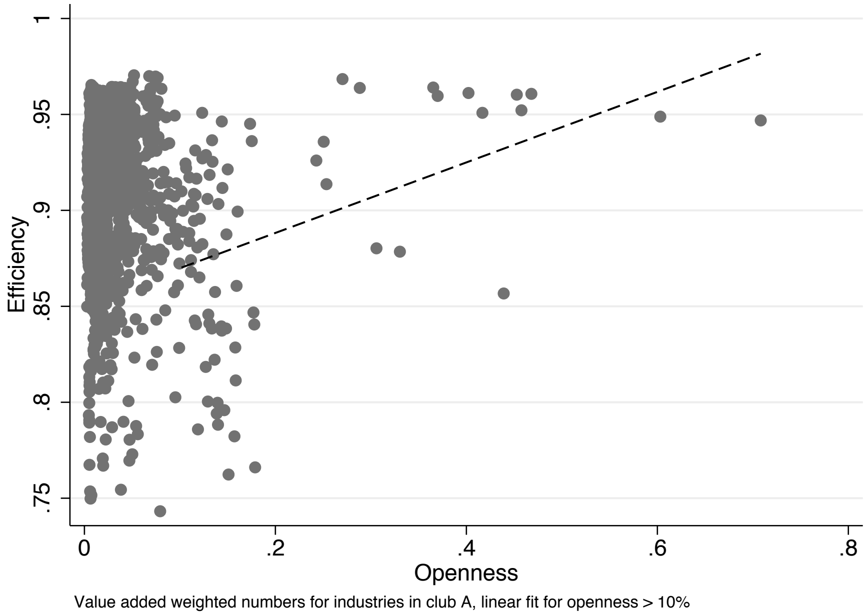
It is often argued in both the international economics (Melitz, 2003) and the industrial organization literature (Caves and Barton, 1990) that increased openness to trade should be positively related with increases in productivity and/or efficiency. Higher exposure to trade facilitates the imitation of an advanced foreign technology and/or places greater pressure on the industries to adopt best practice technologies and improve efficiency in order to cope with competition.[19] In Figure 3, we investigate this by comparing openness to trade (defined as the sum of industry imports and exports over value added) with the level of efficiency, for the industries in club A.[20]

Broadly speaking, our results are in line with Koop (2001), who states that openness does not correlate well with efficiency. Apparently, openness to trade does not wipe out inefficient industries. However, our results provide some indication that there is a pos-

[19] See Connolly (1998), Keller (2002) and Hallward-Driemeier, Iarossi, and Sokoloff (2002).

[20] We also considered using only the import shares, and results are qualitatively similar. Comparing openness to the *change* in efficiency also does not change our findings. Likewise, including the industries in club B does not alter our conclusions.

Figure 3. Efficiency and openness to trade



itive relationship once exposure to openness becomes very substantial. Alternatively, this result might merely corroborate findings in new international economic theory that emphasize the positive effects of openness on firm-level productivity of the very few firms that actually account for the major share of trade flows (Helpman, 2006).[21]

Is there any evidence of technological catch-up?

A frequently expressed hypothesis is that less technologically advanced industries can grow faster than advanced ones because they only need to copy the technology of the latter. In our framework, we should observe catch-up as efficiency improvements. The existence of two different frontiers makes it difficult to analyze this globally. Therefore, we look within technology clubs.

In the preceding sections, we discussed the levels of efficiency of the two technology groups. Compared to their own frontier, industries in club B are found to be efficient. On the other hand, in club A, efficiency is quite dispersed. This group could move closer to their frontier by becoming more efficient.

The evolution of the gap between the two technology clubs is also of interest to study. Recall that industries in each of our two clubs (A and B) are benchmarked against their own frontier, where industries in club A are compared to a higher frontier than industries in club B. Hence, the further away an industry in club A lies from its frontier, the closer it is to the frontier of technology club B. As Figure 2 showed, the average efficiency has increased in club A, while it is fairly stable in club B. Therefore, over our

[21] Incorporating firm-level evidence beyond the already highly disaggregated industry-level data we use here is, however, beyond the scope of this paper and we reserve the issue for further research.

sample period, the difference between industries in both clubs has widened to a seemingly insurmountable gap.

It is interesting to relate our findings with the past literature. Previous studies (Bernard and Jones, 1996a,b; Gouyette and Perelman, 1997; Scarpetta and Tressel, 2002) find evidence that there is little or no convergence in manufacturing. This is not supported by our results. Neither are we in line with those studies which provide evidence of strong convergence across all industries (Arcelus and Arocena, 2000; Boussemart, Briec, Cadoret, and Tavera, 2006). The use of a latent class approach and highly disaggregated industry-level data demonstrates the existence of diverse catch-up patterns in the EU industrial sector. We find evidence that industries in club A catch-up by eliminating inefficiencies while industries in club B do not. In this respect, our findings are closer to studies that use highly disagregated data and compare industries with similar technologies (e.g., Garcia Pascual and Westermann, 2002). A possible explanation for our finding is that industries in club A have the capacity to absorb and assimilate advanced technology due to higher R&D spending. Indeed, the evidence in Figures 1 and 2 supports this rather convincingly.

A follow-up question to ask at this point, is whether there is any evidence of catch-up across countries. Figure 4 provides some *prima facie* evidence. In this figure, we compare the (value added weighted) average efficiency of industries in club A at the beginning of our sample, 1980, in each of our six countries with the subsequent growth of efficiency over our sample period. If there is cross-country technology catch-up, we expect low starting levels of efficiency to be accompanied by high, positive growth in efficiency, and vice versa. Indeed, we find some evidence of technological catch-up. [22]

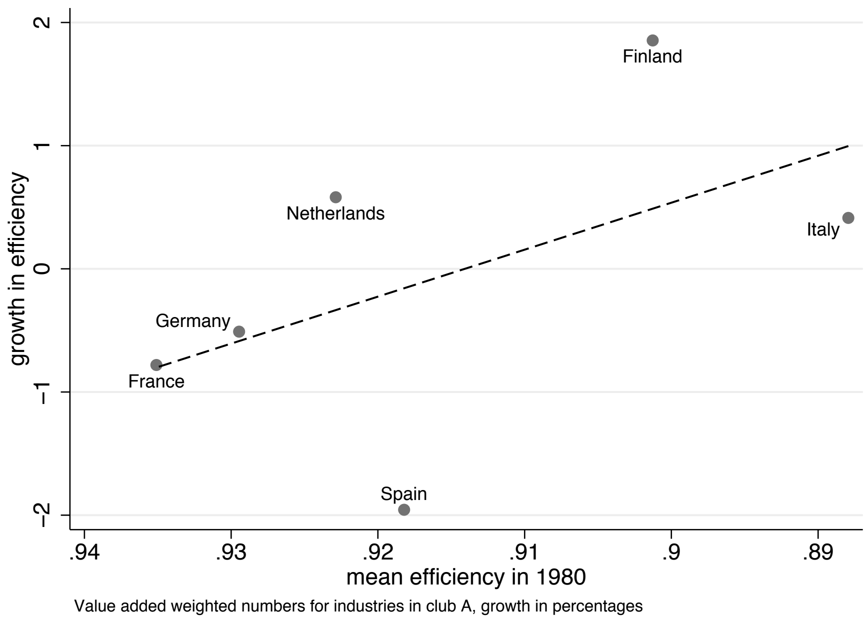
Overall, our results highlight the importance of employing highly disaggregated manufacturing data and comparing similar technologies when analyzing spillovers and catch-up issues. The use of aggregated industry data may lead to serious aggregation bias, as efficient and less efficient industries may erroneously be lumped together. Likewise, lumping industries with a low technology effort (in club B) with industries with a high technology effort (in club A) may lead to a downward bias of the labor elasticity of the latter. A case in point is our finding that, in technology club A, technology catch-up indeed takes place, once we are able to distinguish between technology clubs using highly disaggregated industry data. In this respect, our modeling strategy of combining a stochastic frontier production function with a latent class structure provides useful insights.

5. Conclusion

This paper investigates the forces driving output growth in a panel of manufacturing industries over the period 1980-1997. Relevant past studies typically assume that (i) industries use resources efficiently, and (ii) the underlying production technology is the same for all industries. We address these issues by estimating a stochastic frontier model which explicitly accounts for inefficiency, augmented with a latent class structure which

[22] We exclude industries of club B from this part of the analysis, since, as we have seen in previous section, efficiency is stable over the sample period in that club (which contains 18% of our sample).

Figure 4. Cross-country catch-up



allows for production technologies to differ across classes of industries. Class membership is estimated conditional on R&D intensity. This framework allows us to explore whether industries use different technologies, the sources of output growth in each technology club, potential technology spillovers and catch-up issues across industries and countries.

Our results support the existence of two technology clubs. There seems to be considerable heterogeneity in growth patterns across technology clubs. Technical change is a crucial component for growth for industries in the technologically advanced club, while input (capital, in particular) growth plays an important role in both technology clubs. Switching from one club to another is possible and it depends on the technological effort of the industries. Some evidence of technology spillovers and catch-up is found only within the technologically advanced club, while the distance between the clubs has been enlarged over time. Finally, within the technologically advanced club, we also find some evidence of cross-country catch-up.

Our findings have important policy implications. Policy makers generally agree that higher R&D spending is desirable and are willing to subsidize and/or give tax credits to industries that engage in R&D. According to our results, the effects of an increased R&D effort depend on the allocation of R&D tax credits/subsidies. In both technology clubs, we find some evidence of a positive relationship between R&D and efficiency. Therefore, a preliminary conclusion can be that increasing the R&D effort facilitates the absorption of existing technologies. For industries in the less technologically advanced club, in rare cases, this may involve the adoption of an existing, superior technology. However, increases in R&D effort do not always lead to increased technical growth. For industries in the technologically less advanced club, no technical growth is to be expected. In fact, we find that if R&D spending is to enhance technical growth, it should be aimed at efficient industries in the technologically advanced club.

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Appendix: Data and Sources

Value-Added (*Y*): gross value-added expressed in 1995 constant prices (euros). Gross value-added was deflated by *implicit value-added deflators* to yield deflated gross value-added expressed in 1995 constant prices (euros). We follow the OECD (2002) practice for the construction of the implicit value-added deflators. Data on gross value-added are retrieved from the OECD (2002) *Structural Analysis Database* (STAN).

Physical capital (*K*): gross capital stock expressed in 1995 constant prices (euros). Following common practice in the literature (e.g. Hall and Jones, 1999), we employ the perpetual inventory method to construct a proxy for capital stock, using data on gross fixed capital formation (GFCF). The initial value for the 1980 capital stock is specified as $\mathrm{K}_{1980}= \mathrm{GFCF}_{1980}/(\mathrm{g} + \mathrm{ffi})$, where g is the average geometric growth rate of the gross fixed capital formation (constant prices) series from 1970 to 1980 and δ is the depreciation rate. Instead of assuming a constant depreciation rate, we use the average service life (ASL) of capital per industry (ISDB98-*methods used by OECD countries to measure stocks of fixed capital*, OECD, 1993). Each industry's capital stock is constructed as capital stock minus depreciated capital stock plus gross fixed capital formation ($\mathrm{K}_{\mathrm{t}}= (1 - \mathrm{ffi}) * \mathrm{K}_{\mathrm{t}-1}+\mathrm{GFCF}_{\mathrm{t}}$). Data on gross fixed capital formation (GFCF) are retrieved from the OECD (2002) *Structural Analysis Database* (STAN).

Labor (*L*): annual total hours worked in an industry (in thousands). Data are retrieved from the Groningen Growth and Development Centre (GGDC, 2006) *60-Industry Database*.

Research and Development (*R&D*): R&D intensity, defined as R&D expenditures to value-added ratio. Data on R&D expenditure are retrieved from the OECD (2002) *Business Enterprise Research and Development* (BERD).

Imports (*IMP*), Exports (*EXP*), Trade (*Openness*): import flows, export flows, export+import flows scaled by value-added of the industry. The OECD (2002) *Structural Analysis Database* (STAN) provides information per industry.

Table A.1
Manufacturing Industries and Growth Rates of Output and Inputs

	Y						K						L					
industry	FI	FR	DE	IT	NL	ES	FI	FR	DE	IT	NL	ES	FI	FR	DE	IT	NL	ES
Food products	0.019	0.001	0.003	0.021	0.029	0.009	0.045	0.039	0.021	0.037	0.006	0.040	-0.027	-0.009	-0.011	-0.004	-0.016	-0.005
Textile products	-0.039	-0.019	-0.006	0.010	-0.010	0.002	-0.007	0.025	0.044	0.021	0.026	0.047	-0.076	-0.048	-0.064	-0.022	-0.048	-0.030
Wood products	0.019	0.021	0.002	0.014	0.013	0.021	0.043	0.064	0.017	-0.002	0.091	0.060	-0.036	-0.025	-0.012	-0.024	-0.029	-0.009
Paper products	0.035	0.000	0.017	0.024	0.023	0.010	0.083	0.054	0.031	0.060	0.058	0.061	-0.019	-0.010	-0.009	-0.004	-0.011	0.014
Petroleum products	0.032	-0.084	-0.010	-0.039	0.017	0.030	0.251	-0.040	0.074	0.001	0.043	0.223	-0.011	-0.038	-0.065	-0.019	-0.011	-0.015
Chemicals	0.037	0.019	0.020	0.046	0.039	0.030	0.084	0.052	0.043	0.057	0.092	0.090	-0.009	-0.020	-0.016	-0.019	-0.012	-0.013
Pharmaceuticals	0.037	0.019	0.020	0.046	0.039	0.030	0.068	0.123	0.051	0.138	0.075	0.102	-0.009	-0.020	-0.016	-0.019	-0.012	-0.013
Rubber/plastics	0.035	0.019	0.032	0.024	0.048	0.030	0.031	0.085	0.060	0.029	0.056	0.073	-0.006	-0.011	0.009	0.009	0.010	0.005
Mineral products	0.014	0.010	-0.002	0.013	0.008	0.026	0.047	0.012	0.018	0.035	0.071	0.047	-0.027	-0.029	-0.023	-0.007	-0.019	-0.017
Iron and steel	0.047	0.012	0.008	0.019	0.013	0.039	0.109	0.012	0.032	0.026	0.058	0.118	-0.017	-0.038	-0.037	-0.028	-0.025	-0.034
Non-ferrous metals	0.047	0.012	0.008	0.019	0.013	0.039	0.093	0.083	0.080	0.074	0.084	0.145	-0.017	-0.038	-0.037	-0.028	-0.025	-0.034
Fabricated metal	0.057	0.012	0.007	0.020	0.022	0.039	0.087	0.037	0.022	0.043	0.048	0.080	0.011	-0.020	-0.007	-0.013	-0.006	0.003
Machinery	0.039	0.012	0.010	0.005	0.028	0.025	0.051	0.053	0.025	0.024	0.057	0.092	-0.009	-0.022	-0.019	-0.013	-0.001	-0.002
Office machinery	0.167	0.012	0.109	0.036	0.020	0.020	0.311	0.044	0.104	0.056	0.258	0.178	0.026	0.012	-0.008	0.009	-0.014	0.021
Electrical machinery	0.046	0.012	0.031	0.040	0.020	0.026	0.051	0.042	0.073	0.082	0.144	0.079	-0.006	-0.008	-0.009	-0.010	-0.020	-0.011
Communication	0.210	0.012	0.035	0.040	0.020	0.021	0.133	0.064	0.077	0.117	0.310	0.138	0.064	-0.032	-0.039	-0.020	-0.013	-0.034
Precision instruments	0.097	0.012	0.017	0.036	0.008	0.025	0.097	0.036	0.022	0.011	0.064	0.161	0.020	-0.014	-0.014	-0.005	-0.021	0.002
Motor vehicles	0.022	0.015	0.027	0.015	0.023	0.026	0.051	0.043	0.034	0.075	0.017	0.120	-0.010	-0.037	0.000	-0.038	0.011	0.001
Ships and boats	0.004	0.029	0.052	0.010	0.008	0.021	0.092	0.135	0.117	0.099	0.066	0.220	-0.046	-0.031	-0.061	-0.024	-0.051	-0.013
Aircraft and spacecraft	0.043	0.029	0.052	0.010	0.008	0.021	0.133	0.010	0.062	0.039	0.176	0.072	0.036	-0.016	0.002	0.032	-0.044	0.042
Manufacturing n.e.c.	0.010	0.012	-0.002	0.010	0.011	0.023	0.110	0.052	0.018	0.022	0.099	0.053	-0.026	-0.025	-0.020	-0.005	-0.011	-0.016

Note: *FI*, *FR DE IT NL ES* stand for Finland, France, Germany, Italy, Netherlands and Span, respectively.

Table A.2
Manufacturing Industries and Technology Classes

Manufacturing Industries	ISIC code (Rev. 3)	All years		FI		FR		DE		IT		NL		ES	
		A	*B*	*A*	*B*	*A*	*B*	*A*	*B*	*A*	*B*	*A*	*B*	*A*	*B*
Food products	15-16	108	0	0	18	18	0	18	0	18	0	18	0	18	0
Textile products	17-19	108	0	18	0	18	0	18	0	18	0	18	0	18	0
Wood products	20	108	0	18	0	18	0	18	0	18	0	18	0	18	0
Paper products	21-22	98	10	18	0	14	4	18	0	18	0	18	0	12	6
Petroleum products	23	59	49	18	0	5	13	18	0	0	18	18	0	0	18
Chemicals	24 less 2423	95	13	18	0	18	0	18	0	18	0	5	13	18	0
Pharmaceuticals	2423	61	47	18	0	0	18	18	0	2	16	18	0	5	13
Rubber/plastics	25	108	0	18	0	18	0	18	0	18	0	18	0	18	0
Mineral products	26	105	3	18	0	18	0	18	0	18	0	15	3	18	0
Iron and Steel	271+2731	108	0	18	0	18	0	18	0	18	0	18	0	18	0
Non-ferrous Metals	272+2732	108	0	18	0	18	0	18	0	18	0	18	0	18	0
Fabricated metal	28	108	0	18	0	18	0	18	0	18	0	18	0	18	0
Machinery	29	108	0	18	0	18	0	18	0	18	0	18	0	18	0
Office machinery	30	74	34	18	0	3	15	18	0	18	0	11	7	6	12
Electrical machinery	31	105	3	18	0	18	0	18	0	18	0	15	3	18	0
Communication	32	95	13	15	3	18	0	18	0	18	0	8	10	18	0
Precision instruments	33	81	27	18	0	18	0	18	0	18	0	0	18	9	9
Motor vehicles	34	108	0	18	0	18	0	18	0	18	0	18	0	18	0
Ships and boats	351	90	18	18	0	18	0	18	0	18	0	0	18	18	0
Aircraft and spacecraft	353	89	19	18	0	18	0	18	0	18	0	0	18	17	1
Manufacturing n.e.c.	36+37	108	0	18	0	18	0	18	0	18	0	18	0	18	0
Total		2032	236	375	3	328	50	378	0	344	34	288	90	319	59
χ^2			495		60		298		n.a.		356		282		249

A = technology club *A*, *B* = technology club *B*. χ^2 is Pearson's chi-squared statistic for the hypothesis that the rows and columns in a two-way table are independent.