Technology Regimes and Growth Patterns: Evidence from EU Manufacturing

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Abstract

This paper investigates growth patterns in a panel of EU manufacturing industries over the period 1980-1997. A flexible modeling approach 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 regimes. Both the technology regimes and the parameters within each regime are modeled as a function of R&D intensity. This framework allows us to explore the importance of those three components of output growth in each regime, potential technology spillovers and convergence issues across industries and countries.

Key words: growth, efficiency, R&D, stochastic frontier analysis, latent class
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1 Introduction

An enormous body of literature has tried to explain why some countries or industries produce more than others. In most cases, studies have investigated the relative importance of factors of production, such as physical capital and labor, and unobserved total factor productivity (TFP) in 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 factors and the unexplained residual that reflects all output growth that cannot be ascribed to inputs (see Maddison, 1987, for a survey). The existing empirical literature, however, is still divided as to whether input augmentation or TFP dominates in explaining output growth. [1] The cross-country growth regression literature often bases its regressions on such a production function specification (see, e.g., Mankiw et al., 1992; Islam, 1995), which is often expanded to include various sets of explanatory 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).

The present paper, investigates the components of output growth for a panel of manufacturing industries. In exploring these components, we adopt a flexible and structural modeling approach, where output is a function of only labor and physical capital. We refrain from enhancing the explanatory power of our model by including variables commonly used in the cross country growth regression literature, such as financial development, openness, and institutions. In this respect, we relate closely to the growth accounting literature. At the same time, we introduce some flexibility in how industries transform labor and physical capital into output, by identifying different technology regimes. With our approach, we are able to discuss key issues in the literature related to the use of different technologies, the sources of output growth in different technology regimes, technology spillovers and convergence and draw policy implications. We focus on manufacturing industries in order to decrease the aggregation bias that may occur when studying these issues at the country level (Bernard and Jones, 1996a,b).

Traditionally, the growth accounting literature has referred to the unexplained

[1] Numerous studies point to the role of inputs in generating growth (Baumol, 1986; Barro and Sala-i-Martin, 1991, 1992; Mankiw et al., 1992; Islam, 1995), while more recent empirical studies show that differences in output 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).

residual as 'productivity residual' or 'technical change' (Solow, 1957). However, this interpretation depends, among others, on the strong assumption that economic units are always efficient. In reality, however, economic units (countries or industries) 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. [3] In this paper, we estimate a simple production frontier, which is the empirical analog of the theoretical production possibility frontier, giving some structure to the estimation residual. In particular, we disentangle the residual into inefficiency and measurement error, respectively. In our model, technical change is measured by a shift of the production frontier.

(In)efficiency has only recently gained significant attention in the literature. Theoretical models of inefficiency usually focus mainly on the role of institutions and social arrangements to explain the lack of advanced technology (due to barriers to the adoption of technology) or inadequate use of existed technology (due to rent seeking, corruption, monopoly power, immobility of factors, etc.). [4] 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 changes are decomposed into technical, efficiency, and input changes. For instance, Färe et al. (1994) use data envelopment analysis (DEA) while Koop et al. (1999, 2000) and Limam and Miller (2004) use stochastic frontier analysis (SFA) to examine country-specific inefficiency in a number of developed and developing countries. More recently, a number of studies investigate the role of efficiency in explaining growth for a panel of manufacturing industries in the OECD countries (Koop, 2001; Kneller and Stevens, 2006). With few exceptions (Koop, 2001), all these studies benchmark countries (industries) against a common production frontier.

However, it may be the case that not all industries share a single common best-practice frontier. Recent theoretical contributions (Basu and Weil, 1998; Acemoglu and Zilibotti, 2001) have stressed the 'appropriateness' of technology, as industries (countries) choose the best technology available to them,

[3] In investigating productivity and catch-up, the empirical growth literature typically uses a two-stage approach: Cross-country productivity estimates are retrieved as a residual from a production function and then regressed on a set of potential determinants. See Coe and Helpman (1995) and Keller (2002) for the effects of domestic and foreign R&D stocks on total factor productivity growth; Scarpetta and Tressel (2002) for R&D, product and labor market regulations; Griffith et al. (2004) and Cameron et al. (2005) for R&D, trade and human capital.

[4] See, for instance, the studies of Clark (1987), Parente and Prescott (1994), Parente and Prescott (1999), Krusell and Rios-Rull (1996), and Baily and Solow (2001).

given their input mix. Some industries may share the same technology regime, if their marginal productivity of labor and capital (the technology parameters in the production function) 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).

A handful of studies try to accommodate these technology regimes, allowing for parameter heterogeneity when estimating production frontiers. For instance, Koop (2001) estimates industry-specific frontiers. A problem with that approach, however, is that it is difficult to compare efficiency scores from separate frontiers. Alternatively, one can divide industries into technology regimes on the basis of technology effort, for instance observed R&D expenditure (Hatzichronoglou, 1997; OECD, 2005). However, any *ex ante* division rule is to some degree arbitrary (Orea and Kumbhakar, 2004), and R&D itself may simultaneously affect the technology parameters *within* and the efficiency with each technology regime. Durlauf and Johnson (1995) endogenize the division rule using a regression tree analysis to identify multiple technology regimes of cross-country growth behavior. In their approach, both the parameters and the number of regimes result from a sorting algorithm applied to the whole sample, incorporating a cost to sample splits to avoid overparameterization.

The present paper contributes to the literature in the following respects: First, we account for inefficiency by estimating a stochastic production frontier, which separates inefficiency from measurement error. Second, we model technical change as a shift of the maximum output that is measured by this stochastic frontier, and thereby control for efficiency changes. Third, instead of assuming a common production technology, we estimate regime-specific production technologies by augmenting our stochastic production frontier with a latent class structure. We model the technology regime allocation as a latent class problem, with regime membership conditional on technological effort, measured by R&D intensity. We identify technical, efficiency, and input growth for endogenously determined technology regimes, where a logit model is used as a sorting mechanism with technological effort as a sorting variable. As a result, technology parameters depend on technological effort. The efficiency of industries in different technology regimes is estimated simultaneously, but relative to each regime's specific frontier. We allow for further flexibility by not restricting an industry's regime membership, and allowing industries to switch technology regime.

In general, our paper is similar in scope to the work by Koop (2001), who estimates different frontiers for (six) different industries. However, we differ by endogenizing the technology regime allocation. An attractive feature of our approach is that we can quantify the likelihood of regime membership, and study the impact of technological effort. The latter feature also distinguishes our work from the work of Orea and Kumbhakar (2004), who endogenize technology regimes, but require priors before doing so.

We apply our modeling approach to a sample of 21 EU manufacturing industries for six countries over the period 1980-1997, with three sets of question in mind: (i) do industries use different technologies?; (ii) eventually, what drives output growth?; (iii) is there any evidence of spillovers and catching-up?

The use of a latent class in the specification of the stochastic frontier model allowed detecting two (technology) regimes of industries: a technologically advanced regime (high-tech) and a less technologically advanced regime (low-tech). There seems to be considerable heterogeneity in growth patterns across technology regimes. Technical change is a crucial component for growth for the high-tech industries, while input (capital, in particular) growth plays an important role in both technology regimes. Switching from one regime to another is possible and it depends on the technological effort (R&D) of the industries. Some evidence of convergence is found only within the high-tech regime, while the distance between the regimes has increased over time. Within the high-tech regime, we also find some evidence of cross-country catch-up.

Our findings have important policy implications. For instance, does higher R&D spending result in better use of the existing best-practice technology and/or invention of new technology? Our results corroborate that the 'targeted' group of R&D recipients matters. We find some indication that higher R&D spending increases both the efficiency with which industries absorb the best practice technology and leads to technological advancements for the high-tech industries, whereas for the low-tech industries, higher R&D spending improves the chances of changing to the high-tech regime. Therefore, EU policy makers (Lisbon Strategy) aiming at technology growth should channel R&D tax-cuts mainly to high-tech industries.

The remainder of the paper proceeds as follows. Section 2 presents the methodology and econometric specification for estimation. Section 3 introduces the data. Empirical results are presented in section 4. Section 5 summarizes the findings and concludes.

2 Methodology

First, we introduce a production model which accounts for inefficiency. Next, we augment the frontier with a latent class structure to allow for more than one type of production technology. Finally, we decompose productivity changes for every technology regime 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 (maximum) 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 technological change (Solow, 1957); and ν_{ijt} is and i.i.d. error term distributed as $N(0,\, \sigma_{\nu}^{2})$, which reflects the stochastic character of the frontier.

Two points in equation (1) are worth noting. 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 growth empirical literature where the leader industry, i.e., the industry with the highest level of productivity, defines solely the frontier (Scarpetta and Tressel, 2002; Griffith et al., 2004; Cameron et al., 2005). An implicit, however, non-trivial assumption in this literature is that the leading industry itself constitutes the frontier and is the single benchmark for all other industries. Further, if time dimension is considered, then all technical progress is described by the observations of this single industry. Second, our modeling approach treats the frontier as stochastic through 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 et al., 1994; Gouyette and Perelman, 1997; Arcelus and Arocena, 2000; Boussemart et al., 2006) that do not allow for random shocks in the frontier.[6]

However, some industries may lack the ability to employ existing technologies efficiently (e.g. due to mismanagement) and therefore produce less than the frontier output. If the difference between maximum and actual (observable) outputs is represented by an exponential factor, $\exp\{-\upsilon_{ijt}\}$, then the actual

[5] Stochastic frontier analysis (SFA) was introduced by Aigner et al. (1977), Battese and Corra (1977), and Meeusen and van den Broeck (1977).
[6] Comprehensive reviews of frontier approaches can be found in Kumbhakar and Lovell (2000) and Coelli et al. (1998).

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 as $Y_{ijt} = Y^*_{ijt} \exp\{-\upsilon_{ijt}\}$. 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 normal distribution truncated at zero $N(0, \sigma^2_\upsilon)$, and independent from the noise term, ν_{ijt}.[7] Efficiency, $E = \exp\{-\upsilon_{ijt}\}$ can now be measured as the ratio of actual over maximum output, $E_{ijt} = \frac{Y_{ijt}}{Y^*_{ijt}}$ ($0 \leq E_{ijt} \leq 1$ where $E_{ijt} = 1$ implies full efficiency).

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, 1996c,a,b; Scarpetta and Tressel, 2002; Griffith et al., 2004; Cameron et al., 2005) that measure impediments to this absorptive capacity using TFP changes. However, in their framework the latter can be seen as a combination of 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. [8] Thus, the stochastic production frontier 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 technological change.

2.2 Technology Regimes

Next, we turn to how we model different technology parameters. The empirical literature discusses a range of ways to account for technology heterogeneity. [9] One approach to test wether innovation intensity explains output differentials is to simply specify an according proxy, such as R&D expenditure, as a factor of inputs, too. But that approach would implicitly assume that R&D expenditure in itself contributes to output. More likely, the former enhances factor productivity of labor and capital. Implementing an instrumental variable type

[7] When estimating equation (2), we obtain the composite residual $\exp\{\varepsilon_{ijt}\} = \exp\{\nu_{ijt}\} \exp\{-\upsilon_{ijt}\}$. Its components, $\exp\{\nu_{ijt}\}$ and $\exp\{-\upsilon_{ijt}\}$, are identified by the λ ($=\sigma_u/\sigma_v$) for which the likelihood is maximized (for an overview, see Coelli et al., 1998).

[8] We test whether a Cobb-Douglas specification is indeed preferred to a translog specification. Our tests (not reported here) are in favor of a Cobb-Douglas specification.

[9] See Bos et al. (2005).

of analysis using R&D as instruments for inputs, in turn, would fall short to allow for distinctively different technology regimes reflected by 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 technological regimes. However, any clustering mechanism is to some degree arbitrary since it remains unclear which cut-off levels of R&D to assign industries into different classes is 'appropriate'. Instead, we follow an approach, as agnostic as possible, with respect to imposing structure on the relation between innovation proxies and industry output.

To allow for different technology parameters when estimating productivity without priors regarding class membership, Orea and Kumbhakar (2004) advocate a latent stochastic frontier.[10] In line with Greene (2002, 2005), we specify technology regime allocation as a latent class problem, too. Regime membership is conditional on technological effort measured by R&D intensity. We allow for heterogeneity by introducing a latent sorting of y_{ijt} into z classes, which implies that equation (3) yields group-specific estimates of factor elasticities:[11]

$$y_{ijt} = \beta_{0|z} + \beta_{k|z} k_{ijt} + \beta_{l|z} l_{ijt} + \beta_{t|z} t_{ijt} + \nu_{ijt|z} - \upsilon_{ijt|z} \tag{4}$$

Parameters are obtained from maximizing a weighted log-likelihood function considering each industry-country's contribution to it's group-specific log likelihood. This partial likelihood is shown by Greene (2005) to be:

$$P\left(i, j, t|z\right) = f\left(y_{ijt}|x_{ijt}, \beta_z, \sigma_z, \lambda_z\right) = \frac{\Phi\left(\lambda_z \varepsilon_{ijt|z}/\sigma_z\right)}{\Phi(0)} \frac{1}{\sigma_z} \phi\left(\frac{\varepsilon_{ijt|z}}{\sigma_z}\right), \tag{5}$$

where $\varepsilon_{ijt|z} = y_{ijt} - x'_{ijt}\beta_z$. Note two issues. First, the likelihood maximization does not only depend on inputs and outputs per industry, but also on the inefficiency components in technology reflected by λ and σ. In contrast to clustering on the basis of some innovation proxy, we therefore consider the whole production technology characteristics allowing for inefficiency when obtaining parameters.

[10] 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 is determined by chosen priors in a Bayesian framework. Koop et al. (2000) consider this formulation technology regime membership priors critical.
[11] See (Greene, 2002, section E24.6.4).

Second, the likelihood in equation (5) is conditional on group membership z. More precisely, the weights assigned to each country-industry observation depend on the estimated probability GP of each observation ij to belong to class z, for example high-tech versus low-tech industries. The unconditional likelihood of each industry-country observation is averaged across both classes z and years t and equals the product of (i) the aforementioned group-membership probability and (ii) the observation's contribution to the class z likelihood: $P(i,j) = \sum_{z=1}^{Z} \mathrm{GP}(i,j,z) \prod_{t=1}^{T} P(i,j,t|z)$.

We introduce our measure of innovation in the former part, i.e. as an explanatory variable of group membership probability GP, which is estimated simply as a multinomial logit mode:

$$\mathrm{GP}(i,j,z) = \frac{\exp(RD_{ijt}\theta_z)}{\Sigma_{z=1}^{Z}\exp(RD_{ijt}\theta_z)},\ \theta_Z = 0, \tag{6}$$

where RD denotes $R\&D$ expenditure per industry and θ_z are group specific parameters to estimate. To obtain estimates of group-specific technology parameters β_z in equation (4), predicted probabilities of industry's class membership $GP_{ij|z}$ as well as parameters of R&D intensity parameters θ_z in equation (6), we follow Greene (2005) and maximize iteratively back and forth posterior group probabilities from (6) and the (weighted) log likelihood function in (5).

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

2.3 Decomposing Output Growth

A key aim of this paper is to relate our results to some of major macroeconomic debates as to why and how some industries (countries) grow faster than others. To investigate these issues, we decompose output growth, for each technology regime, into three components namely, input growth, technical growth and efficiency growth. In doing so, we need to totally differentiating equation (2) with respect to time, which yields a convenient expression of output growth:

$$\frac{\dot{y}}{y} = \frac{\partial \ln f_{ijt}}{\partial t} - \frac{\partial \upsilon_{ijt}}{\partial t} + \epsilon_k \frac{\dot{k}}{k} + \epsilon_l \frac{\dot{l}}{l} \tag{7}$$

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 (7) indicates that output growth can be broken down into three components. The first term corresponds to technical growth, $\frac{\partial \ln f_{ijt}}{\partial t}$, where $\frac{\partial \ln f_{ijt}}{\partial t} > 0$, represents an upward shift of the frontier (technological progress). The second term corresponds to efficiency growth, $-\frac{\partial v_{ijt}}{\partial t}$, where $-\frac{\partial v_{ijt}}{\partial t} > 0$ represents 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 factor 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 was 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 *Structural Analysis Database* (STAN). Data on labor are extracted from the Groningen Growth and Development Centre (GGDC) *60-Industry Database*. Finally, data on R&D are obtained from the OECD *Business Enterprise Expenditure on Research and Development* (BERD). The same International System of Industries Classification code (ISIC, ver. 3) was used in all data sources. Definitions of the variables and data are provided in the Appendix. Table 5 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, pertoleum). Similarly, some countries (e.g., Finland) exhibit fast growth in manufacturing output while others (e.g., France, Germany) do not. When it comes to the production inputs, for most countries and industries labor is shrinking while factor growth is driven by capital accumulation.

4 Results

Do industries use different technologies?

We investigate whether there are differences in the use of technology across manufacturing industries by employing a latent class model. In estimating such a model, one has to address the problem of determining the number of classes, z. Theoretically, the maximum number of groups is only limited by the number of cross sections, i.e. the number of countries in our study. Empirically, due to over-specification problems the maximum likelihood estimation may not converge for much smaller group numbers. In our sample, three is the maximum number of classes, z, for which neither multicollinearity nor over-specification prohibit convergence of the maximum likelihood estimator. As stated in Greene (2005), there is no formal test for the optimal number of groups, since the different specifications are not nested. We use the following rules when choosing our preferred specification: 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 if we add another class). We find strong evidence in favor of two classes. For a possible third class, parameters are jointly not significantly different from zero, and the class size is very small. [12]

The evidence in favor of two classes confirms the role of technology effort. As the logit results reveal ("Conditional latent class" in Table 1), a one percent decrease in R&D intensity decreases the probabilities of being high-tech by a factor of 6.28. The importance of technology effort is also reflected in the mean R&D intensity levels: in the first class, R&D intensity is on average 9.7%, whereas it is 7.7% in the second class. Accordingly, we classify the industries in our sample as high-tech or low-tech, respectively (see Table 6 in the Appendix). The same industry can be classified as low-tech for some countries but as high-tech for some others. However, in some countries (e.g., Finland and Germany) the majority of industries fall in one regime (high-tech, in this case).

Next, we explore to what extent the technology parameters and efficiency levels between the two classes differ. Table 1 reports our latent class results, where the technology parameters (the coefficients for K, L and t) and efficiency are conditional on class membership and thereby on R&D. Industries in each of our two classes (high-tech and low-tech) are benchmarked against their own frontier, where high-tech industries are compared to a higher frontier than low-tech industries.

The results are markedly different for our two classes. From Table 1 we observe that the marginal product of capital is not significantly different for high-tech and low-tech industries. 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). On the other hand, high-tech industries benefit from the fact that the marginal productivity of a unit of their labor is twice as high as that of low-tech industries. Importantly, both marginal products are

[12] A broader set of results, including specification tests, is available from the authors upon request.

Table 1
Latent Class Results

	High-tech		*Low-tech*	
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
$\sigma\ (= (\sigma_u^2 + \sigma_v^2)^{1/2})$	0.303	18.605	0.335	0.165
$\lambda\ (= \sigma_u/\sigma_v)$	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

estimated here conditional on R&D. Hence, we may interpret this finding as stating that low-tech industries pay for their low innovation efforts with less productive labor.

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

As stated above, each technology regime is characterized by its own optimal production frontier, where the high-tech frontier is superior to the low-tech frontier. Including a time trend t for each regime allows us to measure technical growth. Interestingly, for the industries that consider the low-tech frontier their benchmark, we find that technical growth is not significantly different from zero. For high-tech industries, on the other hand, technical growth is positive and significant at approximately 1.4% per year.

The latter finding does not necessarily imply that all high-tech industries *indeed* benefit from 1.4% technical growth. The technical growth is measured at the frontier. Hence, we also need to consider the efficiency of high- and low-tech industries. In fact, the average efficiency (E) of the former is more than 10% lower than that of the latter and is also quite dispersed. Low-tech industries appear to be quite efficient and operate very close to their (low-tech) frontier.

This is confirmed by our variance parameters for the compound error, σ and the parameter λ, how much of this variance indeed consists of inefficiency. For the low-tech industries, both parameters are insignificant, as inefficiency does not play a role. However, for the high-tech industries 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 be high-tech. The prior class probabilities (at the data means) show that almost 82% of our industries are expected to be high-tech. As expected, R&D intensity significantly affects the probability of being a high-tech industry.

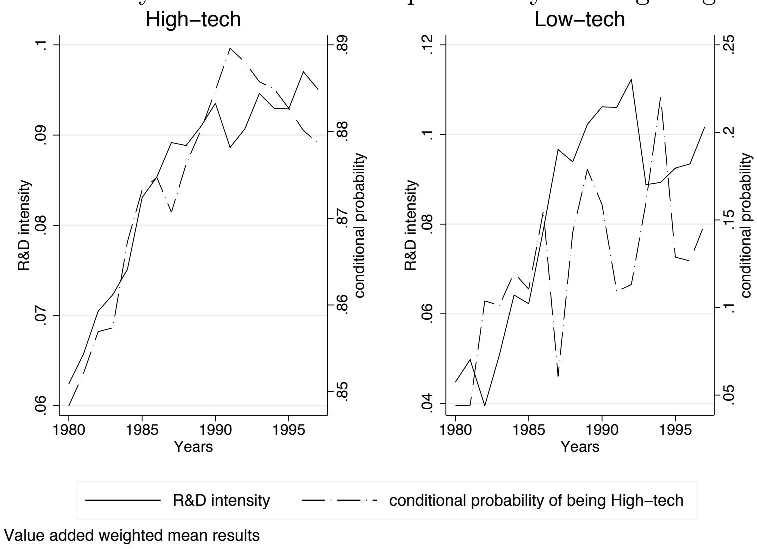
Do industries shift technology regimes?

However, industries are not restricted to one class. In principle, a low-tech industry can develop to become high-tech (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 become high-tech is by engaging in more R&D. Put differently, we expect that the conditional probability of being high-tech increases with R&D intensity.

In Figure 1, we explore this issue further for both groups. We find great increases in the probability of being a high-tech industry during the 1980s. During the same period, we observe a sharp increase in R&D intensity. In the case of high-tech industries, the latter increase almost perfectly matches the former.

For the low-tech industries, the story appears to be rather different. Until 1985, growth in R&D intensity nicely matches the growth in the conditional

Figure 1. R&D intensity and the conditional probability of being a high-tech industry



probability of being high-tech (even if the level of the latter is rather low). From then on, the link between the two developments is - on average - largely gone. Therefore, only some low-tech industries manage to successfully capitalize on their higher R&D intensity by becoming high-tech.

Table 2
Transition between Technology Regimes

	To	
From	*High-tech*	*Low-tech*
High-tech	97.70 %	2.30 %
Low-tech	20.89 %	79.11 %

In Table 2, we further investigate this issue by looking at the transition probabilities of industries switching technology regime. As we saw, some low-tech industries have been rather successful in increasing R&D. These industries may try to make the shift from a low-tech to a high-tech regime. In Table 2, we indeed observed that over the sample period approximately 21% of the low-tech industries manage to shift to the high-tech regime. Average R&D intensity for this group is 17.1%. On the other hand, only 2% of the industries make the opposite move.

Overall, Figure 1 confirms the high discriminatory power of our model. For the low-tech industries, the maximum (average) conditional probability of begin high-tech is approximately 23%, whereas for the high-tech industries, the minimum (average) conditional probability of being high-tech is approximately 85%. Indeed, this explains the low number of regime transitions over our sample period.

How do industries grow?

Now that we have identified two technology regimes, we want to find out how industries grow depending on the technology regime under which they operate. To this purpose, we decompose output growth into three components, using equation (7): input growth, technical growth and efficiency growth. We first investigate growth components in each technology regime. Later, we analyze these components in more detail, by distinguishing different growth patterns *within* each technology regime.

Table 3
Output Growth Decomposition

	output growth	input growth		technical growth	efficiency growth
		K	L		
Technology					
High-tech	0.000	-0.011	-0.002	0.014	0.000
	(0.444)	(0.443)	(0.012)	(0.001)*	(0.014)
Low-tech	-0.003	0.003	-0.002	-0.006	0.001
	(0.405)	(0.405)	(0.006)	(0.005)*	(0.006)

Standard deviations in brackets
(*) Standard errors from frontier estimation for technical growth.

Table 3 reports the decompositions for each of the two technology regimes. The results reveal that technical change plays an important role in output growth in the high-tech regime. It appears that most of the output growth in high-tech industries has been achieved by squeezing more output from given inputs rather than from expanding inputs. In fact, input growth has been negative for these industries. The picture is somewhat different for the low-tech regime. There, output growth, which appears to be negative for the period under investigation, is mainly driven by changes in inputs and technical regress.

However, table 3 reveals that growth levels vary significantly within both technology regimes. Put differently, within each technology regime there are industries with high positive and high negative growth, and Table 3 contains the *average* growth components for these industries. Therefore, in Table 4 we break down the industries in each technology regime 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.

From Table 4, we can draw the following conclusions. First, high growth industries in both the high-tech regime and the low-tech regime benefit from efficiency growth. Efficiency growth increases consistently with total output growth. Second, capital accumulation is important for high-growth industries,

Table 4
Output growth decomposition of high-, medium- and low-growth industries

			output growth	input growth		technical growth	efficiency growth
				K	L		
Technology	Growth	obs.					
High-tech	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)
Low-tech	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.

in particular for low-tech industries. This finding is not surprising, given the latter regime's high marginal rate of technical substitution, which makes capital accumulation an attractive growth strategy. Third, medium growth industries in both technology regimes appear to substitute labor for capital. Once these industries start experiencing high-growth, capital accumulation continues, but no longer at the expense of labor. Fourth, especially in the low-tech regime, low (i.e., negative) growth is almost completely the result of capital depletion.

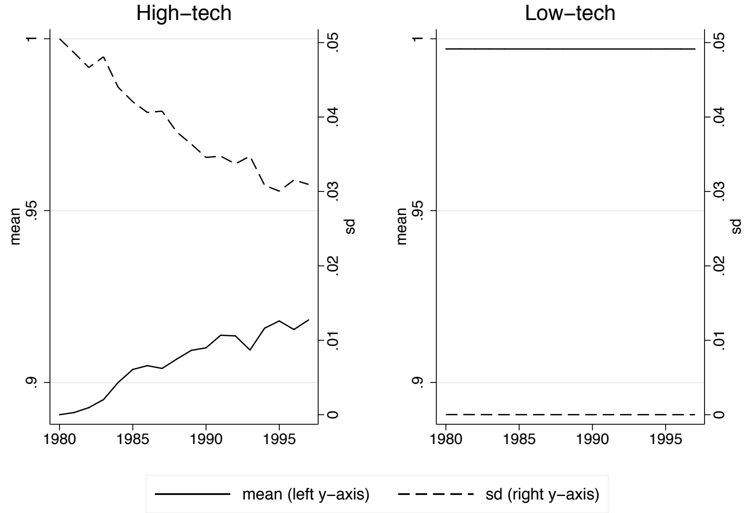
On the whole, there seems to be considerable heterogeneity in the growth patterns across technology regimes. Technical change is a crucial component for growth for the high-tech industries, while input (capital, in particular) growth plays an important role in both technology regimes. These findings are consistent with Koop et al. (1999), Koop (2001), Kumar and Russell (2002) and Limam and Miller (2004). [13]

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

Do we find 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 spillsover across countries, via various mechanisms such as 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 (absorb) the technology (Scarpetta and Tressel, 2002; Griffith et al., 2004; Cameron et al., 2005).

Figure 2. Convergence



Value added weighted mean results

In our model, high-tech leaders operate on, or close to the frontier, and they can try to push the frontier further outward through technical growth. Low-tech leaders 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 the high-tech regime. In both technology regimes, 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.

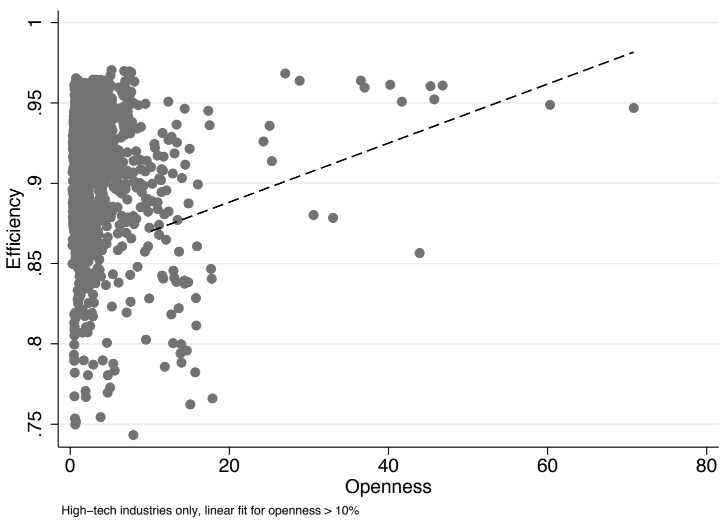
For the high-tech regime, our results provide clear evidence in favor of the leader-follower model. We find positive, significant technical growth of 1.4%. At the same time, Figure 2 reveals that there is strong convergence in the high-tech regime, as average efficiency increases approximately by 4% and the spread (standard deviation) of efficiency drops.

In the low-tech regime, technical growth is not significantly different from zero. However, as discussed above, low-tech leaders may try to shift to the high-tech regime. Figure 2 and our estimation results in Table 1 show that increasing R&D is a means of achieving this shift. In our discussion of the transition probabilities in Table 2, we indeed found that approximately 21% of the low-tech industries manage to shift to the high-tech regime.

Does openness increase efficiency?

It is often argued in the industrial organization literature (Caves and Barton, 1990) that increased openness to trade should be positively related with increases in efficiency. Higher exposure to trade facilitates the imitation of 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. [14] In Figure 3, we investigate this by comparing openness to trade (defined as the sum of import and export share of an industry to value-added) with efficiency, for the high-tech regime. [15]

Figure 3. Openness



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 positive relationship once openness becomes very substantial.

[14] See Connolly (1998), Keller (2002) and Hallward-Driemeier et al. (2002).
[15] We also considered using only the import shares, and results are qualitatively similar. Likewise, including the low-tech regime does not alter our conclusions.

Is there any evidence of convergence?

One oft-expressed hypothesis is that less technologically advanced industries can grow faster than advanced ones because they need only copying technology and practices of the latter. This notion underlies much of the convergence literature. If convergence is the case then 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 regimes.

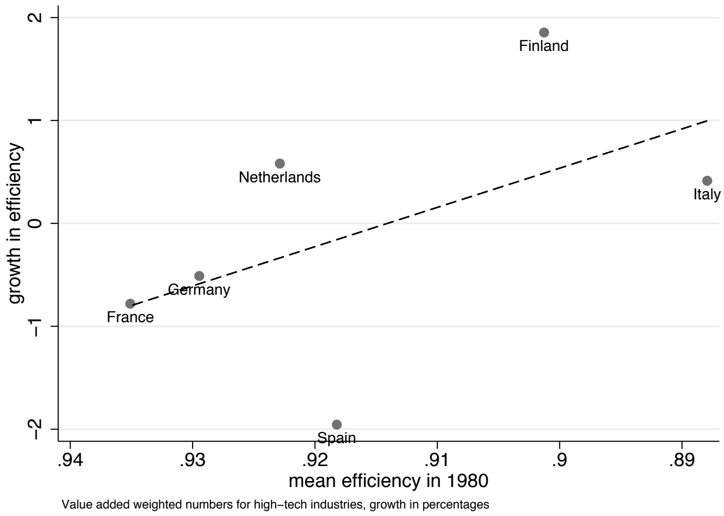
In the preceding paragraphs, we discussed the levels of efficiency of the two technology groups. Compared to their own (low-tech) frontier, low-tech industries are found to be efficient. On the other hand, the level of efficiency in high-tech industries is quite dispersed. This group could move closer to their (high-tech) 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 latent classes (high-tech and low-tech) are benchmarked against their own frontier, where high-tech industries are compared to a higher frontier than low-tech industries. Hence, the further away a high-tech industry is from its class' frontier, the closer it is to the low-tech frontier. As Figure 2 showed, the average efficiency has increased in the high-tech group. Therefore, over our sample period, the difference between high-tech and low-tech industries has widened to a seemingly insurmountable gap.

Previous studies (Bernard and Jones, 1996a,b; Gouyette and Perelman, 1997; Scarpetta and Tressel, 2002) find evidence that there is little or even no convergence in manufacturing. This is not supported by our results. Neither we are in line with those studies which provide evidence of strong convergence across all industries (Arcelus and Arocena, 2000; Boussemart et al., 2006). The rich data used in our analysis provide diverse results for different technology regimes. We find evidence that high-tech industries converge by eliminating inefficiencies while low-tech 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 high-tech industries have the capacity to absorb and assimilate advanced technology due to higher R&D spending. Indeed, the evidence Figures 1 and 2 supports this rather convincingly.

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

Figure 4. Cross-country convergence



Overall, however, our results highlight the importance of employing detailed and highly disaggregated manufacturing data and comparing similar technologies when analyzing convergence 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 low technology effort with industries with high technology effort may lead to a downward bias of the labor elasticity of the latter. A case in point is our finding that, in the high-tech regime, convergence indeed takes place, once we are able to distinguish between technology regimes using highly disaggregated industry data. In this respect our modeling strategy of combining a stochastic frontier 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 allows for production technologies to differ across classes of industries. Class membership is estimated, conditional on R&D intensity rather than determined *ex-ante*. This framework allows us to explore the sources of output growth in each regime, potential technology spillovers and convergence issues across industries and countries.

Our results support the existence of two technology regimes, a high-tech and a low-tech regime. There seems to be considerable heterogeneity in growth patterns across technology regimes. Switching from one regime to another is possible and it depends on the technological effort of the industries. Technical change is a crucial component for growth for the high-tech industries, while input (capital, in particular) growth plays an important role in both technology regimes. Some evidence of convergence and technology spillovers is found only within the high-tech regime while the distance between the regimes has been enlarged over time. Finally, within the high-tech regime, 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 do R&D. According to our results, the effects of increased R&D effort depend on the allocation of R&D. In both high-tech and low-tech industries, we find some evidence of a positive relationship between R&D and efficiency. Therefore, a preliminary conclusion can be that increasing R&D effort facilitates the absorption of existing technologies. For low-tech industries, in rare cases, this may involve the adoption of an existing, superior technology. However, increases in R&D effort does not always lead to increased technical growth. In low-tech industries, 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, high-tech industries, which may be expected to use it for outward shifts of their current frontier.

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Appendix: Data and Sources

Value-Added ($\boldsymbol{Y}$): 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) *STAN Structural Analysis Database.*

Physical capital ($\boldsymbol{K}$): 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 $\mathrm{K}_{1980} = \mathrm{GFCF}_{1980}/(\mathrm{g}+\delta)$, 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 ($\mathrm{K}_{\mathrm{t}} = (1-\delta) * \mathrm{K}_{\mathrm{t-1}} + \mathrm{GFCF}_{\mathrm{t}}$). Data on gross fixed capital formation are retrieved from the OECD (2002) *STAN Structural Analysis Database.*

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

Table 5
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 6
Manufacturing Industries and Technology Classes

		All years		FI		FR		DE		IT		NL		ES	
Manufacturing Industries	ISIC code (Rev. 3)	HT	LT	HT	LT	HT	LT	HT	LT	HT	LT	HT	LT	HT	LT
Food products, beverages and tobacco	15-16	108	0	0	18	18	0	18	0	18	0	18	0	18	0
Textiles, textiles products, leather and footwear	17-19	108	0	18	0	18	0	18	0	18	0	18	0	18	0
Wood, and products of wood and cork	20	108	0	18	0	18	0	18	0	18	0	18	0	18	0
Pulp, paper, paper products, printing and publishing	21-22	98	10	18	0	14	4	18	0	18	0	18	0	12	6
Coke, refined petroleum products and nuclear fuel	23	59	49	18	0	5	13	18	0	0	18	18	0	0	18
Chemicals excluding pharmaceuticals	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 and plastics products	25	108	0	18	0	18	0	18	0	18	0	18	0	18	0
Other non-metallic 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 products (excluding machinery and equipment)	28	108	0	18	0	18	0	18	0	18	0	18	0	18	0
Machinery and equipment, n.e.c.	29	108	0	18	0	18	0	18	0	18	0	18	0	18	0
Office, accounting and computing machinery	30	74	34	18	0	3	15	18	0	18	0	11	7	6	12
Electrical machinery and apparatus, n.e.c.	31	105	3	18	0	18	0	18	0	18	0	15	3	18	0
Radio, television and communication equipment	32	95	13	15	3	18	0	18	0	18	0	8	10	18	0
Medical, precision and optical instruments	33	81	27	18	0	18	0	18	0	18	0	0	18	9	9
Motor vehicles, trailers and semi-trailers	34	108	0	18	0	18	0	18	0	18	0	18	0	18	0
Building and repairing 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
Other Manufacturing (Furniture; Manufacturing n.e.c.; Recycling)	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	

χ^2 calculates and displays Pearson's chi-squared for the hypothesis that the rows and columns in a two-way table are independent.