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Does Technology Spill Over across National Borders and Technology Regimes?

J.W.B. Bos
B. Candelon
C. Economidou

Universiteit Utrecht
Utrecht School of Economics

Tjalling C. Koopmans Research Institute
Utrecht School of Economics
Utrecht University

Janskerkhof 12
3512 BL Utrecht
The Netherlands
telephone +31 30 253 9800
fax +31 30 253 7373
website www.koopmansinstitute.uu.nl

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How to reach the authors

Please direct all correspondence to the second author.

J.W.B. Bos
C. Economidou
Utrecht University
Utrecht School of Economics
Janskerkhof 12
3512 BL Utrecht
The Netherlands.
E-mail: j.bos@econ.uu.nl
c.economidou@econ.uu.nl

B. Candelon
Faculty of Economics and Business Administration
Maastricht University
6200 MD Maastricht
The Netherlands
E-mail: b.candelon@algec.unimaas.nl

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J.W.B. Bos[a]
B. Candelon[b]
C. Economidou[a]

[a]Utrecht School of Economics
Utrecht University

[b]Faculty of Economics and Business Administration
Maastricht University

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Abstract
This paper investigates whether technology spills over across national borders and technology regimes. We advocate a modeling strategy where changes in technical efficiency capture technology spillovers as industries absorb and implement the best-practice (frontier) technology. Recently developed dynamic panel-based techniques are used to determine whether efficiency series move together in the long run (cointegrate) and/or move closer together over time (converge). We contribute to the literature by controlling for technological heterogeneity and for cross-sectional dependence in the data. For a panel of manufacturing industries in six EU countries, we find evidence of long-run relationships among industries' efficiency levels in different countries and technology regimes.
Furthermore, we find convergence among manufacturing industries, both across countries and across technology regimes.

Keywords: technology spillovers, efficiency, panel cointegration, convergence, manufacturing industries

JEL classification: C23, L60, O14

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1. Introduction

Technology is a major driving force of economic growth (Romer, 1990; Rivera-Batiz and Romer, 1991; Grossman and Helpman, 1991). The non-rival characteristics of technology imply investments in technology do not only benefit the investors but also contribute to the the knowledge base which is publicly available to them. These externalities are called technology spillovers (Romer, 1990). Through technology spillovers, countries that operate below the production frontier can increase output by learning from the best practice. Countries benefit from technology flows if they have the 'appropriate' technology (Abramovitz, 1986; Basu and Weil, 1998) and sufficient 'absorptive capacity' (Abramovitz, 1986; Cohen and Levinthal, 1989).

A large amount of empirical literature has examined the significance of purely domestic spillovers (see Mohnen, 1996, for a survey), or domestic spillovers in conjunction with foreign spillovers (Coe and Helpman, 1995).[1] Technology transmission, both domestic and foreign, has been found to play a significant role in promoting productivity and economic growth.

The purpose of this paper is to investigate whether technology flows across industries in the EU manufacturing sector. In particular, we would like to investigate whether industries located in homogenous and presumably integrated countries, benefit from technology spillovers from industries in other countries or in different technology regimes. We focus on industries in the manufacturing sector rather than countries in order to account for aggregation bias due to heterogeneity in existing technologies (Bernard and Jones, 1996a,b).

The present paper contributes to the existing literature in three distinct respects. A first contribution of this paper, is that we measure technology spillovers in a simple and rather 'pure' manner. We propose a flexible modeling approach in exploring technology spillovers by estimating a stochastic production frontier. The latter is the empirical analog of the theoretical production possibility frontier and enables us to measure the maximum frontier output. One important advantage of focusing on maximum (frontier) output, rather than observable output, is that deviations from maximum output reflect sluggish absorption and implementation of the best practice (frontier) technology, whereas improvements in efficiency represent productivity catch-up via technology diffusion. Another advantage of our approach is that we can measure the extent to which an industry increases its output for a given amount of inputs, contrary to most of the literature, which focuses on total factor productivity (TFP) as a measure of spillovers and thereby conflates technical change, input changes, and (possibly) efficiency improvements.[2]

[1] A number of subsequent studies has extended the seminal study of Coe and Helpman (1995) in various ways. For instance, Lichtenberg and Potterie (1998), Keller (1998), Kao, Chiang, and Chen (1999), Frantzen (2000), Lichtenberg and Potterie (2001), Luintel and Khan (2004) and Falvey, Foster, and Greenaway (2004) investigate international technology spillovers at the country-level while Fagerberg and Verspagen (1999), Frantzen (2000), Scarpetta and Tressel (2002), Keller (2002), Frantzen (2002), Griffith, Redding, and van Reenen (2004), Park (2004) and Cameron, Proudman, and Redding (2005) among others, for international intra-industry and inter-industry spillovers.

[2] Empirical studies on technology spillovers usually test for convergence in total factor productivity (TFP) as a proxy of the technology level. TFP is evaluated as a growth accounting (Solow-) residual under rather limiting assumptions about the behavior of economic units (optimizing behavior with no room for inefficiency).

Industries in the manufacturing sector, however, are characterized by different technologies. Recent theoretical and empirical contributions (Basu and Weil, 1998; Acemoglu and Zilibotti, 2001) have stressed the 'appropriateness' of technology as countries (industries) choose the best technology available to them, given their input mix. Industries are members of the same technology regime (club) if their input/output combinations can be described by the same production technology (Jones, 2005). Not accounting for different technologies and estimating a single stochastic frontier function can result in biased estimates of the 'true' underlying technology. Furthermore, omitted technological differences may be erroneously labeled as inefficiency (Orea and Kumbhakar, 2004).

Allowing for different production frontiers to account for heterogeneity in technologies in the manufacturing sector has been largely ignored by the studies that have performed frontier analyses for studying technology spillovers and catch-up (see, for instance, Semenick Alam and Sickles, 2000; Kneller and Stevens, 2006). To the best of our knowledge, only Koop (2001) estimates different frontiers for different manufacturing industries. Our second contribution, therefore, lies in the way we account for differences in technologies. We estimate separate production frontiers for each of the four technology regimes (high tech, medium-high tech, medium-low tech and low tech) in the manufacturing sector as classified by the OECD (2005) [3] As a result, we obtain efficiency levels for industries in each of the technology regimes that reflect the distance to their appropriate technology.

While a large strand in the literature explores technology spillovers across industries (countries), only a few studies pay attention to the time series properties of these spillovers (see Coe, Helpman, and Hoffmaister, 2008, for a survey). A number of studies derive their spillovers estimates from (OLS) regressions, which, with non-stationary data, result in super-consistent (Stock, 1987) but imprecise coefficient estimates with standard errors ill-suited for statistical inference (Kao and Chiang, 2000). Ignoring, however, integration and cointegration properties of the data it is not clear whether one estimates a structural long-run relationship or a spurious one. [4] In this paper, we rely on cointegration and convergence to determine whether efficiency levels move together in the long-term (cointegrate), or, in fact, move closer together over time (converge). For instance, increased integration and competition in the EU can lead to more efficient use of resources among industries. Thus efficiency levels may track one another over time as industries attempt to follow each other's efficiency advances in order to remain

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As a result, the observed output is assumed to be the maximum (frontier) output, in all TFP analyses. In reality, however, economic units may well differ in the efficiency with which they use the best practice (frontier) technology.

[3] Manufacturing industries are classified into different technology regimes according to their technology intensity. The OECD methodology uses two indicators of technology intensity reflecting, to different degrees, 'technology-producer' and 'technology-user' aspects: i) R&D expenditures divided by value added; ii) R&D expenditures divided by production. The division of manufacturing industries into high-technology, medium-high technology, medium-low technology and low technology groups is based on a ranking of the industries according to their average R&D intensity over 1991-99 against aggregate OECD R&D intensities. Industries classified to higher categories have a higher average intensity for both indicators than industries in lower categories.

[4] A few studies (see, for instance, Coe and Helpman, 1995; Keller, 2002) acknowledge that inference tests of their results could be are unreliable and suggest that compelling evidence of panel cointegration is needed to support their estimation strategy.

competitive. Therefore, accepting the cointegration null for a set of industries would indicate a long-run relationship in the technology transfer within the cointegrated set and potential convergence; in contrast, lack of cointegration of an industry's efficiency score with those of its counterparts may reflect the industry's inability to absorb the existing technology.

To the best of our knowledge, there have been only two studies that investigate the time series properties of technical efficiency in the context of technology spillovers and convergence. Cornwell and Wächer (1999) examine whether a long-term relationship exists between country-level technical efficiencies in a sample of 26 OECD countries and whether these efficiencies do converge. Semenick Alam and Sickles (2000) present a firm-level study on the role of market structure and the developments in efficiency for the US airline industry. Their results support fairly strong evidence of cointegration and convergence among EU countries (Cornwell and Wächer, 1999) and existence of a long-run relationship of efficiency levels and, over time, convergence among US carriers (Semenick Alam and Sickles, 2000).

Notwithstanding, both studies rely on cointegration techniques that do not allow for potential cross-sectional dependence. Cross-sectional dependence, which only very gained some attention in the literature, appears to be, however, the case in many macroeconomic applications (e.g. convergence hypothesis tests) where time series are contemporaneously correlated due to (spatial) spillover effects, common unobserved shocks, or a combination of these factors (Pesaran, 2004). If there is cross-sectional dependence, the traditional independence assumption is violated, and cointegration test statistics are biased. Furthermore, none of the aforementioned studies proceeds with estimating long-run cointegrating relationships and discussing the nature of potential long-term linkages. Therefore, the third contribution of this paper lies in the use of panel-based cointegration techniques allowing for cross-sectional dependence and shedding more light on the long-run relationship by estimating the cointegrating relationship using appropriate panel estimators that account for the integration and cointegration properties of the data and allow for consistent and efficient estimates of the long-run relationship.

We apply the proposed methodology to a sample of 21 manufacturing industries for six European countries, over the period 1980-1997. Each industry is allocated to one of the four technology regimes, as classified by the OECD (2005). Hence, taking annual averages for each technology regime in each country, we explore the properties of a total of 24 series, with three sets of questions in mind: (i) are there technology spillovers across countries?; (ii) are there technology spillovers across technology regimes? and lastly (iii) is there any evidence of convergence?

Overall, our results reveal that there is fairly strong evidence that industries' efficiency levels have moved together in the long-term (cointegrate) both across countries and technology regimes. It appears that competitive forces in the EU have led to more efficient use of resources among industries as their efficiency levels have tracked one another over time in an attempt to follow each other's efficiency advances in order to remain competitive. The estimation of the long-run relationships between efficiency levels indicates that geographical proximity (for cross-border spillovers) and technological proximity (for cross-regime spillovers) are of the upmost importance. Finally, industries' efficiency levels have also moved closer together over time (converge) both in cross-country and cross-regime analysis. However, the extent to which convergence takes place across countries and across technology regimes, differs significantly.

The remainder of the paper proceeds as follows. Section 2 considers a model of production that allows for technical inefficiency and presents the econometric methodology and specifications for estimation. Section 2.4 introduces the data. Empirical results are presented in section 3. Section 4 summarizes the findings and concludes.

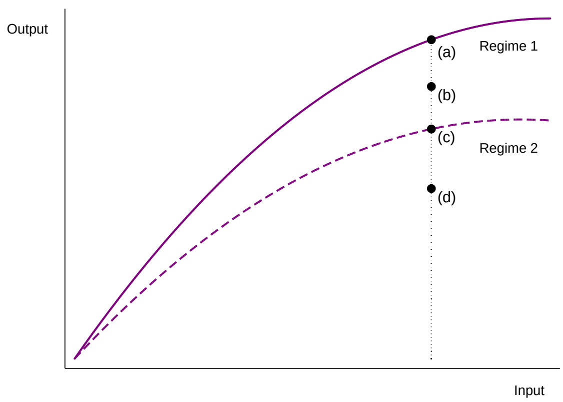
2. Methodology and Data

In this section, we first discuss the concept of technical efficiency and introduce a model of production that enables us to allow for inefficiency. Next, we discuss recent developments in panel-based integration and cointegration analysis to examine whether there is a long-run structural relationship among the efficiency series across countries or across technology regimes. Lastly, we concern ourselves with convergence tests.

2.1. *Technical Efficiency in A Stochastic Frontier Model of Production*

An industry is technically efficient if an increase in its output requires an increase in at least one input. A technically inefficient industry can produce the same output with less of at least one input. Alternatively, it can use the same inputs to produce more of at least one output (Koopmans, 1951). [5]

Figure 1. Technical efficiency



We demonstrate the concepts of technical efficiency and production frontiers with a simple one output, one input example in Figure 1. In the graph, we consider three cases. An industry operating under the frontier of Regime 1 in (a) cannot increase output without increasing its input, whereas an industry operating under the frontier of Regime 1

[5] Industries may also be inefficient because they are unable to combine inputs and outputs in optimal proportions for given prices. In the current paper, we do not consider this 'allocative efficiency', not only because price information is scarce, but also because the positive (negative) technology spillovers that we want to measure should result in reductions (increases) of technical slack. Therefore, in this paper the term 'efficiency' refers to technical efficiency only.

in (b) can try to absorb the (superior) production skills of (a) and increase its technical efficiency. Similarly, an industry operating under the frontier of Regime 2 in (d) can increase its efficiency by absorbing the production skills of an industry operating under the frontier of Regime 2 in (c). The latter industry, however, can not increase its output without either increasing its input, or through positive technical change, i.e. an outward shift of the regime's frontier over time.

We model the performance of our industries by means of a stochastic frontier production model, which accounts for the existence of inefficiency.[6] 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; production technology is characterized by function f and parameter vector β; 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 $N(0, \sigma^2_\nu)$, which reflects the stochastic character of the frontier.

Two points are noteworthy regarding equation (1). 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 - the leader industry, i.e., the industry with the highest level of productivity in the conventional growth empirics (Scarpetta and Tressel, 2002; Griffith, Redding, and van Reenen, 2004; Cameron, Proudman, and Redding, 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. 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 analyses (Färe, Grosskopf, Norris, and Zhang, 1994) that do not allow for random shocks in the frontier.[7]

However, some industries may lack the ability to employ existing technologies efficiently and therefore produce less than the frontier output. If the difference between maximum and actual (observable) outputs is represented by an exponential factor, $\exp\{-u_{ijt}\}$, 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, and $Y_{ijt} = Y^*_{ijt} \exp\{-u_{ijt}\}$. Equivalently:

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

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

[7] Comprehensive reviews of different frontier methodologies can be found in Kumbhakar and Lovell (2000) and Coelli, Rao, and Battese (2005).

where $v_{ijt} \geq 0$ is assumed to be i.i.d., with a normal distribution truncated at zero $|N(0, \sigma_v^2)|$, and independent from the noise term, ν_{ijt}.[8] Efficiency, $E = \exp\{-u_{ijt}\}$ can now be measured as the ratio of actual over optimal 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 non-frontier studies (Bernard and Jones, 1996a,b; Scarpetta and Tressel, 2002; Griffith, Redding, and van Reenen, 2004; Cameron, Proudman, and Redding, 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 measure efficiency, we estimate the following translog stochastic frontier production specification:[9]

$$\begin{aligned} \ln Y_{ijt} = {} & \beta_{ij} + \beta_1 \ln K_{ijt} + \beta_2 \ln L_{ijt} + \tfrac{1}{2}\beta_{11} \ln K^2_{ijt} \\ & + \tfrac{1}{2}\beta_{22} \ln L^2_{ijt} + \beta_{12} \ln K_{ijt} \ln L_{ijt} + \gamma_t D_t + \\ & + \delta_{kt} \ln K_{ijt} D_t + \delta_{lt} \ln L_{ijt} D_t + \nu_{ijt} - u_{ijt} \end{aligned} \tag{3}$$

where β_{ij} are country-industry specific fixed effects.

As Baltagi and Griffin (1988) have shown, Solow's general index of technical change relies on three restrictive assumptions: "constant returns to scale, neutral technical change, and perfect competition in both output and factor input markets" (p. 23). We follow Baltagi and Griffin (1988) and include a set of time dummies D_t, which - interacted with K and L -allow us to measure a general Tornqvist index of technical change as proposed by Diewert (1976).

Our specification relies on two crucial points. First, we want efficiency to be freely estimated (Jondrow, Lovell, Materov, and Schmidt, 1982), and as a result we do not impose any additional constraints on the distribution of efficiency.[10] Second, we follow Greene (2005) and estimate a 'true' fixed effects model, in which the fixed effects are allowed to be correlated with the other parameters, but they are truly independent of the error term and inefficiency.[11]

2.2. *Panel Unit Root and Cointegration Analysis*

We next turn to the econometric approach we follow. The main goal of the paper is to identify and explain the long-run dynamics between efficiency levels of different

[8] When estimating equation (2), we obtain the composite residual $\exp\{\varepsilon_{ijt}\} = \exp\{\nu_{ijt}\}\exp\{-u_{ijt}\}$. Its components, $\exp\{\nu_{ijt}\}$ and $\exp\{-u_{ijt}\}$, are identified by the λ (=σ_u/σ_v) for which the likelihood is maximized (for an overview, see Coelli, Rao, and Battese, 2005).

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

[10] An alternative approach is the one that has been suggested by Battese and Coelli (1995), who impose a common linear trend on ν_{ijt}. In that approach, however, an efficiency series by construct follows a time trend. Therefore, we consider this approach as less appropriate for a cointegration analysis.

[11] To see why this is important, consider the case in which an industry is inefficient, but its inefficiency is constant over time. In that case, if we estimate a fixed effect model in which our fixed effects behave like standard dummy variables, this industry's fixed effect will absorb the inefficiency, and the industry will appear to be efficient.

technology regimes of the EU manufacturing industries in our sample. Increased trade and competition in the EU could lead to more efficient use of the resources among industries. Thus, efficiency levels should track one another over time as industries within each regime attempt to follow each other's efficiency advances in order to remain competitive; otherwise lack of efficiency co-movement could indicate inability to capitalize on technology other industries are employing.

To examine the long-run properties of technology spillovers, captured by the efficiency series, we employ cointegration techniques. Cointegration examines the existence of stationary relationships between non-stationary variables and indicates that variables posses a long run common feature. A series possesses a unit root, i.e. it has a stochastic trend or is non-stationary if its statistical properties do not depend on time, and it is said to be integrated of order d, $I(d)$ if its d-difference does not posses a stochastic trend. If two or more series are themselves non-stationary, but a linear combination of them is, then the series are said to be cointegrated. Cointegrated variables share similar stochastic patterns in the long-run and cannot move too far away from another. In contrast, lack of cointegration suggests that there is no long-term link between each other.

Panel-based cointegration techniques are particularly well-suited for the study of technology spillovers for a number of reasons. First, the focus is on the long-run relationships, which would be obscured if the equations are estimated in first differences instead of in levels of the variables. Second, the increased power of the tests comes from exploiting commonalities across industries (countries), given the limited time span. [12] Third, parameter estimates are super-consistent and therefore robust to omitted variables, simultaneity and endogeneity problems. Thus, one can avoid the difficult task of finding valid instruments for some variables that would be necessary in the case of estimating a short-run relationship.

The implementation of the cointegration procedure entails first confirmation that the data are indeed non-stationary. Combining time-series information with that from cross-section data, panel unit root tests can be more precise and powerful by reducing the error-in-rejection probability (size distortion), especially when the time-series is not very long. Consider the following AR(1) process for panel data:

$$y_{it} = \rho_i y_{it-1} + \delta_i x_{it} + \varepsilon_{it} \tag{4}$$

where y represents the dependent variable, x is a vector of independent variables, ρ and δ are coefficients and ε is the disturbance term.

Several tests have been developed to identify unit roots in panel data, depending on assumptions regarding the homogeneity (heterogeneity) of correlations in the data. In the present study, we consider a variety of them in order to increase the robustness of our results. We start with Levin, Lin, and Chu (2002) (LLC hereafter), who assume that there is a homogenous autoregressive root under the alternative hypothesis (based on Levin and Lin, 1992, 1993). More specifically, the tests proposed by LLC assume that

[12] The advantage of the panel data approach is that it enables us to determine the long-run relation among variables avoiding well-known problems that occur in using traditional time series cointegration testing (i.e., lower power of statistics due to small sample sizes). By allowing data to be pooled in the cross-sectional dimension, panel-based integration and cointegration techniques reduce small sample limitations. The use of the time-series dimension captures the long-run information contained in the data, and at the same time captures the heterogeneity in the short-run dynamics among different industries.

there is a common unit-root process between cross-sections so that $\rho_i = \rho$ for all i. Next, we consider Im, Pesaran, and Shin (1997, 2003), who propose panel unit root tests that permit heterogeneity of the autoregressive root under the alternative so that ρ_i may vary freely between cross-sections. They present two group-mean panel unit root tests designed against the heterogenous alternatives. The two tests are executed with a t-test based on ADF regressions (IPS hereafter) and a Lagrange multiplier (LM) test (IPSLM hereafter). Then we follow Maddala and Wu (1999) (MW hereafter), who suggest the same kinds of panel unit root tests based, however, on a Fisher statistic. Next in line is Breitung (2000), who proposes the unbiased LL statistic (ULL hereafter), which is based on an ordinary regression of transformed variables such that the test is robust against contemporaneous correlation of the errors (see Breitung and Das, 2005). Finally, we test according to Hadri and Larsson (2005) (HL hereafter), who propose a panel unit root test under the null hypothesis of stationarity allowing for specific variances and correlation patterns.

Having established the presence of a unit root in all series of interest, the next step consists of testing for cointegration among efficiency levels. Like panel unit root tests, panel cointegration tests have been motivated by the search for more powerful test than those obtained by applying individual time series cointegration tests, which have lower power, especially when the time dimension is rather small.

Most panel cointegration tests are built from the residuals previously obtained by the panel regression model:

$$y_{it} = x'_{it}\beta + z'_{it}\gamma + \varepsilon_{it} \tag{5}$$

where y_{it} and x_{it} are I(1). For $z_{it} = \mu_i$, several tests have been proposed, such as Dickey-Fuller (DF) and Augmented Dickey Fuller (ADF)-type unit root tests for ε_{it} as a test for the null of cointegration (or no cointegration).

We employ a number of conventional cointegration tests used in the past literature. We start by implementing the asymptotic version of Pedroni's (1999) test. [13] It consists of testing for the stationarity of the residuals obtained from equation (5). Pedroni shows that both standardized sums of individual statistics and statistics computed on the pooled residuals of the equations (respectively group mean panel cointegration statistics and panel cointegration statistics in Pedroni's terminology) are asymptotically normal. Nevertheless, caution has to be exercised in the interpretation of the former group of panel cointegration estimates because their statistical properties are derived under the assumption of cross-sectional independence. [14]

[13] Pedroni (2000; 2004) averages test statistics across cross-sections. He shows that asymptotic properties of these average test statistics are preserved if averaging is done separately for both numerator and denominator of the test statistic.

[14] Conventional cointegration tests rely on the restrictive assumption that time series are independent across units ('cross-sectional independence') which greatly simplifies the derivation of limiting distributions of the panel test statistics. The plausibility of such an assumption, however, has been questioned, as time series are found to be contemporaneously correlated (Pesaran, 2004). Cross-sectional dependence can arise, in general, due to omitted observed common factors, (spatial) spillover effects, unobserved common factors, or general residual interdependence that could remain even when all the observed and unobserved common factors are taken into account. In the presence of cross-sectional dependence, as well as, when the cross sectional dimension is small with respect to the time dimension, these tests are shown to be biased. The panel unit root and cointegration tests developed based on the assumption that the errors of individual series are cross sectionally independent are refereed to as the 'first generation tests'. These tests provide the theoretical basis for more recent developments, the so-called 'second generation tests' that account for cross sectional dependence in

Clearly, this is not necessarily a tenable assumption since countries (industries) have been constantly hit by the same shocks such as the oil price shocks, technological revolutions, exchange rate shocks, monetary shocks and so forth. Therefore for our six EU countries it is very difficult to assume that technology developments are entirely independent. The consequence of violation of the independence assumption is that the test statistics are biased, favoring the existence of cointegration, and that the coefficient estimates may not be super consistent, as usually assumed in panel cointegration estimates. A number of ('second generation') tests have been proposed (Phillips and Sul, 2003; Groen and Kleinbergen, 2003) to allow for cross-sectional dependence.

We test for the null hypothesis of no cointegration by following a methodology proposed in the recent work of Fachin (2007). Fachin introduces block-bootstrapped versions of the well known panel cointegration test of Pedroni (1999). Fachin proposes two bootstrapped tests (FDB1, FDB2) that both rely on the fast bootstrapping procedures suggested by Davidson and MacKinnon (2000). Both procedures incorporate the standard assumptions for efficient maximum likelihood estimators, but generate statistics that have limit properties that are less affected by sample size than standard bootstrapping procedures. FDB1 differs from FDB2 in that the former has, in theory, slightly better limit properties, whereas the latter is somewhat less computationally demanding. As Davidson and MacKinnon (2000, p. 7) point out, "it is almost costless to compute FDB2 if FDB1 is already being computed, it may be useful to do so as a check on the accuracy of the latter." In the original paper, Fachin (2007) shows the validity of the bootstrapped versions of the cointegration tests via Monte-Carlo simulations, but recently Smeekes, Palm, and Urbain (2008) demonstrate theoretically that the bootstrap approach behaves adequately in such a framework. The bootstrapped versions of the group-t and median-t statistic for the null hypothesis of no cointegration are then robust to cross-sectional dependence and small sample bias.

The final step involves the estimation of the long-run cointegrated relationship. Chen, McCoskey, and Kao (1999) have proven that the ordinary-least-squares (OLS) estimator is biased in a cointegrated panel framework and thus may lead to spurious regression. We therefore use a more promising estimator for cointegrated panel regressions proposed by Pedroni (2000). Fully-Modified OLS (FMOLS) addresses potential endogeneity of the regressors and serial corre- lation, in order to obtain asymptotically unbiased estimates of the long run parameters. More specifically, FMOLS is a non-parametric approach that controls for possible correlation between the error term and the first differences of the regressors and removes nuisance parameters (Dreger and Reimers, 2005; Pedroni, 2001). [15] Consider the following time series model:

$$y_{it} = \alpha_i + \beta_i x_{it} + u_{it} \tag{6}$$

where $x_{it} = x_{it-1} + \varepsilon_{it}$, and $\omega_{it} = (u_{it}, \varepsilon_{it})'$. In order to remove the autocorrelation in x_{it} and the correct for the covariance between the error term and the first differences of the regressors, FMOLS estimates the following parameter for the i-th panel member:

panels. See Gutierrez (2003) and Breitung and Pesaran (2005) for recent surveys.

[15] An alternative estimator suggested by Kao and Chiang (2000) is the Dynamic OLS (DOLS) estimator, which also corrects for potential endogeneity of the regressors and serial correlation. Banerjee, Marcellino, and Osbat (2000) have shown that both estimators are asymptotically equivalent. Implementation of DOLS leaves our FMOLS estimates practically unaltered. Results are available upon request.

$$\hat{\beta}_i^* = (X_i'X_i)^{-1}(X_i'y_i^* - T\delta) \tag{7}$$

where the asymptotic distribution of the OLS estimator is conditioned to the long run covariance matrix of the joint residual process, y_i^* is the transformed endogeneous variable and δ a parameter for autocorrelation adjustment. [16]

We employ the FMOLS estimator for dynamic heterogeous panels to estimate long-run equations for cross-border and cross-regime spillovers. For cross-border spillovers normalizing on a certain country, we estimate the following equation:

$$TE_{crt} = \alpha_r + \sum_{\substack{i=1 \\ i \neq c}}^{5} TE_{irt}' \beta_i + \varepsilon_{irt} \tag{8}$$

where i is the country subscript ($i = 1, ..., 5$), c is the country on which the equation is normalized, t is the time subscript ($t =, 1..., 18$), r is the regime subscript ($r = H, MH, ML, L$), and regime-specific fixed effects α_r are included.

Equation (8) is estimated normalizing on each of the six countries, respectively. Similarly, for cross-regime spillovers normalizing on the low technology regime, we estimate the following equation:

$$TE_{igt} = \alpha_i + \sum_{\substack{r=1 \\ r \neq g}}^{3} TE_{irt}' \beta_r + \varepsilon_{irt} \tag{9}$$

where g is the technology regime on which the equation is normalized, i is the country subscript ($i = 1, ..., 6$), country-specific fixed effects α_i are included and other subscripts are the same as for equation (8). Equation (9) is also estimated normalizing on each of the technology regimes, respectively.

2.3. *Convergence*

The presence of cointegration indicates a long-run relationship between the efficiency series. However, this does not necessarily simply convergence of efficiency levels. Tests of convergence in the economic growth literature (Baumol, 1986) determine whether there is a closing of the gap between inefficient and efficient industries over time.

To investigate the convergence hypothesis, we run simple cross-sectional regressions of time-averaged efficiency growth rates on the initial level of efficiency:

$$\Delta E_{ij} = \beta_0 + \beta_1 E_{ij,1980} + \varepsilon_{ij} \tag{10}$$

where ΔE_{ij} denotes the average growth rate of the efficiency level in industry j between 1980 and 1997, $E_{ij,1980}$ is the initial level of efficiency in year 1980 and ε_{ij} an error term.

We test for convergence across technology regimes, by estimating equation (10) for all industries in a country, controlling for technology regime-specific fixed effects. Convergence across technology regimes in *all* countries is tested in the same manner, but with country-technology regime-specific fixed effects. We also test for convergence within technology regimes, by estimating equation (10) for all industries in a technology regime.

[16] Submatrices of the joint long run covariance matrix provides correction factors.

Again, we perform this test both for each country and for all countries jointly, and include country-specific fixed effects in the latter case.

In the tradition of Baumol (1986) and Barro (1991, 1997), a negative and statistically significant coefficient on the initial level of efficiency can be interpreted as indication of convergence of efficiency levels. The higher the initial level of efficiency is, the slower that level should grow. This phenomenon is the result of the public nature of technology that spills over from leaders to followers, as the latter group learns from the former and tries to catch-up.

2.4. *Data*

Our analysis covers 21 two-, three- and four-digit industries in manufacturing for six European countries (Finland, France, Germany, Italy, Netherlands and Spain) over the period 1980-1997. 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) while data on labor are extracted from the Groningen Growth and Development Centre (GGDC) *60-Industry Database*. The same International System of Industries Classification code (ISIC, ver. 3) was used in all data sources. Definitions of the variables and data sources as well as the manufacturing industries considered in our analysis and their ISIC codes are presented in the Appendix, Table A.1.

3. Results

3.1. *Frontier results*

We estimate equation (3) for each technology regime. Table 1 contains the most important frontier results. [17] A casual comparison of the log-likelihood values suggests that the stochastic production frontier has the best fit for the medium-high and low technology regimes. However, both σ (the composite standard deviation) and λ (the ratio of the standard deviation of efficiency over the standard deviation of the noise term) are highly significant for all technology regimes. For high-tech industries, λ is 1.954, and significant at the 1% level, indicating that inefficiency is about twice the size of noise in this technology regime. Much the same holds for medium-high, medium-low and low-tech industries, where λ is 1.947, 2.251 and 2.891, respectively, and also always significant at the 1% level.

For industries in each technology regime, we also calculated the marginal rate of technical substitution ($MRTS$), as the negative of the ratio of the marginal product of labor capital. The $MRTS$ measures the rate at which labor can be substituted for capital, keeping output constant. As expected, the $MRTS$ gradually increases as we move from the high technology regime to the low technology regime and thereby increase capital intensity.

[17] Detailed results are available upon request.

Table 1
Frontier results

	High		*Medium-high*		*Medium-low*		*Low*	
LL (Obs.)	-467.428	(540)	111.082	(432)	-415.489	(756)	139.398	(540)
σ (t-value)	1.344	(23.773)	0.458	(31.299)	1.032	(33.918)	0.477	(38.410)
λ (t-value)	1.954	(6.658)	1.947	(5.853)	2.251	(6.572)	2.891	(8.434)
MRTS (SD)	-3.820	(5.194)	-2.245	(2.154)	-1.585	(3.599)	-1.332	(0.675)
Efficiency (SD)	0.484	(0.061)	0.779	(0.035)	0.580	(0.051)	0.784	(0.050)

Notes: *LL* is log-likelihood; $\sigma = (\sigma_u^2 + \sigma_v^2)^{1/2}$; $\lambda = \sigma_u/\sigma_v$; *MRTS* = marginal rate of technical substitution (marginal product of labor/marginal product of capital).

Compared to their own frontier, industries in the low technology regime are on average the most efficient (78.4%). The least efficient, on average, are industries in the high technology regime (48.4%). The spread of efficiency, however, is the highest for this regime. Figure 2 shows the efficiency distributions for each technology regime. Compared to their own frontier, industries in the medium-high and low technology regime are on average the most efficient. Also, the spread of efficiency levels is relatively low in these regimes. Medium-low technology industries are, compared to their own frontier, on average less efficient. But the spread of efficiency levels in this regime is much higher than the spread in the medium-high technology regime.

Table 2
Mean technical efficiency and growth of technical efficiency

		Finland		France		Germany		Italy		Netherlands		Spain		all countries	
technology	industry	mean	growth	mean	growth	mean	growth	mean	growth	mean	growth	mean	growth	mean	growth
High	AIR	0.486	0.008	0.485	0.020	0.485	-0.003	0.486	-0.001	0.485	0.018	0.487	0.005	0.486	0.011
	MED	0.474	0.108	0.488	-0.003	0.488	-0.010	0.486	0.016	0.488	-0.003	0.484	0.011	0.485	0.020
	OFF	0.452	0.355	0.487	0.008	0.481	-0.005	0.487	0.005	0.485	0.016	0.487	0.007	0.480	0.028
	PHA	0.484	0.022	0.489	0.002	0.488	0.001	0.486	0.020	0.487	0.009	0.487	-0.004	0.487	0.005
	RAD	0.446	0.138	0.488	0.003	0.488	0.002	0.487	0.008	0.488	0.002	0.486	0.015	0.480	0.012
Medium-high	CHE	0.778	-0.002	0.782	0.000	0.782	-0.001	0.774	0.013	0.780	0.004	0.782	0.000	0.780	0.002
	ELE	0.751	-0.005	0.781	0.002	0.781	0.001	0.781	0.001	0.775	0.001	0.781	0.001	0.775	0.007
	MAC	0.776	0.002	0.783	-0.001	0.782	0.000	0.782	0.002	0.782	-0.002	0.781	0.002	0.781	0.000
	MOT	0.779	0.001	0.780	-0.004	0.783	0.002	0.774	0.004	0.774	0.008	0.779	0.005	0.778	0.006
Medium-low	COK	0.582	0.007	0.579	0.008	0.580	0.011	0.580	0.009	0.558	0.085	0.583	0.000	0.577	0.021
	FAB	0.581	0.003	0.585	0.000	0.583	0.001	0.585	0.003	0.586	0.000	0.582	0.000	0.584	0.000
	IAS	0.571	0.033	0.571	0.015	0.580	0.004	0.575	0.011	0.581	0.011	0.584	0.006	0.577	0.011
	NFM	0.557	0.042	0.585	-0.002	0.585	0.004	0.583	0.006	0.583	0.007	0.583	-0.001	0.579	-0.001
	ONM	0.582	0.006	0.578	0.024	0.585	-0.001	0.585	0.000	0.585	0.002	0.585	0.001	0.583	0.003
	RUB	0.574	0.018	0.583	0.013	0.585	0.002	0.585	0.008	0.576	0.014	0.585	0.000	0.581	0.007
	SHI	0.581	0.002	0.580	0.005	0.570	0.008	0.582	0.009	0.581	0.006	0.583	0.005	0.580	0.009
Low	FOD	0.776	0.003	0.787	0.004	0.795	0.000	0.792	0.002	0.767	0.021	0.794	-0.002	0.785	0.005
	MAN	0.779	0.007	0.794	0.003	0.789	-0.001	0.792	0.006	0.791	0.000	0.776	0.007	0.787	0.006
	PAP	0.784	0.007	0.765	0.019	0.794	0.002	0.792	0.001	0.794	0.002	0.775	0.009	0.784	0.003
	TEX	0.759	0.006	0.785	-0.004	0.787	0.005	0.790	-0.003	0.787	-0.001	0.794	0.001	0.784	0.001
	WOD	0.750	0.017	0.785	0.015	0.792	0.001	0.766	-0.003	0.789	0.003	0.788	0.003	0.778	0.006

Note: Growth in technical efficiency, E, is given by $(E_{ij,t} - E_{ij,t-1})/E_{ij,t}$.

Apparently, both the mean level and the spread of efficiency are affected by the diversity of industries in a technology regime. The latter, is particular apparent for industries in the high technology regime, which includes for example the aerospace (AER) and the medical industry (MED), and for industries in the medium-low technology regime, which includes for example the shipbuilding industry (SHI) and the other non-metallic mineral products industry (ONM). As a result, the high and medium-low regimes may have the most potential for convergence (an issue to which we return in Section 3.3).

Figure 2. Technical efficiency

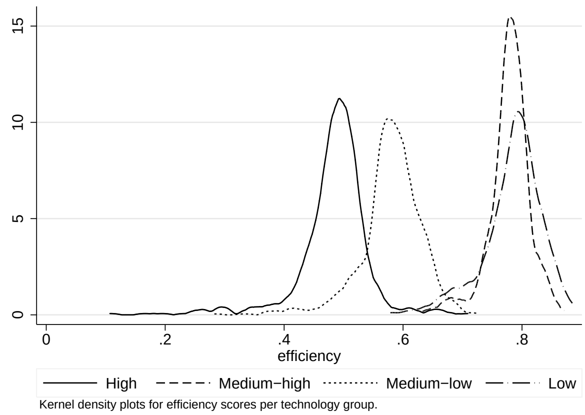


Table 2 contains average efficiency levels as well as average growth rates of efficiency over the sample period for each industry in each technology regime in each country. On the whole, Table 2 reveals few straightforward patterns. The fast growing industries in the medium-high, medium-low and low technology regimes are located in the Netherlands (Motor vehicles (MOT), petroleum products (COK) and food products (FOD), respectively). Overall, the industries in the high technology regime are the fastest growers.

3.2. *Panel unit root and panel cointegration results*

In this subsection, we examine the co-movement of technical efficiency levels across countries and across regimes, respectively. We take annual averages of each technology regime in each country, and study the properties of the resulting 24 series following a three step procedure. The first step consists of examining whether each of the series (country- or regime-specific) are non-stationary by testing for unit roots. In this step, we apply a gamma of the most recent panel unit root tests. Evidence of panel unit roots (i.e., technical efficiency levels ’move’) allows us to proceed to the second step, and test whether the series are cointegrated (i.e., whether the technical efficiency levels in different groups ’co-move’). In this step, we test for panel cointegration, both with tests that do not allow for cross-sectional dependence, and with tests that do. Cointegration of the series under investigation enables us to proceed to the third and final step, and examine the long-run linkages between the co-integrated series. In this step, we employ a number of panel estimators to increase our insight in the strength and direction of spillovers.

Are there spillovers across national borders?

We start by examining spillovers across the countries included in our sample. First, we test for panel unit roots in the efficiency series. Panel unit root tests for technical efficiency levels for each country of our sample are reported in Table B.1 in the Appendix. All panel-unit root tests, LLC, IPS, IPSLM, MW, ULL and HL support strong unit root evidence as the null hypothesis cannot be rejected while the alternative of stationary can be rejected at 5% (the opposite holds for the HL test, as the null hypothesis is different from that of the rest of the tests). The only exception is the HL test for Germany, where we find weak evidence of stationarity. Overall, we conclude that the efficiency series for the four technology regimes in each country are non-stationary and therefore all of them are included in the cointegration analysis, which is our next step.

Table 3

Panel Cointegration across Countries

	Group t-statistic	Pedroni	basic bootstrap	FDB1	FDB2
Mean	-1.83	3.34	9.20	7.50	7.40
Median	-3.24		9.00	6.70	6.60

Note: FDB1 and FDB2 indicate the two fast bootstrapped tests proposed by Fachin (2007).

In Table 3, we report two classes of panel cointegration tests. The first class contains group t-statistics, Pedroni's test and basic bootstrap tests. This class of conventional tests does not control for cross-sectional dependence. The second class consists of the two fast bootstrap methods proposed by Fachin (2007), which control for cross-sectional dependence. All test statistics reject the null hypothesis of no cointegration at 10% and the hypothesis of one cointegrating vector is accepted. Therefore, we conclude that the efficiency levels in the sample countries included here move together in the long run.

A natural question that follows is whether we can infer anything about the nature of long-run linkages among efficiency levels across countries. These linkages can be positive or negative, depending on the mechanisms at work. For instance, competition can force industries to increase their competitive capacity by reforming management styles and updating production technology, therefore enhancing the adoption of existing advanced technology. It can also hamper the absorption of technology, in case industries draw inputs from limited resource spaces and produce output to satisfy demand that typically is not completely inelastic. In the latter case, an industry may absorb technology at the expense of another industry (Aitken, Hanson, and Harrison, 1997; Aitken and Harrison, 1999; Girma, 2005). As a result, either market-stealing (on the output side) or skill-stealing (on the input side) results in a negative long-run linkage among efficiency developments. Geographical proximity and intensity of trade also have a dual effect

Table 4
Panel Estimation across Countries

Country	β_{FI}	β_{FR}	β_{DE}	β_{IT}	β_{NL}	β_{ES}
Finland	-	-1.314	-1.960	-0.145	1.608	4.483
		(6.242)	(2.232)	(0.522)	(17.627)	(21.956)
France	-0.214	-	0.064	-0.400	0.355	0.237
	(9.331)		(10.902)	(10.386)	(11.635)	(5.691)
Germany	-0.061	0.267	-	-0.154	0.746	-0.934
	(3.062)	(2.221)		(1.101)	(5.282)	(1.040)
Italy	0.425	-0.547	-0.234	-	-0.159	-1.614
	(12.523)	(7.720)	(2.507)		(5.311)	(9.736)
Netherlands	0.545	0.931	0.746	0.244	-	-1.348
	(11.203)	(3.262)	(3.724)	(3.356)		(10.677)
Spain	0.202	0.731	1.784	0.551	-0.665	-
	(11.003)	(1.673)	(2.506)	(5.546)	(9.448)	

In all estimations, technical regime-specific fixed effects are introduced but not reported for sake of space. They are available from the authors upon request.

on spillovers (Audretsch and Feldman, 2004). Industries in countries that trade more than others and/or share a common border, ceteris paribus, could experience stronger positive or negative long-run linkages in their technology absorption, either via higher technology flows, or via skill-stealing, assuming that labor is sufficiently mobile.

In order to assess the long-term linkages among efficiency levels in these countries, we estimate the long-run cointegrating equation (8) using the group mean fully modified ordinary least square (FMOLS) with unit specific correction factors proposed by Pedroni (2000), the Least Square Dummy Variable estimator, FMOLS with averaged correction factors (Kao, Chiang, and Chen, 1999), group mean FMOLS with averaged correction factors (Kao, Chiang, and Chen, 1999), FMOLS with unit specific correction factors (Pedroni, 2000) and FMOLS with unit specific correction factors for heterogenous panels (Kao, Chiang, and Chen, 1999). In Table 4, we report the group mean FMOLS estimator proposed by Pedroni (2000). [18]

We find strong evidence of a positive long-run linkage among a number of countries, in particular France and Germany (0.064, 0.267), France and the Netherlands (0.931, 0.355), and Germany and the Netherlands (0.746, 0.746). Geographical proximity and competition may explain the association of the efficiency levels of industries in these countries. Interestingly, the positive long-run linkage is strongest between pairs of unequal size (France and the Netherlands, Germany and the Netherlands), as smaller countries may follow in the footsteps of their larger neighbor.

On the other side, we also find strong evidence of a negative long-run linkages among a number of countries, most notably France and Italy (-0.547, -0.400), Germany and Italy (-0.234, -0.154) and the Netherlands and Spain (-0.665, -1.348). This negative association may be explained by a variety of reasons that this study cannot identify, including the effects of market-stealing (for example between France and Italy) or skill-stealing.

[18] Since we use series for each of the four technology regimes in each country, we include regime-specific fixed effects (not reported here). Results from the other estimators are qualitatively similar and available upon request.

To exemplify the economic significance of these results, consider the following question: ceteris paribus, how much is the average change in output for industries in France that results from the sample period change in technical efficiency in, say, Finland? From Table 4, we observe that for France, β_{FI} is -0.214. Using the period average efficiency scores, we can calculate the elasticity, which is -0.21. Given that Finnish industries on average increase their efficiency by 41.76% over the sample period, French industries are expected to decrease their average efficiency by -8.77% (-0.21$\times$41.76), *purely* as a result of the negative spillovers from Finland. From the average output level in 1980, we can calculate the average reduction in 1980 output that would result from these negative spillovers, which turns out to be 2178.94 million euros, or 22.58% of the average 1980 output of French industries.

Lastly, for a number of pairs of countries we observe opposite signs for the long-run linkages. For example, whereas the coefficient for Germany in the panel estimation for Spain is 1.784, the coefficient for Spain in the panel estimation for Germany is -0.934. Likewise, the coefficient for Italy in the panel estimation for Spain is 0.551, whereas the coefficient for Spain in the panel estimation for Italy is -1.614. Since the estimator in these cases behaves differently, depending on the normalization, we refrain from giving further economic meaning to these results.

Are there spillovers across technology regimes?

Next, we turn to testing whether technology spills over across technology regimes. First, we again test for panel unit roots in the efficiency series. Panel unit root tests for technical efficiency levels for each technology regime in our sample are reported in Table B.2 in the Appendix. We find strong support for unit roots for all tests included, and for all regimes. Therefore, in each technology regime the efficiency series in the six countries are non-stationary.

Table 5

Panel Cointegration across Regimes

	Group t-statistic	Pedroni	basic bootstrap	FDB1	FDB2
Mean	-2.68	0.37	11.20	12.20	12.10
Median	-3.36		13.10	13.50	13.90

Note: FDB1 and FDB2 indicate the two fast bootstrapped tests proposed by Fachin (2007).

Hence, we include all regimes in the panel cointegration tests reported in Table 5. Again, we report both tests that do not control for cross-sectional dependence and tests that do. All test statistics are slightly above 10% indicating that test statistics is close to the nominal size. We thus take the decision to consider that the null hypothesis is rejected and thus to conclude in favor of the hypothesis of one cointegrating relationship. This result is confirmed by the Pedroni (2000) statistics.

So far, we have established that there is co-movement of the efficiency of industries with different technologies in the EU manufacturing sector. In order to investigate the type of long-run linkages implied between the different technology regimes, we proceed by estimating long-run cointegrating equation (9), using the same set of estimators described previously for our country analysis. As before, in Table 6 we report the group mean FMOLS estimator proposed by Pedroni (2000). [19]

Table 6
Panel Estimation across Regimes

Regime	β_H	β_{MH}	β_{ML}	β_L
High	-	0.972	-0.227	-2.406
		(14.777)	(8.142)	(9.586)
Medium-high	0.417	-	-0.073	-0.136
	(8.534)		(0.075)	(1.668)
Medium-low	-0.232	0.843	-	0.013
	(1.739)	(7.228)		(7.195)
Low	-2.876	-1.100	5.258	-
	(5.795)	(1.227)	(32.910)	

In all estimations, country-specific fixed effect are introduced but not reported for sake of space. They are available from the authors upon request.

From Table 6 we can infer that technology spills over to neighboring technology regimes. We observe strong positive long-run linkages between industries in the high and medium high regimes (0.417, 0.972). The presence of some dominant technologies in the high and medium-high technology regime industries could be responsible for the evidence of positive linkages between efficiency levels in these two groups of industries. Industries in the medium-low and low regimes also operate with positive long-run linkages (5.258, 0.013). Finally, industries in the medium-low regime benefit from a positive long-run linkage with the medium-high regime (although the opposite is not the case). In these types of regimes, medium-low and low, technology tends to be rather stable which appears to have facilitated technology spillovers.

Positive linkages suggest that it is indeed easiest to appropriate technology that is closely related to your own. Negative long-run linkages exist for the other combinations in Table 6, perhaps reflecting the skill-stealing we described earlier.

We can illustrate the economic significance of these results in the same manner as for the cross-border spillovers. For technology regime spillovers, consider the following question: ceteris paribus, how much is the average change in output for industries in the medium-high technology regime that results from the period change in technical efficiency in the high technology regime? From Table 6, we observe that for medium-high technology industries, β_H is 0.417. Using the period average efficiency scores, we can calculate the elasticity, which is 0.26. As high technology industries on average have increased their efficiency by 28.83% over the sample period, medium-high technology industries are expected to increase their average efficiency by 7.50% (0.26×28.83) as a result of the positive spillovers from the high-technology industries. From the average output level in 1980, we can again calculate the average reduction in 1980 output that would result from these negative spillovers, which turns out to be 361.61 million euros, or 3.82% of the average 1980 output of medium-high technology industries.

[19] Since we use series for each of the counties in our sample, we include country-specific fixed effects (not reported here). Results from the other estimators are qualitatively similar and available upon request.

3.3. *Convergence results*

We now turn to the analysis of convergence. We start by examining whether there is convergence in the manufacturing sector as a whole within each country and across all countries of our sample. We then go one step further, and test the convergence hypothesis within each technology regime.

Is there convergence across national borders?

We start by estimating equation (10) for the manufacturing sector in each country and across countries. Table 7 reports the convergence coefficient, β_1, for each country and all countries. The results also provide evidence of convergence within each of the countries. However, the evidence appears to be the strongest for Finland and Germany. The Netherlands and Spain follow at a modest distance, and convergence is the lowest in France and Spain.

Table 7
Convergence across technology regimes in the manufacturing sector

area	β_0		β_1		elasticity	R^2_{adj}
all countries	0.124	***	-0.190	***	-0.114	0.800
Finland	0.156	***	-0.248	***	-0.125	0.702
France	0.076	***	-0.118	***	-0.077	0.801
Germany	0.112	***	-0.166	***	-0.111	0.942
Italy	0.076	***	-0.116	***	-0.070	0.885
Netherlands	0.101	***	-0.155	***	-0.089	0.892
Spain	0.096	***	-0.146	***	-0.089	0.789

All regressions with robust standard errors; regressions for each country with technology regime-specific fixed effects; regressions for the EU area with country-technology regime-specific fixed effects; significance at the 10/5/1 % level (*/**/***), semi-elasticities in the form of $\delta(y)/\delta(lnx)$.

It is interesting to relate these findings with the past literature. Our results run counter to the lack of (or very little) evidence of convergence documented in the literature for the manufacturing sector (Hansson and Henrekson, 1997; Bernard and Jones, 1996a,b). This is mainly due to the fact the majority of the past studies test for convergence in total factor productivity (TFP) as a proxy of the technology level. TFP is measured as a growth accounting (Solow-) residual under rather limiting assumptions about the existing technology (represented by a Cobb-Douglas production function and Hicks neutral technology change) and the behavior of economic units (optimizing behavior with no room for inefficiency). To benefit from spillovers, industries have to incur (costly) input changes. In contrast, we are line with Arcelus and Arocena (2000), who also perform a frontier analysis and focus on efficiency to measure technology spillovers. Efficiency changes do not require input changes therefore they can be considered a more 'pure' measure of technology adoption. Indeed, Arcelus and Arocena (2000) find a high degree of catching-up among 14 OECD countries over 1970-1990 in the manufacturing sector.

Is there convergence across technology regimes?

Although convergence in the manufacturing comes out particularly strong in each and every country and across countries in our sample, a justified concern is that aggregate (manufacturing sector) analysis of technology spillovers and productivity can mask important variations in convergence patterns due to different technology across industries (Garcia Pascual and Westermann, 2002; Scarpetta and Tressel, 2002; Boussemart, Briec, Cadoret, and Tavera, 2006).

Table 8
Convergence within each technology regime in the manufacturing sector

technology	area	β_0		β_1		elasticity	R^2_{adj}
	Finland	0.177	***	-0.458	***	-0.098	0.969
	France	0.002	***	-0.015	***	-0.008	0.005
	Germany	0.093	***	-0.178	***	-0.088	0.985
High	Italy	0.075	***	-0.154	***	-0.067	0.805
	Netherlands	0.111	***	-0.240	***	-0.089	0.968
	Spain	0.107	***	-0.229	***	-0.085	0.648
	all countries	0.136	***	-0.284	***	-0.114	0.766
	Finland	0.092	***	-0.118	***	-0.083	0.942
	France	0.081	***	-0.103	***	-0.082	0.809
	Germany	0.014	***	-0.019	***	-0.016	0.156
Medium-high	Italy	0.075	***	-0.094	***	-0.071	0.997
	Netherlands	0.058	***	-0.073	***	-0.057	0.398
	Spain	0.089	***	-0.113	***	-0.086	0.950
	all countries	0.078	***	-0.099	***	-0.076	0.854
	Finland	0.102	***	-0.175	***	-0.081	0.929
	France	0.081	***	-0.136	***	-0.076	0.936
	Germany	0.102	***	-0.168	***	-0.102	0.965
Medium-low	Italy	0.079	***	-0.132	***	-0.074	0.943
	Netherlands	0.100	***	-0.172	***	-0.084	0.980
	Spain	0.118	***	-0.201	***	-0.114	0.906
	all countries	0.094	***	-0.158	***	-0.085	0.937
	Finland	0.088	***	-0.109	***	-0.075	0.980
	France	0.079	***	-0.104	***	-0.083	0.886
	Germany	0.063	***	-0.077	***	-0.063	0.600
Low	Italy	0.080	***	-0.100	***	-0.073	0.871
	Netherlands	0.089	***	-0.112	***	-0.081	0.993
	Spain	0.100	***	-0.128	***	-0.098	0.865
	all countries	0.087	***	-0.110	***	-0.083	0.909

All regressions with robust standard errors; regressions for the EU area with country-specific fixed effects; significance at the 10/5/1 % level (*/**/***), semi-elasticities in the form of $\delta(y)/\delta(lnx)$.

This concern, that heterogeneity in existing technologies might be an issue in efficiency performance and in studying the convergence hypothesis in the manufacturing, has been validated in previous sections of our paper. In Section 3.1, we described the mean and growth of efficiency in four technology regimes (groups) across countries in our sample. From Figure 2, we observed that the average efficiency was relatively low for industries in high and medium-low technology regimes. In addition, the spread of efficiency was relatively high for these technology regimes. Table 2 then showed that almost all industries in all technology regimes and countries exhibited positive growth of efficiency. In sum, our frontier results suggest that there is ample room for (differences in) convergence, in particular among industries located in high and medium-low technology regimes.

Our next step, therefore, involves investigation of convergence across industries with similar technology. Table 8 contains the results from estimating equation (10), per technology regime in each of the countries and across countries. Negative and significant values for β_1 indicate that there is convergence in all technology regimes. Indeed, the high technology regime experiences the strongest convergence, both within each country (with the exception of France) and across countries. In the medium-low technology regime, convergence is also strong, as in the low technology regime, while the medium-high technology regime, on average, experiences the lowest level of convergence.

In the lower technology regimes (low and medium-low), the fact that the existing technology tends to be rather stable appears to have facilitated technology spillovers and convergence. This finding is in line with the literature (Scarpetta and Tressel, 2002). In contrast, our finding of strong convergence in the high technology regime appears at first to be surprising, since patent laws, product and market differentiation can reduce the scope for technology spillovers. Our results suggest the presence of some dominant technologies in the high technology regime industries could be responsible for the evidence of convergence. However, within the high technology regime, there appears to be significant heterogeneity across countries with elasticities ranging from -0.008 (France) to -0.098 (Finland). Likewise, in the medium-high technology regime (with elasticities ranging from -0.016 for Germany to -0.086 for Spain). Perhaps, persisting institutional differences, in particular related to product and labor market regulations, affect technology adaptation, particularly for the most technologically advanced and innovative industries. [20] This may explain the relatively large country variations in convergence patterns in our high and medium-high technology regimes.

Overall, our findings yield (i) strong evidence of convergence across countries is documented when technical efficiency is used to study the convergence hypothesis in the manufacturing sector; and (ii) even stronger evidence of convergence across technology regimes, when we disaggregate the manufacturing sector into different sub-sectors and control for differences in technology. However, the strength the convergence varies, depending on the regime.

[20] Differences in the stringency of regulatory settings across countries could have an impact on technology adaptation and convergence. Product and labor market regulations, for instance, can reduce incentives to invent and adopt better technology and catch up with the technological leader. Specifically, strict (anti-competitive) product market regulation is found to hinder the adoption of existing technologies, possibly because it reduces competitive pressures or technology spillovers (Nicoletti, Bassanini, Ernst, Jean, Santiago, and Swaim, 2001; Bassanini and Ernst, 2002). There is also evidence that strict employment protection legislation results in high hiring and firing costs that impede productivity improvements, especially when wages and/or internal training do not offset these higher costs, thereby resulting in sub-optimal adjustments of the workforce to technology changes and less incentives to innovate (Scarpetta and Tressel, 2002).

4. Conclusion

This paper investigates whether technology spills over across national borders and technology regimes. We advocate a modeling strategy where changes in technical efficiency capture technology spillovers as industries absorb and implement the best-practice (frontier) technology. By estimating a frontier model of production, we are able to measure the technical efficiency with which industries employ their production technology.

We contribute to the literature by controlling for technological heterogeneity and for cross-sectional dependence in the data. More specifically, we take into account the appropriateness of the technology that industries use, and benchmark each industry against other industries within the same technology regime. Hence, in our analysis, a (positive) technology spillover (i.e., an increase in efficiency) is indeed an improvement in the use of the existing technology, rather than a change in the latter. Also, we control for the fact countries and technology regimes are not necessarily cross-sectionally independent and use recently developed dynamic panel-based techniques to determine whether efficiency series move together in the long run (cointegrate) and/or move closer together over time (converge).

We use a panel of 21 manufacturing industries in four technology regimes and six EU countries over the period 1980-1997, and - after taking country- and regime-specific annual averages - study the properties of the resulting 24 technical efficiency series. We, first, ask whether technology spills over across borders, and find that technical efficiency series are cointegrated with each other across all countries. A further analysis of the long-run linkages reveals the importance of geographical proximity for cross-country technology spillovers. Next, we ask whether technology spills over across regimes, and find that technical efficiency series are cointegrated with each other across all technology regimes. Here, technological proximity appears to be very important, as positive long-run linkages exclusive exist between closer technology regimes.

We also find fairly strong evidence of convergence, both across countries and technology regimes. Over time, the technical efficiency of industries in the manufacturing sector have moved closer together. However, the extent to which this has happened differs. In the northern countries (Finland, Germany), convergence is the strongest. In particular, industries in the high technology regime emerge as the drivers behind the convergence of efficiency.

Future research should explain the mechanisms behind the positive and negative long-run linkages as no formal efforts have been made to explain these mechanisms in the present study. Also, being able to control for cross-sectional dependence when investigating the long-run cointegrating relationships would greatly enhance the understanding of technology spillovers.

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Appendix A. Variables 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) *STAN Structural Analysis Database*.

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 $K_1 980 = GFCF_1 980/(g + \delta)$, 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 (OECD, 1993). Each industry's capital stock is constructed as capital stock minus depreciated capital stock plus gross fixed capital formation ($K_t = (1 - \delta) * K_{t-1} + GFCF_t$). Data on gross fixed capital formation are retrieved from the OECD (2002) *STAN Structural Analysis Database*.

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*.

Table A.1
Manufacturing Industries

Industry	Abbreviation	ISIC code (Rev. 3)
Coke, refined petroleum products and nuclear fuel	COK	23
Textiles, textiles products, leather and footwear	TEX	17-19
Building and repairing ships and boats	SHI	351
Food products, beverages and tobacco	FOD	15-16
Non-ferrous Metals	NFM	272+2732
Other non-metallic mineral products	ONM	26
Wood, and products of wood and cork	WOD	20
Iron and steel	IAS	27+2731
Machinery and equipment, n.e.c.	MAC	36+37
Chemicals (excl. pharmaceuticals)	CHE	24 less 2423
Pulp, paper, paper products, printing and publishing	PAP	21-22
Manufacturing n.e.c.; recycling	MAN	29
Motor vehicles, trailers and semi-trailers	MOT	34
Fabricated Metal products (excl. mach. and equip.)	FAB	28
Aircraft + spacecraft	AIR	353
Rubber and plastics products	RUB	25
Pharmaceuticals	PHA	2423
Electrical machinery and apparatus	ELE	31
Medical, precision and optical instruments	MED	33
Radio, television and communication equipment	RAD	32
Office, accounting and computing machinery	OFF	30

Appendix B. Panel unit root tests

Table B.1
Panel Unit Root Tests across Countries

Finland	test	p-val	root
Levin-Lin-Chu (LLC)	8.262	1.000	I(1)
Im-Pesaran-Shin (IPS)	-0.474	0.318	I(1)
Im-Pesaran-Shin, LM (IPSLM)	-0.090	0.536	I(1)
Maddala-Wu (MW)	8.078	0.426	I(1)
Unbiased LL (ULL)	0.115	0.546	I(1)
Hadri-Larsson (HL)	2.444	0.007	I(1)
France	test	p-val	root
Levin-Lin-Chu (LLC)	1.369	0.915	I(1)
Im-Pesaran-Shin (IPS)	0.435	0.668	I(1)
Im-Pesaran-Shin, LM (IPSLM)	0.734	0.232	I(1)
Maddala-Wu (MW)	5.419	0.712	I(1)
Unbiased LL (ULL)	0.217	0.586	I(1)
Hadri-Larsson (HL)	2.878	0.002	I(1)
Germany	test	p-val	root
Levin-Lin-Chu (LLC)	-0.257	0.399	I(1)
Im-Pesaran-Shin (IPS)	-0.405	0.343	I(1)
Im-Pesaran-Shin, LM (IPSLM)	-0.874	0.809	I(1)
Maddala-Wu (MW)	7.365	0.498	I(1)
Unbiased LL (ULL)	-0.950	0.170	I(1)
Hadri-Larsson (HL)	1.626	0.052	I(0)
Italy	test	p-val	root
Levin-Lin-Chu (LLC)	0.283	0.611	I(1)
Im-Pesaran-Shin (IPS)	0.917	0.821	I(1)
Im-Pesaran-Shin, LM (IPSLM)	2.084	0.019	I(0)
Maddala-Wu (MW)	2.952	0.937	I(1)
Unbiased LL (ULL)	0.596	0.724	I(1)
Hadri-Larsson (HL)	3.210	0.001	I(1)
Netherlands	test	p-val	root
Levin-Lin-Chu (LLC)	3.597	1.000	I(1)
Im-Pesaran-Shin (IPS)	-0.734	0.231	I(1)
Im-Pesaran-Shin, LM (IPSLM)	1.146	0.126	I(1)
Maddala-Wu (MW)	13.830	0.086	I(1)
Unbiased LL (ULL)	-0.697	0.243	I(1)
Hadri-Larsson (HL)	3.087	0.001	I(1)
Spain	test	p-val	root
Levin-Lin-Chu (LLC)	5.284	1.000	I(1)
Im-Pesaran-Shin (IPS)	0.692	0.756	I(1)
Im-Pesaran-Shin, LM (IPSLM)	0.841	0.200	I(1)
Maddala-Wu (MW)	2.748	0.949	I(1)
Unbiased LL (ULL)	-0.277	0.390	I(1)
Hadri-Larsson (HL)	2.816	0.002	I(1)

All panel unit root tests include an intercept and a trend. The number of lags is two. For LLC, IPS, IPSLM, MW and ULL the null hypothesis is that all time series are I(1), while for HL the null is that all time series are stationary and the length of the kernel window is 3.000. Tests for LLC, IPS and ULL are left-sided and tests for IPSLM, MW and HL are right-sided. We reject the null hypothesis of no unit root if p-value < 0.05.

Table B.2
Panel Unit Root Tests across Regimes

High	test	p-val	root
Levin-Lin-Chu (LLC)	2.341	0.990	I(1)
Im-Pesaran-Shin (IPS)	0.489	0.687	I(1)
Im-Pesaran-Shin, LM (IPSLM)	0.985	0.162	I(1)
Maddala-Wu (MW)	6.071	0.913	I(1)
Unbiased LL (ULL)	-0.503	0.308	I(1)
Hadri-Larsson (HL)	3.384	0.000	I(1)
Medium-high	test	p-val	root
Levin-Lin-Chu (LLC)	-1.219	0.111	I(1)
Im-Pesaran-Shin (IPS)	-0.257	0.399	I(1)
Im-Pesaran-Shin, LM (IPSLM)	0.819	0.206	I(1)
Maddala-Wu (MW)	9.536	0.657	I(1)
Unbiased LL (ULL)	-0.439	0.330	I(1)
Hadri-Larsson (HL)	1.928	0.027	I(1)
Medium-low	test	p-val	root
Levin-Lin-Chu (LLC)	0.946	0.828	I(1)
Im-Pesaran-Shin (IPS)	0.039	0.516	I(1)
Im-Pesaran-Shin, LM (IPSLM)	0.145	0.442	I(1)
Maddala-Wu (MW)	14.127	0.293	I(1)
Unbiased LL (ULL)	0.069	0.527	I(1)
Hadri-Larsson (HL)	3.246	0.001	I(1)
Low	test	p-val	root
Levin-Lin-Chu (LLC)	6.789	1.000	I(1)
Im-Pesaran-Shin (IPS)	0.081	0.532	I(1)
Im-Pesaran-Shin, LM (IPSLM)	1.186	0.118	I(1)
Maddala-Wu (MW)	10.657	0.559	I(1)
Unbiased LL (ULL)	0.328	0.628	I(1)
Hadri-Larsson (HL)	4.555	0.000	I(1)

All panel unit root tests include an intercept and a trend. The number of lags is two. For LLC, IPS, IPSLM, MW and ULL the null hypothesis is that all time series are I(1), while for HL the null is that all time series are stationary and the length of the kernel window is 3.000. Tests for LLC, IPS and ULL are left-sided and tests for IPSLM, MW and HL are right-sided. We reject the null hypothesis of no unit root if the p-value < 0.05.