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Innovation, Technology Transfer and Labor Productivity Linkages: Evidence from a Panel of Manufacturing Industries

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Abstract

The paper explores the linkages between labor productivity, innovation and technology spillovers in a panel of manufacturing industries. The roles of R&D, human capital and international trade are considered in stimulating innovation and/or facilitating technology transfer. Using panel-based unit root tests and cointegration analysis, the results indicate the existence of a single long-run equilibrium relation between labor productivity, innovation and technology transfer. Further, R&D, trade and human capital have statistically and, especially the latter, quantitatively important effects on labor productivity both directly via innovation and indirectly as they enhance technology diffusion.

Keywords: productivity, innovation, technology transfer, manufacturing industries, panel cointegration.

JEL classification: C23, L60, O30

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1. Introduction

One of the main challenges in policy agendas and in particular in Lisbon's agenda for the European Union is to raise labor productivity. That means better exploitation of new technologies that already exist, but also increasing the rate of technological innovation. A question of interest in this respect is to what extent labor productivity could benefit from these two sources of growth namely, technological innovation and technology spillovers across national borders.

The pivotal role of innovation and international transmission of technology in the process of economic growth has been emphasized in the context of open economy endogenous growth models (Grossman and Helpman, 1991; Rivera-Batiz and Romer, 1991) while a large strand in the empirical literature provides evidence that technology originating in a particular country transcends its national borders and contributes also to the productivity growth of other countries (Coe and Helpman, 1995; Bloom *et al*., 2002).

Recently, a growing body of literature assesses the manner in which technology is adopted and its impact on industry's productivity (Scarpetta and Tressel, 2002; Griffith *et al*., 2004; Cameron *et al*., 2005; Cameron, 2005). In these contexts, the ability of an industry to innovate and take advantage of technology spillovers depends on the level of R&D stock, human capital, involvement in international trade and (product and labor) market regulations among other factors. Overall, the empirical evidence suggests that innovation and technology transfer are important sources of productivity, but as to the mechanism at work - whether it is R&D, human capital, international trade or any other factor in stimulating innovation and/or facilitating technology transfer - existing studies offer mixed evidence.

Although some studies in this strand of literature account for potential biases induced by simultaneity, omitted variables and unobserved country-industry specific effect, they do not explicitly test for the integrating and cointegrating properties of the data. In their modeling approach, these papers do stress that there is a long-run cointegrating relationship among the variables (Cameron *et al*., 2005: 778-779) without, however, elaborating further[1].

The purpose of this paper is to assess empirically the long-run linkages between labor productivity and the two aforementioned channels of technology adoption in a panel of manufacturing industries. To explore these linkages, we exploit our data in an efficient manner by considering the application of panel-based unit root tests and cointegration analysis.

On the modeling front, the econometric specification we estimate is based on a production function framework that allows for innovation and

[1] An exception is the study of Cameron (2005), which investigates productivity convergence between Japan and the USA employing dynamic panel-based techniques (panel-based unit root results are reported in the Appendix A2.2).

technology diffusion. The approach we consider resembles that of Cameron *et al*. (2005) in that it allows for technology diffusion across national borders and has the advantage that one can test explicitly whether a number of factors have an impact on labor productivity, and if so, via which channel, innovation and/or technology transfer.

On the econometric front, to avoid spurious regression problems due to I(1) nature of the variables and to exploit the long-run information of the data, we consider the application of panel-based unit root tests and cointegration analysis. By allowing data to be pooled in the cross-sectional dimension, panel methods can improve upon small sample limitations. The use of time-series dimension allows deriving also the long-run information contained in the data while considering the heterogeneity in the short-run dynamics among different units. It enables, therefore, one 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). The cointegrating vectors are estimated using fully modified OLS (FMOLS) procedure, which accounts for the integration and cointegration properties of the data and allows for consistent and efficient estimators of the long-run relationship.

Our evidence is based on 21 manufacturing industries in six European countries and the US over the period 1980-1997. The industry-level data enable us to assess forces underlying aggregate productivity performance while accounting for unobserved heterogeneity. We focus on the manufacturing sector since it is the sector where international technology spillovers are most likely to materialize. Manufacturing data also permit exploration of possible influences of different technology regimes and market structures on productivity. We consider certain market-structure prototypes and examine their influences on innovation and technology transfer, and in turn, on labor productivity.

Overall, our empirical results indicate that there is a single equilibrium relation between labor productivity, innovation and technology diffusion. Innovation and technology transfer are found to be statistical significant and, especially the former, quantitatively important for productivity gains. The dual role of R&D, international trade and human capital in stimulating innovation as well as facilitating technology transfer also finds strong support. Finally, the results provide evidence of productivity convergence across industries, and the convergence is stronger for the high-technology industries.

The remainder of the paper proceeds as follows. Section 2 presents the theoretical framework and the econometric specification for estimation. Section 3 introduces the data. Section 4 contains the results of the econometric estimations. Section 5 summarizes the findings and concludes.

2. Theoretical Framework

Our modeling strategy begins by investigating the factors influencing the level of labor productivity in a group of *N* countries (*i* = 1,…, *N*) and *J* manufacturing industries (*j* = 1,…, *J*) in each country. We assume the production that takes place in each industry *j* of country *i* at time *t* can be described as:

$$Y_{ijt} = A_{ijt} F_j (K_{ijt}, L_{ijt})$$

(1)

where K_{ijt} and L_{ijt} denote physical capital and labor, respectively; A_{ijt} is technical efficiency or total factor productivity (TFP) that varies across countries, industries and time.

We assume the production function for the manufacturing industries can be described by a Cobb-Douglas function of the form:

$$Y_{ijt} = A_{ijt} K_{ijt}^{\alpha} L_{ijt}^{1-\alpha}$$

(2)

We rewrite the production function in terms of output per unit of labor:

$$\frac{Y_{ijt}}{L_{ijt}} = (\frac{K_{ijt}}{L_{ijt}})^{\alpha} A_{ijt}$$

(3)

To implement the estimation of the production function, we take logarithms and obtain the following log-linear regression equation (where lower-case letters denote the logarithms of variables):

$$y_{ijt} = \alpha k_{ijt} + a_{ijt}$$

(4)

Equation (4) is an identity, but in practice a_{ijt} is the TFP in country *i*, industry *j*, at time *t*, which is not observed and appears, when it comes to estimation, as an error term in the equation.

The growth of TFP in industry *j* in country *i* is influenced from domestic innovation and/or international technology transfer. Following the related literature (Griffith *et al*., 2002; Cameron *et al*., 2005) it can be modeled as:

$$\Delta a_{ijt} = a_{ij}^{*} + \lambda_{ij} GAP_{ijt-1} + u_{ijt}$$

(5) where a_{ij}^{*} is the long run (sector-specific) innovation; GAP_{ijt} is the technology gap between country *i* and the frontier country *F*, i.e. the country with the highest technological level in each industry at any point in time, measured as: $GAP_{ijt-1} = TFP_{ijt-1} - TFP_{Fjt-1}$; λ_{ij} parameterizes the rate of technology transfer; and u_{ijt} is a country-industry specific technology shock.

Equation (5) in levels yields,

$$a_{ijt} = a_{ij}^{*} + \lambda_{ij} GAP_{ijt-1} + \gamma a_{ijt-1} + u_{ijt}$$

(6)

There is an extensive theoretical and empirical literature that argues factors such as R&D, human capital and international trade could have a dual effect on productivity via stimulating innovation (a_{ij}^{*}) and facilitating technology transfer (λ_{ij}).

Endogenous growth theory models emphasize the role of R&D in stimulating innovation as well as facilitating the transfer of new technologies by raising the ability of a country to absorb new technologies[2]. Likewise, human capital contributes to the absorptive capacity of a country by enabling the imitation of advanced foreign technologies and to creation of new ones[3]. Another important conduit of knowledge adoption is international trade[4]. In particular imports can affect both technology transfer and innovation. Quality imported goods embody foreign technology. As industries successfully imitate the production of these goods, they gain more insight as to how these goods are engineered. Imitation of foreign technology, in turn, improves the chances of invention[5].

Therefore, we model the parameters of innovation, a_{ij}^{*}, and technology transfer, λ_{ij}, to be functions of R&D, human capital and imports share, as:

[2]See Aghion and Howitt (1998), Griliches and Lichtenberg (1984), Cohen and Levinthal (1989), Griffith *et al.* (2004) and Cameron *et al.* (2005).
[3] Classical references include Abramovitz (1986), Mankiw *et al*. (1992), Barro and Sala-i-Martin (1995) and Krueger and Lindahl (2001).
[4] See Ben-David and Loewy (1998), Edwards (1998), Frankel and Romer (1999), Griffith *et al*. (2004) and Cameron *et al.* (2005).
[5] See Connolly (1998) for a discussion of the 'learning-to-learn' effect.

$$a^*_{ij} = \varphi_{ij} + \delta X_{ijt-1} \quad \text{and} \quad \lambda_{ij} = \psi + \nu X_{ijt-1}$$

(7)

where φ_{ij} is the country-industry fixed effect controlling for unobserved heterogeneity, X_{ijt-1} is a vector of control variables that includes R&D, human capital and imports share and ψ a constant.

Combining equations (4), (6) and (7), the empirical specification under estimation is:

$$y_{ijt} = \varphi_{ij} + \alpha k_{ijt} + \gamma a_{ijt-1} + \psi GAP_{ijt-1} + \delta X_{ijt-1} + \nu X_{ijt-1} GAP_{ijt-1} + u_{ijt}$$

(8) where δX_{ijt-1} captures the effect of the innovation while the interaction term $\nu X_{ijt-1} GAP_{ijt-1}$ captures the effect of technology transfer on labor productivity.

For the non-frontier countries, the technology gap, *GAP*, is negative, and the larger it gets, the further the country lies behind the frontier. Therefore, for productivity gains, the estimated coefficient on *GAP* is expected to be negative. In presence of technology transfer, the estimated coefficients on $X_{ijt-1} GAP_{ijt-1}$ are also expected to be negative. The rest of the estimated coefficients are expected to be positive, according to the economic theory.

3. Data

Our sample consists of 21 manufacturing industries in six EU countries (Finland, France, Germany, Italy, Netherlands, Spain) and the

US over the period 1980-1997. The time span was mainly determined by the availability of R&D investment data. Annual raw data are extracted from various sources. To construct industry-specific TFP indices, we extract data on value-added and investment (to construct the capital stock) from the OECD (2002) *STAN* and labor from the Groningen Growth and Development Centre (2006) *60-Industry Database*. Data on R&D and import flows are obtained from the OECD (2002) *BERD* and OECD (2002) *Bilateral Trade Database*, respectively. The same International System of Industries Classification (ISIC) code was used for all industry-level data. Finally, country-level data on human capital are retrieved from the de la Fuente and Domènech (2000) database[6]. A detailed description of the variables and data sources is presented in the appendix.

Manufacturing data allow the exploration of possible influences of different technology regimes and market structures on productivity performance. Following Scarpetta and Tressel (2002), we consider three market-structure prototypes[7] (low-technology, 'LT', high-technology-low-concentration, 'HTLC', and high-technology-high-concentration, 'HTHC')

[6] To avoid contradictionary findings reported in the literature on the relationship between human capital and productivity/growth (Engelbrecht, 1997; Griffith *et al*., 2004), we use human capital estimates from the de la Fuente and Domènech (2000) database, which contains more reliable data from all existing human capital databases. De la Fuente and Domènech (2000) construct a revised version of the Barro and Lee (1996) data set for a sample of OECD countries using previously unexploited sources, correcting for measurement errors and removing sharp breaks in the data that reflect changes in classification criteria. It is then shown that these revised data perform much better than past human capital databases in a number of growth specifications. For further discussion, see de la Fuente and Domènech (2000).

[7] The division of the manufacturing industries into certain market-structure prototypes was based on the returns to innovation (proxied by the R&D intensity) and the degree of market concentration (proxied by the Herfindal index). For a discussion on the methodology, see Scarpetta and Tressel (2002).

and examine their effects on productivity[8]. The manufacturing industries considered in our analysis, their ISIC code and market-structure typologies are provided in Table A.1 in the appendix.

As an illustration, Table A.2 in the appendix shows the three countries with the highest level of TFP in each industry during the period 1980-97. The comparison of TFP levels suggests that USA is the technological frontier in more than half of the industries, while for the rest is either Germany or France. What matters, however, in our modeling approach is not the identity of the frontier *per se*, but rather the distance from the frontier, which captures potential technology spillovers.

4. Econometric Methodology and Results

Our purpose is to estimate equation (8) on a panel of pooled annual time series. Before embarking at panel unit root tests and cointegration analysis, we first test for heterogeneity in the sample, which could be present due to different technology trajectories and market structures. The results of standard Chow-type *F*- and White's tests are reported in Table 1. The findings indicate that the relationship under investigation is

[8] LT industries: low returns to innovation (e.g. R&D) and large number of firms competing on price. Production processes and products are similar. HTLC industries: high returns to innovation and relatively large number of firms each of which has some market power. HTHC industries: high returns on innovation and small number of firms dominate the market. In HT industries, firms invest heavily in technology to improve production processes and specialize in specific products designs.

characterized by heterogeneity of dynamics and error variance across groups, supporting thus the application of panel data techniques.

(Table 1 goes about here)

4.1. Panel Unit Roots

The implementation of the cointegration procedure entails first confirmation that the data are indeed non-stationary. This can be done by applying a suitable unit root test for panel data. The null hypothesis of non-stationary is tested using the panel unit root test of Im, Pesaran and Shin (2003), which allows each member of the cross-section to have a different autoregressive root and autocorrelation structures under the alternative hypothesis and has been shown to be highly powerful in accepting the null when it is true. All variables in our model are tested in both levels and first differences. Results are reported in Table 2. Panel unit root tests support the hypothesis of a unit root in all variables, as well as the hypothesis of zero integration in first differences. These findings allow testing for cointegration.

(Table 2 goes about here)

4.2. Panel Cointegration

We use the Pedroni (1999) framework, which is designed for heterogeneous dynamic panels, to test for cointegration among the variables in our model. Based on cointegration residuals, Pedroni develops seven different panel cointegration statistics for the null hypothesis of no cointegration allowing for heterogeneous fixed effects, determinist trends and heterogeneous short-run dynamics. Pedroni cointegration results are reported in Table 3. The calculated test statistics reject the null hypothesis of no cointegration at 1% and the hypothesis of one cointegrating vector is accepted.

(Table 3 goes about here)

4.3. Panel Estimation

Having established that the variables are structurally related, the long-run equation is estimated using the between-group panel FMOLS estimator, which is appropriate for heterogeneous cointegrated panels (Pedroni, 2000)[9]. The FMOLS methodology takes explicitly into account the integration and cointegration properties of the data, and corrects for serial correlation in the errors as well as the simultaneity bias of the regressors since the latter are endogenously determined in non-stationary processes. FMOLS estimates of the cointegrating relationship for the panel as a whole are reported in Table 4[10].

(Table 4 goes about here)

[9] Unlike the within-group estimators that impose common slope coefficients, the between-group estimators allow for heterogeneous coefficients for individual members of the cross-section and exhibit relatively minor size distortions in small samples.

[10] An alternative estimation approach is the dynamic ordinary least squares (DOLS) methodology, developed by Kao and Chiang (2001). It is virtually equivalent and, in our case, provides similar results, which are available upon request.

The estimated coefficients of capital intensity (k), innovation (X) and technology transfer ($X \times GAP$) are found to be quantitatively and statistically significant. The dual role of research and development (*RD*), imports share (*IMP*) and human capital (*HC*) is confirmed as they do impact on labor productivity via two channels: directly through innovation and indirectly through technology transfer. In addition, the role of autonomous technology transfer is also robust since the estimated coefficient on the technological gap (*GAP*) is negative and statistically significant, suggesting convergence within each industry across countries. Further, the lagged value of productivity (*a*) has a positive and statistically significant impact on labor productivity.

Next, we divide our industries into different market-structure prototypes and technology regimes, and explore their impact on productivity performance. Capital intensity and past productivity consistently enter as significant factors of labor productivity. The findings also support evidence of productivity convergence in an industry, with stronger effects for the high-technology industries (denoted by HT in the table). Productivity catch-up is also the case in low-technology industries (denoted by LT in the table); however, the effect is quantitatively smaller. A possible explanation is that high-tech industries have higher capacity to absorb and assimilate best practice technologies due to heavy investment in R&D and human capital and, further, are more involved in trade. The latter, places greater pressure on industries to adopt best-practice technology and consequently, industries move closer to the technological frontier[11].

Further, R&D, international trade and human capital are found to be statistically significant for both HT and LT industries; however their effects appear to be quantitatively larger for the case of HT and, in particular, for the HTHC. However, in all technology regimes and market-structure prototypes, it is the human capital, which mainly boosts innovation and enchases the adoption of new technology.

Overall, our findings corroborate the role of innovation and technology diffusion as major channels of productivity gains. They are also in line with findings of previous studies that provide evidence of a robust role of capital intensity (Spiegel, 1994), autonomous technology transfer across industries, and R&D-based innovation as well as technology transfer (Cameron *et al*., 2005). Additionally, our findings provide evidence of strong and statistically significant effects of trade and human capital both in promoting innovation and technology transfer[12].

Concerning the role of trade, our preferred measure is import flows from the frontier country scaled by the value-added of the recipient industry. We also employed a number of alternative measures such as

[11] See Connolly (1998), Keller (2002) and Hallward-Driemeier *et al*. (2002).

[12] We checked the sensitivity of our results by altering the identity of the frontier. For instance, the US was dropped out from the sample and the frontier was defined to be the European country with the highest TFP for each industry. An alternative frontier was defined as the average of the three leading countries for each industry. The results do not alter significantly.

imports of machinery and equipment from the frontier (Keller, 2000), imports from the whole world (Cameron *et al*., 2005), imports from other OECD countries excluding the frontier, and imports from non-OECD (Griffith *et al*., 2004) to avoid potential biases. The results, robust to almost all specifications, underline the dual role of imports as an important conduit of knowledge transmission as well as a means of improving the chances of invention.

Lastly, with regard to the role of human capital, our findings are in line with past studies (Griffith *et al*., 2004) and give support to the literature that argues that omission of human capital leads to biased (overestimated) R&D coefficients (Engelbrecht, 1997). According to this literature, human capital not only enhances the ability of the workforce to work with new technologies created by innovation efforts, and therefore, facilitates the realization of R&D spillovers (e.g., Redding, 1996), but it also accounts for other aspects of innovation not captured by the R&D sector. Therefore, not adequately accounting for the role of human capital could lead to serious bias. Our estimated long-run elasticity of productivity to human capital, however, is much larger compared to some of the previous studies (Engelbrecht, 1997) and closer to the microeconomic literature on private returns from schooling (Ashenfelter *et al*., 1999) and to the literature that uses the de la Fuente and

Domènech (2000) human capital database (Bassanini and Scarpetta, 2001).

5. Conclusion

The present study considers the application of recent developments in panel-based unit root tests and cointegration analysis to evaluate the linkages between labor productivity, innovation and technology spillovers for 21 European and US manufacturing industries over the period 1980-1997.

The existence of a single long-run equilibrium relation between labor productivity, innovation and technology diffusion is empirically established. The effect of innovation and technology transfer on productivity levels is found to be statistically significant and quantitatively important.

Our results further corroborate the dual role of R&D, international trade and human capital as important mechanisms in stimulating innovation and facilitating technology transfer. Their effects are quantitatively larger for the technologically advanced industries and, in particular, for the high-concentrated ones. Among the proposed mechanisms, human capital has the largest impact on labor productivity, both via innovation and technology transfer, especially for the technologically advanced industries of the manufacturing sector.

Finally, there is also some evidence of productivity catch-up across industries and this finding comes across particularly strong in technologically advanced industries. Productivity catch-up is also the case in the less technology-advanced industries; however, the effect is quantitative smaller.

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Appendix

A. Tables

Table A.1: *Manufacturing Industries.*

MANUFACTURING INDUSTRIES	**Abbreviation**	**ISIC code (Rev. 3)**	**Market Structure(*)**
Food products, beverages and tobacco	FOD	15-16	LT
Textiles, textiles products, leather and footwear	TEX	17-19	LT
Wood, and products of wood	WOD	20	LT

and cork			
Pulp, paper, paper products, printing and publishing	PAP	21-22	LT
Coke, refined petroleum products and nuclear fuel	COK	23	LT
Chemicals excluding pharmaceuticals	CHE	24 less 2423	HTHC
Pharmaceuticals	PHA	2423	HTHC
Rubber and plastics products	RUB	25	LT
Other non-metallic mineral products	ONM	26	LT
Iron and Steel	IAS	271+2731	LT
Non-ferrous Metals	NFM	272+2732	LT
Fabricated Metal products (excluding machinery and equipment)	FAB	28	LT
Machinery and equipment, n.e.c.	MAC	29	HTLC
Office, accounting and computing machinery	OFF	30	HTHC
Electrical machinery and apparatus, n.e.c.	ELE	31	HTHC
Radio, television and communication equipment	RAD	32	HTHC
Medical, precision and optical instruments	MED	33	HTLC
Motor vehicles, trailers and semi-trailers	MOT	34	HTHC
Building and repairing ships and boats	SHI	351	LT
Aircraft and spacecraft	AIR	353	HTHC
Other Manufacturing (Furniture; Manufacturing n.e.c.; Recycling)	OMA	36+37	HTLC

(*) *HT*, *LT*, *HTHC*, *HTLC* stand for High-Technology, Low-Technology, High-Technology-High-Concentration, High-Technology-Low-Concentration, respectively. Source: Scarpetta and Tressel (2002).

Table A.2: *Technology Leaders (TFP), 1980-1997.*

Industries	**Countries**	**Industries**	**Countries**
FOD	1. US 2. Spain	*FAB*	1. US 2. Germany

	3. Finland		3. France
TEX	1. France 2. US 3. Germany	*MAC*	1. Germany 2. Netherlands 3. France
WOD	1. Netherlands 2. Germany 3. US	*OFF*	1. Netherlands 2. Spain 3. France
PAP	1. US 2. France 3. Spain	*ELE*	1. US 2. Netherlands 3. Germany
COK	1. Germany 2. Spain 3. France	*RAD*	1. Germany 2. France 3. Netherlands
CHE	1. Germany 2. Spain 3. France	*MED*	1. US 2. Spain 3. France
PHA	1. US 2. France 3. Italy	*MOT*	1. US 2. Netherlands 3. Spain
RUB	1. France 2. US 3. Spain	*SHI*	1. France 2. US 3. Germany
ONM	1. France 2. US 3. Netherlands	*AIR*	1. France 2. US 3. Netherlands
IAS	1. US 2. France 3. Germany	*OMA*	1. Netherlands 2. Spain 3. US
NFM	1. Finland 2. Netherlands 3. Germany		

B. Data

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 were retrieved from the OECD (2002) *Structural Analysis Database* (STAN).

Physical capital (*K*): gross capital stock expressed in 1995 constant prices (euros). Following common practice in the literature (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). Initial value for the 1980 capital stock is specified as $K_{1980}=GFCF_{1980}/(g+\delta)$, 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 calculated 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 were obtained from the OECD (2002) *Structural Analysis Database* (STAN).

Labor input (*L*): total annual hours worked (employment*average hours worked) in an industry. Data on labor were retrieved from the Groningen Growth and Development Centre (GGDC) *60-Industry Database*, 2006.

R&D (*RD*): ratio of Business Enterprise Research and Development (BERD) expenditure to value-added. Following common practice in the literature (Cameron *et al.*, 2005), flows of constant price R&D were converted into R&D capital stock. The initial value is computed as: $R\&D_{STOCK} = R\&D_{FLOWS} / (g + \delta)$, where g is the proportional rate of growth of $R\&D_{FLOWS}$ (BERD) at constant prices and δ the rate of depreciation (10% per annum). By applying the perpetual inventory method, the R&D stock for each industry is calculated. R&D capital stock is expressed in 1995 constant prices (euros).

Imports share (*IMP*): import flows from the frontier country scaled by value-added of the recipient industry. The OECD (2002) *Bilateral Trade Database* provides information per industry on the source of imports from trading partners.

Human capital (*HC*): average years of schooling. Country-level data retrieved from the de la Fuente and Domènech (2000) database. The data are provided quinquennially. Following Harrigan (1997), we interpolate between five-yearly observations and extrapolate till we cover our time span using STATA's linear interpolation and extrapolation function.

Technology gap (*GAP*): the difference between total factor productivity levels of country *i* and the frontier country for a given industry *j*, $GAP_{ijt-1} = TFP_{ijt-1} - TFP_{Fjt-1}$. In calculating TFP, we follow the methodology described in Park (2004).

Table 1: *Tests for Dynamic Heterogeneity across Groups.*

	ADF(3)	AR(3)	WHITE'S TEST
Labor productivity (*y*), capital intensity (*k*), technology gap (*GAP*), total factor productivity (*a*), R&D (*RD*), imports share (*IMP*), human capital (*HC*), R&D-based technology diffusion (*GAP**RD*), imports-based technology diffusion (*GAP**IMP*), human capital-based technology diffusion (*GAP**HC*)	17.44*	27.28*	52.95*

The ADF(3) column reports the parameter equality (the null hypothesis) across the relationship in the panel. The AR(3) column reports tests of parameter equality (the null hypothesis) conducted in a fourth-order autoregressive model of the relationship under study. White's test displays the equality of variances (the null hypothesis) across the investigated relationship in the panel.

(*) Significant at 1%.

Table 2: *Panel Unit Root Tests.*

Variables		Without trend	With trend
Labor Productivity (*y*)	*Levels*	-1.27(2)	-1.51(2)
	Differences	-4.59(1)*	-4.29(1)*
Capital intensity (*k*)	*Levels*	-1.23(3)	-1.44(3)
	Differences	-4.47(2)*	-5.12(1)*
Total factor productivity (*a*)	*Levels*	-0.97(3)	-1.18(2)

	Differences	-4.35(1)*	-4.71(1)*
Technology Gap (*GAP*)	*Levels*	-1.26(2)	-1.38(3)
	Differences	-5.77(1)*	-5.98(2)*
Research and Development (*RD*)	*Levels*	-1.45(3)	-1.51(3)
	Differences	-4.36(2)*	-4.54(2)*
Imports Share (*IMP*)	*Levels*	-1.31(3)	-1.83(3)
	Differences	-4.84(2)*	-4.90(2)*
Human Capital (*HC*)	*Levels*	-1.20(2)	-1.49(2)
	Differences	-4.64(1)*	-4.72(2)*
R&D-based technology diffusion (*GAP*RD*)	*Levels*	-1.44(3)	-1.56(3)
	Differences	-4.61(2)*	-4.94(2)*
Imports-based technology diffusion (*GAP*IMP*)	*Levels*	-1.47(3)	-1.83(3)
	Differences	-4.81(2)*	-5.22(2)*
Human Capital-based technology diffusion (*GAP*HC*)	*Levels*	-1.52(3)	-1.69(2)
	Differences	-4.75(1)*	-4.92(1)*

Figures in brackets denote the number of lags in the augmented term that ensures white-noise residuals. The optimal lag length was determined by the Akaike Information criterion as well as by the Schwarz-Bayes Information criterion.
(*) Significant at 1%.

Table 3: *Panel Cointegration Tests.*

Industries	**Panel v-stat**	**Panel ρ-stat**	**Panel pp-stat**	**Panel adf-stat**	**Group ρ-stat**	**Group pp-stat**	**Group adf-stat**
All industries	-8.876*	-8.326*	-7.731*	-7.512*	-8.254*	-8.290*	-7.806*
LT	-7.559*	-7.275*	-7.111*	-7.007*	-7.206*	-7.250*	-7.178*
HT	-9.587*	-9.130*	-7.098*	-7.009*	-9.056*	-9.098*	-7.244*
HTLC	-6.988*	-6.555*	-6.130*	-6.028*	-6.361*	-6.398*	-6.229*
HTHC	-8.225*	-8.072*	-7.555*	-7.219*	-8.008*	-8.055*	-7.733*

(*) Rejection of the null hypothesis of no cointegration at 1%.

Table 4: *Fully-Modified OLS Estimates (dependent variable is labor productivity, y).*

	k/l	**$a_{(-1)}$**	**$GAP_{(-1)}$**	**$RD_{(-1)}$**	**$IMP_{(-1)}$**	**$HC_{(-1)}$**	**$GAP_{(-1)}$ ***	**$GAP_{(-1)}$ ***	**$GAP_{(-1)}$ ***
All industries	0.061	0.357	-0.252	0.198	0.325	0.316	-0.048	-0.111	-0.214
LT	0.036	0.244	-0.197	0.209	0.267	0.287	-0.038	-0.099	-0.147
HT	0.077	0.413	-0.310	0.234	0.376	0.408	-0.065	-0.134	-0.276
HTLC	0.041	0.278	-0.210	0.213	0.265	0.286	-0.041	-0.114	-0.188
HTHC	0.062	0.444	-0.214	0.238	0.313	0.314	-0.049	-0.117	-0.239

*k/*l: capital intensity; *a*: total factor productivity level; *GAP*: technology gap; *RD*: ratio of Business Enterprise R&D expenditure to value-added; *IMP*: import share from the frontier; and *HC*: human capital.