International Patent Pattern and Technology Diffusion*

Kurt A. Hafner**

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Department of Economics; University of Bamberg, Germany

Abstract

The paper focuses on the impact of R&D expenditure on factor productivity using international patent applications as a technology diffusion channel. Considering the relationship between research and productivity, the pattern of international patenting reflects the link between the source and the destination of transferred technology. To deal with nonstationarity and cointegration, I use estimation techniques proposed by Kao and Chiang (1998). I find that patent related foreign R&D spillover effects are present. Moreover, Non-G7 countries benefit more from foreign rather than domestic R&D activities. Estimates also show that there are no significant spillover effects from bilateral trade but confirm the impact of technology diffusion through FDI inflows.

JEL-Classifaction: C12; C23; O30; O40

Keywords: Productivity, R&D, Technology Diffusion, Nonstationary Panels

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**Graduate School: “Markets and Social Systems in Europe”, Lichtenhaidestrasse 11, 96052 Bamberg, Germany. Email: kurt.hafner@sowi.uni-bamberg.de

1. Introduction

Are international R&D spillovers trade related and technology mainly embodied in intermediate goods? Eaton and Kortum (2002, 2001), for example, use a Ricardian model of trade and show that given a country's resources the efficient level of output with trade is higher than without trade. Hence, trade provides countries with foreign goods and technology. Coe and Helpman (1995) among others confront the question empirically by relating the direction of technology diffusion to bilateral trade shares. They find that trade related spillover effects are present and are stronger the more open an economy on international trade is. Keller (1998), however, shows by Monte Carlo Simulations, that randomly created bilateral trade patterns explain more of the variation in total factor productivity (TFP) than those empirically observed. Additionally, long-run trended data such as productivity and R&D expenditure require appropriate estimation techniques to avoid spurious results. In applying a more sophisticated estimation technique on the data set of Coe and Helpman (1995) and trough re-examining their econometric findings, Kao, Chiang and Chen (1999) confirm the impact of domestic R&D on TFP but reject any diffusion of foreign R&D. Moreover, according to Keller (2004), there is no strong empirical evidence for learning-by-exporting spillovers beside case studies dealing with East Asia's export success in the 1960's. While there might be a theoretical consensus about trade related spillover effects and the importance of a country's openness to trade, empirically it seems to be difficult to quantify the extent and direction of technology diffusion from international trade.

The same criticism applies to the second strand of the literature that considers foreign direct investments (FDI) as a channel for technology diffusion. Following Keller (2004), such subsidiaries might pick up new technologies from their host countries (outward FDI technology sourcing) or provide technology to domestic firms (inward FDI technology transfer). Again, the macro evidence is not straightforward, as Xu and Wang (2000) mentioned, and the impact of technology transfer either from or to host countries still needs empirical validation. However, much of the literature on FDI spillovers uses micro (firm or plant level) data instead and account for heterogeneity across sectors and firms within a country. Recently, empirical micro evidence for economically important FDI spillover effects have been found by Haskel, Pereira, and Slaughter (2002) and Griffith, Redding and Simpson (2003) for the United Kingdom and by Keller and Yeaple (2005) for the United States. Branstetter (2004) finds evidence for FDI spillover both from and to investing Japanese firms in the United States. In spite of that, the implied economic magnitude still is unclear. Moreover, case studies, such as the paper by Larrain, Lopez-Calva and Rodriguez-Claré (2000) analyzing the impact of Intel's FDI into Costa Rica in the 1990s, may offer some fruitful insights on how to determine firm specific technology transfer. However, country specific analysis using micro data as well as particular case studies do not overcome the lack of general quantitative evidence and understanding.

I propose to use the pattern of international patenting to analyze technology diffusion and follow the argumentation of Eaton and Kortum (1999): *"we think that patenting abroad is a much more direct, albeit imperfect, indicator of where ideas are going"*. The idea is that patenting domestic research efforts abroad determines the transfer of technology. Local firms may take legal advantage of patented foreign know-how by paying royalties. Adding foreign knowledge to a country's own R&D stock–even in the case of limited domestic R&D spending–is likely to increase the efficiency of domestic input factors. Considering the relationship between research and productivity, the pattern of international patenting reflects the link between the source and the destination of transferred technology. In this context, international spillover effects are patent related.

A patent holder receives a temporary legal monopoly at the cost of public disclosure of the underlying technical information. To protect themselves from imitators, inventors have to patent their innovations at home and abroad. The inventor's choice is to relate the costs of filing a patent application and of technical disclosure to the likelihood of imitation and the monopoly rents in specific markets. Hence, strategic and/or market seeking decisions drives inventors to patent only the best and most valuable innovations. However, patent figures show that most of the patents are filed at home rather than abroad. This might be the result of either technological immobility or less foreign protection as mentioned by Eaton and Kortum (1999). Given the tight distribution of productivity levels across countries in relation to the skewness of domestic research activity, Eaton and Kortum (1999) reject technology immobility and point to a lesser protection provided by foreign patents. However, according to Branstetter and Sakakibara (2004), there is no empirical evidence for the case of Japan that stronger patents induce more innovation and therefore more patents applications. Moreover, the bulk of foreign patent applications are filed and received by the five leading research nations: United States, Japan, Germany, Great Britain and France. The United States is the dominating source of foreign patents followed by Germany and Japan. Concurrently, the same pattern holds regarding business related R&D (BERD) expenditure. Hence, in explaining the small variation in productivity levels, we might expect a higher impact due to foreign rather than domestic research activity for smaller and/or less advanced countries given the asymmetric R&D spending pattern across countries. International patent statistics by the World Intellectual Property Organization (WIPO) and OECD provide only count numbers. Specific information about the value of patents is not given. However, some patents are more valuable and their economic impact differs between countries. Hence, using patent count data serve mainly to determine the direction rather than the magnitude of international technology diffusion.[1]

To sum up, this paper examines the effects of domestic and foreign business related R&D expenditure on factor productivity (FP) and use the pattern of international patenting as the technology diffusion channel. Patent related spillover effects for G7 and Non-G7 OECD countries are the main interest. However, I incorporate trade and FDI spillover effects as a robustness test to the analysis and discuss the overall picture of foreign technology diffusion. The structure of the paper is described as follows. The next section reviews the underlying theoretical framework and introduces patent-, trade- and FDI related technology diffusion channels. In Section 3, there is a brief discussion of the pooled data and its use for technology diffusion. Section 4 analyzes nonstationary issues and estimation techniques. The results of the testing procedures and empirical estimations are in section 5. Section 6 concludes.

2. Framework

This section discusses the theoretical framework and the regression specification used to quantify foreign technology diffusion (patent (P)-, trade (M)- and FDI (F) related spillover effects). To start with, let us consider the following aggregated production function:

$$Y = A * F(K, L), \tag{1}$$

where Y is aggregate output, K as capital and L as workforce are input factors respectively and A represents technical change. There are two ways to achieve output growth: either to augment the use of input factors by higher capital investment and labor effort or to increase the efficiency of input factors and therefore A.

Coe and Helpman (1995) regard output growth as driven by innovation in the production of intermediate goods based on the Grossman and Helpman (1991) model. In a simple form, final output Y is produced by an aggregate of intermediate inputs which itself is the result of the use of primary input factors and research activity. Intermediate inputs can be either horizontally differentiated which leads to output growth proportional to the measure of available

[1] Recently, there are studies using patent statistics as a proxy for technological progress as proposed by Grillich (1990). Chiang and Xu (2005), for example, use foreign patent applications as a technology stock from abroad to quantify patent related spillover effects. However, I belief that patents should be related to R&D expenditure and not be used as a technology proxy.

intermediate goods, or vertically differentiated which affects input productivity by their different qualities. In both cases, aggregate output increases with the usage of intermediate goods. Thus, the part of output growth, which is not attributable to the accumulation of primary inputs, is due to the R&D investments in the intermediate goods production. Hence, international trade with intermediate goods provides countries with technology embedded goods and creates access to foreign technology knowledge. As outlined, empirical results seeking spillover effects by embedded technology in input factors are mixed. Consequently, the paper focuses on technical change A and its impact on input efficiency. In this case, an increase of R&D expenditure as a proxy for technical change augments the efficiency of input factors used in final output production. As mentioned, foreign patent applications transfer technology at the cost of public disclosure. In addition to domestic research, countries gain access to foreign financed know-how in legally using and/or modifying foreign patented technology. As a result, input productivity and output is likely to increase.

To keep the analysis comparable to other studies, I follow Coe and Helpman (1995) and define TFP by a Cobb-Douglas functional form with constant returns:

$$TFP = Y/[K^{\beta} L^{(1-\beta)}] = A, \tag{2}$$

where β is the production elasticity of capital. Taking the log of equation (2) leads to the following equation:

$$\log TFP = \log Y - \beta \log K - (1-\beta)\log L = \log A. \tag{3}$$

However, I try to explain productivity variation of single rather than total input factors. Taking into account the time and cross section dimension, the empirical equation for FP is:

$$\log FP_{i,t} = \alpha_i + \alpha^d \log S_{i,t}^d + \alpha^f b_{i,t} \log S_{i,t}^f + \varepsilon_{i,t}, \qquad i = 1,...,N \text{ and } t = 1,...,T, \tag{4}$$

where i is country and t is time index, $S_{i,t}^d$ and $S_{i,t}^f$ represents domestic and foreign R&D capital stock as technical change respectively and $\varepsilon_{i,t}$ is the error term. The term $b_{i,t}$ captures intensity of foreign technology diffusion.

Since the benefits of domestic research activity depend on domestic markets and traded volumes, the impact on FP due to domestic R&D spending differ between G7 and Non-G7 countries. Hence, modification of equation (4) leads to:

$$\log FP_{i,t} = \alpha_i + \alpha^d \log S_{i,t}^d + \alpha_{G7}^d \log S_{i,t}^d + \alpha^f b_{i,t} \log S_{i,t}^f + \varepsilon_{i,t}, \tag{5}$$

with G7 as a dummy variable, which is equal to one for the major seven countries and zero otherwise.

Patent Related Spillover Effects

Foreign R&D capital stock is defined as the patent weighted average of domestic R&D capital stocks from abroad:

$$S^{f}_{i,t} \equiv S^{f,P}_{i,t} = \frac{1}{\sum_{j \neq i} a_{ji,t}} \sum_{j \neq i} (a_{ji,t} S^{d}_{j,t}), \qquad j = 1,..., N, \tag{6}$$

with $a_{ji,t}$ as patent application of country j in country i. Note that the ratio of $a_{ji,t} / \sum_{j \neq i} a_{ji,t}$ defines country's j technology diffusion to country i.

Patent count data serve mainly to determine the direction rather than the intensity of international technology diffusion. Nevertheless, for OECD countries there might be no difference between the impact of foreign and domestic R&D capital stocks and therefore no need to specify technology intensity explicitly:

$$b_{i,t} \equiv b^{P}_{i,t} = 1. \tag{7}$$

Nevertheless, defining foreign technology intensity one could possibly take into account of two different measures. First, the use of patent related foreign technology should be more efficient in countries with own research activity and higher domestic R&D spending. This reflects the idea of being a leading research country and a major recipient of foreign patents and therefore of having self-reinforcing economic strength and capabilities. Relating business related R&D expenditure ($R\&D_{i,t}$) to GDP ($Y_{i,t}$), technology intensity is defined as:

$$b_{i,t} \equiv b^{P}_{i,t} = R\&D_{i,t} / Y_{i,t}. \tag{8}$$

However, equation (8) reduces the possibility to explain high productivity levels for small countries by foreign technology diffusion. Moreover, the business cycle problem inherent to patent data is aggravated as domestic GDP is now additionally in the denominator.

Second, market seeking and/or strategic decisions by inventors of major research countries lead in small countries to a high non-resident to resident patent application ratio. Given quite similar productivity levels across OECD countries, technology intensity from abroad must be higher in countries with a high share of foreign patent applications. For this reason, the ratio of foreign patent applications to total patent applications may serve as a proxy for technology intensity:

$$b_{i,t} \equiv b_{i,t}^{P} = \sum_{j \neq i} a_{ji,t} / \sum_{j} a_{ji,t} , \qquad j = 1,...,N . \qquad (9)$$

Trade- and FDI Related Spillover Effects

For the case of trade related spillover effects, foreign R&D capital stock as in Coe and Helpman (1995) is the average of domestic R&D capital stocks from abroad weighted by bilateral import shares:

$$S_{i,t}^{f} \equiv S_{i,t}^{f,M} = \frac{1}{m_{i,t}} \sum_{j \neq i} m_{ji,t} S_{j,t}^{d} , \qquad j = 1,...,N , \qquad (10)$$

with $m_{ji,t}$ as imports from country j to country i and $m_{i,t}$ as total imports of country i. Note that the ratio $m_{ji,t} / m_{i,t}$ is the trade related technology diffusion channel. Coe and Helpman (1995) also propose to use an additional measure to capture technology intensity. Given a same composition of imports and a similar trade pattern between two countries a country that imports more relative to its GDP should benefit more from foreign R&D spillover effects. Accordingly, trade related technology intensity is given by:

$$b_{i,t}^{f} \equiv b_{i,t}^{f,M} = m_{i,t} / Y_{i,t} . \qquad (11)$$

Turning to FDI related spillover effects, the use of the perpetual inventory method and FDI inflow data determine foreign FDI capital stock as:

$$S_{i,t}^{f} \equiv S_{i,t}^{f,F} = (1-\delta) S_{i,t-1}^{f,F} + \sum_{j \neq i} FDI_{ji,t-1} , \qquad j = 1,...,N , \qquad (12)$$

with $FDI_{ji,t}$ as foreign direct investment from country j to country i and δ as a time- and country-invariant depreciation rate. Note that there is no reason to express FDI related technology intensity explicitly:

$$b_{i,t}^{f} \equiv b_{i,t}^{f,F} = 1 . \qquad (13)$$

3. Data

The paper measures the impact of international technology diffusion on factor productivity. Owing to the more reliable data on labor input and to a lack of data for an adequate stock of business sector capital either for distinctive countries or for a specific period I use labor factor productivity (LFP) data. For this reason, equation (4) and equation (5) are specified by: $FP = LFP$. Calculating labor productivity figures, there is a qualitative difference between the usage of the number of persons engaged and the number of hours actually worked. As proposed in the literature, worked hours are used as labor input. Figures on labor productivity per hour worked in constant US$ (PPP) are from the *Total Economy Database* provided by the Groningen Growth and Development Center.

Data on business related R&D expenditure (BERD) have been published by the OECD since about 1965 (*R&D and TBP Database*) mainly for the G7 countries as well as for Switzerland. In order to get a complete (balanced) data set for all OECD countries from the beginning of 1965, one has to estimate missing R&D expenditure figures. Coe and Helpman (1995) estimated such missing figures by relating real R&D expenditure to real output and investment.[2] However, the lack of R&D data as well as the restriction of adequate patent numbers limits the analysis in this paper to 1981-2001 and to 18 OECD countries[3]. Converting R&D expenditure flows into R&D capital stocks I use the perpetual inventory method and follow the procedure suggested by Griliches (1979) in calculating the R&D benchmark capital stock for each country.[4] The time- and country-invariant depreciation rate is assumed to 10%.[5] The R&D expenditure data are from the OECD *Main Science and Technology Database* and are in million constant US$ (PPP).

The OECD also has been publishing patent figures since the early 1980s. As discussed, country specific patent data and the pattern of international patent applications are the main interest in defining technology diffusion (i.e. domestic innovations seeking protection abroad by foreign patent applications). The OECD does not provide such differentiated data. Patent statistics published by the WIPO however do. Since 1975, the WIPO offers annual figures on foreign patent application and grants broken down by and for each country (*Industrial Prop-*

[2] The reader is referred to the cited paper for further details and discussions.
[3] The 18 OECD countries are respectively: Australia, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Japan, Netherlands, Norway, Spain, Sweden, United Kingdom and USA.
[4] See appendix (A) for an analytical derivation as well as Table A.1 for further information.
[5] Given depreciation rates for capital stocks between 5% and 15% used in comparable studies, I also run regressions assuming a 5 percent rate of depreciation. As expected, the results do not change and the main conclusions remain valid. The estimation results are listed in Table B.3 in appendix (B).

erty Statistics Publication B Part I).[6] Moreover, patent data have been collecting by the WIPO for more than 150 years (for at least some countries) and–in addition–for poorer and less developed countries.

Incorporating trade and FDI related spillover effect to the analysis figures consist of data published by the OECD in the *Monthly Statistics of International Trade* and the *International Direct Investment Statistics.* To relate domestic R&D capital stocks to bilateral trade patterns, figures on import as well as on GDP in million US$ are used. GDP data (market price, value) is from the OECD *Economic Outlook Database*. To generate FDI inflow capital stocks, once again the perpetual inventory method is used and a R&D deflator as well as PPP data converts FDI figures into million constant US$ (PPP).[7] Due to the restriction of adequate FDI inflow data over the period 1981–2001, Greece, Iceland, Ireland and Norway are withdrawn from the pooled sample in the case of FDI related spillover effects reducing the number of observed units to 14 countries.

Indexation and Aggregation Bias

As in Coe and Helpman (1995), I calculate LFP as indexed figures (1995=1). However, due to the indexation bias of the right hand side regressors in Coe and Helpman (1995) criticized by Lichtenberg and Van Pottelsberghe (1998), domestic and foreign R&D variables are expressed in levels. Moreover, technology diffusion weights as by foreign patent applications (and by bilateral import shares) sum up to one and might indeed have an aggregation bias: the more the foreign patent applications (imports) in a single country are, the higher the foreign R&D capital stock is. In this context, a merger between countries would always increase the foreign R&D capital stock. An alternative approach would be a ratio of foreign patent application (or imports as proposed by Lichtenberg and Van Pottelsberghe (1998)) to foreign GDP instead. This formulation would reflect the intensity as well as the direction of technology transfer. Since it will also aggravate the business cycle problem with foreign GDP in the denominator, I prefer to deal with the aggregation bias but to rest on R&D capital stock expressed by equation (6) and (10).

[6] Figures based on patent applications instead of grants are more reliable. Table B.4 in appendix (B) presents data on foreign patent application filled by non-residents from 18 OECD countries for 2001.

[7] See Table A.2 in appendix (A) for further information. The R&D deflator is derived from BERD figures published in million current as well as in million constant US$ (PPP) in the *Main Science and Technology Database* by the OECD. PPP data is from the OECD *Economic Outlook Database*.

4. Nonstationary Panels and Estimation Techniques

In general, productivity as well as R&D expenditure data exhibit a clear trend and unit root tests confirm nonstationarity, whereas the error term of the pooled regression may or may not be stationary. If the error term is stationary, variables are cointegrated and there is common trend binding all variables. If not, the estimated relationship is spurious and no long-run relationship between variables exists. Moreover, the cointegration literature does not assume strict exogenous regressors. There might also be feedback from productivity to R&D and endogeneity as well as by serial correlation drives and biases estimators.[8]

To deal with nonstationarity and endogeneity and to avoid spurious correlation among variables, I use estimation techniques proposed by Kao and Chiang (1998) and adopt their techniques as in Kao, Chiang and Chen (1999) and Funk (2001).[9] The advantage of not transforming variables in differences but of relying on level terms is to make use of the embedded information about common trends and long-run equilibrium properties. Hence, analyzing the steady state equilibrium between domestic productivity and foreign R&D expenditure levels quantifies foreign technology diffusion properly.

Unit Root Tests

There are three common tests for unit roots on a balance data set: Levin, Lin & Chu (2002) (LLC) tests, Im, Pesaran & Shin (2003) (IPS) tests and the residual-based Lagrange multiplier test by Hadri (2000) (LMH).[10]

Suppose that a variable is driven by its lagged value, an autoregressive coefficient and an error term. The autoregressive coefficient ρ_i of the lagged value determines the degree of dependence or nonstationarity. The LLC test assumes that each ρ_i is the same for all units ($\rho_i = \rho$), that the error term is a stationary process and that units are independent across sections.[11] For unit roots, the LLC test proposes a null hypothesis of unit roots or nonstationarity ($H_0 : \rho = 1$) against the alternative hypothesis that all individual series in the panel data are stationary ($H_1 : \rho < 1$). Relaxing the restrictive assumption of a homogeneous ρ across units assumed by the LLC tests, the IPS test allows for heterogeneous autoregressive coefficients. The general IPS setting is based on averaging individual unit roots test statistics and assumes

[8] Baltagi (2001) provides an excellent overview for nonstationary issues as well as cointegration.
[9] A GAUSS code for the estimation techniques is freely available on the homepage of Chihwa Kao at Syracuse University, NY: http://web.syr.edu/~cdkao/.
[10] For the case of an unbalanced data, Maddala and Wu (1999) and Choi (2001) modified a Fisher type test.
[11] To allow for a limited degree of dependence across units, cross sectional averages are subtracted from the observed data without affecting the limit distribution of the panel unit root test, see Levin, Lin and Chu (2002).

that the error term is serially correlated across cross-sectional units. The IPS test examines the null hypothesis of each series has a unit root ($H_0 : \rho_i = 1$) against the alternative hypothesis of at least one individual series in the panel is stationary ($H_1 : \rho_i < 1$). Finally, LMH limits the determination of a variable to a random walk of part of the error term and to a stationary error process. As a result, there is no autoregressive coefficient. The LMH test assumes that each time series is level or trend stationary ($H_0 : \mathit{stationary}$) against the alternative hypothesis of a unit root in panel data ($H_1 : \mathit{nonstationary}$). All test procedures have in common that a deterministic component such as an individual and/or time trend can be included. Moreover, their adjusted test statistics obey asymptotically the standard normal distribution.

LLC and IPS require that $N \to \infty$ such that $N/T \to 0$, i.e. N should be small enough relatively to T. As a result, in finite samples there are size distortions if N is small or N is large relative to T. Moreover, both tests suffer a dramatic loss of power if time trends are included. Given the fact that classical hypothesis testing ensures that the null hypothesis is not rejected unless there is no strong evidence against it, I try to overcome this lack of power by testing both nonstationarity as well as stationarity for the null hypothesis.

Cointegration Tests

To test for the long-run cointegration relationship (i.e. stationary of the error term), one can either use the corresponding error terms from the error correction (EC) model or the proposed cointegration tests presented by Kao (1999), McCoskey and Kao (1998) and Pedroni (1995).

Turning to the EC model, the first step is to estimate long-run equilibrium values in levels by removing units as well as time effects (transformation for a two-way fixed effects model). The resulting residuals (i.e. error correction terms) are used in the second step to estimate the EC model. The t-statistic of the lagged error correction term now indicates whether it is significantly different from zero or not. A cointegration relationship amongst variables exists, if the t-statistic is significant.

Alternatively, cointegration tests as proposed by the literature can be used. Such tests analyze either the null hypothesis of no cointegration, as the Dickey-Fuller and the augmented Dickey-Fuller type tests proposed by Kao (1999) or the Phillips and Perron type tests of Pedroni (1995) do, or the null hypothesis of cointegration, as the residual-based Lagrange Multiplier test by McCoskey and Kao (1998) does. All tests have in common that residuals are derived by estimating the cointegration variables. However, only for tests presented by Kao (1999) and Pedroni (1995) can residuals be derived from OLS estimation. For McCoskey and Kao (1998) an efficient estimation technique other than OLS is needed for.

Estimation Techniques: Panel-, Fully Modified- and Dynamic-OLS

The presence of cointegration and unit roots considerably affects the asymptotic distributions in time series as well as in panel analysis. However, cointegration equations have attractive properties: as the number of observations increase in T and N, the OLS estimation of the cointegrated variables converges in the long-run equilibrium to the true value. Nevertheless, for moderate sample size, the estimation bias remains substantial due to endogeneity and serial correlation. To deal with, Kao and Chiang (1998) discuss three different estimators: OLS with bias correction, full modified (FM) and dynamic (D) OLS estimators. While the FM-OLS estimator corrects for endogeneity and serial correlation by modifying and adjusting the dependent variable, the DOLS estimator however introduces leads and lags of the differentiated regressors to the estimation. Kao and Chiang (1998) derive the following limiting distribution: the OLS estimator is normal distributed with non-zero mean, whereas the FM- and DOLS estimators are asymptotically normal with zero mean. They find that the OLS estimator has a non-negligible bias in finite samples and that the DOLS estimator performs better in estimating the panel equations than does the OLS estimator with bias correction or the FM-OLS estimator. As a result, they propose to use the DOLS estimator dealing with cointegration and unit roots.[12]

5. Empirical Results

In examining the effects of domestic and foreign business related R&D expenditure on labor productivity, I use the pattern of international patenting as the main technology diffusion channel. To keep the analysis comparable to estimations of Coe and Helpman (1995) and to Kao, Chiang and Chen (1999), I first estimate patent related spillover effects for all OECD countries by Kao and Chiang (1998)'s estimation techniques and discuss the different technology intensity measures. Next, countries are divided between G7 and Non-G7 countries and estimations are reduced to the use of the DOLS estimator. Finally, I incorporate trade and FDI related spillover effects as robustness tests to complete and validate the estimation of foreign technology diffusion.

5.1 Patent Related Spillover Effects

To start with, unit roots test have to confirm that the pooled data exhibit unit roots and follow a nonstationary path. The null hypothesis is nonstationarity for LLC and IPS and stationarity for LMH.

[12] For further information as well as for analytical derivation see Kao and Chiang (1998).

Turning to the null hypothesis of nonstationarity and assuming either one or two lags, Table 1 shows test statistics and p-values in parenthesis from LLC and IPS for two cases: first for an individual trend and second for an individual and time trend.

Table 1: Unit Root Tests by Levin, Lin and Chu (2002) and Im, Peseran and Shin (2003)
(Annual data for 18 countries 1981-2001; Observations: 342 with Lag(1); Observations: 324 with Lag(2)

	LLC, Lag(1)	**LLC, Lag(2)**	**IPS, Lag(1)**	**IPS, Lag(2)**
Individual				
$\log LFP$	-0.844 (0.199)	-0.375 (0.354)	4.625 (1)	4.225 (1)
$\log S^{d}$	-1.282 (0.1)	0.495 (0.69)	2.891 (0.998)	2.583 (0.995)
(6): $\log S^{f,P}$	-8.753 (0)	0.94 (0.827)	-1.161 (0.123)	-1.015 (0.155)
(6)/(8): $b^{P}\log S^{f,P}$	3.972 (1)	3.735 (1)	4.175 (1)	3.498 (1)
(6)/(9): $b^{P}\log S^{f,P}$	-3.368 (0)	-4.958 (0)	-1.131 (0.871)	-0.984 (0.163)
Individual and Time				
$\log LFP$	-1.841 (0.033)	-0.175 (0.431)	-0.155 (0.439)	0.401 (0.656)
$\log S^{d}$	-6.784 (0)	-0.015 (0.494)	-5.985 (0)	-0.684 (0.247)
(6): $\log S^{f,P}$	-10.91 (0)	3.082 (1)	3.760 (1)	3.291 (1)
(6)/(8): $b^{P}\log S^{f,P}$	-0.716 (0.237)	-0.507 (0.306)	2.749 (0.997)	2.069 (0.981)
(6)/(9): $b^{P}\log S^{f,P}$	-3.208 (0)	-3.7 (0)	-0.089 (0.464)	-0.608 (0.271

Notes: The null hypothesis is nonstationarity while the alternative hypothesis for LLC (IPS) is that all (some) individual series are stationary with identical (individual) first order autoregressive coefficient. Both, the adjusted test statistics for LLC (t-star) and IPS (w[t-bar]) convergence asymptotically to a standard normal distribution. The p-values are in parenthesis.

Table 1 leads to the following conclusions: In the case of individual trends, both testing procedures confirm unit roots for labor productivity and domestic R&D capital stock at a 10% level or better. For foreign R&D capital stocks, LLC confirms nonstationarity for both lags only for the case of R&D-expenditure weighted foreign R&D capital stocks by equation (6) and (8). IPS however confirms unit roots for all specifications of foreign R&D capital stocks. Adding a time trend to the test procedures, the IPS still confirms unit roots for all variables except for domestic R&D capital stock with lag(1). The LLC testing procedure however rejects nonstationarity at the 5% level for all variables except for equation (6) and (8), if variables are lagged by one period. In the case of two lags, LLC confirms nonstationarity except for equation (6) and (9).

Given these somehow mixed results by LLC for the case of individual and time trends, test statistics and p-values by LMH for level stationarity and trend stationarity with lag(1) are shown in Table 2. The overall result is that the null hypothesis of stationarity is rejected for every variable and for each specification of the disturbance term. The LMH test confirms unit roots and nonstationarity for the whole data set. Bearing in mind the lack of power of unit root tests since time trends are included and given the results in Table 2, I conclude that the variables are nonstationary.

Table 2: Stationary Tests by Hadri (2000)
(Annual data for 18 countries 1981-2001; Observations: 378 with Lag(1))

	Homo. Disturbance	Hetero. Disturbance	Ser. Corr. Disturbance
Level Stationarity			
$\log LFP$	50.428 (0)	48.542 (0)	7.021 (0)
$\log S^{d}$	51.782 (0)	51.587 (0)	7.035 (0)
(6): $\log S^{f,P}$	46.829 (0)	49.906 (0)	6.789 (0)
(6)/(8): $b^{P} \log S^{f,P}$	43.212 (0)	34.240 (0)	6.712 (0)
(6)/(9): $b^{P} \log S^{f,P}$	40.158 (0)	41.417 (0)	6.357 (0)
Trend Stationarity			
$\log LFP$	18.036 (0)	15.111 (0)	8.147 (0)
$\log S^{d}$	33.659 (0)	32.083 (0)	7.092 (0)
(6): $\log S^{f,P}$	13.310 (0)	25.254 (0)	8.571 (0)
(6)/(8): $b^{P} \log S^{f,P}$	25.678 (0)	22.802 (0)	7.508 (0)
(6)/(9): $b^{P} \log S^{f,P}$	20.457 (0)	17.985 (0)	7.779 (0)

Notes: The null hypothesis is level or trend stationarity while the alternative hypothesis is nonstationarity. The test statistics for the null of level stationarity (Z_{μ}) as well as for the null of trend stationarity (Z_{τ}) converge asymptotically to a standard normal distribution. The p-values are in parenthesis. Test statistics and p-values are given for three distinctive assumptions about the disturbance term: homogenous, heterogeneous and temporally serially correlated.

Once confirmed that the variables are nonstationary and before turning to the empirical results, a regression containing all variables must have a stationary error term in order to avoid spurious results. Test procedures based on the EC model as well as on test statistics from Pedroni (1995) and Kao (1999) are given in Table 3.

Taking the EC model, the first testing procedure uses the lagged error correction term and analyzes statistical significance by means of the usual t-statistics of the EC model. The t-statistics are significantly different from zero for all model specifications–equation (4) with (6) in combination with technology intensity measures (7)-(9)–which means that the error term is stationary. Turning to the tests of no cointegration by Pedroni (1995), both test statistics reject the null hypothesis and confirm cointegration. Test statistics from Kao (1999) are somehow mixed. Especially for the case of endogeneous regressors with respect to the errors–test statistics DF_{ρ}^{*} and DF_{t}^{*}–the null hypothesis of no cointegration for equation (4) with (6) and (8) is not rejected. However, given the overall picture of test statistics confirming cointegration, I conclude that there is long-run relationship between the cointegrated variables. Finally, with nonstationary and cointegrated data the focus turns to the empirical results.

Table 3: Cointegration Tests based on the EC Model, Pedroni (1995) and Kao (1999); Patent Related Spillover Effects
(Pooled data for 18 countries from 1981-2001)

Equation:	(4) with (6)/(7)	(4) with (6)/(8)	(4) with (6)/(9)
EC-Model [a]			
t-statistics of the EC-modell	-3.62 (0)	-3.74 (0)	-3.63 (0)
Pedroni (1995) [b]			
PC_1	-7.579 (0)	- 6.286 (0)	-7.510 (0)
PC_2	-7.397 (0)	- 6.135 (0)	-7.329 (0)
Kao (1999) [c]			
DF_ρ	1.462 (0.07)	2.697 (0)	1.603 (0.05)
DF_t	1.404 (0.08)	2.583 (0)	1.4 (0.08)
DF_ρ^*	-2.619 (0)	-0.504 (0.3)	-2.388 (0.01)
DF_t^*	-0.93 (0.176)	-0.202 (0.42)	0.936 (0.175)

Notes: Test statistics converge asymptotically to a standard normal distribution. The p-values are given in parenthesis.

[a] The first step is to estimate long-run equilibrium values in levels by removing units as well as time effects (transformation for a two-way fixed effects model). The resulting residuals (i.e. error correction term) are used in the second step to estimate the EC model. The t-statistic from the EC model indicates weather the lagged error correction term is significantly different from zero or not. A cointegration relationship amongst variables exits, if the t-statistics is significant. Lag(1).

[b] Two test statistics are given by Pedroni (1995) based on a pooled Phillips and Perron type test with the null hypothesis of no cointegration. Regressors are assumed to be strictly exogenous. Residuals are derived from an OLS estimation.

[c] Kao (1999) presents four Dickey-Fuller type test statistics with the null hypothesis of no cointegraion. While DF_ρ and DF_t are based on the assumption of strict exogeneity of the regressors, DF_ρ^* and DF_t^* do account for endogeneity with respect to the errors. Residuals are derived from an OLS estimation.

Patent Related Spillover Effects by OLS with Bias Correction, FM-OLS and DOLS

Table 4 lists coefficients and their test statistics in parenthesis obtained by OLS with bias correction, FM-OLS and DOLS for the three technology intensity measures.

Starting with the impact of domestic R&D capital stock on labor productivity, the estimated coefficients for equation (4) with (6) and (7) are fairly comparable to the results from Kao, Chiang and Chen (1999) re-estimating Coe and Helpman's (1995) paper.[13] Moreover, the estimated coefficient by OLS with bias correction and FM-OLS are quite similar, whereas the coefficient from the DOLS estimator is about two percent higher. This is the result of the two different ways of removing the nuisance parameter (serial correlation) and dealing with endogeneity: The FM-OLS estimator corrects the dependent variable by the long-run covariance and applies usual OLS. Hence, coefficients will change only slightly. The DOLS estima-

[13] Both papers estimate the impact of domestic R&D amongst others on total factor productivity. However, the impact regarding either total or labor productivity figures should not vary a great extent. For the impact of domestic R&D on productivity, the coefficient is 9.7% for Coe and Helpman (1995) using pooled OLS. For Kao, Chiang and Chen (1999) the coefficient is 8.4% by the use of OLS with bias correction or FM-OLS and 10.7% by DOLS.

tor however introduces leads and lags with a bigger impact on coefficients compared to pooled OLS. Turning to equation (4) with (6) in combination with either (8) or (9), estimates suggests higher elasticities for domestic R&D capital stock, which vary between 11.6 and 20%. As a first result, the estimated coefficients for domestic R&D capital stock differ largely depending on the estimation technique and on the assumptions on foreign R&D capital stocks. However, the t-statistics are significantly large and domestic R&D capital stock is significant at the 5% level in each case.

Table 4: Labor Factor Productivity by OLS with Bias Correction, FM-OLS and DOLS; Patent Related Spillover Effects
(Pooled data for 18 countries from 1981-2001)

Equation:	**(4) with (6)/(7)**	**(4) with (6)/(8)**	**(4) with (6)/(9)**
OLS with Bias Correction			
$\log S^d$	0.081 (2.796)**	0.194 (6.436)**	0.119 (4.519)**
$b^P \log S^{f,P}$	0.221 (6.496)**	0.430 (1.353)	0.041 (6.322)**
R^2	0.674	0.616	0.6735
FM-OLS			
$\log S^d$	0.078 (2.558)**	0.2 (6.299)**	0.116 (4.210)**
$b^P \log S^{f,P}$	0.219 (6.133)**	0.505 (1.514)	0.041 (5.947)**
R^2	0.668	0.613	0.667
DOLS			
$\log S^d$	0.099 (2.58)**	0.19 (4.792)**	0.129 (3.737)**
$b^P \log S^{f,P}$	0.174 (3.90)**	0.449 (1.078)	0.036 (4.248)**
R^2	0.652	0.6	0.631
No. of Observation	378	378	378

Notes: The bias corrected t-statistics are reported in parenthesis. * (**) denotes that the coefficient is significantly different from zero at a 10% (5%) level. All equations include unreported, country-specific constants. Assumptions for DOLS: Lag(2) and Lead(2).

To quantify the impact of foreign R&D capital stocks on domestic labor productivity, the estimated coefficients in Table 4 are multiplied by their intensities. Given ratios of domestic R&D expenditure to GDP less than three percent, the impact of foreign R&D capital stock reduces for equation (6) and (8) to almost two percent in the best and zero in the worst case. For the case of patent weighted intensity by equation (9), a ratio less than one reduces the estimated coefficient for equation (6) and (9) even further. Such low coefficients for foreign technology diffusion in relation to the impact of domestic R&D are not very plausible, otherwise one could not explain–as mentioned–the small variation in productivity levels across different countries. However, without any additional specification for technology intensity as by equation (7), the impact of foreign R&D capital stock on domestic factor productivity has reasonable values of about 22 percent for OLS with bias correction/FM-OLS and 17.4 percent for DOLS. All coefficients are significant at a 5% level.

Given the superiority of the DOLS estimator over OLS with bias correction and FM-OLS and considering equation (6) and (7) as an adequate approximation of technological spillover effects, I conclude that patent related spillover effects are present. As a result, a one percent increase in domestic or foreign R&D capital stock leads to a 10% or 17.4% increase in domestic labor productivity respectively.

Patent Related Spillover Effects for G7 and Non-G7 Countries by DOLS

However, the impact of domestic R&D on factor productivity differs between G7 and Non-G7 countries. Table 5 shows estimation results by DOLS for equations (5) with (6) in combination of (7)-(9). Cointegration test statistics by Pedroni (1995) are also given.

Table 5: Labor Factor Productivity for G7 and Non-G7 Countries by DOLS; Patent Related Spillover Effects
(Pooled data for 18 countries from 1981-2001)

Equation:	**(5) with (6)/(7)**	**(5) with (6)/(8)**	**(5) with (6)/(9)**
DOLS			
$\log S^d$	0.107 (2.89)**	0.158 (4.217)**	0.117 (3.613)**
G7 $\log S^d$	0.144 (1.568)	0.204 (2.25)**	0.196 (2.294)**
$b^P \log S^{f,P}$	0.139 (3.072)**	0.629 (1.644)	0.032 (4.014)**
R^2	0.683	0.657	0.68
Cointegration-Test: Pedroni (1995)			
PC_1	-7.314 (0)	-6.664 (0)	-7.783 (0)
PC_2	-7.138 (0)	-6.504 (0)	-7.596 (0)
No. of Observation	378	378	378

Notes: The bias corrected t-statistics (p-values) of the coefficients (of the cointegration-tests) are reported in parenthesis. * (**) denotes that the coefficient is significantly different from zero at a 10% (5%) level. All equations include unreported, country-specific constants. The variable G7 acts as a dummy variable, which is equal to one for the seven mayor countries and zero for the non-G7 countries. Assumption: Lag(2) and Lead(2). Two test statistics are given by Pedroni (1995) based on a pooled Phillips and Perron type test with the null hypothesis is no cointegration. Regressors are assumed to be strictly exogenous. Residuals are derived from an OLS estimation.

To start with, test statistics from Pedroni (1995) confirm cointegration[14]. As before, coefficients for foreign R&D capital stock expressed by (6) in combination with (8) or (9) are too low and are not considered due the discussed lack of plausibility. Hence, the analysis reduces to the first column in Table 5.

[14] Test statistics from Kao (1999) given in Table B.2 in appendix (B) also confirm cointegration for equation (5) with (6) and (7).

Indeed, the impact of domestic research activity for the G7 countries rises to 25% while for the Non-G7 countries it remains nearly unchanged. Again, both coefficients are comparable to Kao, Chiang and Chen (1999) and to Coe and Helpman (1995). The elasticity for foreign R&D capital stock reduces to 13.9% but is still significant at a 5% level. As expected, the impact on labor productivity for Non-G7 countries is higher due to foreign rather than domestic R&D activities emphasizing the importance of technological spillover effects from abroad for these countries.

5.2 Patent-, Trade- and FDI Related Spillover Effects

To discuss the overall picture of foreign technology diffusion and the robustness of the derived results, I incorporate trade and FDI spillover effects to the analysis. Bearing in mind that the impact on labor productivity differs between G7 and Non-G7 countries and that patent related spillover effects are best quantified without any specific technology intensity, a regression dealing with technology diffusion can be written as:

$$\log LFP_{i,t} = \alpha_i + \alpha^d \log S_{i,t}^d + \alpha_{G7}^d G7 \log S_{i,t}^d + \alpha^{f,P} \log S_{i,t}^{f,P} + \alpha^{f,M} b_{i,t}^M \log S_{i,t}^{f,M} + \alpha^{f,F} \log S_{i,t}^{f,F} + \varepsilon_{i,t},$$

$$i = 1,...,N \text{ and } t = 1,...,T, \quad (14)$$

with patent-, trade- and FDI related spillover effects as described by equation (6), equation (10) with (11) and equation (12) respectively.

Table 6 shows the impact on labor productivity for G7 and Non-G7 countries according to three different scenarios: first, patent- and trade related spillover effects, second, patent- and FDI related spillover effects and third, patent-, trade- and FDI related spillover effects. Table B.1 in appendix (B) confirms unit roots for foreign R&D expenditure weighted by trade share and FDI capital inflow stocks. Moreover, test statistics of Pedroni (1995) in Table 6 as well as of Kao (1999) in Table B.2 in appendix (B) attest stationarity of the error term and therefore cointegration for each regression.

In the first case of including bilateral trade pattern, the estimated results are quite close to those derived for equation (5) with (6) and (7) in Table 5: the coefficient for patent related foreign R&D spillover (12,5%) effects remains significant at a 5% level and still exceeds the coefficient for domestic R&D capital stock for Non-G7 countries (10.4 %). Interestingly, the DOLS estimator neglects any statistically significance of trade related spillover effects as in

Kao, Chiang and Chen (1999). However, the coefficients are slightly reduced in comparison to the corresponding figures in Table 5.

Table 6: Labor Factor Productivity for G7 and Non-G7 Countries by DOLS; Patent, Trade and FDI Related Spillover Effects
(Pooled data for 18 countries for equation (5) with (6)/(7) and (10)/(11) and 14 countries for equation (5) with (6)/(7) and (12)/(11) and equation (14) from 1981-2001)

Equations:	**(5) with (6)/(7) and (10)/(11)**	**(5) with (6)/(7) and (12)/(13)**	**(14)**
DOLS			
$\log S^{d}$	0.104 (2.85)**	0.0533 (1.89)*	0.0439 (1.557)
G7 $\log S^{d}$	0.138 (1.515)	0.095 (2.305)**	0.089 (2.162)**
$\log S^{f,P}$	0.125 (2.819)**	0.668 (2.68)**	0.069 (2.735)**
$b^{M} \log S^{f,M}$	-0.008 (-0.025)		0.21 (1.38)
$\log S^{f,F}$		0.058 (6.83)**	0.058 (6.837)**
R^2	0.657	0.917	0.922
Cointegration-Test: Pedroni (1995)			
PC_1	-7.304 (0)	-17.15 (0)	-17.045 (0)
PC_2	-7.128 (0)	-16.736 (0)	-16.635 (0)
No. of Observation	378	294	294

Notes: The bias corrected t-statistics (p-values) of the coefficients (of the cointegration-tests) are reported in parenthesis. * (**) denotes that the coefficient is significantly different from zero at a 10% (5%) level. All equations include unreported, country-specific constants. The variable G7 acts as a dummy variable, which is equal to one for the seven mayor countries and zero for the non-G7 countries. Assumption: Lag(2) and Lead(2). Two test statistics are given by Pedroni (1995) based on a pooled Phillips and Perron type test with the null hypothesis is no cointegration. Regressors are assumed to be strictly exogenous. Residuals are derived from an OLS estimation.

Considering the second case and adding FDI inflow stocks instead of trade weighted R&D stocks to the analysis, the R&D coefficients are almost reduced by 50%. However, the key results remain robust: patent related R&D spillover effects are present and the impact on labor productivity for Non-G7 countries is higher due to foreign rather than domestic R&D activities. According to the theory, there is a positive impact on domestic labor productivity of about 5.8 % from FDI inflows. All coefficients are significant at 10% level or better.

Finally, estimation of equation (14) leads to no major change in the results, except that the coefficient for domestic R&D capital stock for Non-G7 countries gets insignificant. With regard to the main conclusions, estimates again confirm the impact and importance of patent- and FDI related spillover effects on labor productivity and neglects any bilateral trade significance.

6. Conclusion

I propose to use international patent applications as a diffusion channel to question the impact of technology spillover effects on input factor productivity. Considering the relationship between research and productivity, international patent pattern reflects the link between the source and the destination of transferred technology. Analyzing a panel data set with 18 OECD countries from 1981 to 2001 by estimation techniques dealing with nonstationary and cointegration, I find evidence that patent related foreign spillover effects are present. Moreover, foreign technology diffusion on labor productivity–due to a one percent increase in domestic R&D spending abroad–varies between 7-14%. For Non-G7 countries, the impact on labor productivity is always higher due to foreign rather than domestic R&D activities. Additionally, including trade- and FDI related spillover effects, estimates show that there is no significant influence on labor productivity from bilateral trade, but confirm the importance of FDI inflows. The evidence of patent related spillover effects is robust emphasizing the role of international patent pattern as a main technology diffusion channel.

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Appendix

Appendix (A) lists specific details on assumptions and methods of calculation. Further estimation results and Tables are given in the appendix (B). All data and calculations are available upon request.

(A) Assumptions and Methods of Calculation

To convert flow figures into stock variable, I use the perpetual inventory method. Suppose the following relationship between steady state stock variable S^* and its flow value F^*:

$$(1+g)^{t+1} S^* = (1-\delta)(1+g)^t S^* + (1+g)^t F^*, \qquad t = 0,...,T, \qquad \text{(A.1)}$$

with g as the annual average growth rate and δ as a time-invariant depreciation rate. Rearranging equation (A.1) leads to:

$$S^* = \frac{F^*}{(\delta + g)}. \qquad \text{(A.1.1)}$$

Assuming a positive annual growth rate ($g > 0$), the expected value of stocks and flows is given by:

$$E(S_t) = (1+g)^t S^*, \ E(F_t) = (1+g)^t F^*. \qquad \text{(A.2)}$$

Finally, substitution of equation (A.2) in equation (A.1.1) leads to S_0 as the benchmark:

$$S_0 = E(S_t) = \frac{E(F_t)}{(\delta + g)}. \qquad \text{(A.3)}$$

Subsequent stock data are given by:

$$S_t = (1-\delta) S_{t-1} + F_{t-1}, \qquad t = 1,...,T. \qquad \text{(A.4)}$$

R&D Capital Stock Data

R&D benchmark figures for each country are calculated according equation (A.3) using BERD expenditure flows ($S^d_{i,0}$ for $i = 1,...,18$). The annual average growth rate of R&D expenditure is calculated over the period were R&D data in the *Main Science and Technology*

Database were published by the OECD. The expected flow is the first year for which the data were available as proposed by Grillich (1979) and applied in Coe and Helpman (1995). The country- and time-invariant depreciation rate is assumed to 10%. Table A.1 summarizes figures for the 18 OECD countries.

Table A.1: R&D Capital Stock Data
(BERD Expenditure in million constant US$ (PPP))

	R&D Expenditure Data		R&D Flow	R&D Stock
	Available	Avg. Growth	1981	Benchmark
Australia	1981-2001	9.633	590.961	3010.100
Belgium	1981-2002	4.471	1664.318	11501.288
Canada	1981-2002	5.627	2811.163	17989.101
Denmark	1981-2002	8.084	469.921	2598.537
Finland	1981-2002	9.065	494.054	2591.381
France	1981-2002	3.066	10528.354	80575.198
Germany	1981-2002	2.739	19239.356	151026.375
Greece	1981-2001	10.843	46.079	221.076
Iceland	1981-2002	20.289	2.814	9.290
Ireland	1981-2001	10.946	109.359	522.094
Italy	1981-2002	2.320	4461.281	36212.654
Japan	1981-2002	4.921	25561.785	171309.289
Netherlands	1981-2002	2.929	2292.401	17731.359
Norway	1981-2002	4.905	495.340	3323.209
Spain	1981-2002	8.489	797.862	4315.433
Sweden	1981-2001	6.590	2058.273	12406.660
U.K	1981-2002	1.794	12089.344	102499.844
United States	1981-2002	3.626	81589.277	598782.230

Notes: The benchmark relates to the year 1981 for all countries and is calculating following equation (A.3) and the procedure suggested by Grillich (1979). Depreciation rate is assumed to 10%.

FDI Capital Stock Data

Due to negative figures for some countries at the beginning of the sample, the annual growth rate as well as the expected flow is calculated by FDI inflow data of the first 10 years (instead–as proposed by Grillich (1979)–of the first year for which published data is available. The benchmark for FDI inflow stocks for each country follows equation (A.3) ($S_{i,0}^{f,F}$ for $i = 1,...,14$). The country- and time-invariant depreciation rate is assumed to 10%. Table A.2 lists figures for 14 OECD.

Table A.2: FDI Inflow Stock Data
(FDI Inflow in million current US$)

	FDI Inflow Data		FDI Expected Inflow			FDI Stock
	Available	Avg. Growth	Period	Avg. Growth	Expected Flow	Benchmark
Australia	1980-2001	5.003	1980-1990	3.481	832.292	3574.319
Belgium	1980-2001	23.061	1980-1990	5.911	448.677	1523.832

Canada	1980-2001	19.229	1980-1990	11.081	227.801	23325.615
Denmark	1980-2001	23.110	1980-1990	8.427	42.472	125.821
Finland	1980-2001	26.242	1980-1990	34.411	7.751	14.777
France	1980-2001	14.092	1980-1990	4.511	1053.932	4013.439
Germany	1981-2001	22.927	1981-1990	7.307	262.162	754.861
Italy	1980-2001	16.641	1980-1990	10.754	283.288	769.563
Japan	1980-2001	21.485	1980-1990	9.233	190.633	546.361
Netherlands	1980-2001	16.741	1980-1990	4.393	553.980	2134.699
Spain	1980-2001	14.848	1980-1990	11.621	456.787	1208.488
Sweden	1981-2001	18.450	1981-1990	4.897	163.808	558.990
U.K	1980-2001	10.979	1980-1990	5.159	1818.099	6532.963
United States	1980-2001	11.238	1980-1990	2.842	9802.068	46651.229

Notes: The benchmark relates to the year 1980 for all countries except for Germany and Sweden with 1981 accordingly and is calculated following equation (A.3). Depreciation rate is assumed to 10%.

(B) Additional Estimation Results and Tables

Table B.1: Unit Root Tests by Levin, Lin and Chu (2002) and Im, Peseran and Shin (2003)
Annual data for 18 countries for equation (10)/(11) and for 14 countries for equation (12) from 1981-2001

	LLC, Lag(1)	**LLC, Lag(2)**	**IPS, Lag(1)**	**IPS, Lag(2)**
Individual				
(10)/(11): $b^M \log S^{f,M}$	-1.417 (0.08)	o.44 (0.67)	-2.16 (0.02)	-1.03 (0.152)
(12): $\log S^{f,F}$	3.304 (1)	4.906 (1)	7.081 (1)	6.124 (1)
Individual and Time				
(10)/(11): $b^M \log S^{f,M}$	-0.403 (0.343)	2.636 (0.996)	-1.04 (0.15)	-0.232 (0.592)
(12): $\log S^{f,F}$	3.059 (1)	5.149 (1)	-0.291 (0.385)	-0.463 (0.322)

Notes: The null hypothesis is nonstationarity while the alternative hypothesis for LLC (IPS) is that all (some) individual series are stationary with identical (individual) first order autoregressive coefficient. Both, the adjusted test statistics for LLC (t-star) and IPS (w[t-bar]) convergence asymptotically to a standard normal distribution. The p-values are given in parenthesis.

Table B.2: Cointegration Tests by Kao (1999);
Patent-, Trade- and FDI Related Spillover Effects;
(Pooled data for 18 countries for equation (5) with (6)/(7) and equation (5) with (6)/(7) and (10)/(11) and 14 countries for equation (5) with (6)/(7) and (12)/(13) and equation (14) from 1981-2001)

Equations:	**(5) with (6)/(7)**	**(5) with (6)/(7) and (10)/(11)**	**(5) with (6)/(7) and (12)/(13)**	**(14)**
Kao (1999)				
DF_ρ	1.8 (0.04)	1.787 (0.037)	-2.433(0.01)	-2.387 (0.01)
DF_t	1.617 (0.05)	1.612 (0.05)	-2.186 (0.01)	-2.084 (0.02)
DF_ρ^*	-2.075 (0.02)	-2.043 (0.02)	-7.922 (0)	-7.873 (0)
DF_t^*	-0.803 (0.211)	-0.797 (0.213)	-3.068 (0)	-2.995 (0)

Note: Test statistics converge asymptotically to a standard normal distribution. The p-values are given in parenthesis. Kao (1999) presents four Dickey-Fuller type test statistics with the null hypothesis of no cointegraion. While DF_ρ and DF_t are based on the assumption of strict exogeneity of the regressors, DF_ρ^* and DF_t^* do account for endogeneity of the regressors with respect to the errors. Residuals are derived from an OLS estimation.

Table B.3: Labor Factor Productivity for G7 and Non-G7 Countries by DOLS; Patent-, Trade- and FDI Related Spillover Effects; Depreciation Rate: 5 %

(Pooled data for 18 countries for equation (5) with (6)/(7) and equation (5) with (6)/(7) and (10)/(11) and 14 countries for equation (5) with (6)/(7) and (12)/(13) and equation (14) from 1981-2001)

Equations:	**(5) with (6)/(7)**	**(5) with (6)/(7) and (10)/(11)**	**(5) with (6)/(7) and (12)/(13)**	**(14)**
DOLS:				
$\log S^{d}$	0.104 (2.842)**	0.104 (2.83)**	0.049 (1.785)*	0.04 (1.446)
G7 $\log S^{d}$	0.145 (1.569)	0.141 (1.535)	0.103 (2.602)**	0.097 (2.469)**
$\log S^{f,P}$	0.144 (3.2)**	0.129 (2.903)**	0.057 (2.39)**	0.058 (2.408)**
$b^{M} \log S^{f,M}$		-0.05 (-0.16)		0.207 (1.429)
$\log S^{f,F}$			0.061 (7.20)**	0.062 (7.216)**
R^2	0.693	0.703	0.92	0.923
Cointegration-Test:				
Pedroni (1995)				
PC_1	-7.346 (0)	-7.35 (0)	-17.27 (0)	- 17.18 (0)
PC_2	-7.168 (0)	-7.173 (0)	- 16.855 (0)	-16.77 (0)
Kao (1999)				
PC_1 DF_{ρ}	1.741 (0.04)	1.742 (0.04)	-2.684(0)	-2.635 (0)
PC_1 DF_{t}	1.516 (0.06)	1.518 (0.06)	-2.35 (0.01)	-2.257 (0.01)
PC_1 DF_{ρ}^{*}	-2.162 (0.02)	-2.128 (0.02)	-8.3 (0)	-8.25 (0)
PC_1 DF_{t}^{*}	-0.867 (0.193)	-0.857 (0.196)	-3.19 (0)	-3.118 (0)
No. of Observation	378	378	294	294

Notes: The bias corrected t-statistics (p-values) of the coefficients (of the cointegration-tests) are reported in parenthesis. * (**) denotes that the coefficient is significantly different from zero at a 10%t (5%) level. All equations include unreported, country-specific constants. The variable G7 acts as a dummy variable, which is equal to one for the seven mayor countries and zero for the non-G7 countries. Assumption: Lag(2) and Lead(2). Two test statistics are given by Pedroni (1995) based on a pooled Phillips and Perron type test with the null hypothesis is no cointegration. Regressors are assumed to be strictly exogenous. Kao (1999) presents four Dickey-Fuller type test statistics with the null hypothesis of no cointegraion. While DF_{ρ} and DF_{t} are based on the assumption of strict exogeneity of the regressors, DF_{ρ}^{*} and DF_{t}^{*} do account for endogeneity of the regressors with respect to the errors.

Table B.4: Patent Application filed by non-residents in 2001

	Patent applications filed by non-residents in 2001, broken down according to the country of residence of the applicant																			
		AU	**BE**	**CA**	**DE**	**DK**	**ES**	**FI**	**FR**	**GB**	**GR**	**IE**	**IS**	**IT**	**JP**	**NL**	**NO**	**SE**	**US**	**other**	**TOTAL**
AU	**Australia**		587	1859	7365	903	462	1424	3599	5852	46	195		1213	6057	1629	515	3253	37570	12120	84649
BE	**Belgium**	1780		2245	25806	1153	907	2010	8298	7776	78	318		3822	23117	6007	543	3945	49589	17282	154676
CA	**Canada**	1738	607		8616	907	481	1462	4244	5947	43	201		1375	7454	1641	515	3303	41752	12466	92752
DE	**Germany**	3478	2040	4055		2092	1352	3508	11744	13479	115	516		5055	32150	7738	1073	7292	85615	30874	212176
DK	**Denmark**	3447	1947	3991	31611		1305	3412	11321	13346	111	505		4902	26968	7474	1055	7140	82638	27978	229151
ES	**Spain**	3448	1948	3997	31726	2023		3414	11402	13352	112	506		4947	27253	7476	1045	7129	82870	28081	230729
FI	**Finland**	3433	1939	3966	31554	2000	1305		11313	13297	111	505		4896	26945	7450	1044	7106	82256	27916	227036
FR	**France**	1791	1459	2301	26964	1161	984	2024		7879	79	320		3976	25140	6205	545	3985	50485	18034	153332
GB	**United Kingdom**	3590	2244	4218	32344	2114	1351	3608	11604		112	641		5009	29773	7890	1186	7482	86995	30045	230206
GR	**Greece**	1780	1379	2237	25725	1134	896	2003	8246	7750		314		3809	22967	5956	543	3940	49376	17213	155268
IE	**Ireland**	1779	1378	2239	25716	1145	897	2003	8255	7812	78			3805	22966	5966	544	3939	49387	17246	155155
IS	**Iceland**	1668	572	1761	6088	896	429	1406	3198	5594	35	194		1140	4087	1539	523	3215	33473	10831	76649
IT	**Italy**	1781	1382	2253	25867	1141	896	2012	8300	7799	78	315			23598	5997	543	3954	49837	17286	153039
JP	**Japan**	1774	714	1940	15035	931	521	1615	5383	6168	48	198		1499		3409	518	3458	47750	17270	108231
NL	**Netherlands**	1781	1427	2251	25862	1154	902	2016	8293	7788	78	329		3826	23409		543	3978	49708	17480	150825
NO	**Norway**	1704	656	1840	7272	1011	454	1579	3595	5925	37	208		1232	4683	1807		3600	35422	11568	82593
SE	**Sweden**	3450	1945	3999	31627	2012	1301	3415	11331	13342	111	505		4909	27101	7482	1045		82806	27969	224350
US	**United States of America**	3102	1533	8364	27015	1645	984	2847	9213	11855	75	514		3629	66578	3631	777	4762		38226	184750