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The Pattern of International Patenting and Technology Diffusion*

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Abstract

The paper focuses on the impact of R&D expenditure on labor productivity using international patent applications as a technology diffusion indicator. Considering the relationship between research and productivity, the pattern of international patenting reflects the channel between the source and the destination of transferred technology. Accounting for nonstationarity and cointegration, I find that patent-related foreign R&D spillovers are present for a panel of 18 OECD countries. Moreover, Non-G7 OECD countries benefit more from foreign rather than domestic R&D activities. Estimates also show that there is no significant spillover effect from bilateral trade, but confirm the impact of FDI on domestic labor productivity.

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

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1. Introduction

There is an unobservable link between research in one country and productivity in other countries. As widely discussed by Keller (2004), trade, FDI and patents best reflects these unobservable connections. While many studies question empirically bilateral trade and FDI as possible technology diffusion channels, patents are not used to quantity foreign spillover effects in an appropriate way. Recently, there are empirical studies such as Xu and Chiang (2005) or Chen and Yeng (2005) using patent statistics as a proxy for technological progress as proposed by Griliches (1990). To quantify patent-related spillover effects properly, I take the view that patents should be related to R&D expenditure as a channel and not be used as a proxy for technology. In distinguishing between the source of technology and the transmission, one is able to measure and compare different technology diffusion channels. To my knowledge, there is no empirical work on foreign patents and its use as a channel to quantify foreign spillover effects. Hence, I propose to use the pattern of international patenting to analyze technology diffusion empirically and follow Eaton and Kortum (1999): *"we think that patenting abroad is a much more direct, albeit imperfect, indicator of where ideas are going"*. Accordingly, patents reflect in a direct way the channel between the source and the destination of transferred technology.

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In general, productivity as well as R&D expenditure data is nonstationary, and both variables are cointegrated within a long-run relationship. To account for nonstationarity and cointegration, and to deal with endogeneity, I use estimation techniques proposed by Kao and Chiang (2000). 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. In analyzing the steady state equilibrium between productivity and R&D expenditure, estimates in levels by Kao and Chiang's (2000) estimation techniques measure the unobservable connection best and quantify foreign spillover effects properly.

The structure of the paper is described as follows. The next section discusses foreign technology diffusion and R&D spillovers, and outlines their empirical evidence. Section 3 analyzes the theoretical framework and introduces patents, trade- and FDI-related spillover effects. In section 4, I discuss the pooled data and its use for technology diffusion. Section 5 analyzes nonstationary issues and estimation techniques. The results of the testing procedures and empirical estimations are in section 6. Section 7 concludes. Appendix (A) and (B) list specific details on assumptions and calculation as well as further estimates and testing results.

2. Foreign Technology Diffusion and R&D Spillovers

Discussing foreign technology diffusion, I first revise bilateral trade and FDI as traditional approaches for technology diffusion and outline their empirical evidence. In doing so, I am able to pass to foreign patents as an alternative technology diffusion channel and emphasis its use to quantify patent-related spillover effect.

2.1. Traditional Approches

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Are international R&D spillovers trade-related and is technology mainly embodied in intermediate goods? Coe and Helpman (1995), among others, confront this question empirically by relating the direction of technology diffusion to bilateral trade shares and analyzing the impact on total factor productivity (TFP). They find that trade-related spillover effects are present and are stronger the more open an economy to international trade and that causation runs mainly from R&D to productivity than vice versa (Frantzen, 1998). Keller (1998), however, shows by Monte Carlo simulations that randomly created bilateral trade patterns explain more of the variation in 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

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of Coe and Helpman (1995) and through 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 technology. Moreover, according to Keller (2004), there is no strong empirical evidence for learning-by-exporting spillovers beside case studies dealing with East and Southeast Asia's export success in the 1960s. Indeed, country studies, such as Ghatak, Milner and Utkulu (1997) for Malaysia, Biswal and Dhawan (1998) for Taiwan and Liu, Burridge and Sinclair (2002) for China, find evidence for an export-led growth taking into account cointegration and testing for causality. 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.

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The same criticism applies to a second strand of the literature that considers FDI as a channel for technology diffusion. Following Keller (2004), such subsidiaries might pick up new technologies from their host countries (outward FDI technology transfer) or provide technology to domestic firms (inward FDI technology transfer). Again, the macro evidence is not straightforward, as Xu and Wang (2000) mention, and the impact of technology transfer either from or to host countries still needs empirical validation. Chakraborty and Basu (2002), for example, find amongst other things that GDP in India is not Granger caused by inward FDI and that the causality is vice versa. 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 Larrain, Lopez-Calva and Rodriguez-Claré (2000),

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which analyze the impact of Intel's FDI in 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.

Given these mixed results for trade- and FDI related spillover effects, I use the pattern of international patenting as a channel for technology diffusion. The idea is that patenting domestic research efforts abroad determines the transfer of technology. Local firms may take legal advantage of patented foreign knowledge 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. In this context, international spillover effects are patent-related.

2.2. The Pattern of International Patenting

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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 drive 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 (2001), there is no empirical evidence in the case of Japan that stronger patents induce more innovation and therefore more patents. 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 submitted foreign patents followed by Germany and Japan as shown in Table B.4 in Appendix B.[1] 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 may serve to determine the direction rather than the magnitude of international technology diffusion.

In summary, the paper examines the effects of domestic and foreign business related R&D expenditure on labor productivity by the use of international patent applications as the technology diffusion channel. Patent-related spillover effects for G7 and Non-G7 OECD countries are of main interest. Additionally, I incorporate trade and FDI spillover effects to discuss the overall picture of technology diffusion and carry out some robustness tests.

3. Framework

This section discusses the theoretical framework and introduces the regression equation used to quantify foreign technology diffusion (i.e. patent (*P*)-, trade (*M*)- and FDI (*F*)-related spillover effects). Let us first consider the following aggregated production function:

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

[1] Table B.4 in Appendix (B) presents data on foreign patent application filled by non-residents from 18 OECD countries for 2001.

where Y is aggregate output, K as capital and L as workforce are input factors 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, in which case output growth depends on the measure of available intermediate goods, or vertically differentiated, in which case productivity depends on the quality of inputs. 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 R&D investments in the intermediate goods production. Hence, international trade in intermediate goods creates access to foreign technology.

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. An increase of R&D expenditure–used as a proxy for technical change–augments the efficiency of input factors used in final output production. In using and/or modifying foreign technology, countries increase their technological knowledge and capabilities. As a result, domestic input productivity and output are likely to increase.

3.1. The Regression Model

Contrary to Coe and Helpman (1995) and other related studies, I try to explain the impact of technical change on productivity of single rather than total input factors.[2] In specifying TFP,

[2] Coe and Helpman (1995) assume a Cobb-Douglas functional form with constant returns and define TFP as output divided by input factors according to their elasticity. To keep the analysis comparable, I assume aggregated output produced by a single input factor.

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figures are more susceptible to calculation and measurement errors and estimated coefficients might be less reliable due to inherent biases. Due to the more reliable data on labor input and to a lack of data for an adequate stock of business sector capital, I use labor productivity (LP). Nonetheless, I also list estimates on TFP in section 6.3. as part of the robustness tests. Taking into account the time and cross section dimension, the regression equation for LP is:

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$$\log LP_{i,t} = \log A_{i,t} = \alpha_i + \alpha^d \log S^d_{i,t} + \alpha^f b_{i,t} \log S^f_{i,t} + \varepsilon_{i,t}\,,$$

$$i = 1,\ldots,N \text{ and } t = 1,\ldots,T\,, \quad (2)$$

where i is country and t is time index, $S^d_{i,t}$ and $S^f_{i,t}$ represents domestic and foreign R&D capital stock and $\varepsilon_{i,t}$ is the error term. The term $b_{i,t}$ captures intensity of foreign technology diffusion. Note, that the right hand side of equation (2) is a proxy for technical change A.

Since the benefits of domestic research activity depend on domestic markets and traded volumes, the impact on LP due to domestic R&D spending differ between G7 and Non-G7 countries. Hence, modification of equation (2) leads to:

$$\log LP_{i,t} = \alpha_i + \alpha^d \log S^d_{i,t} + \alpha^d_{G7} G7 \log S^d_{i,t} + \alpha^f b_{i,t} \log S^f_{i,t} + \varepsilon_{i,t}\,, \quad (3)$$

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

3.2. Variable Definitions

By the use of the perpetual inventory method, I follow Coe and Helpman (1995) and calculate the domestic R&D capital stock as described in Appendix A. Turning to foreign R&D capital stocks and their intensity, definitions of $S^f_{i,t}$ and $b_{i,t}$ differ according to the channel for technology diffusion and are explained in the following subsections.

Patent-Related Spillover Effects

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

$$S_{i,t}^{f} \equiv S_{i,t}^{f,P} = \frac{1}{\sum_{j\neq i} a_{ji,t}} \sum_{j\neq i} (a_{ji,t} S_{j,t}^{d}), \qquad j = 1,\ldots,N, \tag{4}$$

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 *j*'s technology diffusion channel to country *i*.

Patent count data mainly serve to determine the direction rather than the intensity of technology diffusion. Hence, as a reference, I do not specify foreign technology intensity explicitly:

$$b_{i,t} \equiv b_{i,t}^{P} = 1. \tag{5}$$

However, in gauging technology intensity to distinguish between the impact of foreign and domestic research and therefore between countries, one could use two different measures. First, the use of patent-related foreign technology should be more efficient in countries with their own research activity and with higher domestic R&D spending. Hence, a country that spends more on R&D relative to its GDP should benefit more from foreign technology diffusion. In relating business related R&D expenditure ($R\&D_{i,t}$) to GDP ($Y_{i,t}$), I define patent-related foreign technology intensity as:

$$b_{i,t} \equiv b_{i,t}^{P} = R\&D_{i,t} / Y_{i,t}. \tag{6}$$

Nevertheless, equation (6) decreases the availability to explain high productivity levels in small countries via 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 from major research countries lead to a high non-resident to resident patent application ratio in small countries. Given almost similar productivity levels across OECD countries, the impact of foreign technology from abroad must be higher in countries with a high share of foreign patent applications to domestic patent applications. For this reason, the ratio of foreign to total patent applications may also serve as a proxy for patent-related foreign technology intensity:

$$b_{i,t} \equiv b_{i,t}^{P} = \sum_{j \neq i} a_{ji,t} / \sum_{j} a_{ji,t} , \qquad j = 1,...,N . \qquad (7)$$

Trade- and FDI-Related Spillover Effects

To capture trade-related spillover effects, Coe and Helpman (1995) define foreign R&D capital stock as the average of domestic R&D capital stocks from abroad weighted by bilateral import shares:

$$S_{i,t}^{f} \equiv S_{i,t}^{f,M} = \frac{1}{m_{i,t}} \sum_{j \neq i} (m_{ji,t} S_{j,t}^{d}) , \qquad j = 1,...,N , \qquad (8)$$

where $m_{ji,t}$ is country *j*'s import and $m_{i,t}$ is total imports of country *i*. Note that the ratio of $m_{ji,t} / m_{i,t}$ defines the trade-related diffusion channel. Coe and Helpman (1995) also propose the use of an additional measure to capture technology intensity and therefore openness to trade. Given the 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, a measure of trade-related foreign technology intensity is:

$$b_{i,t} \equiv b_{i,t}^{M} = m_{i,t} / Y_{i,t} . \quad (9)$$

Due to the lack of adequate bilateral FDI inflow data, the procedure to determine foreign technology stocks differs in the case of FDI-related spillover effects. Instead of calculating technology diffusion channels and relating them to domestic R&D stocks from abroad, I use aggregate FDI inflow data to calculate FDI inflow stocks:

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$$S_{i,t}^{f} \equiv S_{i,t}^{f,F} = (1-\delta) S_{i,t-1}^{f,F} + \sum_{j \neq i} FDI_{ji,t-1} , \qquad j = 1,\ldots,N , \quad (10)$$

with $FDI_{ji,t}$ as foreign direct investment from country j to country i and δ as a time- and country-invariant depreciation rate. Again, the benchmark for the FDI inflow stock is calculated as described in Appendix A. Note that equation (10) is a proxy of foreign technology by FDI and interpretation is different compared to equation (4) and (8), where patents and bilateral trade are diffusion channels. Hence, I do not express FDI-related technology intensity explicitly:

$$b_{i,t} \equiv b_{i,t}^{F} = 1 . \quad (11)$$

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4. Data

The paper measures the impact of international technology diffusion on LP. Calculating productivity figures, one can distinguish the number of persons engaged and the number of hours actually worked. I use worked hours 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 (GGDC). Figures on TFP are calculated from TFP growth rates provided from the *Total Economy Growth Accounting Database* by the GGDC.

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The OECD has published data on BERD since about 1965 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.[3] However, the lack of R&D data as well as patent numbers limits the analysis in this paper to 1981-2001 and to 18 OECD countries.[4] 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.[5] The time- and country-invariant depreciation rate is assumed to 10%.[6] The R&D expenditure data is from the OECD *Main Science and Technology Database* and is in million constant US$ (PPP)

The OECD also has been publishing patent figures since the early 1980s. As discussed, I use country specific patent data as the main technology diffusion channel. The OECD does not provide bilateral 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 Property Statistics Publication B Part I*). However, figures based on patent applications instead of grants are more reliable and complete. I prefer to use patent applications. Moreover, the WIPO lists patent data 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 effects to the analysis, figures consist of data published by the OECD in the *Monthly Statistics of International Trade* and the *International Direct Investment Statistics,* respectively. To relate domestic R&D capital stocks to

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[3] The reader is referred to the paper for further details and discussions.
[4] 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.
[5] See Appendix (A) for an analytical derivation as well as Table A.1 for further information.
[6] Given depreciation rates for capital stocks between 5% and 15% used in comparable studies, I also run regressions assuming a depreciation rate of 5%. As expected, the results do not change and the main conclusions remain valid. Table B.3 in Appendix (B) lists the results.

bilateral trade patterns, I use figures on import as well as on GDP in million current US$. GDP data (market price, value) is from the OECD *Economic Outlook Database*. To generate FDI inflow capital stocks, I apply once again the perpetual inventory method.[7] A R&D deflator as well as PPP data converts FDI figures into million constant US$ (PPP).[8] Due to the lack of adequate FDI inflow data over the period 1981–2001, Greece, Iceland, Ireland and Norway are chopped from the pooled sample in the case of FDI-related spillover effects. This reduces the number of observed units to 14 OECD countries.

Like Coe and Helpman (1995), I calculate LP and TFP as indexed figures (1995=1). However, due to the index 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 signified 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. This formulation would reflect the intensity as well as the direction of technology transfer but circumvent the aggregation bias. Since it will also aggravate the business cycle problem with foreign GDP in the denominator, I rather ignore the aggregation bias and rest on R&D capital stock expressed by equation (4) and (8). Nonetheless, I compare the alternative weighting measures in section 6.3. as part of the robustness tests.

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Indexation and Aggregation Bias

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[7] The OECD provides FDI flow- and stock data in their *International Direct Investment Statistics*. However, data on inward and outward positions are not complete for some countries or periods. I therefore prefer to use FDI flow data and to calculate stock variables.

[8] See Table A.2 in Appendix (A) for further information. The R&D deflator is derived from BERD figures published in million current US$ (PPP) 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*.

5. 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 a 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 strictly exogenous regressors. There might also be feedback from productivity to R&D and endogeneity as well as serial correlation drives and biases estimators.[9]

To address nonstationarity and endogeneity and to avoid spurious correlation among variables, I use estimation techniques proposed by Kao and Chiang (2000) and adopt their techniques as in Kao, Chiang and Chen (1999) and Funk (2001).[10] 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, in analyzing the steady state equilibrium between domestic productivity and foreign R&D expenditure, estimates in levels quantify foreign technology diffusion properly.

Unit Root Tests

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

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, as Breitung and Meyer (1994), that

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[9] Baltagi (2001) provides an excellent overview for nonstationary issues as well as cointegration.
[10] 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/.

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 that the error term is serially correlated across cross-sectional units. The IPS test examines the null hypothesis that each series has a unit root ($H_0 : \rho_i = 1$) against the alternative hypothesis that 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 stationary ($H_0 : \textit{stationarity}$) against the alternative hypothesis of a unit root in panel data ($H_1 : \textit{nonstationarity}$). 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.

According to Baltagi (2001, p.239): *"LLC and IPS tests require* $N \to \infty$ *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 rejected only if there is strong evidence against it, I try to overcome this lack of power by testing both nonstationarity as well as stationarity for the null hypothesis.

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[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).

Cointegration Tests

To test for the long-run cointegration relationship (i.e. stationarity of the error term), one can either use the corresponding error terms in the error correction (EC) model or the proposed cointegration tests presented by Kao (1999), McCoskey and Kao (1998) and Pedroni (2004).

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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.

Cointegration 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 (2004) does, 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 (2004) can residuals be derived from OLS estimation. For McCoskey and Kao (1998) an efficient estimation technique other than OLS is necessary.

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

The presence of cointegration and unit roots considerably affect 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. Consequently, Kao and Chiang (2000) 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 introduces leads and lags of the differentiated regressors to the estimation. Kao and Chiang (2000) derive the following limiting distribution: the OLS estimator is normally distributed with non-zero mean, whereas the FM-OLS 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 to accommodate cointegration and unit roots.[12]

6. Empirical Results

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 using Kao and Chiang (2000)'s estimation techniques. Next, I divide countries between G7 and Non-G7 and reduce estimates to the use of the DOLS estimator. I also incorporate trade- and FDI-related spillover effects to complete the analysis of technology diffusion. Finally, I conduct some robustness tests to validate the derived results.

6.1. Patent-Related Spillover Effects

Initially, nonstationary and cointegration tests have to confirm that the data is nonstationary and the variables are cointegrated. Once confirmed, I quantify patent-related spillover effects and discuss the impact of the different technology intensity measures on labor productivity.

[12] For further information as well as for analytical derivation see Kao and Chiang (2000).

Test Results for Unit Roots

To analyze whether the data follows a nonstationary path or not, I apply unit root tests by LLC and IPS as well as by LMH. The null hypothesis is nonstationarity for LLC as well as IPS and stationarity for LMH. Table 1 shows test statistics and *p*-values in parenthesis for an individual and time trend. Turning to the null hypothesis of nonstationarity, the LLC and IPS testing procedure do not reject the null hypothesis and therefore confirm nonstationarity for all variables at least at the 10% level in the case of two lags. If there is one lag, the results for the domestic R&D capital stock and foreign R&D capital stock by equation (4) are somehow mixed. Especially for the domestic R&D capital stock, both testing procedure reject nonstationarity. However, turning to the null hypothesis of stationarity, the LMH testing procedure confirms unit roots and nonstationarity for the entire set of data. Given the results in Table 1 by LMH and by LLC and IPS, especially for two lags, I conclude the all variables are nonstationary.

[Table 1]

Test Results for Cointegration

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 to avoid spurious results. Test procedures based on the EC model as well as on test statistics from Pedroni (2004) and Kao (1999) are in Table 2. Considering the EC model first, the 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 (2) with (4) in combination with technology intensity measures (5)-(7), showing that the error term is stationary. Turning to the tests of no cointegration by

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Pedroni (2004), both test statistics reject the null hypothesis and confirm cointegration. Test statistics from Kao (1999) are somehow mixed. Especially for the case of endogenous regressors with respect to the errors, test statistics DF_{ρ}^{*} and DF_{t}^{*}, test results do not reject the null hypothesis of no cointegration for equation (2) with (4) and (6). However, given the overall picture of test statistics confirming cointegration, I conclude that there is a long-run relationship between the cointegrated variables. Finally, with nonstationary and cointegrated data, the focus turns to the empirical results.

[Table 2]

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

Table 3 lists coefficients and their test statistics in parentheses estimated 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 (2) with (4) and (5) 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 percentage points higher. This is the result of the two different ways of removing the nuisance parameter (serial correlation) and accounting for 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 estimator, however, introduces leads and lags with a bigger impact on coefficients compared to pooled OLS. Turning to equations (2) with (4) in combination with either (6) or

[13] Both papers estimate the impact of domestic R&D amongst others variables on TFP. However, the impact of domestic R&D on either total or labor productivity should not vary largely. The coefficient is 0.097 for Coe and Helpman (1995) using pooled OLS. For Kao, Chiang and Chen (1999) the coefficient is 0.084 by the use of OLS with bias correction or FM-OLS and 0.107 by DOLS.

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(7), estimates suggest a higher elasticity for domestic R&D capital stock, which vary between 0.11-0.20 percent. 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 least at the 5% level in each case.

[Table 3]

To quantify the impact of foreign R&D capital stocks on domestic labor productivity, I multiply the coefficients with 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 equations (4) and (6) to almost 0.02 percent in the best and zero in the worst case. For the case of patent weighted foreign R&D capital stocks given by equations (4) and (7), a ratio less than one reduces the estimated coefficient 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 the small variation in productivity levels across different countries. However, without any additional specification for technology intensity as by equation (5), the impact of foreign R&D capital stock on domestic factor productivity is about 0.22 percent for OLS with bias correction/FM-OLS and 0.17 percent for DOLS. All coefficients are significant at a 1% level.

Given the superiority of the DOLS estimator over OLS with bias correction and FM-OLS and considering equations (4) and (5) as an adequate approximation of technology spillover effects, I conclude that there are patent-related spillover effects. Hence, a one percent increase in domestic or foreign R&D capital stock leads to a 0.10 percent or 0.17 percent increase in domestic labor productivity, respectively.

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

However, the impact of domestic R&D on factor productivity differs between G7 and Non-G7 OECD countries. Table 4 shows estimation results by DOLS for equations (3) with (4) in combination with (5)-(7). I also list cointegration test statistics by Pedroni (2004) although a cointegrated relationship amongst productivity and R&D expenditure will not change due to a division of countries.

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[Table 4]

As expected, test statistics from Pedroni (2004) confirm cointegration. Again, coefficients for foreign R&D capital stock expressed by (4) in combination with (6) or (7) are too low. Due to the discussed lack of plausibility in explaining productivity levels across OECD countries, the analysis reduces to equation (3) with (4) and (5) in the first column in Table 4. The impact of domestic research activity for G7 countries rises to 0.25 percent while for Non-G7 OECD countries it remains nearly unchanged. However, the differences between both sets of countries are not statistically significant in this case. 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 0.14 percent but is still significant at a 1% level. As expected, the impact on labor productivity for Non-G7 OECD countries is higher due to foreign rather than domestic R&D activities. This emphasizes the importance of technological spillover effects from abroad for these countries. Nevertheless, tests do not confirm that the coefficient for foreign R&D capital stock is significantly larger than the coefficient for domestic R&D capital stock.

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6.2. Patent-, Trade- and FDI-Related Spillover Effects

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

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

$$i = 1,\ldots,N \text{ and } t = 1,\ldots,T, \quad (12)$$

with patent-, trade- and FDI-related spillover effects as described by equation (4) with (5), equation (8) with (9) and equation (10) with (11), respectively.

Table 5 shows the impact on labor productivity for G7 and Non-G7 OECD countries by DOLS 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 stocks related to bilateral trade and FDI. Moreover, test statistics of Pedroni (2004) as well as of Kao (1999) in Table B.2 in Appendix (B) show stationarity of the error term for each regression and therefore confirm cointegration. I also repeat the estimates of equation (3) with (4) and (5) in the first column in Table 5.

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Including bilateral trade pattern, estimates in the first scenario are quite close to those derived for equation (3) with (4) and (5): the coefficient for patent-related foreign R&D spillover effects (0.125) remains significant at a 1% level and still exceeds the coefficient for domestic R&D capital stock for Non-G7 OECD countries (0.104). Interestingly, the DOLS es-

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timator negates any statistical significance of trade related spillover effects as in Kao, Chiang and Chen (1999). However, coefficients are slightly lower compared to the first column.

Considering the second scenario and adding FDI inflow stocks instead of trade weighted R&D stocks to the regression, the domestic R&D coefficients for Non-G7 countries reduces by more than 50%. Coefficients for G7 countries as well as for patent-related spillover effects are substantially lower than those in the first column. However, the differences between both sets of countries are now statistically significant (the coefficient for G7 countries is significant at a 1% level) and my key results remain robust: there are patent-related R&D spillover effects, and the impact on labor productivity for Non-G7 countries is higher due to foreign rather than domestic R&D activities. According to the estimates, there is a positive impact on domestic labor productivity of about 0.06 percent from FDI inflows. Both coefficients for technology diffusion are significant at a 1% level. Finally, testing whether the coefficient for patent-weighted foreign R&D capital stock is significantly larger than the coefficient for domestic R&D capital stock lead to ambiguous results: significance is rejected by the DOLS estimator but confirmed by the FM-OLS estimator.

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By the third scenario, estimation of equation (12) leads to no major change in the results compared to the second scenario and coefficients as well as test results rarely change due to the incorporation of bilateral trade as a diffusion channel. Estimates again confirm the impact and importance of patent- and FDI-related spillover effects on labor productivity and negate any bilateral trade significance.

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[Table 5]

6.3. Robustness Tests

This section returns to patents once again and analyses three modifications to the econometric modeling to test the robustness of the derived results for patent-related spillover effects. First, I apply TFP instead of LP as the dependent variable. Second, I use randomly created weights by Monte Carlo Simulation to calculate foreign R&D capital stocks and to respond to Keller's (1998) critique on using a specific weighing choice as in equation (4). Third, being aware of the aggregation-bias using patent-based weights as in equation (4), I introduce a different weighting method to reflect the direction of technology transfer.

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To compare, I estimate equation (3) with (4)/(5) by the use of the DOLS estimator. Equation (4) changes respectively, whereas equation (5) remains unchanged. According to the modification, nonstationarity testing results from LLC and IPS are in Table 6 as one goes down rows, whereas estimation results and cointegration test statistics from Kao (1999) are in the corresponding column of Table 7.

[Table 6]

Total Factor Productivity

The GGDC also provides TFP data for 13 countries[14] over a period of 21 years. Test statistics confirm nonstationarity of TFP in the first row of Table 6 and cointegration in the first column of Table 7. I also find a highly significant impact of domestic R&D on TFP (0.171). However, I do not find any significant patent-related spillover effect on TFP contrary to the estimated results in Table 4 but comparable to the results of Kao, Chaing and Chen (1999) for the case of trade-related spillover effects. One could possibly argue by the smaller number of countries and/or calculation and measurements errors, but I suggest further work on TFP and its use to quantify foreign spillover effects. To summarize, there are patent-related spillover effects in the case of labor productivity, whereas in the case of TFP there are none.

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[14] The 13 OECD countries are respectively: Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Spain, Sweden, United Kingdom, and USA.

Random Shares for Patent-Related Spillover Effects by Monte Carlo Simulation

If randomly assigned weights generate statistically significant results, as Keller's (1998) Monte Carlo Simulation on the results of Coe and Helpman (1995), the finding and size of spillovers are independent of the weighting method. If so, the choice of patent-based weights in equation (4) or any other empirically observed pattern cannot be used to quantify patent-related spillover effects. However, before turning to the estimation results, one has to be sure that the variables are nonstationary: test statistics by LLC with one lag and IPS with both lags reject the null hypothesis of nonstationarity of randomly weighted foreign R&D stocks. Given nonstationarity of the remaining variables–as listed and discussed in Table 1–a stationary error term and therefore cointegration is not likely to exist. This is confirmed at least by the DF_ρ and DF_t tests of Kao (1999) in the second column of Table 7. Hence, the findings of randomly created spillover effects are spurious owing to absent cointegration and Keller's (1998) critique is inappropriate. Table 7 does not report t-statistics of the estimated coefficients.

[Table 7]

Non Aggregation-Bias: Alternative Patent-Based Weighting Approach

Accounting for the aggregation-bias, I change the patent-based weighting approach by the use of foreign GDP instead of the sum of foreign patent applications in the denominator of equation (4). Turning to Table 6, the LLC as well as IPS testing procedure confirms nonstationarity for alternative weighted foreign R&D capital stocks at least for the 10% level. Three of four tests from Kao (1999) in Table 7 confirm cointegration and the estimated coefficients for domestic R&D capital stocks for G7 and Non-G7 OECD countries are significant at the 1% level. Table 7 shows also a significant impact on labor productivity of foreign R&D capital stocks. Quantifying patent-related spillover effects, the estimated coefficient (0.023) in Table

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7 is low compared to the corresponding coefficient (0.139) in Table 4. A possible explanation could be the absorbing effect of foreign GDP as part of the weighting approach and the distortion of foreign business cycle impacts. However, according to the estimates in Table 4 and Table 7, the result of patent-related spillover effects is robust to the patent weighting scheme.

7. Conclusion

I use international patent applications as a diffusion channel to measure the impact of technology spillover effects on factor productivity. In considering the relationship between research and productivity, the pattern of international patenting 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 appropriate to data exhibiting nonstationarity and cointegration, I find evidence of patent-related foreign spillover effects. Moreover, a one percent increase in R&D spending abroad raises labor productivity between 0.08 and 0.14 percent. For Non-G7 OECD countries, the impact on labor productivity is higher due to foreign rather than domestic R&D activities. However, this conclusion should be taken with some care since test statistics are mixed confirming significance. Additionally, estimates show that there is no significant influence on labor productivity from bilateral trade, whereas FDI inflows are confirmed as a major source of technology transfer. Conducting robustness tests, the evidence of patent-related spillover effects on labor productivity is robust to different patent-based weighting scheme. Moreover, randomly assigned weights as a counterfactual to determine foreign R&D are shown to be inappropriate emphasizing the role of foreign patents as a main technology diffusion channel.

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Appendix

Appendix (A) lists specific details on assumptions and methods of calculation. Appendix (B) lists further estimates and tables. 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 average 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:

$$S_0 = E(S_t) = \frac{E(F_t)}{(\delta + g)}, \qquad t = 0. \qquad \text{(A.3)}$$

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

By the use of BERD expenditure flows, R&D benchmark stocks ($S^{d}_{i,0}$ for $i = 1,...,18$) are calculated according equation (A.3). I calculate the average as well as the annual average growth rate of R&D expenditure by the period, in cases where the OECD has published R&D data in the *Main Science and Technology Database*. The expected flow is the first year for which the data is available as proposed by Griliches (1979) and applied in Coe and Helpman (1995). The country and time-invariant depreciation rate is assumed to 10%. Table A.1 lists figures in million constant US$ (PPP) for 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	Ann. Growth	1981	Benchmark
Australia	1981-2001	6.292	9.633	590.961	3010.100
Belgium	1981-2002	2.505	4.471	1664.318	11501.288
Canada	1981-2002	3.157	5.627	2811.163	17989.101
Denmark	1981-2002	5.117	8.084	469.921	2598.537
Finland	1981-2002	6.186	9.065	494.054	2591.381
France	1981-2002	1.886	3.066	10528.354	80575.198
Germany	1981-2002	1.764	2.739	19239.356	151026.375
Greece	1981-2001	7.837	10.843	46.079	221.076
Iceland	1981-2002	48.393	20.289	2.814	9.290
Ireland	1981-2001	7.985	10.946	109.359	522.094
Italy	1981-2002	1.619	2.320	4461.281	36212.654
Japan	1981-2002	2.743	4.921	25561.785	171309.289
Netherlands	1981-2002	1.833	2.929	2292.401	17731.359
Norway	1981-2002	2.734	4.905	495.340	3323.209
Spain	1981-2002	5.534	8.489	797.862	4315.433
Sweden	1981-2001	3.584	6.590	2058.273	12406.660
U.K	1981-2002	1.453	1.794	12089.344	102499.844
United States	1981-2002	2.113	3.626	81589.277	598782.230

Notes: The benchmark relates to the year 1981 for all countries and is calculated following equation (A.3) and the procedure suggested by Griliches (1979). Depreciation rate is assumed to 10%. Average and annual average growth rates are calculated over the period, where R&D expenditure data was published.

FDI Capital Stock Data

Due to negative figures for some countries at the beginning of the sample, I calculate the average- and annual average growth rates as well as the expected flow by the use of FDI inflow data over the first 10 years. The benchmark for FDI inflow stocks ($S^{f,F}_{i,0}$ for $i = 1,...,14$) for each country follows equation (A.3). A R&D deflator as well as PPP data converts FDI figures into million constant US$ (PPP). The country and time-invariant depreciation rate is assumed to 10%. Table A.2 lists figures in million current US$ for 14 OECD countries.

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	Ann.Growth	Exp. Flow	Benchmark
Australia	1980-2001	5.003	1980-1990	3.481	13.285	1747.813	7506.069
Belgium	1980-2001	23.061	1980-1990	5.911	19.444	942.221	3200.048
Canada	1980-2001	19.229	1980-1990	11.081	27.191	478.381	48983.791
Denmark	1980-2001	23.110	1980-1990	8.427	23.756	89.191	264.224
Finland	1980-2001	26.242	1980-1990	34.411	42.452	16.277	31.033
France	1980-2001	14.092	1980-1990	4.511	16.260	2213.257	8428.221
Germany	1981-2001	22.927	1981-1990	7.307	24.730	582.583	1677.469
Italy	1980-2001	16.641	1980-1990	10.754	26.812	594.905	1616.082
Japan	1980-2001	21.485	1980-1990	9.233	24.891	400.328	1147.358
Netherlands	1980-2001	16.741	1980-1990	4.393	15.951	1163.358	4482.868
Spain	1980-2001	14.848	1980-1990	11.621	27.798	959.252	2537.825
Sweden	1981-2001	18.450	1981-1990	4.897	19.304	364.017	1242.201
U.K	1980-2001	10.979	1980-1990	5.159	17.830	3818.008	13719.223
United States	1980-2001	11.238	1980-1990	2.842	11.011	20584.343	97967.582

Notes: The benchmark relates to the year 1980 for all countries except for Germany and Sweden with 1981 as the benchmark year. Figures are calculated following equation (A.3). Depreciation rate is assumed to 10%. Average- and annual average growth rates as well as the expected flow are calculated over the first 10 years, where FDI inflow data was published

(B) Additional Estimation Results and Tables

Table B.1: Unit Root Tests by Levin, Lin and Chu (2002) [a] **; Im, Peseran and Shin (2003)** [b]
(Annual data for 18 countries for equation (8)/(9) and for 14 countries for equation (10) from 1981-2001)

Individual and Time:	LLC, Lag (1)	LLC, Lag (2)	IPS, Lag (1)	IPS, Lag (2)
(8)/(9): $b^M \log S^{f,M}$	-0.403 (0.343)	2.636 (0.996)	-1.04 (0.15)	-0.232 (0.592)
(10): $\log S^{f,F}$	3.423 (1)	5.224 (1)	1.54 (0.938)	2.567 (1)

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

[a] The null hypothesis is nonstationarity while the alternative hypothesis is that all individual series are stationary with identical (individual) first order autoregressive coefficients.

[b] The null hypothesis is nonstationarity while the alternative hypothesis is that some individual series are stationary with identical (individual) first order autoregressive coefficients.

Table B.2: Cointegration Tests by Pedroni (2004) [a] **and Kao (1999)** [b] **;**
Patent-, Trade- and FDI-Related Spillover Effects
(Pooled data for 18 countries for equation (3) with (4)/(5) and equation (3) with (4)/(5) and (8)/(9) from 1981-2001; 14 countries for equation (3) with (4)/(5) and (10)/(11) and equation (12) from 1981-2001)

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Equations:	(3) with (4)/(5)	(3) with (4)/(5) and (8)/(9)	(3) with (4)/(5) and (10)/(11)	(12)
Pedroni (2004)				
PC_1	-7.314 (0)	-7.304 (0)	-16.839 (0)	-16.864 (0)
PC_2	-7.138 (0)	-7.128 (0)	-16.434 (0)	-16.457 (0)
Kao (1999)				

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DF_ρ	1.79 (0.037)	1.787 (0.037)	-2.552 (0.01)	-2.57 (0.01)
DF_t	1.617 (0.05)	1.612 (0.05)	-2.273 (0.01)	-2.294 (0.01)
DF_ρ^*	-2.075 (0.02)	-2.043 (0.02)	-8.074 (0)	-8.144 (0)
DF_t^*	-0.803 (0.211)	-0.797 (0.213)	-3.133 (0)	-3.144 (0)

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

[a] Two test statistics are given by Pedroni (2004) 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.

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

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

(Pooled data for 18 countries for equation (3) with (4)/(5) and equation (3) with (4)/(5) and (8)/(9) from 1981-2001; 14 countries for equation (3) with (4)/(5) and (10)/(11) and equation (12) from 1981-2001)

Equations:	**(3) with (4)/(5)**	**(3) with (4)/(5) and (8)/(9)**	**(3) with (4)/(5) and (10)/(11)**	**(12)**
DOLS:				
$\log S^d$	0.104 (2.842)***	0.104 (2.83)***	0.039 (1.475)	0.04 (1.543)
$G7\ \log S^d$	0.145 (1.569)	0.141 (1.535)	0.133 (3.415)***	0.137 (3.522)***
$\log S^{f,P}$	0.144 (3.2)***	0.129 (2.903)***	0.084 (3.637)***	0.079 (3.356)***
$b^M \log S^{f,M}$		-0.05 (-0.16)		-0.012 (-0.083)
$\log S^{f,F}$			0.065 (8.413)***	0.065 (7.855)***
R^2	0.693	0.706	0.92	0.923
Cointegration-Test:				
Pedroni (2004) [a]				
PC_1	-7.346 (0)	-7.35 (0)	-16.657 (0)	-16.71 (0)
PC_2	-7.168 (0)	-7.173 (0)	-16.256 (0)	-16.31 (0)
Kao (1999) [b]				
DF_ρ	1.741 (0.04)	1.742 (0.04)	-2.684(0)	-2.681 (0)
DF_t	1.516 (0.06)	1.518 (0.06)	-2.342 (0.01)	-2.392 (0.01)
DF_ρ^*	-2.162 (0.02)	-2.128 (0.02)	-8.229 (0)	-8.342 (0)
DF_t^*	-0.867 (0.193)	-0.857 (0.196)	-3.18 (0)	-3.211 (0)
No. of Observation	378	378	294	294

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Notes: The bias corrected *t*-statistics (*p*-values) of the coefficients (of the cointegration-tests) are reported in parentheses. * (**) [***] denotes that the coefficient is significantly different from zero at a 10% (5%) [1%] level. All equations include unreported, country-specific constants. The variable G7 acts as a dummy variable, which is equal to one for the seven major countries and zero for the Non-G7 OCED countries. Assumption: Lag (2) and Lead (2).

[a] Two test statistics are given by Pedroni (2004) 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.

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

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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

Notes: The last column is the total number of foreign patent applications received by the country in the corresponding row. The United States, for example, is the dominating source of submitted foreign patents followed by Germany and Japan, whereas the number of received foreign patents ranks Spain followed by the UK and Denmark in the first place.
Source: Industrial Property Statistics Publication B Part I by WIPO

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Tables

Table 1: Unit Root Tests by Levin, Lin and Chu (2002) [a] ; Im, Pesaran and Shin (2003) [b] ; Hadri (2000) [c]
(Annual data for 18 countries from 1981-2001; Observations: 342 with lag (1); Observations: 324 with lag (2)

Individual and Time:	**LLC, Lag (1)**	**LLC, Lag (2)**	**IPS, Lag (1)**	**IPS, Lag (2)**	**LMH**
$\log LP$	1.245 (0.89)	3.199 (1)	-0.147 (0.44)	0.259 (0.60)	10.574 (0)
$\log S^{d}$	-4.814 (0)	2.775 (1)	-5.71 (0)	-0.772 (0.22)	8.07 (0)
(4): $\log S^{f,P}$	-8.403 (0)	7.972 (1)	3.587 (1)	3.005 (1)	8.914 (0)
(4)/(6): $b^{P} \log S^{f,P}$	3.150 (1)	3.802 (1)	2.623 (1)	1.844 (0.97)	8.741 (0)
(4)/(7): $b^{P} \log S^{f,P}$	-1.11 (0.13)	-1.358 (0.08)	-0.085 (0.466)	-0.7 (0.24)	10.163 (0)

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

[a] The null hypothesis is nonstationarity while the alternative hypothesis is that all individual series are stationary with identical (individual) first order autoregressive coefficients.

[b] The null hypothesis is nonstationarity while the alternative hypothesis is that some individual series are stationary with identical (individual) first order autoregressive coefficients.

[c] The null hypothesis is trend stationarity for LMH while the alternative hypothesis is nonstationarity. Assumption: Error term is heteroskedastic across units and serially correlated over time.

Table 2: Cointegration Tests by the EC Model [a] , Pedroni (2004) [b] and Kao (1999) [c] ; Patent-Related Spillover Effects
(Pooled data for 18 countries from 1981-2001)

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Equation:	**(2) with (4)/(5)**	**(2) with (4)/(6)**	**(2) with (4)/(7)**
EC-Model:			
t-statistics of the EC-modell	-3.62 (0)	-3.74 (0)	-3.63 (0)
Pedroni (2004):			
PC_1	-7.579 (0)	- 6.286 (0)	-7.510 (0)
PC_2	-7.397 (0)	- 6.135 (0)	-7.329 (0)
Kao (1999):			
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)

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

[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 whether the lagged error correction term is significantly different from zero or not. A cointegration relationship amongst variables exits if the *t*-statistics is significant. Assumption: Lag (1).

[b] Two test statistics are given by Pedroni (2004) 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.

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

Table 3: Labor Productivity Estimation Results by OLS with Bias Correction, FM-OLS and DOLS; Patent-Related Spillover Effects
(Pooled data for 18 countries from 1981-2001)

Equation:	**(2) with (4)/(5)**	**(2) with (4)/(6)**	**(2) with (4)/(7)**
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 in parentheses. * (**) [***] denotes that the coefficient is significantly different from zero at a 10% (5%) [1%] level. All equations include unreported, country-specific constants. Assumptions for DOLS: Lag (2) and Lead (2).

Table 4: Labor Productivity Estimation Results for G7 and Non-G7 OECD Countries by DOLS; Patent-Related Spillover Effects
(Pooled data for 18 countries from 1981-2001)

Equation:	**(3) with (4)/(5)**	**(3) with (4)/(6)**	**(3) with (4)/(7)**
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 (2004) [a]			
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 in parentheses. * (**) [***] denotes that the coefficient is significantly different from zero at a 10% (5%) [1%] level. All equations include unreported, country-specific constants. The variable *G7* acts as a dummy variable, which is equal to one for the seven major countries and zero for the non-G7 countries. Assumption: Lag (2) and Lead (2).

[a] Two test statistics are given by Pedroni (2004) based on a pooled Phillips and Perron type test in which the null hypothesis is no cointegration. Regressors are assumed strictly exogenous. Residuals are derived from an OLS estimation.

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Table 5: Labor Productivity Estimation Results for G7 and Non-G7 OECD Countries by DOLS; Patent-, Trade- and FDI-Related Spillover Effects

(Pooled data for 18 countries for equation (3) with (4)/(5) and equation (3) with (4)/(5) and (8)/(9) from 1981-2001; 14 countries for equation (3) with (4)/(5) and (10)/(11) and equation (12) from 1981-2001)

Equations:	**(3) with (4)/(5)**	**(3) with (4)/(5) and (8)/(9)**	**(3) with (4)/(5) and (10)/(11)**	**(12)**
DOLS:				
$\log S^{d}$	0.107 (2.89)***	0.104 (2.85)***	0.044 (1.658)*	0.045 (1.689)*
G7 $\log S^{d}$	0.144 (1.568)	0.138 (1.515)	0.128 (3.225)***	0.131 (3.305)***
$\log S^{f,P}$	0.139 (3.072)***	0.125 (2.819)***	0.085 (3.574)***	0.082 (3.405)***
$b^{M} \log S^{f,M}$		-0.008 (-0.025)		0.003 (0.019)
$\log S^{f,F}$			0.062 (8.403)***	0.062 (7.838)***
R^2	0.683	0.657	0.919	0.92
No. of Observation:	378	378	294	294

Notes: The bias corrected *t*-statistics (*p*-values) of the coefficients (of the cointegration-tests) are in parentheses. * (**) [***] denotes that the coefficient is significantly different from zero at a 10% (5%) [1%] level. All equations include unreported, country-specific constants. The variable G7 acts as a dummy variable, which is equal to one for the seven major countries and zero for the Non-G7 countries. Assumption: Lag (2) and Lead (2).

Table 6: Unit Root Tests by Levin, Lin and Chu (2002) [a]; Im, Peseran and Shin (2003) [b]

(Annual data for 18 (13) countries from 1981-2001)

Individual and Time:	**LLC, Lag (1)**	**LLC, Lag (2)**	**IPS, Lag (1)**	**IPS, Lag (2)**
TFP:				
$\log TFP$	0.209 (0.58)	2.531 (1)	-1.278 (0.1)	-0.319 (0.37)
Random Shares:				
$\log S^{f,P}$	-4.814 (0)	-0.576 (0.28)	-5.71 (0)	-4.46 (0)
Non Aggregation-Bias:				
$\log S^{f,P}$	-1.533 (0.063)	1.614 (0.95)	-1.343 (0.09)	1.397 (0.92)

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

[a] The null hypothesis is nonstationarity while the alternative hypothesis is that all individual series are stationary with identical (individual) first order autoregressive coefficients.

[b] The null hypothesis is nonstationarity while the alternative hypothesis is that some individual series are stationary with identical (individual) first order autoregressive coefficients.

Table 7: Productivity Estimation Results for G7 and Non-G7 OECD Countries by DOLS; Patent-Related Spillover Effects
(Pooled data for 18 (13) countries from 1981-2001)

	TFP	**Random Shares**	**Non Aggregation-Bias**
Equation:	**(3) with (4)/(5)**	**(3) with (4)/(5)**	**(3) with 4/(5)**
Dependent Variable:	*log TFP*	*log LP*	*log LP*
DOLS:			
$\log S^{d}$	0.171 (4.94)***	0.134	0.14 (3.51)***
$G7\ \log S^{d}$	0.155 (1.5)	0.146	0.218 (2.46)***
$\log S^{f,P}$	-0.01 (-0.26)	0.085	0.023 (1.7)*
R^2	0.64	0.69	0.67
Cointegration-Test:			
Kao (1999) [a]			
DF_{ρ}	1.739 (0.04)	-0.636 (0.26)	1.963 (0.02)
DF_{t}	1.56 (0.06)	-0.704 (0.24)	1.751 (0.04)
DF_{ρ}^{*}	-1.4 (0.08)	-6.158 (0)	-1.776 (0.04)
DF_{t}^{*}	-0.57 (0.28)	-2.244 (0.01)	-0.72 (0.24)
No. of Observation	273	378	378

Notes: The bias corrected *t*-statistics (*p*-values) of the coefficients (of the cointegration-tests) are in parentheses. * (**) [***] denotes that the coefficient is significantly different from zero at a 10% (5%) [1%] level. All equations include unreported, country-specific constants. The variable *G7* acts as a dummy variable, which is equal to one for the seven major countries and zero for the non-G7 countries. Assumption: Lag (2) and Lead (2).

[a] Kao (1999) presents four Dickey-Fuller type test statistics with the null hypothesis of no cointegration. While DF_{ρ} and DF_{t} are based on the assumption of strict exogeneity of the regressors, DF_{ρ}^{*} and DF_{t}^{*} account for endogeneity of the regressors with respect to the errors. Residuals are derived from an OLS estimation.