IKD
Open University research centre on Innovation, Knowledge and Development

Does International Trade Transfer Technology to Emerging Countries? A Patent Citation Analysis

WORKING PAPER
No 14

SEPTEMBER 2005

Elif Bascavusoglu
Faculty of Social Sciences
The Open University
Walton Hall
Milton Keynes MK7 6AA

Phone +44 (0)1908 659666
E-mail: e.bascavusoglu@open.ac.uk

Does International Trade Transfer Technology to Emerging Countries? A Patent Citation Analysis*

Elif Bascavusoglu†

Abstract

The purpose of this paper is to assess empirically whether trade flows carry disembodied knowledge to emerging countries. Endogenous growth theory predicts that productivity growth rates of countries are related through international trade linkages and associated embodied and disembodied knowledge spillovers. Patent statistics are an output indicator of innovation. This allow patent citations to reflect the process of knowledge diffusion. Combining an endogenous growth framework with a patent citation analysis, we evaluate whether more exporting or importing countries tend to cite more foreign patents, i.e. learn more from foreign technology. The empirical estimation concerns the relative number of backward citations and bilateral trade flows between 18 emerging and 10 technology source countries, at a sectoral level, for the period of 1980-1998. We contribute to the previous literature by taking into account several proximity measures and by distinguishing sector's technological intensities. Our results show that trade transfers technology across countries and sectors, but the extent of the diffusion depends mainly on cultural and historical proximities and the level of technical capacity of host countries.

Keywords : Knowledge Diffusion, International Trade, Patent Citations.

JEL Classification : F1, F2, O3

*We are grateful to Prof. Silverman for providing data, and the participants of Ateliers de la MSE (Paris, 2005) and FDI and Spillovers Workshop (Paris, 2005) for comments and suggestions.

†Innovation, Knowledge and Development Centre, Department of Economics, Open University and TEAM-CNRS, Université Paris 1, Panthéon-Sorbonne. Email: E.Bascavusoglu@open.ac.uk

1 Introduction

In 2005, according to statistics of International Monetary Found (IMF), the output of the emerging countries exceeds half of the world's total output[1]. As stated by the World Trade Organization (WTO), the liberalization in trade and investment regimes has played a central role in this expansion (OMC 2003). Since neo-classical theory predicts that a higher rate of growth and wealth will result from a decrease in trade barriers and tariffs, openness implies higher productivity. The acknowledgement of international trade as one of the main channels of growth goes back to Adam Smith.

More recently, endogenous growth theory predicts that growth rates of countries are related through international trade linkages and associated embodied and disembodied knowledge spillovers, i.e. knowledge externalities (Grossman and Helpman 1991). Knowledge is inherently non-rival in its use, and hence its creation and diffusion are likely to lead spillovers and increasing returns. It is this non-rival property of knowledge that is at the heart of the theoretical models that predict endogenous growth from research and development (R&D) investments (Romer 1990; Grossman and Helpman 1991; Aghion and Howitt 1998). In this context, the development of a country depends heavily on its knowledge capital, which in turn is determined by the rate of national innovation and international technology diffusion. Three mechanisms have been identified to assess the impact of trade openness on technology diffusion (Redding and Proudman 1998): the degree of international openness can affect the rate of domestic innovation, the quantity of transferred technology or the adoption rate of more advanced countries' technologies.

The empirical literature has long focused on the role of exports, given the exporting firms'

[1]We refer here to IMF' statistics adjusted by the Economic Intelligence Unit analysts, which include the newly industrialized countries such as South Korea, Taiwan, Hong Kong and Singapore (The Economist 2006). The argument behind this adjustment is that excluding these countries is equivalent to underestimating the eventual success of the developing economies in the catching-up process. We'll come back to this debate in Section 4, when we discuss the definition of "developing" and "emerging" countries.

high productivity growth (Aw and Hwang 1995; Clerides, Lach, and Tybout 1998; Bernard and Jensen 1999). The positive impact of exports on learning effects has been demonstrated for emerging countries such as South Korea and China (Kraay 1999; Hahn 2004). Another branch of empirical research, initiated by Coe and Helpman (1995), has analyzed the knowledge capital incorporated in imported goods. The impact of these externalities on the host countries' growth has been largely verified (Coe, Helpman, and Hoffmaister 1997; Keller 2000; Potterie and Lichtenberg 2001). In the same context, multinational firms and foreign direct investment flows have also been considered as a channel of technology transfer to the host countries (Blomstrom 1986; de Mello 1999; Sjoholm 1999).

However, very few studies have attempted to analyze the mechanisms by which the international trade transmits technological knowledge. The purpose of this paper is to achieve a better understanding of the interactions between international trade and technological diffusion, using a direct and precise measure, patent citations.

Whilst patent documents have been widely used in the economics of innovation, the use of patent citations is relatively recent. Initiated by Jaffe, Trajtenberg and Henderson (1993), the patent citations indicator has been used to measure the spatial distribution of the technological diffusion (Jaffe and Trajtenberg 1998; Maurseth and Verspagen 2002; Bottazzi and Peri 2003; Thompson and Fox-Kean 2005).

In this paper, following the work by MacGarvie (2005a, 2005b) and Peri (2005), we combine flows of bilateral trade with number of cited patents, in order to evaluate the interactions between embodied and disembodied knowledge. We expand previous studies by considering a North-South context and a sectoral level in the technology diffusion process. The objective of this paper is a better understanding of the technology transfer by trade linkages. Particularly, by assuming that patent citations reflect a direct process of learning, we seek to evaluate whether the emerging countries which are involved in international trade tend to cite their commercial partners.

We present an empirical evaluation of citations from 18 emerging countries to patents of 10 countries that we consider as "source" of knowledge. Our study covers the period 1980-1998 and 18 manufacturing sectors. We attempt to evaluate first the impact of bilateral trade on the disembodied knowledge flows for the whole sample, and then, we distinguish sectors' R&D intensities.

This paper contributes to the previous literature in mainly three ways. Our principal concern is to assess the particularities of emerging countries as host countries in the technology diffusion process. For this purpose, we adopt and apply Caballero and Jaffe's theoretical model (1993) to emerging countries. Secondly, in our empirical specification, we extent the original model by introducing cultural and historical proximities between commercial partners, for a better understanding of knowledge flows. Although the use of a common language, as a vector of communication has been highlighted in the previous literature for developed countries (Keller 2002; MacGarvie 2005a; Peri 2005), this paper is the first to consider historical proximities in our knowledge in a North-South context. Finally, in contrast with previous studies (MacGarvie 2005a), we conduct an analysis at a sectoral level of manufacturing industry, and especially, we distinguish between high, medium and low technological intensities of sectors, in order to assess the interaction between knowledge diffusion and technological specialization.

The remainder of this paper is as follows. Section 2 presents a brief survey of literature on the relationship between international trade and growth. We outline in Section 3 the empirical model and the estimation method. Section 4 describes data and the variables. Our results are reported in Section 5. Section 6 concludes.

2 Related Literature

Since the neo-classical theory predicts a higher rate of growth and wealth from the decrease of trade barriers and tariffs, openness implies a higher productivity. International trade, especially exporting activity, has been considered to be one of the main channels of growth.

Empirical literature concludes that exporting firms differ from non-exporting firms in many aspects; they are more intensive in capital and technology and pay higher wages (Bernard and Jensen 1999, p2.). Cases studies, specially on South-Asian countries, underline the "learning by exporting" effects (Rhee and Pursell 1984; Hou and Gee 1995)[2]. As a World Bank Report on South Asian Miracle puts out:

> "Buyers want low-cost, better-quality products from major suppliers. To obtain this, they transmit tacit and occasionally proprietary knowledge from their other, often OECD-economy suppliers" World Bank, 1993, p.320 (cited by Clerides et al., (1998), p.1).

While it is widely accepted that exporting firms are more productive, there is no evidence so far concerning learning by exporting. In fact, the direction of the causality relation between exporting and productivity is not so obvious. Are firms exporting because they are more productive or do they become more productive after exporting? This raises the problem of self selection, i.e. is it that exporters are more productive *before* entering in foreign markets.

At an aggregate level, exports and growth are positively correlated (David 1992; Ben-David 1993; Edwards 1993; Sachs and Warner 1995; Sebastian 1998). In fact, exports have been often considered as key to welfare creation, thus reflecting a mercantilistic vision (Girma and Kneller 2004).

[2] Arrow (1962) defines the notion of "learning" as an aptitude for a system to entertain and increase continuously its function, by considering its previous results, into a dynamic process of creating knowledge.

Dollar (1992) finds that commercial distortions reduce growth, and hence, openness to trade is significant in explaining the growth of real per capita GDP. By analyzing the convergence of European countries, Ben David (1993) shows that countries which converge are those involved in trade liberalization. Sachs and Warner (1995) analyze the impact of trade openness using a dummy variable and find that it accelerates growth. Edwards (1998) associates total factor productivity growth with nine different openness measures and concludes that more open countries had higher rates of growth. His results are robust to openness measures, estimation techniques and time periods.

However, some authors have serious reservations about these studies, suggesting a contingent relationship between exports and growth, depending heavily on countries' characteristics and methodological bias[3]. In order to overcome with this kind of problems, a branch of the literature has focused on microeconometric analysis.

The starting point of these firm level studies is the observed higher rate of exporting firms. Nevertheless, there is still no consensus about the direction of the causality between high growth rates and exports. In a cross sectional study about Colombia, Morocco and Mexico; Clerides, Lach and Tybout (1998) find a learning by exporting effect only for Morocco, and a self selection effect for the whole sample. Studies by Aw and Hwang (1995, 2000) for Taiwanese firms, by Bernard and Wagner (1997) on German firms, by Bernard and Jensen (1999) on American firms, and by Isgut (2001) on Colombian firms are among others which find evidence of self selection effect but no learning by exporting. Finally, Delgado et al. (2002), in a study of Spanish firms, concludes that learning by exporting only concerns relatively young firms.

However, after controlling for self selection effects, some studies find a positive learning effect from exports. Using a similar methodology to Clerides et al. (1998), Bigsten et al. (2004) and van Biesebroeck (2004) find evidence of productivity gains by exports. In a study of Italian

[3]See Rodriguez and Rodrik (1999) for a critical discussion of these studies.

firms, Castellani (2002) shows that the learning is associated to the export intensity. Kraay (1999) and Hahn (2004) show also evidence about higher productivity rates from exporting activities for respectively Chinese and Korean firms.

Endogenous growth theories provide the "missing link" between openness and growth via knowledge spillovers (Lejour and Nahuis 2001). In this context, knowledge originating in a particular country or region increasingly transcends national boundaries and contributes to the productivity growth of other geographic areas, or at least, reduces duplication of the research effort[4].

International trade can be a source of spillovers through demonstration effects when domestic firms learn the innovative content of imported goods. Coe and Helpman (1995), Coe, Helpman and Hoffmaister (1997) and Lichtenberg and van Pottelsberghe de la Potterie (1998) examine the influence of foreign trade partners' R&D on domestic total factor productivity. The empirical results confirm that foreign R&D influences domestic productivity and that the more countries are open to international trade the more they benefit. Greenwood et al. (1997) attribute 60 percent of US long-term growth to embodied knowledge. Some authors have extended Coe and Helpman's framework, by including country characteristics (Keller 2000) or by restricting trade to capital goods (Xu and Wang 1999) or by using different estimation technique (Kao and Chen 1999).

The foreign direct investment (FDI) as a channel of embodied knowledge diffusion has also been suggested, by emphasizing three mechanisms; demonstration effects, labor mobility and linkages between buyers and suppliers[5]. The empirical literature is however ambiguous. While there seems to be evidence of spillover effects of outward FDI (Hanel 1993; Potterie and Lichtenberg 2001) as well as inward FDI (Findlay 1978; Blomstrom 1986; Borensztein, De Gre-

[4]See Grossman and Helpman (1991) for a review the endogenous growth theory.

[5]For an exhaustive survey for FDI spillovers; see surveys by Blomström and Kokko (1999), Cincera and van Pottelsberghe (2001) and Saggi (2002).

gorio, and Lee 1998; Balasubramanyam, Salisu, and Sapsford 1996), there's no consensus about its magnitude[6].

However, empirical evidence on the effect of technological externalities on trade is rather limited. More often, international trade and/or international investment is considered as the carrier of international spillovers of knowledge and new technology, without exploring the mechanisms of knowledge diffusion. This paper aims to fill this gap, using patent citation as a measure of disembodied knowledge flows.

Following Jaffe, Trajtenberg and Henderson (1993) and Jaffe and Trajtenberg (1998), we consider patent citations as a paper trail of knowledge flows. Like scientific papers, patent documents contain references to earlier patent documents, we can then assume a knowledge flow from the cited patent to the citing one[7]. Employing patent statistics as an output indicator of innovation allows patent citations to reflect the process of knowledge diffusion[8].

Despite the noisy nature of the citation data, the latter have been used for many purposes as to assess the market value of patents (Trajtenberg 1990; Harhoff and Vopel 1999; Hall, Jaffe, and Trajtenberg 2005), to track the geographic boundaries of knowledge flows (Jaffe and Henderson 1993; Thompson and Fox-Kean 2005; Maurseth and Verspagen 2002; Bottazzi and Peri 2003), or to assess the impact of university (basic) research (Jaffe and Trajtenberg 1996; Sampat, Mowery, and Ziedonis 2003)[9].

Nevertheless, empirical research combining patent citations with trade and investment flows is rather scarce. Sjöholm (1996) finds a correlation between Swedish patent citations and

[6]See Haddad and Harrison (1993) and Aitken and Harrison (1999) for examples of the negative or null impact of FDI on home countries.

[7]As Griliches (1991) points out, the main difference between academic citations and patent citations is the existence of patent examiners, who have the possibility to add some cited patents if necessary.

[8]For a discussion about the use of patent statistics as an innovation indicator, see Griliches (1991).

[9]It's generally admitted that citations added by patent examiner bring some noise in data. Nevertheless, a recent inventor survey on USPTO patents from Jaffe, Trajtenberg and Fogarty (2000) provide evidence that at least half of the citation flows correspond to some kind of knowledge flow, while about a one quarter on citation flows correspond to a very substantial knowledge flow. See also Duguet and MacGarvie (2005) for a survey of EPO patents.

bilateral imports, suggesting that imports contribute to international knowledge spillovers. Globerman, Kokko and Sjöholm (2000) evaluate technology sourcing of Swedish multinational and small and medium sized enterprizes (SME) and find that outward FDI increases citations. Brandstetter (2001) analyzes FDI and citation flows between USA and Japan, and shows a positive impact of FDI on knowledge spillovers. Using micro level data on French firms, MacGarvie (2005b) finds that both importers and exporters learn more from foreign technology then firms not involved in international trade. At a regional level, Peri (2005) compares knowledge and trade flows, and concludes that there is a lesser impact of distance on the former. Whether in a macro, meso or micro level, there are no studies evaluating the case of developing or emerging countries so far. The interaction between knowledge and trade flows has been only explored between industrialized countries. Even if the technology transfer literature highlights the role of imports in developing countries' growth, there's a lack of analysis on the mechanisms of these spillovers generated by international transactions. This is the principal motivation of the present paper.

3 Empirical Model and Estimation Method

3.1 Empirical Model

Our empirical specification is derived from the theoretical model developed by Caballero and Jaffe (1993). The authors combine an approach of creative destruction and knowledge spillovers, in a growth model, in order to determine and measure the intensity and the impacts of knowledge spillovers on growth.

In this context, the probability that a patent N granted at year T will cite another patent n

given at year t is given by the following:

$$\alpha(n,N) = \delta e^{(-\beta(n,N)(T,t)}(1-e^{-\gamma(T-t)}) \tag{1}$$

where β is the rate of obsolescence and γ, the rate of diffusion. The citation frequency rises with the diffusion of knowledge and decreases with the patent' obsolescence[10].

In Caballero and Jaffe's analysis, the fact that a patent N at time T cites another patent n granted at t, is a proof that N_T uses the information contained in n_t. Hence, we can use the citation frequency in order to measure $\alpha(n,N)$. If $C_{T,t}$ is the number of citations from patents granted at time T to patents granted at time t, and S_T and P_t correspond respectively to the number of patents granted at time T ant t, the estimated citation probability would be given by:

$$\alpha^*(n,N) = \frac{C_{T,t}}{S_T P_t} \tag{2}$$

The relationship between $\alpha(n,N)$ and $\alpha^*(n,N)$ is a function of the relationship between the number of citation and the number of ideas effectively used (ϕ), and the relationship between the number of innovations and the number of patents (ψ). By assuming some parameters (ϕ and ψ) for these two relationships and by incorporating them into (1), Caballero and Jaffe obtain the relation between the fonction and the probability of citation :

$$\alpha^*(n,N) = \phi_T \psi_T \psi_t \alpha(n,N) \tag{3}$$

[10]The probability to have an idea of $(T-t)$ years old is given by $(1-e^{-\gamma(T-t)})$; if $\gamma \to \infty$ the diffusion is instantaneous. When $\gamma = 0$, this means that the previous ideas are not available, and hence, each inventor begin at zero (Caballero and Jaffe 1993).

This last equation allows us the re-write Eq. (1):

$$\alpha(n, N) = \phi_T \psi_T \psi_t \delta e^{(-\beta(n,N)(T,t)}(1 - e^{-\gamma(T-t)}) \tag{4}$$

Jaffe and Trajtenberg (1996, 1998) reformulate this citation probability as the ratio of the number of citations of a given patent to the number of potentially citing and cited patents, in the same country/sector cohort. Eq (1) becomes then:

$$E[C_{IiTtj}] = (N_{IT})(N_{ijt})\alpha_{IiTtj}(e^{-\beta_{IiTtj}(T-t)})(1 - e^{-\gamma(T-t)}) + \epsilon_{IiTtj} \tag{5}$$

where C_{IiTtj} is the number of citations from a patent granted in country I, at time T to another patent granted in country i, at time t, and in sector j. N_{IT} and N_{ijt} correspond respectively to the potential number of citing and cited patents. It is also possible to write this equation (5) :

$$N_{IiTtj} \equiv \frac{C_{IiTtj}}{(N_{IT})(N_{ijt})} = \alpha_{IiTtj}(e^{-\beta_{IiTtj}(T-t)})(1 - e^{-\gamma(T-t)}) + \epsilon_{IiTtj} \tag{6}$$

By estimating Eq (6) for France, Germany, Great Britain, Japan and United States; Jaffe et Trajtenberg have shown that some countries cite each other's patents more often than others. MacGarvie (2005a) develops this finding by analyzing the determinants of these cross-country citations. The author introduces a vector corresponding to some potential channels for diffusion such as technological proximity, geographic distance, language barriers and trade among others. The objective of this paper is to take forward analysis of this topic, by an empirical estimate at sectoral level and in a North-South context. For this purpose, we construct a vector δX_{IiTt}, which contains these bilateral characteristics and introduce it in our econometric specification.

3.2 Estimation Method

It is possible to estimate the specification (6), either by a non linear or a semi-parametric approach. However, the semi parametric approach is less restricted (on the form of citation function), and allows us to consider the count nature of our data. We choose then to use a discrete probability model, the Poisson Regression (Greene 1994). The non linear form of the citation function is introduced by introducing a separate parameter for each value of $(T-t)$[11].

We consider then an alternative specification of Jaffe and Trajtenberg :

$$N_{IiTtj} = \exp^{\alpha_{(T-t)}\alpha_T\alpha_t\alpha_I\alpha_i\alpha_j\delta X_{IiTtj}} \tag{7}$$

where X_{IiTtj} reflects the bilateral characteristics of countries, and $\alpha_{(T-t)}$ varies following each lapse of time between T and t. By taking natural logarithms, equation (7) becomes :

$$\ln(C_{IiTtj}) = \ln(N_{ITj}) + \ln(N_{itj}) + \delta X_{IiTtj} + \alpha_{(T-t)} + \alpha_T + \alpha_t + \alpha_I + \alpha_i + \alpha_j + \epsilon_{IiTtj} \tag{8}$$

where N_{ITj} and N_{itj} are respectively the number of granted patents in citing country I and cited country i, in sector j. C_{IiTtj} is the number of citations from citing country I at time T, to patents of cited country i, at time t and for the sector j.

The Poisson regression provides the standard framework to estimate count data[12]. Let C_{it} be the number of citations, the Poisson model assume that each C_{it} is modeled by a Poisson distribution, with parameter λ_{it}. The citation probability is hence expressed by[13] :

$$Prob(Y_i = C_i|x_i) = \frac{e^{-\lambda_i}{\lambda_i}^{C_i}}{C_i!} \tag{9}$$

[11] In this approach, though, the cross country differences are only explained by changes in the explanatory variables δX_{IiTt}.

[12] For a survey on the specification and estimation of count models, see Greene (1994) and Winkelmann and Zimmermann (1995).

[13] For the sake of simplicity, we do not consider the temporal and sectoral dimensions in following formulations.

λ_{it} specifies the expected value and variance of the model as a function of explanatory variables and parameters to estimate:

$$E(C_i|x_i) = e^{x_i b} = \lambda_i \tag{10}$$
$$V(C_i|x_i) = e^{x_i b} = \lambda_i$$

As we can see from the above equations, the Poisson Model assume equidispersion, i.e. equality between expected value and the variance.

$$E(C_i|x_i, \beta) = V(C_i|x_i, \beta) = \lambda_i \tag{11}$$

This last property makes the Poisson Model very restrictive, and its non respect yields the same implications as heteroscedasticity in a model of Ordinary Least Squares (OLS) (Cameron and Trivedi 1998). Furthermore, the Poisson Model assumes homogeneity, given that the conditional expectation has a determinist form depending on the explanatory variables. Given the nature of our data, where we have both temporal and sectoral dimensions, the non-consideration of specific effects may lead to overdispersion. In the panel data context, this problem is resolved by using a random or fixed effect approach. If the specific effects are correlated with the explanatory variables, the random effect model is no longer consistent. We should use then a negative binomial model by introducing a random error term v_i:

$$E = (C_i|x_i, v_i) = \exp(x_i b)\exp(\varepsilon_i) = \lambda_i v_i \tag{12}$$

where $v_i = \exp(\varepsilon_i)$ is a non-observable heterogeneity term. It reflects a specification error from omitted or non-observable exogenous variables with $E(v_i = 1)$ and $V(v_i = \sigma^2{}_v)$. This specification allows us to evaluate the implications of non observable heterogeneity without knowing the complete distribution of v_i, given that we know the moments of v_i :

$$\begin{aligned} E &= (C_i|x_i, v_i) = \exp(x_i b)E(v_i = \lambda_i) \\ V &= (C_i|x_i) = E[E(C_i|x_i, v_i)] + V[E(C_i|x_i, v_i)] = \lambda_i(1 + \sigma^2{}_v\lambda_i) \end{aligned} \tag{13}$$

We note that for $\sigma^2{}_v$, the variance of this distribution is superior to the one from the standard Poisson model. That is what allows us to interpret the overdispersion as a result of the omission of non observable heterogeneity[14].

In our empirical specification, the rate of citation by the potentially citing patent N_{it} to the potentially cited patent N_{IT} is given by $E(C_{IiTt}|\lambda_{IiTt}) = \lambda_{IiTt}$. This rate depends on observable factors such as N_{IT}, N_{it} and X_{IiTt}. Hence, the conditional expectation of the dependant variable is given by :

$$E(C_{IiTt}|N_{IT}, N_{it}, X_{IiTt}) = \exp(\ln(N_{IT}) + \ln(N_{it}) + \ln(X_{IiTt})) \tag{15}$$

However, the Negative Binomial Model could also be insufficient to explain the frequency of zero citations[15]. In fact, it is possible that a country does not cite any patent from another country in the given sector and time period. This would provoke an excess of zeros in our sample. Given that the excess zeros are a characteristic of the expectation and not the variance, one should consider alternative models which allow the generalization of the specification of

[14]By assuming that v_i is distributed by Gamma, the distribution of the Binomial Negative Law is given by (Gourieroux and Trognon 1984):

$$f(c|\lambda, \alpha) = \frac{\Gamma(c + \alpha^{-1})}{\Gamma(y+1)\Gamma(\alpha^{-1})}(\frac{\alpha^{-1}}{\alpha^{-1} + \lambda})(\frac{\lambda}{\alpha^{-1} + \lambda}), \alpha = \sigma^2{}_v \geq 0 \tag{14}$$

Note that this distribution is equivalent to the Poisson distribution if $\alpha = 0$. A likelihood test which examine the nullity hypothesis of α allows us to discriminate one of these two models. A $\alpha = 0$ significantly different from 0 indicate an overdispersion, and conclude to estimation of the Negative Binomial Model.

[15]For each regression, we test the presence of overdispersion. If it is the case, a Negative Binomial Model is more appropriate then a Poisson Model.

the expectation and the variance. Initiated by Lambert (1992), the Zero Inflated Poisson (ZIP) and the Zero Inflated Negative Binomial (ZINB) Models have the property of correcting the excess zeros. These models are an extension of the Poisson Model, and assume that the citation decision has two steps. Consequently, the process that generates zeros and the positive values are different. C_i has the zero value with a probability of φ_i, where φ_i follows either a logit or probit model:

$$\varphi_i = \frac{\exp(\gamma_i z_i)}{1+\exp(\gamma_i z_i)} \tag{16}$$

where z_i represent the vector of the variables which affect the decision of not citing a patent[16]. In the second step, the probability of each count (including zeros) is determined by a Poisson or Binomial Negative Distribution. We hence have :

$$\begin{aligned} Prob(c_i &= 0) = \varphi_i + (1-\varphi_i)\exp^{(-\varphi_i)} && (17)\\ Prob(C &= c_i|C>0) = (1-\varphi_i)\frac{\exp^{(-\varphi_i)}\,\varphi_i^{(c_i)}}{c_i!} && (18)\end{aligned}$$

Practically, it is the Vuong Test (1989) which allow us to choose between the models corrected for excess zeros and the standard ones. If the Vuong test confirms an excess zero, which is very probable given the nature of our sample, we proceed to a regression using the appropriate zero inflated model.

[16]Given that we have no reason to suspect a difference between these two steps, we consider same vector of variables in the both steps ($x_i = z_i$).

4 Description of Data and Variables

4.1 Data and Descriptive Statistics

Our study evaluates the role of bilateral imports and exports in knowledge spillovers to the developing countries at the sectoral level. The endogenous variable of the econometric model is the number of patent citations, a direct measure of disembodied knowledge flows.

We used two principal sources to construct an original database, in order to evaluate the impact of the embodied knowledge flows on the disembodied knowledge flows. The first one is the NBER Patent and Citation Dataset, described in Hall, Jaffe and Trajtenberg (2001). This dataset contains all the patents granted by U.S. Patent Office (USPTO) from 1963 to 2002 and all the citations made by each patent to others, from 1975 to 2002[17]. Our bilateral trade flows come from the NBER World Trade Data, described in Feenstra et al. (2005). This database presents the world trade flows at Standard International Trade Classification (SITC Rev.3) level for the period of 1962-2000. The other sources of data are presented in Appendix (A.3). We've used a number of correspondence tables to construct the final database which has an aggregated data over 19 sectors[18].

As we want to analyze the technology transfer in a North-South context, we should only consider Northern innovative countries with a certain stock of knowledge as "technology source" countries[19]. If we look at the total number of patents granted by USPTO, we can see that the innovative activities are concentrated in a number of countries (See Figure 1)[20]. These are the same countries that invest in R&D (OCDE 2003; OCDE 2005) and are classified among

[17]The original database described in Hall *et al.*(2001) concerns only the period 1975-1999. We completed this database by the data available on Bronwyn Hall's personal homepage (http://emlab.berkeley.edu/users/bhhall/bhdata.html).

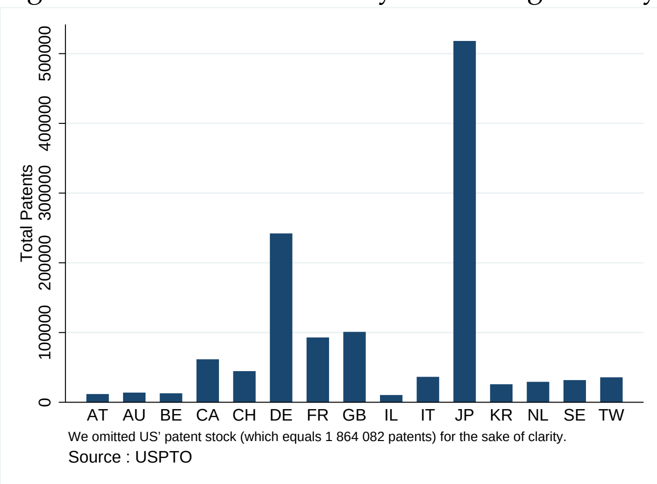
[18]See Appendix A.1 for the details of database construction.

[19]We consider knowledge stock at national as well as sectoral level. The choice of countries hold at both level of analysis. However, for the sake of clarity, following figures are at a national level.

[20]These countries are United States, Japan, Germany, United Kingdom, France, Canada, Switzerland, Taiwan, Sweden, Netherlands, Italy, South Korea, Austria, Australia, Belgium and Israel.

the high income countries according to the World Bank[21]. But a closer look the evolution of granted patents in time reveals us that some of these innovative activities only began in the early 1990 (Figure 2). Hence, countries like Taiwan, South Korea, Israel or Austria can not be considered among the technology source countries, even if they attempt a high growth rate of innovations. Hence, only United States, Japan, Germany, Canada, France, Switzerland, Sweden, Netherlands and Italy would be taken as a technology source countries. A last look at the distribution of citations by cited countries confirms our choice, as these 10 countries account for $71,94\%$ of citations (Figure 3).

Figure 1: Number of Patent by Innovating Country



Our host countries are the emerging economies. As pointed very briefly in the introduction, the category of emerging countries has no clear-cut definition. In order to distinguish between emerging and developing countries, we can refer to the definition of "developing countries" given by Arocena and Sutz :

> "When the transition from agrarian societies to industrial societies framed world history, "developing" countries were those unable to move along industrialization

[21]The high income classification corresponds to more then 9 076$ per capita. For more details, see World Bank (WorldBank 2005).

Figure 2: Evolution of Patents Application by Innovating Country

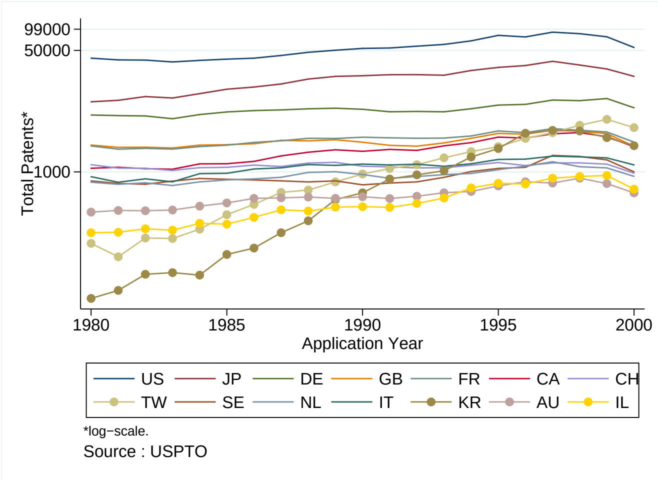
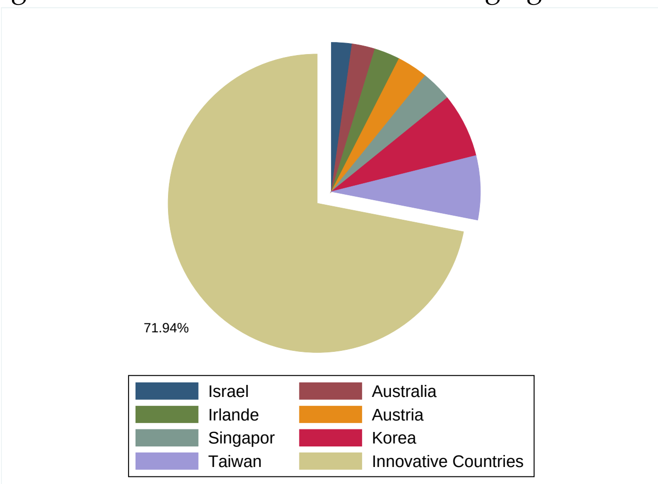


Figure 3: Citation Distribution of Emerging Countries



roads; consequently, the expansion of the industrial West was for them a source of subordination, and so they became in fact not "developing" but underdeveloped countries. Today, when we are living the transition to the knowledge society, the economy of developed countries is solidly based on science, technology, innovation and advanced education. "Developing" countries are "the rest", those unable to use knowledge - its generation, transmission and application - as a fundamental tool for economic growth and social improvement." Arocena et Sutz (2005), p.1.

We consider that the term of emerging countries here corresponds to countries which already have the capacity to assimilate and use the technology developed elsewhere. Our sample is hence composed of 18 emerging countries, including some newly industrialized countries, as listed at the Appendix A.2[22].

The following figures are derived from our original sample constructed by combining USPTO and World Trade Databases[23]. Figure (4) highlights the evolution of the flows of citation and trade for the estimation period and sample countries. One can remark the relative stability of the citation flow, compared to the rise of trade flows. This situation confirms the continuing relevance of our research question, whether trade flows are a vector of knowledge transmission.

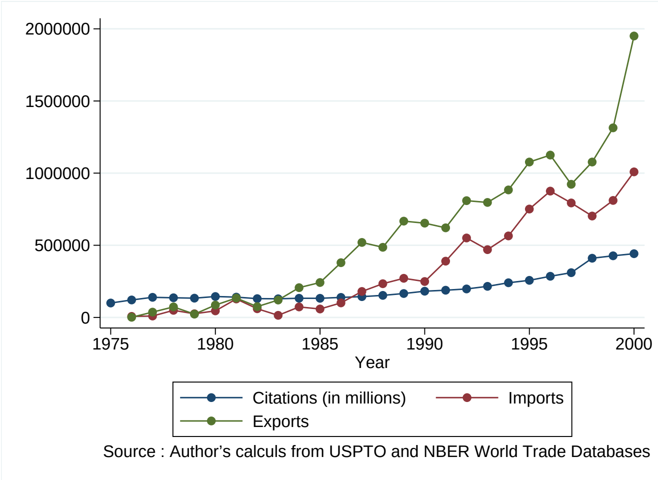
The sectoral distribution gives us some information about the composition of emerging countries' innovative activities (See Figures 5 and 6). The inter-sectorial distribution of citations flows seems rather homogenous except in four sectors[24]. In fact, 80% of the sectoral citations occurs in manufacture of textiles, paper products, electrical machinery and professional, scientific equipment. We can hence conclude that a very considerable part of knowledge flows

[22]Our host countries are Argentina, Brazil, China, Czech Republic, Hong Kong, Hungary, Iceland, India, Israel, Korea, Malaysia, Mexico, New Zealand, Russian Federation, Singapore, South Africa and Venezuela. The major part of our sample is classified as middle and high income countries by World Bank except India, which is classified as a low income country.

[23]The final database used in this paper has thus [18 x 10 x 19 x 18 =] 61 560 observations, of which 43% are zeros.

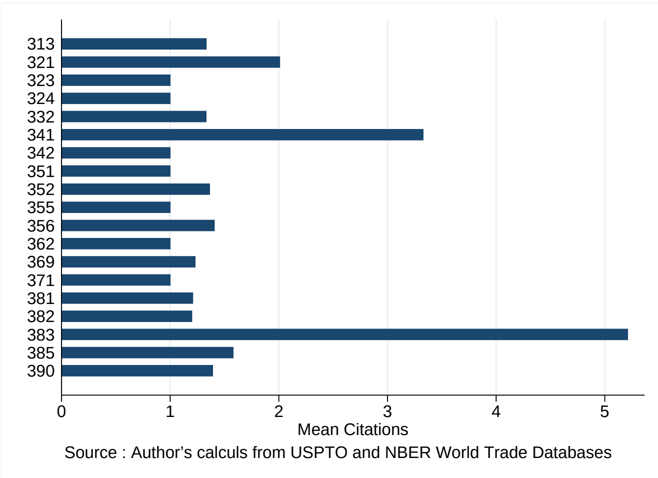
[24]See Appendix A.4 for the list of sectors.

Figure 4: Distribution of Trade and Citation Flows



to developing countries occurs in middle-high technology intensive sectors[25].

Figure 5: Sectoral Distribution of Patent Citations

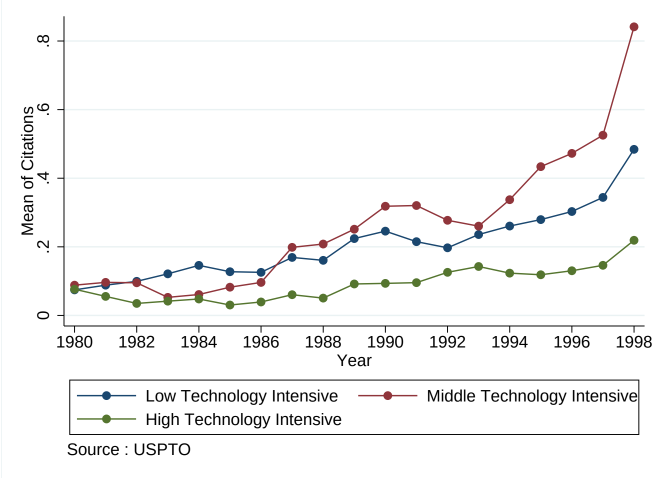


4.2 Variables and Expected Signs

Our independent variable is the number of citations C made by the country I, in each separate sector j and year T, from the country i, assuming that patent citations represent a link to pre-

[25]The definition of high/medium/low technological intensity comes from Hatzichronoglou (1997), based on sectoral direct and indirect R&D intensity, and is presented in Appendix A.5.

Figure 6: Citation Distribution According to Sector's Technological Intensity



existing knowledge upon which the inventor builds. We limit the period of analysis to 1980-1998, in order to reduce the truncation bias[26]. As we are concerned by the relationship between disembodied and embodied knowledge flows, all observations on citations to patents in the same country are removed[27]. We also take into account several factors which could influence the disembodied knowledge flows, such as geographic, technological or cultural distances.

Given that patent citations occur more between sectors using similar technologies, we use the technological proximity index developed by Jaffe (1986). The technological similarity between two countries I and i is given by the following equation:

$$\omega_{Ii} = \frac{\sum_{k=1}^{K} N_{Ik} N_{ik}}{\sqrt{\sum_{k=1}^{K} N_{Ik}^2 \sum_{k=1}^{K} N_{ik}^2}}$$

where $k = 1, 2, ..., K$ indicates sectors and N stands for the number of patents. The more the technological fields of the countries I et i are similar, the more ω_{Ii} would be close to the

[26]See Hall et al. (2001) for a discussion about the truncation problem of citation data.

[27]It's widely accepted that citation flows are more concentrated in intra-sectoral and intra-national level (Jaffe and Trajtenberg 1998). But in this paper we're principally concerned with the North-South technology diffusion and furthermore, given the level of research and development investments and patenting activities of our sample, we believe that in our case, technology diffusion rely mainly on foreign knowledge.

unity. If the two countries have no patent in the same sector, ω_{Ii} would be nil. We expect the technological proximity index to have a positive effect on the disembodied knowledge flows between two commercial partners.

The tacit nature of disembodied knowledge flows makes the geographic distance important for the technology diffusion. It's widely accepted in the empirical literature that technological spillovers are geographically bounded (Jaffe and Henderson 1993; Audretsch and Feldman 1996). We use a geodesic distance measure from CEPII Distance Database[28]. We consider that the distance will act as a barrier to the technology diffusion.

Finally, we believe that in the process of technological diffusion, the cultural factors may be as important as the economic ones. In order to test this hypothesis, we constructed a number of variables of cultural proximity, to evaluate the cultural and historical linkages which can affect the degree of communication between countries. The first one is the use of a common language. Our dummy variable is equal to 1 if the two countries share a common language. The potential importance of language as a contributor to embodied and disembodied knowledge flows has several foundations (Peri 2002). The transactions costs hypothesis of Williamson (1989) argues that communication across language barriers being more expensive, increase the economic distance between potential partners not sharing a common language (Eichengreen and Irwin 1996). We can consider that language affinities provide an automatic channelling of information along linguistic lines (Helliwell 1998). However, the complexity of culture can not be approximated by the language similarities (Hussler 2004)[29]. The degree of common cultural and historical links may also further the density of internationally shared knowledge and values. Hence we also construct another dummy variable concerning countries' colonial relationship and colonial link. Both of these variables are from CEPII Distance Database.

[28]Geodesic distances are calculated following the great circle formula, which uses the geographic coordinates of the capital cities.

[29]See Hussler (2004) for the construction and use of other cultural proximity index.

5 Results

5.1 Disembodied Flows, Trade and Proximities: An Overall View

Tables 1 and 2 show estimation results. The likelihood ratio test ($\alpha = 0$) has detected over-dispersion, hence we use a Negative Binomial law rather then a Poisson Law in our regressions. Furthermore, the Vuong Statistic which is superior to 1.96 in each regression confirms our prediction about the excess zeros. The resulting regression method is then the Zero Inflated Negative Binomial (ZINB) Model[30]. Each estimation is associated with two different tables, i.e. two estimation steps. The first one models the process of zero citation from the innovators of citing country I to patents hold by country i in each group of sector/year. The coefficients indicate then the variation of the probability of being in the country group which doesn't cite the trade partner's patents. The second step shows the impact of the explanatory variables on the citation number[31].

Table 1 presents the basic regression, in order to evaluate the impact of bilateral trade on disembodied knowledge flows. The coefficients of total trade (i.e. exports + imports) and imports are positive and robust[32]. However, the export variable is not significant in the first step. Hence, a decrease of export flows do not affect the process of not citing the trade partner's patents, whereas its increase will raise the probability of citations. We remark, however, that in the second step, the impact of exports is higher then the imports. These results seem to confirm the ambiguity of previous studies concerning learning by exporting effect. Import flows appear to be the main vector of technology diffusion for emerging countries, conforming to

[30]Each regression includes dummy variables for countries, sectors and years. We also assume that the observations are independent between the country pairs but not necessarily within the groups.

[31]When we include the same variables in both equation, as in this case, the signs of the corresponding coefficients from the first step are often in opposite direction of the coefficients of the second. This make substantive sense since the first stage estimation, which is a binary process, is predicting membership in the group that always has zero outcomes, i.e. zero citations. So in the first stage, a positive coefficient implies lower productivity, whilst in the second stage, a negative coefficient would indicate a lower productivity.

[32]The coefficients have opposite signs in the two steps.

Table 1: Disembodied Knowledge Flows and Bilateral Trade

	ZINB(1)	ZINB(2)	ZINB(3)	ZINB(4)
First Step : Probability not to cite				
Bilateral Trade	-0.235***	-0.114		
	(-4.08)	(-0.88)		
Imports			-0.514***	
			(-5.81)	
Exports				0.116
				(1.42)
FDI	2.479			
	(0.59)			
Technological Proximity		-0.551	-0.515	-0.436
		(-1.36)	(-1.43)	(-1.15)
Citing Country's Patents	-0.477***	0.129	-0.205*	0.156
	(-7.59)	(1.31)	(-2.13)	(1.71)
Cited Country's Patents	0.092	-1.380***	-1.066***	-1.393***
	(0.42)	(-16.58)	(-10.02)	(-17.74)
Constant	-13.811	6.509*	242.679*	259.702
	(-0.03)	(1.97)	(2.19)	(1.60)
Number of Observations	61560	61560	61560	61560
Likelihood Ratio Test	1145.14	1131.60	1094.19	1137.76
Prob>chibar2	0.000	0.000	0.000	0.000
Vuong Statistic	9.006	6.540	6.460	7.060
Second Step : Probability to cite				
Bilateral Trade	0.141***	0.187***		
	(14.04)	(16.94)		
Imports			0.068***	
			(4.03)	
Exports				0.142***
				(19.09)
FDI	-0.215			
	(-0.43)			
Technological Proximity		0.719***	0.715***	0.724***
		(11.46)	(10.51)	(11.70)
Citing Country's Patents	0.819***	0.874***	0.867***	0.840***
	(81.44)	(76.04)	(49.39)	(74.54)
Cited Country's Patents	0.589***	0.810***	0.803***	0.794***
	(17.43)	(38.63)	(37.78)	(36.23)
Constant	-13.161***	-13.601***	-17.913**	-14.647***
	(-56.85)	(-57.28)	(-2.95)	(-3.48)
Number of Observations	61560	61560	61560	61560
Log-Likelihood	-29569.17	-29184.03	-30502	-30080.41
LR chi2	6590.217	6291.537	6250.611	6399.894
Prob>chibar2	0.000	0.000	0.000	0.000

Standard errors in brackets.
*Significant at 10%; ** significant at 5%; *** significant at 1%
All variables are in logarithms, except the dependent variable.

the technology transfer literature (Coe, Helpman, and Hoffmaister 1997). Meanwhile, for exporting firms, the impact of exports is more important then imports, suggesting a self selection effect (Aw and Hwang 1995; Clerides, Lach, and Tybout 1998; Bee Yan Aw and Roberts 2000; Isgut 2001). Finally, the first column of both estimations shows the foreign direct investment variable. The negative, although non significant, sign of this variable in the second step indicates the complementary relationship between trade and investment flows (Lipsey and Weiss 1984; Head and Ries 2001). We therefore choose not to include the FDI variable in what follows. This omission lead to an increase of the total trade variable, which passes from 0.141 to 0.187.

The rest of the explanatory variables have coefficients that have opposite signs in the two steps, or are not significant at all. The largest coefficients are associated to the number of patents of citing and cited countries, in all specifications. We can interpret these variables as the propensity to cite. A one unit increase of the number of patents of the cited country (i) leads to a rise of citations of 2.30, and the same increase at the citing country (I), of approximatively 1.80. Meanwhile, in the both of the cases, the resulting increase of the citations is more than proportional to the increase in the number of patents, indicating a learning process. Countries with more inventive activities, i.e. more patent applications, will have more capacity to benefit from foreign innovations, confirming Cohen and Levinthal (1989). These values are higher then those found by MacGarvie (2005a) and Hussler (2004), but this may be due to the different levels of development and innovative activity of analyzed countries in both studies[33].

The results also show a high impact of technological proximity, confirming that diffusion is more likely between technologically similar countries and sectors (Jaffe and Trajtenberg 1998; Orlando 2000; Peri 2002; Hu and Jaffe 2003). Hence, we do not have evidence so far of different diffusion patterns between North-North and North-South contexts.

[33] MacGarvie's study evaluate the determinants of citations between Australia, Canada, France, Germany, Italy, Japan, Netherlands, United Kingdom and United States, whilst Hussler evaluates the geography of knowledge spillovers within Europe. Given the North-South context of our study, it is more plausible to have a learning effect

Table 2: Disembodied Knowledge, Trade and Proximities

First Step : Probability not to Cite			
	ZINB(4)	ZINB(5)	ZINB(6)
Bilateral Trade	-0.275***		
	(-5.37)		
Imports		-0.509***	
		(-6.50)	
Exports			-0.271***
			(-6.98)
Technological Proximity	-0.083	-0.661	-0.106
	(-0.06)	(-0.22)	(-0.07)
Distance	1.493***	1.477***	1.595***
	(13.52)	(10.80)	(13.70)
Common Language	-0.212	-0.359	0.105
	(-1.04)	(-1.29)	(0.56)
Historical Links	-2.377***	-2.666***	-2.449***
	(-7.85)	(-5.57)	(-7.57)
Citing Country's Patents	-0.515***	-0.582***	-0.552***
	(-8.37)	(-8.49)	(-8.64)
Cited Country's Patents	0.019	0.001	0.096
	(0.24)	(0.02)	(1.22)
Constant	10.623***	8.440***	10.657***
	(6.23)	(5.23)	(5.92)
Number of Observations	61560	61560	61560
Likelihood Ratio Test	571.34	632.45	591.76
Prob>chibar2	0.000	0.000	0.000
Vuong Statistic	7.503	8.005	8.305
Second Step : Probability to Cite			
Bilateral Trade	0.182***		
	(13.72)		
Imports		0.102***	
		(7.43)	
Exports			0.114***
			(12.83)
Technological Proximity	0.840	2.030*	0.216
	(1.23)	(2.41)	(0.33)
Distance	-0.705***	-0.573***	-0.666***
	(-20.86)	(-16.34)	(-19.46)
Common Language	0.397***	0.305***	0.353***
	(12.17)	(9.71)	(11.31)
Historical Links	0.645***	0.403***	0.600***
	(9.22)	(5.64)	(8.86)
Citing Country's Patents	0.818***	0.838***	0.783***
	(58.60)	(53.86)	(56.29)
Cited Country's Patents	0.992***	0.967***	0.997***
	(73.56)	(69.97)	(83.73)
Constant	-8.564***	-11.358***	-9.144***
	(-21.73)	(-28.00)	(-24.12)
Number of Observations	61560	61560	61560
Log-Likelihood	-29410.4	-30131.46	-29718.62
LR chi2	6992.02	6877.18	7054.46
Prob>chi2	0.000	0.000	0.000

Standard errors in brackets.
*Significant at 10%; ** significant at 5%; *** significant at 1%
All variables are in logarithms, except the dependent variable.

In order to have a more precise look on the mechanisms of knowledge flows, Table 2 presents the regressions into which different measures of proximity between trading countries have been introduced. The impact of imports is robust, having the same direction at the two steps. Moreover, the export variable also has the expected sign at the first step, contrary to the baseline specification. It appears that once we control for the proximity effect, the impact of import flows decreases.

The geographic distance is negative and significant, conforming to the geographic boundaries of knowledge flows (Audretsch and Feldman 1996; Sjoholm 1996; Bottazzi and Peri 2003). As expected, distance reduces the extent of transmitted knowledge, whether in a North-North or a North-South context. Peri (2005) finds that 19% of regional knowledge flows disappear when passing country borders. These results are attenuated by Hussler (2004), who finds a negative effect of 0.23% of geographic distance on knowledge spillovers within Europe[34]. In a setting more similar to the present study, MacGarvie (2005a) finds a negative coefficient on the bilateral trade variable when geographic distance is introduced (among other distance measures). Whilst our results suggest a more important negative effect of distance on disembodied knowledge flows (0.666 versus 0.151 in MacGarvie), our trade variables are still significant[35].

Conversely, the cultural proximity variables seem to foster technological diffusion (Lundvall 1992; Taeube 2004). In all specifications, to share a common language favors patent citations, confirming previous studies by Keller (2001) and MacGarvie (2005a). The impact of historical proximity, approximated by the colonial relationship, is even more important. It is natural to expect a privileged relationship between countries sharing a common history, given that the influence of old colonists' power lasts long after the independence. But then again,

from patent applications.

[34]However, we don't think that Peri's findings are overestimated, given the disaggregated nature of his study.

[35]The correlation between trade and geographic distance is about O.48, which allow us to introduce both variables in the regression. See Disdier and Head (2004) for an extensive analysis of effects of distance on bilateral trade flows.

we note a decrease in the significance of the technological proximity variable, which is only significant in ZINB(5) where we only consider the impact of import flows. We consider that in the first estimations, this variable captured some other proximity measures than technological similarity. This result underlines again the important role of cultural, historical and geographic proximities on the technology diffusion process (Hussler 2004).

5.2 Technological Intensity : Does it Make a Difference?

In this section, we evaluate more precisely the role of trade in relation to disembodied knowledge flows, by distinguishing between sectors with low, medium and high technological intensity. Descriptive statistics have shown that most citations occur in low and medium technology intensive sectors (See Figure 6). This latter's percentage has passed from 36% to 54% during the analyzed period, to the detriment of the low technological intensity sectors' citations (which passed from 31% in 1980 to 14% in 1998), indicating that emerging countries become more specialized in technology intensive sectors over time.

In low technology sectors, we note a substantial decrease in the coefficients of the bilateral trade and import variables (Tables 1 and 2). The impact of exports is highest among the three trade variables, indicating again a learning by exporting effect. Export activities seem to foster disembodied knowledge flows, even in low-tech sectors. The coefficient of technological proximity also is much smaller then in the first specifications. It appears that the variables of common language and particularly, colonial relationship determine the scope of disembodied knowledge flows, rather then the use of similar technologies. This lack of dependance on foreign technology in sectors less intensive in R&D has been already emphasized by previous studies (Schiff and Olarreaga 2003; Schiff and Wang 2004). Schiff and Olarreaga (2003) found that the R&D content of trade does not affect the growth of total factor productivity in low R&D intensive industries, in a North-South context. Learning in low technology sectors seems to depend on South-South trade (Schiff and Wang 2004).

In sectors with medium technological intensity, there's a notable increase in the coefficients of the trade and technological proximity variables. On the other hand, geographic distance no longer affects the probability to cite. It seems that trade flows carry disembodied knowledge flows to emerging countries in these sectors. This transfer is more important, the more similar is the technology used in trade partners (Kokko, Tansini, and Zejan 1994). From a certain threshold, the distance does not seem to be an obstacle to knowledge flows. This finding highlights the importance of technological capacity level of emerging countries.

Finally, for the high technology sectors, we note a decrease of the impact of trade, whereas technological proximity is rather high. Hence we can conclude that emerging countries patenting in high tech sectors are less dependent on their commercial partners, in terms of technology transfer, than are countries specialized in sectors relatively less intensive in R&D. However, the drop in the number of observations should be noted, indicating that for the moment, only a few emerging countries have reached this stage of innovative capacity. Most of our sample countries remains specialized in medium technology intensive sectors, as described above.

This analysis according to the sectors' technological intensity underlines clearly the role of developing countries' absorptive capacity and technical level in the catching-up process. Our results indicate that technology transfer to emerging countries occurs mostly in middle technology sectors. These findings are in line with the technological gap literature. Kokko *et al.* (1994) report that in Uruguay, technological spillovers exist only where the technological gap between local and foreign firms is medium. In low tech sectors, the impact of trade flows on diffusion of disembodied knowledge is very small. Previous studies arrived to same conclusions when studying the relationship between local firms' productivity growth and level of technology gap in developing (Kokko 1994) or developed (Imbriani and Reganati 1999) countries. On the other hand, in high tech sectors, developing countries no longer rely on foreign

Table 3: Sectors with Low Technological Intensity

First Step : Probability of not to Cite			
	(1)	(2)	(3)
Bilateral Trade	-3.508***		
	(-4.26)		
Imports		-1.079*	
		(-2.33)	
Exports			-0.672***
			(-4.95)
Technological Proximity	5.573	-2.089	-2.838*
	(0.18)	(-0.13)	(-2.03)
Distance	2.109***	1.068*	0.835*
	(3.59)	(2.31)	(2.49)
Common Language	0.222	-3.995**	-1.540
	(0.29)	(-2.63)	(-1.89)
Historical Links	-1.592***	-1.146	-1.225
	(-1.16)	(-1.31)	(-1.88)
Citing Country's Patents	0.562	-1.788***	-1.475***
	(1.58)	(-3.80)	(-4.83)
Cited Country's Patents	-1.466***	-1.283***	-1.174***
	(-3.67)	(-4.68)	(-6.59)
Constant	-0.983	12.066	5.202
	(-0.08)	(1.80)	(1.32)
Number of Observations	22117	21405	21525
Likelihood Ratio Test	119.40	119.19	86.37
Prob>chibar2	0.000	0.000	0.000
Vuong Statistic	6.060	7.070	7.683
Second Step : Probability to Cite			
Bilateral Trade	0.067***		
	(1.72)		
Imports		0.047*	
		(2.05)	
Exports			0.127***
			(2.75)
Technological Proximity	0.086***	0.062**	0.125***
	(5.23)	(3.04)	(5.46)
Distance	-0.064	-0.082*	-0.062
	(-1.84)	(-2.23)	(-1.86)
Common Language	0.215***	0.095*	0.214***
	(5.36)	(2.40)	(5.72)
Historical Links	1.912***	1.227*	1.955***
	(3.88)	(2.22)	(4.05)
Citing Country's Patents	0.937***	1.011***	0.951***
	(6.62)	(5.86)	(6.78)
Cited Country's Patents	0.977***	0.994***	0.958***
	(5.62)	(4.10)	(5.10)
Constant	-11.480***	-12.205***	-11.589***
	(-29.66)	(-27.90)	(-30.72)
Number of Observations	23037	21716	22074
Log-Likelihood	-8787.234	-8491.456	-8562.639
LR chi2	3419.149	3233.345	3391.156
Prob>chi2	0.000	0.000	0.000

Standard errors in brackets.
*Significant at 10%; ** significant at 5%; *** significant at 1%
All variables are in logarithms, except the dependent variable.

Table 4: Medium Technology Intensive Sectors

First Step : Probability to not to Cite			
	(1)	(2)	(3)
Bilateral Trade	-3.009***		
	(-5.13)		
Imports		-1.460*	
		(-2.35)	
Exports			-3.472***
			(-5.83)
Technological Proximity	1.136	-2.133*	-0.176*
	(0.61)	(-0.05)	(-0.65)
Distance	0.363	0.163	0.629
	(1.36)	(0.51)	(1.90)
Common Language	-1.571***	-1.649**	-1.638***
	(-3.25)	(-1.68)	(-2.36)
Historical Links	-2.284***	-5.738***	-6.619***
	(-4.52)	(-4.50)	(-5.67)
Citing Country's Patents	-0.478*	-0.545*	-0.752***
	(-2.40)	(-2.12)	(-3.70)
Cited Country's Patents	-1.937***	-0.022	-0.254
	(-6.48)	(-0.01)	(-0.48)
Constant	9.002	-14.884	5.293
	(0.64)	(-0.60)	(0.73)
Number of Observations	22117	21405	21525
Likelihood Ratio Test	248.87	235.36	295.06
Prob>chibar2	0.000	0.000	0.000
Vuong Statistic	6.060	7.070	7.683
Second Step : Probability to Cite			
Bilateral Trade	0.173**		
	(3.05)		
Imports		0.109***	
		(3.56)	
Exports			0.187***
			(6.49)
Technological Proximity	1.519*	2.355**	1.203*
	(1.55)	(3.28)	(2.55)
Distance	0.019	-0.005	-0.001
	(0.56)	(-0.14)	(-0.03)
Common Language	0.292***	0.275***	0.275***
	(7.96)	(6.91)	(7.41)
Historical Links	1.015***	1.062***	1.073***
	(3.71)	(2.97)	(1.93)
Citing Country's Patents	0.655***	0.629***	0.609***
	(4.95)	(6.99)	(6.67)
Cited Country's Patents	0.793***	0.709***	0.722***
	(3.43)	(3.79)	(1.71)
Constant	-12.098***	-12.256***	-11.549***
	(-27.35)	(-29.38)	(-26.93)
Number of Observations	22117	21405	21525
Log-Likelihood	-9477.743	-9223.987	-9379.857
LR chi2	4577.847	4539.764	4598.544
Prob>chi2	0.000	0.000	0.000

Standard errors in brackets.

*Significant at 10%; ** significant at 5%; *** significant at 1%

All variables are in logarithms, except the dependent variable.

Table 5: High Technology Sectors

First Step : Probability to not to Cite			
	(1)	(2)	(3)
Bilateral Trade	-0.210***		
	(-4.02)		
Imports		-0.291***	
		(-5.11)	
Exports			-0.042
			(-1.77)
Technological Proximity	-0.512**	-0.447**	-0.343*
	(-3.01)	(-2.85)	(-2.10)
Distance	0.294***	0.256***	0.289***
	(4.81)	(4.11)	(4.76)
Common Language	0.008	0.008	0.028
	(0.11)	(0.08)	(0.36)
Historical Links	-0.239	-0.222	-0.189
	(-1.84)	(-1.63)	(-1.44)
Citing Country's Patents	-0.905***	-0.980***	-0.920***
	(-2.76)	(-2.99)	(-1.99)
Cited Country's Patents	-0.979***	-0.963***	-0.982***
	(-2.07)	(-2.90)	(-2.25)
Constant	-8.179***	-8.650***	-8.975***
	(-11.57)	(-11.03)	(-13.15)
Number of Observations	10267	10164	10328
Likelihood Ratio Test	25.53	26.80	28.33
Prob>chibar2	0.000	0.000	0.000
Vuong Statistic	4.353	4.651	4.819
Second Step : Probability to Cite			
Bilateral Trade	0.073**		
	(3.05)		
Imports		0.109***	
		(3.56)	
Exports			0.087***
			(6.49)
Technological Proximity	1.519*	2.355**	2.203*
	(1.55)	(3.28)	(2.55)
Distance	0.019	-0.005	-0.001
	(0.56)	(-0.14)	(-0.03)
Common Language	0.092***	0.075***	0.075***
	(7.96)	(6.91)	(7.41)
Historical Links	0.015***	0.062***	0.073***
	(2.71)	(2.97)	(2.93)
Citing Country's Patents	0.955***	0.929***	0.909***
	(4.95)	(2.99)	(2.637)
Cited Country's Patents	0.893***	0.909***	0.922***
	(3.43)	(3.79)	(4.71)
Constant	-12.098***	-12.256***	-11.549***
	(-27.35)	(-29.38)	(-26.93)
Number of Observations	10267	10164	10328
Log-Likelihood	-4576.207	-4501.819	-4570.679
LR chi2	1186.349	1172.502	1172.818
Prob>chi2	0.000	0.000	0.000

Standard errors in brackets.
*Significant at 10%; ** significant at 5%; *** significant at 1%
All variables are in logarithms, except the dependent variable.

technology carried by trade flows. This indicates that in order to benefit from commercial partners' knowledge, developing countries have to build their own technological abilities, confirming previous results on developed countries (Castellani and Zanfei 2003). However, once a threshold has been achieved and countries has developed a certain level of innovative capacity, knowledge seems to flow by other means than international trade.

6 Conclusion

The purpose of this paper was to investigate the mechanisms of technology transfer through trade flows in emerging countries. Using patent citations, which provide a direct and precise measure of innovative firm's learning process, we evaluated the role of international trade on disembodied knowledge diffusion in a North-South context.

In broad outline, the results show that trade flows carry knowledge across borders. The more a country is involved in international trade, the more it tends to cite foreign patents. We can hence conclude that our sample countries learn and assimilate the knowledge incorporated in import and export flows from Northern countries. However, our results show that technology diffusion by means of international trade is not a uniform process, and this analysis enables us to highlight some particular aspects.

Our principal research question was to assess how emerging countries differ from industrialized countries in the knowledge diffusion process. For this purpose, we first identified the different effects of technological, geographic and cultural proximities on disembodied knowledge flows.

The first consequence of introducing the different proximity effects is the shift between the impact of import and export flows. Our results indicate a learning by exporting effect for emerging countries[36], confirming previous studies. Exporter countries are more likely to cite their partner's patents than are importers.

Concerning the effects of each proximity measure, we have some interesting results. Cultural and historical proximities seem to foster disembodied knowledge flows, and their effect is more significant than technological proximity. This result relativises the role of technological distance and stresses the role played by more intangible proximities. The important role of communication skills (Keller 2002; MacGarvie 2005a) and cultural proximity (Hussler 2004) as a determinant of cross-country citations has been already stressed for North-North diffusion. This issue seem to be even more important regarding emerging countries. The tacit nature of knowledge, combined with the potential lack of technological endowments in the host countries, emphasizes the extent of cultural linkages.

We also found that historical proximity, approximated here by colonial presence of Northern countries in the South, is particularly important for developing countries. Effectively, most of the developing countries have been colonized by today's industrialized economies. It seems that the past colonial relationship reshapes also disembodied and embodied flows to Southern countries. This present study is the first to our knowledge to consider the role of historical linkages in the technology diffusion process.

But the most important factor of knowledge diffusion appears to be technological specialization, and thus, the technical capacity of our sample countries. Our findings differ significantly when we distinguish between technological intensities. In medium technology intensive sectors, where the emerging countries are mostly specialized, technological proximity appear to be more important, whereas the negative impact of geographic distance disappears. We can hence conclude that once emerging countries acquire a certain level of technical capacity in

[36]It should be noted that our analysis doesn't allow us to distinguish between learning by exporting effect and self selection problem. However, as we do not have firm level data, this problem does not arise.

some sectors, they benefit more easily from foreign knowledge. The results of the regression on the high technology sectors confirm this finding, given that the emerging countries seem to depend less on their commercial partners.

This paper enriches the previous literature in several ways. Firstly, the use of patent citations allows us to evaluate directly the learning process in technological fields. Second, by distinguishing sectors' technological intensity and considering proximity effects, we reduce the potential biases in the analysis of trade flows. Finally, this paper furnishes a cross country evaluation of the knowledge flows in a North-South context, at a sectoral level, a subject rather unexplored in the literature. The most important contribution of this study is to establish that the role of cultural and historical factors should not be underestimated in technology transfer analysis.

References

Aghion, P. and P. Howitt (1998). *Endogenous Growth Theory*. The MIT Press.

Aitken, B. J. and A. E. Harrison (1999). Do Domestic Firms Benefit from Direct Foreign Investment? Evidence from Venezuela. *American economic Review 89*(3), 605–618.

Arocena, R. and J. Sutz (2005). Innovation systems and developing countries. Technical Report 02-05, DRUID Working Paper.

Arrow, K. (1962). *The Rate and Direction of Inventive Activity*, Chapter Economic Welfare and the Allocation of Resources for Inventions. Princeton Univ.

Audretsch, D. and M. Feldman (1996). R&D spillovers and the geography of innovation and production. *The American Economic Review 86*(3), 630–640.

Aw, B. Y. and A. Hwang (1995). Productivity in the export market: A firm level analysis. *Journal of Development Economics 47*, 313–332.

Balasubramanyam, V. N., M. Salisu, and D. Sapsford (1996). Foreign direct investment and growth in EP and IS countries. *The Economic Journal 106*, 92–105.

Bee Yan Aw, Chung, S. and M. Roberts (2000). Productivity and the turnover in the export market: Micro-level evidence from the republic of korea and taiwan (china). *The World Bank Economic Review 14*(1), 65–90.

Ben-David, D. (1993). Equalizing exchange: Trade liberalization and income convergence. *Quarterly Jounal of Economics 108*(3).

Bernard, A. and J. Wagner (1997). Exports and succes in german manufacturing. *Weltwirtschaftliches Archives 133*, 134–157.

Bernard, A. B. and J. B. Jensen (1999). Exceptional Exporter Performance : Cause, effect, or Both? *Journal of International Economics 47*, 1–25.

Biesebroeck, J. V. (2004). Exporting raises productivity in sub-saharan african manufacturing plants. *Journal of International Economics*, forthcoming.

Bigsten, A., P. Collier, Dercon, S. Fafchamps, M. B. Gauthier, J. Gunning, A. Oduro, R. Oostendorp, C. Pattillo, M. Söderbom, F. Teal, and A. Zeufack (2004). Do african manufacturing firms learn from exporting? *Journal of Development Studies 40*(3), 115–141.

Blomström, M. and A. Kokko (1999). How foreign investment affects host countries. Technical Report 1745, The World Bank.

Blomstrom, M. (1986). Foreign investment and productive efficiency: The case of mexico. *Journal of Industrial Economics 35*(1), 97–110.

Borensztein, E., J. De Gregorio, and J.-W. Lee (1998). How does foreign direct investment affect economic growth?1. *Journal of International Economics 45*(1), 115–135.

Bottazzi, L. and G. Peri (2003). Innovation and spillovers in regions: Evidence from european patent data. *European Economic Review 47*(4), 687–710.

Brendstetter, L. G. (2001). Are knowledge spillovers are international of intranational in scope? microeconometric evidence from the u.s. and japan. *Journal of International Economics 53*(1), 53–79.

Caballero, R. and A. Jaffe (1993). *How High are the Giants' Shoulders: An Empirical Assessment of Knowledge Spillovers and Creative Destruction in a Model of Economic Growth*. Cambridge, MA: MIT Press: NBER Macroeconomics Annual.

Cameron, A. and P. Trivedi (1998). *Regression Analysis of Count Data*. Cambridge UK : Cambridge University Press.

Castellani, D. (2002). Export behaviour and productivity growth: Evidence from italian manufacturing firms. *Weltwirtschaftliches Archiv 138 (4), 605-628. 138*(4), 605–628.

Castellani, D. and A. Zanfei (2003). Technology gaps, absorptive capacity and the impact of inward investments on productivity of european firms. *Economics of Innovation and New Technology 12*(6), 1–19.

Cincera, M. and B. van Pottelsberghe de la Potterie (2001). International R&D spillovers: A survey. *Cahiers Economiques de Bruxelles 169*, 3–32.

Clerides, S. K., A. Lach, and J. Tybout (1998). Is Learning by Exporting Important? Microdynamic Evidence from Colombia, Mexico, and Morocco. *The Quarterly Journal of Economics 113*, 903–947.

Coe, D. and E. Helpman (1995). International R&D spillovers. *European Economic Review 39*(5), 859–887.

Coe, D. T., E. Helpman, and A. W. Hoffmaister (1997). North-South R&D spillovers. *Economic Journal 107*(440), 134–49.

Cohen, W. and R. Levin (1989). *Empirical Studies of Innovation and Market Structure*. in R. Schmalensee & R. Willig : Handbook of Industrial Organisation, North Holland.

David, D. (1992). Outward-oriented developing economies really do grow more rapidly: Evidence from 95 LDCs, 1976-85. *Economic Development and Cultural Change*, 523–544.

de Mello, L. (1999). Foreign direct investment-led growth: Evidence from time series and panel data. *Oxford Economic Papers 51*, 133–151.

Disdier, A.-C. and K. Head (2004). The puzzling persistance of the distance effect on bilateral trade. Development Studies Working Paper 186, Centro Studi Luca D'Agliano.

Duguet, E. and M. MacGarvie (2005). How well do patent citations measure flows of technology? evidence from french innovation surveys. *Economics of Innovation and New Technology 14*(5), 375–393.

Edwards, S. (1993). Openness, trade liberalization and growth in developing countries. *Journal of Economic Literature 31*(3), 1358–1393.

Eichengreen, B. and D. A. Irwin (1996). The role of history in bilateral trade flows. NBER Working Papers 5565, National Bureau of Economic Research, Inc.

Findlay, R. (1978). Relative backwardness, direct foreign investment and the transfer of technology: A simple dynamic model. *Quarterly Journal of Economics 92*, 1–16.

Girma, Sourafel, G. D. and R. Kneller (2004). Entry to export markets and productivity: A microeconometric analysis of matched firms. *Review of International Economics, Vol.12 12*, 855–866.

Globerman, Steven, A. K. and F. Sjöholm (2000). International technology diffusion: Evidence from swedish patent data. *Kyklos 53*, 17–38.

Gourieroux, C., M. A. and A. Trognon (1984). Pseudo-maximum likelihood methods : Applications to poisson models. *Econometrica 52*, 701–720.

Greene, W. H. (1994). Accounting for excess zeros and sample selection in poisson and binomial regression models. *Working paper No. EC-94-10. New York University*.

Greenwood, J., Z. Hercowitz, and P. Krusell (1997). Long-run implications of investment-specific technological change. *American Economic Review 87*(3), 342–62.

Griliches, Z. (1991). Patent statistics as economic indicators: A survey. *Journal of Economic Literature 28*, 1661–1707.

Grossman, G. M. and E. Helpman (1991). *Innovation and Growth in Global Economy*. Cambridge MA: MIT Press.

Haddad, M. and A. Harrison (1993). Are there positive spillovers from direct foreign investment? : Evidence from panel data for morocco. *Journal of Development Economics 42*(1), 51–74.

Hahn, C. (2004). Exporting and performance of plants: Evidence from korean manufacturing. Working Paper 10208, NBER Working Paper No. 10208.

Hall, B. H., A. Jaffe, and M. Trajtenberg (2005). Market value and patent citations. *Rand Journal of Economics* (36).

Hall, B. H., A. B. Jaffe, and M. Trajtenberg (2001). The NBER patent citation data file: Lessons, insights and methodological tools. NBER Working Papers 8498, National Bureau of Economic Research, Inc.

Hanel, P. (1993). Interindustry flows of technology: An analysis of the canadian patent matrix and input-output matrix for 1978-1989. Technical report.

Harhoff, D., N. F. S. F. and K. Vopel (1999). Citation frequency and the value of patented innovation. *Review of Economics and Statistics 81*(3), 511–515.

Hatzichronoglou, T. (1997). Revision of the high-technology sector and product classification. *STI Working Paper, OECD 2*.

Head, K. and J. Ries (2001). Overseas investment and firm exports. *Review of International Economics 9*(1), 108–22.

Helliwell, J. F. (1998). *How Much Do National Borders Matter?* Washington DC:Brookings Institution.

Hou, C.-M. and S. Gee (1995). *National Innovation Systems: A Comparative Analysis*, Chapter National Systems Supporting Technical Advance in Industry: the Case of Taiwan. New York: Oxford University Press.

Hu, A. G. Z. and A. B. Jaffe (2003). Patent citations and international knowledge flow: the cases of korea and taiwan. *International Journal of Industrial Organization 21*(6), 849–880.

Hussler, C. (2004). Culture and knowledge spillovers in europe: New perspectives for innovation and convergence policies? *Economics of Innovation and New Technology 13*(6), 523–541.

Imbriani, C. and F. Reganati (1999). Productivity spillovers and regional differences: some evidence on the italian manufacturing sector. Technical Report 48, CELPE (Centre of Labour Economics and Economic Policy), University of Salerno, Italy.

Isgut, A. E. (2001). What's different about exporters: Evidence from colombian manufacturing. *Journal of Development Economics 37*(5).

Jaffe, A. B. (1986). Technological opportunity and spillovers of R&D: Evidence from firms'patents, profits and market value. *American Economic Review 76*(5), 984–1001.

Jaffe, A. B. and M. Trajtenberg (1996). Flows of knowledge from universities and federal labs: Modeling the flowof patent citations over time and across institutional and geographic boundari. NBER Working Papers 5712, National Bureau of Economic Research, Inc.

Jaffe, A. B. and M. Trajtenberg (1998). International knowledge flows: Evidence from patent citations. NBER Working Papers 6507, National Bureau of Economic Research, Inc.

Jaffe, A. B., M. Trajtenberg, and M. S. Fogarty (2000). Knowledge spillovers and patent citations: Evidence from a survey of inventors. *American Economic Review 90*(2), 215–218.

Jaffe, Adam B., T. M. and R. Henderson (1993). Geographic localisation of knowledge spillovers as evidenced by patent citations. *Quarterly Journal of Economics 108*(3), 577–598.

Kao, Chihwa, C. M.-H. and B. Chen (1999). International R&D spillovers: An application of estimation and inference in panel cointegration. *Oxford Bulletin of Economics and Statistics 61*, 693–771.

Keller, W. (2000). Do trade patterns and technology flows affect productivity growth? *World Bank Economic Review 14*, 17–49.

Keller, W. (2001). Knowledge spillovers at the world's technology frontier. CEPR Discussion Papers 2815, C.E.P.R. Discussion Papers.

Keller, W. (2002). Geographic localization of international technology diffusion. *American Economic Review 92*(1), 120–142.

Kokko, A. (1994). Technology, market characteristics, and spillovers. *Journal of Development Economics 43*(2), 279–293.

Kokko, A., R. Tansini, and M. Zejan (1994). Productivity spillovers from fdi in the uruguayan manufacturing sector. Working Paper 2, Stockholm School of Economics.

Kraay, A. (1999). Exportations et performances economiques: Etude d'un panel d'entreprises chinoises. *Revue d'Economie du Developpement 1*(2), 183–207.

Lambert, D. (1992). Zero-inflated poisson regression with an application to defects in manufacturing. *Technometrics 31*, 1–14.

Lejour, A. and R. Nahuis (2001). Openness, growth and R&D spillovers: uncovering the missing link? Research Memorandum 168, CPB.

Lichtenberg, F. R. and B. v. Pottelsberghe de la Potterie (1998). International R&D spillovers: A comment. *European Economic Review 42*(8), 1483–1491.

Lipsey, R. E. and M. Y. Weiss (1984). Foreign production and exports of individual firms. NBER Reprints 0558, National Bureau of Economic Research, Inc.

Lundvall, G. (1992). *National System of Innovation: Towards a Theory of Innovation and Interactive Learning*. London: Francis Printer.

M. Delgado, J. F. and S. Ruano (2002). Firm productivity and export markets: A non-parametric approach. *Journal of International Economics 57*(2), 397–422.

MacGarvie, M. (2005a). The determinants of international knowledge diffusion as measured by patent citations. *Economics Letters 87*, 121–126.

MacGarvie, M. (2005b). Do firms learn from international trade? *Review of Economics and Statistics*.

Maurseth, P. B. and B. Verspagen (2002). Knowledge spillovers in europe: A patent citations analysis. *Scandinavian Journal of Economics 104*(4), 531–45.

OCDE (2003). *Science and Technology Indicators*. OCDE. Paris, France.

OCDE (2005). *OECD Factbook*. OCDE. Paris, France.

OMC (2003). *World trade Report*. Organisation Mondiale du Commerce, Genève.

Orlando, M. J. (2000). On the importance of geographic and technological proximity for R&D spillovers : an empirical investigation. Research Working Paper RWP 00-02, Federal Reserve Bank of Kansas City.

Peri, G. (2002). Knowledge flows and knowledge externalities. CESifo Working Paper Series CESifo Working Paper No., CESifo GmbH.

Peri, G. (2005). Determinants of knowledge flows and their effect on innovation. *The Review of Economics and Statistics 87*(2).

Potterie, B. V. P. D. L. and F. Lichtenberg (2001). Does foreign direct investment transfer technology across borders? *The Review of Economics and Statistics 83*(3), 490–497.

Redding, S. and J. Proudman (1998). Productivity convergence and international openness. Technical report.

Rhee, Yung, B. R.-L. and G. Pursell (1984). *Korea's Competitive Edge: Managing Entry into World Market*. Washington, D.C.: World Bank.

Robert C. Feenstra, Robert E. Lipsey, H. D. A. C. M. and H. Mo (2005). World trade flows: 1962-2000. Working Paper 11040, NBER.

Rodriguez, F. and D. Rodrik (1999). Trade policy and economic growth: A skeptic's guide to cross-national evidence. Technical Report 7081, National Bureau of Economic Research, Inc.

Romer, P. (1990). Endogenous technological change. *Journal of Political Economy 98*(5), 71–102.

Sachs, J. and A. Warner (1995). Economic reform and the process of global integration. *Brookings Papers on Economic Activity 1*, 1–118.

Saggi, K. (2002). Trade, foreign direct investment, and international technology transfer: A survey. *World Bank Research Observer 17*(2), 191–235.

Sampat, B. N., D. C. Mowery, and A. A. Ziedonis (2003). Changes in university patent quality after the bayh-dole act: a re-examination. *International Journal of Industrial Organization 21*(9), 1371–1390.

Schiff, M. and Y. Wang (2004). On the quantity and quality of knowledge: The impact of openness and foreign research and development on north-north and north-south technology spillovers. Policy Research Working Paper 3190, World Bank.

Schiff, Maurice, W. Y. and M. Olarreaga (2003). North-south and south-south trade-related technology diffusion: An industry level analysis. Discussion Paper 3711, CEPR.

Sebastian, E. (1998). Openness, productivity and growth: What do we really know. *Economic Journal 108*, 383–398.

Sjoholm, F. (1996). International transfer of knowledge: The role of international trade and geographic proximity. *Weltwirtschafliches Archiv 132*(1), 97–115.

Sjoholm, F. (1999). Technology gap, competition and spillovers from direct foreign investment: Evidence from establishment data. *Journal of Development Studies 36*(1), 53–75.

Taeube, F. A. (2004). Proximities and innovation: evidence from the indian it industry in bangalore. Technical report.

The Economist (19.01.2006). Climbing back. *19 Janvier*, 11–91.

Thompson, P. and M. Fox-Kean (2005). Patent citations and the geography of knowledge spillovers: A reassessment. *American Economic Review 95*(1), 450–460.

Trajtenberg, M. (1990). A penny for your quotes: Patent citations and the value of innovations. *RAND Journal of Economics 21*(1), 172–187.

Vuong, Q. (1989). Likelihood ratio tests for model selection and non-nested hypotheses. *Econometrica 57*(2), 307–334.

Wilkelmann, R. and K. Zimmermann (1995). Recent developments in count data modelling : Theory and application. *Journal of Economic Surveys 9*, 1–24.

WorldBank (2005). *World Development Indicators*. World Bank. Washington, USA.

Xu, B. and J. Wang (1999). Capital goods, trade and R&D spillovers in the oecd. *Canadian Journal of Economics 32*, 1258–1274.

A Appendix

A.1 Data Construction

Our primary source of data comes from NBER Patent and Citation Dataset[37] and UNIDO Trade and Production Database[38]. NBER data contains all the patents granted by U.S. Patent Office (USPTO) and all citations made by each patent to others, from 1975. The USPTO assign each patent to an original patent class. This United States Patent Classification (USPC) System consists about 400 main patent classes and 120 000 patent subclasses. In order to match patent citations over sectors and countries with UNIDO data which is presented in International Standard Industrial Classification (ISIC. Rev2), we needed to use several correspondence tables.

First correspondence table was between USPC System and the International Patent Classification (IPC). We'd like the thank Prof. Brian Silverman for providing these data. Once we had the IPC number for each patent on our database, we used a concordance that links the International Patent Classification (IPC) system to the U.S. Standard Industrial Classification (SIC) system at the four-digit SIC level, in order to have a SIC number for each citing and cited patent. This concordance table also come from Prof. Silverman[39]. The next step was to link these SIC numbers to ISIC Rev.2 Classification in order to match the two databases.

Using Jon Haveman's industrial concordance tables, we connected our 4-digit SIC numbers to 3-digit ISIC Rev.3 Classification System. Finally, the last step consisted to link ISIC Rev.3 Classification system to ISIC Rev.2, based on the United Nations' correspondence tables.

[37] See Hall et al. (2001) for details.

[38] See Nicita and Olarreaga (2001) for details

[39] See Prof. Silverman's homepage (http://www.rotman.utoronto.ca/ silverman/ipcsic/documentation_IPC-SIC_concordance.htm) for details.

A.2 Summary Statistics on Host Countries

Country	Exports of goods and services (% of GDP)	Imports of goods and services (% of GDP)	FDI, net inflows (BoP, million US$)	GDP growth (%)	High-tech exports (% of manuf. d exports)	Industry Value Added (% of GDP)	Trade in goods (% of GDP)
Argentina	10.89	11.52	10418.31	-0.79	9.04	28.06	18.12
Brazil	10.66	12.18	32779.24	4.40	18.61	27.97	18.90
China	25.87	23.20	38399.3	8.00	18.58	50.22	43.89
Czech Republic	64.46	67.54	4987.079	3.89	8.15	40.92	109.79
Hong Kong	145.50	141.91	61923.9	10.20	23.28	14.22	252.01
Hungary	74.88	78.73	1694.3	5.20	26.42	33.10	128.51
Iceland	34.99	42.10	155.3281	5.60	12.26	26.64	53.23
India	13.89	14.65	2496.042	3.94	5.01	26.60	20.53
Israel	40.40	45.43	5077	7.53	25.09	59.84	n.a.
Korea	40.82	37.67	9283.4	8.49	34.82	36.19	65.00
Malaysia	124.41	104.46	3787.6	8.86	59.53	50.73	199.50
Mexico	31.00	32.94	16597.6	6.60	22.40	28.01	60.05
New Zealand	35.94	34.22	3369.842	2.66	10.16	25.29	52.09
Russian Federation	44.06	24.03	2713	10.00	13.53	37.95	57.84
Singapore	n.a.	n.a.	17219.54	297.73	9	62.56	37.05
South Africa	28.86	25.86	968.831	4.15	6.97	31.13	46.62
Venezuela, RB	28.45	16.32	4701	3.69	2.83	40.47	39.60

Source: World Development Indicators - World Bank

A.3 Description of Variables and Sources

Bilateral Trade	Bilateral flows of imports and exports NBER World Trade Database - NBER ISIC Rev3, 1960-2000
Patent Citations	Number of citations per country and sector NBER Patent and Citations Database - NBER 1963-1999
Technological Proximity	Index of technological proximity by Jaffe et al. (1986) between citing and cited countries $\omega_{ij} = \frac{\sum_{k=1}^{N} N_{ik} f_{jk}}{\sqrt{\sum_{k=1}^{F} N_{ik}^2 \sum_{k=1}^{F} N_{jk}^2}}$ NBER Patent and Citations Database - NBER 1963-1999
Geographic Distance	Geodesic distance between capitals Distance Database- CEPII
Language	Share (or not) of a commun language between two countries (Official or national language, or language spoken by at least 20% of the country) Distance Database - CEPII
Colonial Presence	Presence colonial (or not) of technology source country in the developing country, for a long time and with a substantial participation in the colonized country's government. Distance Database- CEPII

All variables are converted in constant dollar.

A.4 Description of ISIC Rev.2 3-Digit

ISIC Code	Description
313	Beverages
321	Textiles
323	Leather products
324	Footwear except rubber or plastic
332	Furniture except metal
341	Paper and products
342	Printing and publishing
351	Industrial chemicals
352	Other chemicals
355	Rubber products
362	Glass and products
369	Other non-metallic mineral products
381	Fabricated metal products
382	Machinery except electrical
383	Machinery electric
385	Professional and scientific equipment
390	Other manufactured products

Source: United Nations Statistics Division - UN

A.5 Industries Classified According to their Technological Intensity

High Technology	ISIC Rev2
Aerospace	3845
Computers, Office Machinery	3825
Electronics-communication	3832
Pharmaceutical	3522
Middle-High Technology	
Scientific Instruments	385
Motor Vehicles	3843
Electrical machinery	383-3832
Chemicals	351+352+3522
Other Transport Equipment	3842+3844+3849
Non-Electrical Machinery	382-3825
Middle-Low Technology	
Rubber and Plastic Products	355+356
Shipbuilding	3841
Other Manufacturing	39
Non-Ferrous Metals	372
Non-Metallic Mineral Products	36
Fabricated Metal Products	381
Petroleum Refining	351+354
Ferrous Metals	371
Low Technology	
Paper Printing	34
Textile and Clothing	32
Food, Beverages and Tobacco	31
Wood and Furniture	33

Source: (Hatzichronoglou 1997)