Technology Diffusion via Patent Collaborations: The Case of European Integration

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NOTICES

Summary

List of Tables

List of figures

Abstract

This paper aims to study the impact of potential determinants for technology diffusion via patent collaborations between emerging and developed countries in Europe by implementing an econometric estimation with panel data. First, we use the probability of patent collaborations as the explained variable under LOGIT estimations. Then, we use the intensity of collaborations under both OLS/GLS and Poisson estimations. We especially study the impact of the European Union integration of Eastern Europe countries on such technological collaborations with European Western countries. We also analyze the impact of further explanatory variables such as common borders, geographic distance, Gross Domestic Products, populations, income inequalities, Research and Development expenditures, technological gap, technological distance public expenditures in education, bilateral trade and Foreign Direct Investments. The results show that the European integration of emerging countries does not significantly increase the probability of patent collaborations. But it does significantly increase the intensity of patent collaborations. Emerging countries' exports to developed countries is the main determinant for both the probability and the number of patent collaborations. The impact is significant and positive.

JEL Classifications: F13, O33

Keywords: Technology Diffusion, Patent Collaborations, Econometric Estimation, European Union Integration.

1. Introduction

There is a growing interest in the analysis of international technology diffusion in the economic literature. There is a development issue for emerging countries because technology diffusion permits to improve industries that enhance economic development, especially capital intensive industries. Moreover, firms can use modern technologies, increase their workers' wage and improve working conditions. New products may also appear in these emerging countries with technology diffusion. Generally, technology diffusion comes from developed countries' innovations. Then, emerging countries acquires new products and new processes previously discovered by developed countries. Information diffusion involves technology diffusion and makes that the entire world can benefit from converging technology levels (Geroski, 2000; Keller, 2002). In this paper, we identify the channels and determinants for technology diffusion from developed countries to emerging countries.

1.1. Economic Literature

The issue of technology diffusion has been studied in the economic literature. Keller (2004) makes a wide survey for this topic. A first factor of technology diffusion is Research and Development (R&D) investment owing to R&D spillovers, the sources of which we need to find. Generally, the speed of technology diffusion between two countries increases with the volume of trade between them, especially the trade of intermediate goods (Rivera-Batiz and Romer, 1991; Grossman and Helpman, 1991; Eaton and Kortum, 2002). Emerging countries import intermediate goods from developed countries and need to use modern technology to produce finished goods. Usually, international trade involves information flows between countries because of business interactions. Coe and Helpman (1995) find close results empirically by showing that the R&D spillovers effect increases with the openness of international trade. The role of "learning-by-exporting" is also mentioned in several studies (Rhee, Ross-Larson and Pursell, 1984; Clerides, Lach and Tybout, 1998; Bernard and Jensen, 1999; Keller, 2004; Keller, 2010). The economic literature has also proven that the speed of technology diffusion between two countries increases with Foreign Direct Investments (FDI) stock because of FDI spillovers for the country receiving it (Griliches and Hausman, 1986; Keller, 2002; Griffith, Redding and Simpson, 2003; Keller, 2010). For example, Japanese R&D investments in Asian emerging economies increased nine-fold from 1993 to 2007 (Source: UNCTAD). Emerging countries like China, Korea or India benefited from such Japanese investments. Multinational Firms (MNF) use labor force from a foreign country where they are located. Spillovers between countries appear because of worker training by MNF (Aitken and Harrisson, 1999; Fosfuri, Motta and Rønde, 2001). This is the reason why the relationship between MNF and subsidiaries located in foreign countries clearly overrides FDI (Markusen, 2002). International trade and FDI represent two important factors of technology diffusion. Ethier and Markusen (1996) studies the choice between international trade and FDI for a firm that wishes to sell its product in a foreign country by using a theoretical dynamic framework with technological externalities. A firm from the domestic country discovers a new product and benefits from a temporary monopoly (equal to two periods in the model). The firms from the foreign country do not invest in research in order to discover new products. The firm has a choice between exporting from its domestic country and locating a part of its output in the foreign country. According to the authors, localization involves greater absorption of information for other firms in the foreign country that can produce the new product faster. Then, technology diffusion seems to be faster with localization than with exports. But it represents a cost for the domestic firm because the new product is no longer in a monopoly situation. The choice between exporting and locating depends on the transport cost of exports and the monopoly rent of localization.

The economic literature analyzes the impact of public policy instruments (especially trade policies) on technology diffusion. The reference model without diffusion is the framework of Spencer and Brander (1983) that analyzes the positive effect of a R&D subsidy on domestic R&D investment and national welfare in an international duopoly. Cheng (1987) designs a close framework within a dynamic model. Considering international technology diffusion, he shows that the R&D subsidy that only satisfies domestic interest may benefit from the foreign firm. It may also enhance diffusion. Grossman and Helpman (1991) implement a theoretical macroeconomic model with technological spillovers and study the economic impact of trade openness for a small country. They show that trade policies that reduce (respectively promote) international trade, especially trade of intermediate goods, like tariffs or quotas (respectively subsidies) have a negative (respectively positive) effect on innovations and technology diffusion via knowledge spillovers. For example, a tariff cut involves an increase in trade volume, trade through variety of intermediate goods and stock of human capital through variety. Then, spillovers to foreign countries are greater. Jaffe and Stavins (1995) study the impact of environmental policy instruments like environmental taxes or energy efficiency subsidies on technology diffusion by implementing an empirical analysis for 48 states over 1979-1988. They find a positive impact of such a form of policy instruments. Reppelin-Hill (1999) makes an econometric study of the relationship between the trade openness and the speed of clean technology diffusion by using the example of the steel industry. He demonstrates that diffusion of clean technology is *"faster in countries that have more open trade policy regimes* [p. 284]*."* Geroski (2000) makes a survey of factors of technology diffusion. Information diffusion involves technology diffusion. He suggests that governments can subsidize technological externalities *"to promote … communication … and to motivate them* [p. 621]*."* Van Dijk and Szirmai (2006) show a preponderant role of industrial policies on technology diffusion in the case of Indonesian paper making machinery over 1923-2000. Policies like import-substituting industrialization over 1974-1984 or export-oriented industrialization over 1984-1997 involved an increase in technology diffusion. Battisti (2008) also uses the example of environment and establishes that technology diffusion is a low process. Governments' policies may increase R&D investment but *"should also look at the adoption and the extent of use of innovations because that is the place where the generation of the benefits from inventions takes place* [p. 528]*."* Bustos (2011) shows that the Mercosur integration of Argentina involved a technologic upgrading of domestic firms because free trade may facilitate the adoption of new technologies in order to increase the productivity.

The economic literature also studies the impact of other variables that influence the speed of technology diffusion. The geographic distance between two countries has an impact on technology diffusion owing to its effect on the bilateral trade. Generally, previous studies proved that technology diffusion is faster inside a country than between two countries (Jaffe, Trajtenberg and Henderson, 1993; Eaton and Kortum, 1999; Branstetter, 2001). There is a border effect. Nevertheless, Irwin and Klenow (1994) do not find that the speeds of technology diffusion are not significantly different by taking the example of US firms as compared to foreign firms in semi-conductors industry from 1974 to 1992. Other papers study the significant negative effect of the distance in kilometers on the speed of technology diffusion (Keller, 2002; Bottazi and Peri, 2003).

The impact of industrial protection is also studied through the role of patent publications. Patents may slow down technology diffusion because they involve a monopoly length on a new product or a new process. There is an optimal patent length (Nordhaus, 1969; Scherer, 1972; Tandon, 1982; Klemperer, 1990; Gilbert and Shapiro, 1990). Nevertheless, patent citations by other firms can be considered as a way to measure technology diffusion. Eaton and Kortum (1999) consider that patent publications in foreign countries are one possible measure of technology diffusion (even it is not a perfect indicator according to them) and show that the diffusion may depend on the ability to file a patent in the country and the patent cost. The economic literature has studied the case of patent collaborations. It relates to an interesting measure of technology diffusion by considering collaborations between developed and emerging countries. For example, social network structures influence knowledge flows and actors' performances (Cowan and Jonard, 2004; Schilling and Phelps, 2007). Fleming et al. (2007) prove that patent collaborations enhance productivity by considering a small-world regional structure. Guan and Chen (2012) shows that non OECD members improved their technological performances with collaborations with OECD members. Breschi and Lissoni (2009) study the relationship between geography and knowledge diffusion by illustrating that co-invention networks are localized because researchers are not likely to relocate. The economic literature also uses gravity equations to find potential determinants for technological collaborations. Technological distance, common languages and common borders are significant determinants (Guellec and Van Pottelsberghe de la Potterie, 2001; Picci, 2010). Maggioni, Nosvelli and Uberti (2007) find a significant impact of geographical and technological distance by using 109 European regions over 1998-2002. Montobbio and Sterzi (2012) study the specific case of emerging countries. They find a negative and significant effect of geographic distance and a positive and significant effect of technological proximity and common language. They also illustrate that stronger intellectual property rights increase international technological collaborations from subsidiaries of multinational firms. Nevertheless, we have to mention an important limit by using patent collaborations as the explained variable. According to Bergek and Bruzelius (2010), patent collaboration statistics may be the result of simple inventor movements. They show that 40 percent of 53 patents filed by ABB, a Swiss-Swedish firm, are the result of inventor movements.

1.2. Presentation of the Study

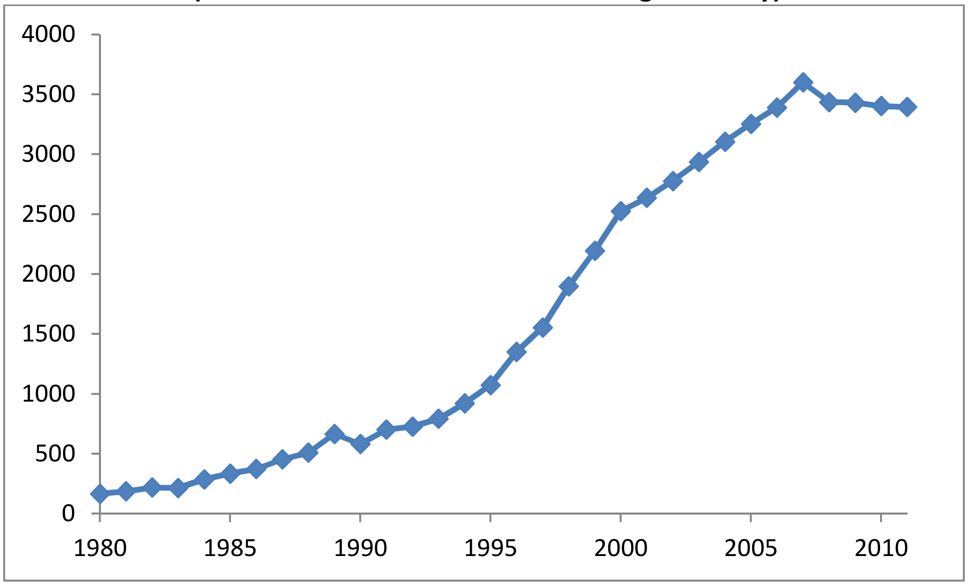
In this paper, we study the impact of potential determinant for technology diffusion by using patent collaborations between developed and emerging countries as the explained variable. Here, patent collaborations denote the number of patents filed by an inventor from an emerging country when there is a foreign co-inventor from a developed country. The applicant is located in the emerging country while the foreign co-inventor is located in the developed country. They have to pay a patent filing cost that depends on the patent length. In this case, co-inventors benefit from an industrial protection on the market of the country where they filed the patent.

We study the impact of potential explanatory variables on both the probability and the intensity of patent collaborations. First, we run LOGIT estimations by using the probability of collaborations. Then, we run both conditional and total estimations by using the intensity. With conditional estimations, we only integrate the cases where the number of collaborations at least equals to one and we run both OLS/GLS and Poisson estimations. With total estimations, we integrate all the cases and we only run Poisson estimations.

We focus on the European Union (EU). We use data for Eastern and Western Europe countries over the period 2000-2011. In this paper, we denote countries of the former “Eastern Bloc” as European emerging countries and Western Europe countries as European developed countries. We consider patent collaborations between these two groups of countries i.e. the number of patents filed at the European Patent Office (EPO) by an inventor located in a European emerging country when there is a foreign co-inventor located in a European developed country. Inventors from non EU countries can file patents in the EPO.[1] Then, inventors benefit from an industrial protection in the European market.

There is a growing interest for patent collaborations in the European Union. See Figure 1. Technological collaborations represent a way to benefit from foreign source of productivity in Europe, especially for Eastern transition economies.

Figure 1 – Evolution of the Number of Patent Collaborations Filed at the European Patent Office by an EU Inventor (with an EU Co-Inventor from a Foreign Country) over 1980-2011



Source: OECD.

We aim to study the impact of European integration of Eastern countries on their patent collaborations with European developed countries. European integration is measured by a dummy that equals to one when the emerging country is a European Union member and zero, otherwise. Here, European integration relates to: (i) free trade between emerging and developed countries owing to the customs union, (ii) common exterior import tariffs, (iii) European internal market with the free movements of goods, capital, services and people. We consider the impact of European integration as the impact of removing policy instruments like tariffs or quantitative restrictions. We aim to study the impact of trade policy on patent collaborations and technology diffusion.

Picci (2010) studies the impact of a dummy variable for EU members on the number of internationalized patents and generally find a positive impact, except for one case where the coefficient is significantly negative. Nevertheless, the author uses a general structure by using 56 countries without only studying the technological relationships between developed and emerging

[1] For example, inventors located in Russia filed patents at the EPO while Russia is not an EU member, neither an EPO member.

countries. In this paper, we focus on the collaborations between European developed and emerging countries. Furthermore, we aim to study the impact of transition economies' European integration on both the probability and the intensity of patent collaborations with developed countries while the economic literature is essentially focused on the intensity. These two points denote the main contributions of our paper.

We also study the impact of gravity equation variables like common borders, geographic distance, populations and Gross Domestic Product (GDP). Then, we analyze the impact of each country's R&D expenditures and of public expenditures in education. These two variables relate to investments in human capital. We also analyze the impact of the technological gap and of the technological distance between Eastern and Western Europe countries. We define the technological gap as a difference in the level of innovations while the technological distance is a difference in the structure of innovations. Finally, we study the impact of imports, exports and FDI.

The results illustrate a positive and significant impact of the European integration on the intensity of patent collaborations under both conditional and total estimations while the impact on the probability of patent collaborations under LOGIT regressions is not significant. The most significant determinant for both the number and the probability of patent collaborations is emerging countries' exports to developed countries. However, the impact of imports and FDI is not significant. The geographic distance is also a significant determinant by reducing collaborations while common borders only significantly increase the number of patent collaborations under conditional estimations. Emerging countries' GDP significantly increases the probability of patent collaborations but does not influence the intensity. Developed countries' GDP never significantly influences patent collaborations. Each population may significantly increase both the probability and the intensity even if we find one case where developed countries' population reduces the number of collaborations under OLS/GLS estimations. Income inequalities significantly reduce the probability of patent collaborations because the impact of the ratio of GDP per capita is positive. But the impact on the intensity of collaborations is not significant. Emerging countries' R&D expenditures significantly increase the number of patent collaborations under OLS/GLS estimations while it does not significantly influence the probability. The impact of developed countries' R&D expenditures is not significant. The technological gap and the technological distance significantly reduce the number of collaborations under Poisson total estimations. European emerging countries' public expenditures in education significantly increase the probability of patent collaborations while the effect on the intensity is not significant.

Section 2 introduces the general framework of the paper. Section 3 presents the database. Section 4 presents the results of LOGIT estimations by using the probability of patent collaborations as the explained variable. Section 5 presents the results of both Conditional and Total estimations by using the number of patent collaborations. Section 6 summarizes and discusses the results. Section 7 verifies whether or not the results hold by using the number of years from the European integration to the last year of the database instead of a dummy variable. Section 8 concludes.

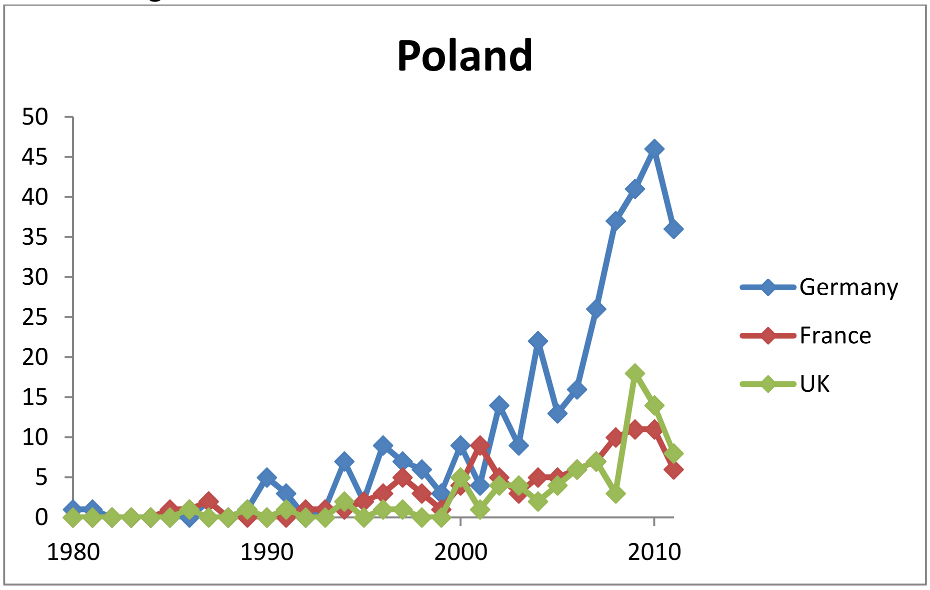
2. General Framework

This paper aims to study the impact of potential determinants for international technology diffusion from developed countries to emerging countries by using the example of European Union.

Let us define a way to measure the speed of technology diffusion. We use Patent collaborations as the explained variable by referring to the economic literature mentioned in the general introduction. Patent collaborations are defined as the number of patents filed at the European Patent Office (EPO) by an inventor located in a European emerging country when there is a co-inventor from a European developed country. Using the example of Russia, it is possible that the patent applicant does not come from an EU member country. The variable PAT_{ijt} denotes the number of patents filed by an inventor of the emerging country i with a co-inventor from the developed country j at time t. Such a variable denotes patent collaborations. As we said in the general introduction, the main problem is that statistics may integrate simple inventor movements that do not relate to collaborations.

Let us study a significant example of patent collaboration. Figure 2 illustrates the evolution of Polish patent collaborations with three European developed countries over 1980-2011.

Figure 2 – Poland's Patent Collaborations over 1980-2011: Evolution of the Number of Patents Filed with a Foreign Co-Inventor



Source: OECD.

We analyze the evolution of the number of patents filed domestically by Polish inventors with German, French and British co-inventors. Poland joined the European Union in 2004. The number of patent collaborations with German co-inventors increased sharply from 2005. Such an example proves that the European integration may have a significant impact on patent collaborations. Nevertheless, we cannot make the same conclusion for the collaboration with French or British co-inventors. Other variables influence patent collaborations. For example, the geographic distance seems to be a significant source of collaboration because there is a common border between Poland and Germany.

We try to identify potential sources of international technology diffusion. According to previous studies and economic intuitions, we assume that the following variables are potential sources.

- The study of the effect of European integration is the stronger innovation of the paper with respect to previous studies. We aim to find whether or not technology diffusion to European is stronger after they integrate European Union (EU). European integration means that members have to remove all trade policy instruments on imports from other members. Then, we analyze the impact of free trade. We denote as EU_{it} a dummy variable which equals to one when the emerging country i is an EU member and to zero, otherwise. We look forward to a positive impact of such a dummy variable.

- Technology collaborations may be stronger when countries share a common border because it seems easier to innovate together. We denote as CB_{ij} a dummy variable which equals to one when countries i and j share a common border and to zero, otherwise. Then, the expected impact is positive.
- Geographic distance may also influence technology diffusion via patent collaborations for the same reason. We denote as $DIST_{ij}$ the geographic distance between countries i and j. The expected impact of distance is negative.
- Patent collaborations may depend on each country's market size. We can use two indicators: population and GDP. We denote as POP_{it} (POP_{jt}) country i (j)'s population and Y_{it} (Y_{jt}) country i (j)'s GDP.
- Income inequalities between the two countries may reduce collaborations. We aim to verify whether or not economic proximity is a significant determinant for technology diffusion by using the ratio of GDP per capita y_{it}/y_{jt} between emerging and developed countries, where $y = Y/POP$.
- R&D expenditures may be significant explanatory variables because they measure innovations. Furthermore, the role of human capital may be prominent since R&D expenditures are knowledge investments (Eaton and Kortum, 1996; Xu, 2000). We denote as R_{it} (R_{jt}) emerging (developed) country i (j)'s R&D expenditures at time t.
- The technological gap may be a significant variable. It relates to the difference in the level of innovations between the two countries Then, we analyze the impact of the ratio of the share of R&D expenditures in GDP between the country i and the country j. We denote as r_{it} (r_{jt}) the share of the country i (j)'s R&D expenditures in its GDP, where $r = R/Y$. Then, the ratio is: r_{it}/r_{jt}. An increase in its ratio denotes a drop in the technological gap between the two countries. The reason is that emerging countries' R&D expenditures are lower than developed countries'.[2]
- We analyze the impact of the technological distance that we can define as the difference in the structure of innovations. Such a technological distance relates to the technological proximity mentioned in the economic literature as we said in the general introduction. We denote as TD_{ijt} the technological distance between the country i and the country j at time t. We use a method close to Jaffe (1988). We use the number of patent filed by domestic inventors for 36 technologies. We calculate the share of the number of patents over the total number of patents for each technology. Then, we calculate the sum of the difference in shares between the two countries in absolute terms for the 36 technologies at each period. Denoting k the index for technologies and pat the number of patents, we have: $TD_{ijt} = \sum_{k=1}^{k=36} |pat_{itk} - pat_{itk}|$. An increase in such a variable involves an increase in the technological distance i.e. a drop in the technological proximity. The expected sign of the impact of such a variable is negative.
- We also study the impact of public expenditures in education that represents another way to measure investments in human capital with respect to R&D investments.
- Finally, technology diffusion may depend on bilateral trade and FDI (Grossman and Helpman, 1991; Coe and Helpman, 1995). Trade and FDI increase business relationships. Then, the effect

[2] The ratio r_{it}/r_{jt} is lower than one under 1042 cases over 1092 in our database.

on technological collaborations may be positive. We denote as X_{ijt} emerging country i's exports to developed country j, M_{ijt} emerging country i's imports from developed country j, and FDI_{ijt} emerging country i's FDI from developed country j. The expected impacts of these variables are positive.

Table 1 illustrates the expected impact of each explanatory variable on technology diffusion via patent collaborations.

Table 1 – Expected Impact of Each Explanatory Variable

EU_{it}	CB_{ij}	$DIST_{ij}$	Y_{it}	Y_{jt}	POP_{it}	POP_{jt}	y_{it}/y_{jt}	R_{it}
+	+	−	+	+/−	+	+/−	+	+
R_{jt}	r_{it}/r_{jt}	TD_{ijt}	EDU_{it}	EDU_{jt}	X_{ijt}	M_{ijt}	FDI_{ijt}	
+	+	−	+	+	+	+	+	

Source: author.

We expect a negative impact of the geographic distance between developed and emerging countries because it seems complex to implement technological collaborations when potential co-inventors are distant. Furthermore, as we have mentioned in the general introduction, the economic literature demonstrates a negative impact of the geographic distance on the technology diffusion. The expected impacts of developed countries' market size (GDP and population) are ambiguous. First, innovations may increase with GDP and population. Inventors from developed countries may be encouraged to collaborate with foreign inventors. But they may also be encouraged to file patents in their own country rather in the emerging country owing to a stronger market size. We have no reason to expect negative impact for other explanatory variables.

First, we study the impact of these variables on the probability of patent collaborations between emerging country i and developed country j by using LOGIT estimations. Second we study their impact on the intensity of patent collaborations by using both conditional and total estimations.

3. Data

We use panel data with:

- 13 emerging countries (index i):
  - 8 EU members since 2004: Czech Republic, Estonia, Lithuania, Latvia, Hungary, Poland, Slovakia, Slovenia
  - 2 EU members since 2007: Romania, Bulgaria
  - 3 non EU members: Russia, Ukraine, Croatia[3]
- 7 European developed countries (index j): France, Germany, United Kingdom, Austria, Belgium, Netherlands, Italy
- Over the period 2000-2011 (index t).

Table 2 illustrates the definition and the source of data.

[3] Croatia is an EU member since 2013.

Table 2 – Definition and Source of Each Variable

Variable	Definition	Source
PAT_{ijt}	Number of patents filed at the European Patent Office by an inventor from the emerging country i with a co-inventor from the developed country j at time t.	OECD
EU_{it}	Dummy variable which equals to one when the emerging country i is a European Union member at time t and to zero, otherwise.	-
CB_{ij}	Dummy variable which equals to one the emerging country i shares a common border with the developed country j and to zero, otherwise.	-
$DIST_{ij}$	Geographic distance between the emerging country i's biggest city and the developed country j's, in kilometers.	CEPII
Y_{it}	Gross Domestic Product of the emerging country i at time t, in USD	World Bank WDI
Y_{jt}	Gross Domestic Product of the emerging country j at time t, in USD	World Bank WDI
POP_{it}	Population in the emerging country i at time t, number of residents	World Bank WDI
POP_{jt}	Population in the developed country j at time t, number of residents	World Bank WDI
R_{it}	Research and Development expenditures of the emerging country i at time t, in USD	World Bank WDI
R_{jt}	Research and Development expenditures of the developed country j at time t, in USD	World Bank WDI
PAT_{itk}	Number of patents filed by an inventor located in the country i at time t for the technology k.	WIPO
PAT_{jtk}	Number of patents filed by an inventor located in the country j at time t for the technology k.	WIPO
EDU_{it}	Public expenditures in education of the emerging country i at time t, in USD	World Bank WDI
EDU_{jt}	Public expenditures in education of the developed country j at time t, in USD	World Bank WDI
X_{ijt}	Exports from the emerging country i to the developed country j at time t, in USD	COMTRADE
M_{ijt}	Imports of the emerging country i from the developed country j at time t, in USD	COMTRADE
FDI_{ijt}	Foreign Direct Investments from the developed country j to the emerging country i at time t, in USD	OECD

Source: author.

Table 3 – Data Description of European Integration and Probability of Patent Collaborations

	Number of Country Pairs			Frequency		
$P_{ijt} \geq 1$ / $EU_{it} = 1$	Yes	No	Total	Yes	No	Total
Yes	252	322	574	0.2308	0.2949	0.5256
No	220	298	518	0.2014	0.2729	0.4744
Total	472	620	1,092	0.4322	0.5678	1

Source: author.

Table 3 illustrates the number of cases where the emerging country is an EU member and the number of case where patent collaborations occur between the emerging and the developed countries, over 1,092 cases. Emerging countries are EU members under around 53 percent of the

1,092 cases. A too high share would lead to biased results. Furthermore, patent collaboration occurs under 23 percent of the cases when emerging countries are EU members while it only occurs under 20 percent of the cases when they are not. Nevertheless, when emerging are EU members, patent collaboration does not occur under 29 percent of the cases.

4. Probability of Patent Collaborations under LOGIT Estimations

We run LOGIT estimations where the explained variable is the probability of patent collaborations $P(PAT_{ijt} \geq 1)$. Under the regression (A), we estimate the direct impact of emerging countries' European integration. We integrate gravity equations variables in the regression (B) by using GDP as the measure of market sizes. We use populations instead of GDP in the regression (C). We also estimate the impact of income inequalities under the regression (D) by using the ratio of GDP per capita. We integrate the impact of R&D expenditures under the regression (E), of the ratio of the share of R&D expenditures in GDP and of the technological distance under the regression (F), and of public expenditures in education under the regression (G). Finally, we study the impact of exports, imports and FDI under the regression (H). Table 4 illustrates the marginal effects of each regression.

We run Hausman tests for each regression to make the choice between country i and country j fixed effects (dummy for each country) versus country pair ij random effects. We also run Fischer tests to estimate whether or not time fixed effect are significant. Finally, we test for multi-collinearity by using the method of Variance Inflation Factors (VIF). See Appendix A. This is the reason why we cannot integrate populations and GDP as explanatory variables in the same estimation: the VIF test indicates that there is a multi-collinearity problem. We cannot integrate populations under the regression (G) owing to collinearity with respect to public expenditures in educations.

Furthermore, the value of marginal effects may change with the value of explanatory variables. We calculate marginal effects by specifying $EU_{it} = 1$ instead of the mean value of EU_{it}. Then, we calculate marginal effects for $EU_{it} = 0$. We find that the value of marginal effects is the same under both cases as compared to the "at-means" marginal effects.

Table 4 – Marginal Effects under LOGIT Estimations

$P(PAT_{ijt} \geq 1)$	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)
EU_{it}	0.3058*	0.0352	0.0371	0.0061	0.0067	0.0401	0.0473	-0.0025
	(0.1695)	(0.0773)	(0.0596)	(0.0590)	(0.0780)	(0.0637)	(0.0792)	(0.0795)
CB_{ij}		0.1194	0.1198	0.1181	0.1235	0.1169	0.1202	0.1424
		(0.1305)	(0.1305)	(0.1292)	(0.1323)	(0.1288)	(0.1301)	(0.1380)
$\log DIST_{ij}$		-0.4499***	-0.4405***	-0.4422***	-0.4487***	-0.4336***	-0.4485***	-0.1784*
		(0.1198)	(0.1190)	(0.1187)	(0.1197)	(0.1164)	(0.1201)	(0.0995)
$\log Y_{it}$		0.3323*						
		(0.1830)						
$\log Y_{jt}$		0.2477						
		(0.5021)						
$\log POP_{it}$			0.4789		0.8401	0.4345		0.9363
			(0.9877)		(1.0900)	(0.9909)		(1.1101)
$\log POP_{jt}$			2.5116*		3.2268	2.4665*		2.9352
			(1.4574)		(2.4537)	(1.4601)		(2.4825)
$\log(y_{it}/y_{jt})$				0.2114**				
				(0.0879)				
$\log R_{it}$					0.1431			0.1403
					(0.1113)			(0.1185)
$\log R_{jt}$					0.1758			0.0614
					(0.3354)			(0.3248)
$\log(r_{it}/r_{jt})$						-0.0675		
						(0.1309)		
$\log TD_{ijt}$						0.1421		
						(0.1268)		
$\log EDU_{it}$							0.2095*	
							(0.1240)	
$\log EDU_{jt}$							-0.1393	
							(0.3791)	
$\log X_{ijt}$								0.1031**
								(0.0440)
$\log M_{ijt}$								0.0379
								(0.0737)
$\log FDI_{ijt}$								0.0348
								(0.0252)
Observations	1,092	1,092	1,092	1,092	1,092	1,092	1,092	1,092
Pseudo R-Squared	0.0002	0.3888	0.3770	0.3786	0.3888	0.3781	0.3886	0.3976
Panel Effects (a)	Country i RE	Country i FE	Country i FE	Country i FE	Country i FE	Country i FE	Country i FE	Country i FE
		Country j FE	Country j FE	Country j FE	Country j FE	Country j FE	Country j FE	Country j FE
		Time FE			Time FE		Time FE	Time FE
Hausman Test (b)	0.5367	0.0000	0.0374	0.0000	0.0000	0.0814	0.0000	0.0000
Fischer Test (c)	0.2790	0.0000	0.2754	0.1280	0.0000	0.2724	0.0000	0.0000

Source: author.

Note: Robust standard-errors are between parentheses. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$. (a) FE (RE) denotes fixed (random) effects. (b) The choice between fixed and random effects depends on the Hausman test. Probabilities of random effects are given. (c) Time fixed effects depend on the Fischer test. Probabilities of non-significant time fixed effects are given.

According to the regression (A), the European integration significantly increases the probability of patent collaborations between emerging and developed countries without taking into account any other explanatory variable. Nevertheless, the results do not hold under other regressions. Marginal effects of the European Integration on the probability are no longer significant. The probability of patent collaborations depends on other variables.

There is a significant role of the geographic distance. The probability of patent collaboration decreases with the geographic distance. In spite of modern telecommunications, technological collaborations are complex when co-inventors are geographically distant. Nevertheless, the existence of a common border does not significantly influence the probability of patent collaboration.

The levels of GDP and population relate to the market size. According to the regression (B), the probability of patent collaborations significantly increases with emerging countries' GDP. The effect of developed countries' GDP is not significant. Developed countries' population significantly increases the probability under two cases while emerging countries' population has not any significant impact. According to the regression (D), income inequalities significantly reduce the probability of patent collaborations because the effect of the ratio of GDP per capita is significant and positive.

R&D investments do not significantly increase the probability of patent collaborations. The technological gap is not a significant determinant because the effect of the ratio of the share of R&D expenditures in GDP is not significant. The impact of the technological distance is not significant too. But the impact of emerging countries' public expenditures in education is positive and significant. The role of human capital is significant via education.

Emerging countries' exports to developed countries significantly increase the probability of patent collaborations while the effects of imports and FDI are not significant. Technological collaborations occur due to trade flows from emerging to developed countries.

5. Intensity of Patent Collaborations

We study now the impact of each explanatory variable on the intensity of the patent collaborations by using the number of collaborations instead of the probability. First, we run conditional estimations by considering the number of collaborations only when it at least equals to one. Then, we run total estimations.

5.1. Conditional Estimations

Here, the explained variable is the number of patent collaborations when they occur. Then, there are only 620 data. Table 5 illustrates the results.

Table 5 – Results of Poisson Conditional Estimations for Intensity of Patent Collaborations

$\log PAT_{ijt}/PAT_{ijt} \geq 1$	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)
EU_{it}	0.2006**	0.1907	0.2889***	0.2357***	0.2024**	0.2881***	0.1781	0.2037**
	(0.0950)	(0.1217)	(0.0935)	(0.0686)	(0.0993)	(0.0939)	(0.1157)	(0.1017)
CB_{ij}		0.1083	0.5088**	0.1074	0.1064	0.5412**	0.1089	0.0179
		(0.0930)	(0.2596)	(0.0928)	(0.0932)	(0.2604)	(0.0929)	(0.1026)
$\log DIST_{ij}$		-0.3638***	-0.2917*	-0.3543***	-0.3690***	-0.2917	-0.3613***	-0.2068
		(0.1342)	(0.1767)	(0.1328)	(0.1349)	(-0.1785)	(0.1345)	(0.1584)
$\log Y_{it}$		0.0181						
		(0.2015)						
$\log Y_{jt}$		0.8625						
		(0.6719)						
$\log POP_{it}$			0.3396***		1.8603	0.3431***		1.7347
			(0.0604)		(1.9608)	(0.0628)		(1.8851)
$\log POP_{jt}$			0.5220***		0.5873	0.5293***		-0.4990
			(0.0906)		(1.8884)	(0.0920)		(1.8423)
$\log(y_{it}/y_{jt})$				0.0713				
				(0.0749)				
$\log R_{it}$					0.2319			0.2272
					(0.1653)			(0.1778)
$\log R_{jt}$					0.7622			0.7358
					(0.5201)			(0.5098)
$\log(r_{it}/r_{jt})$						0.0873		
						(0.1281)		
$\log TD_{ijt}$						0.0912		
						(0.2442)		
$\log EDU_{it}$							-0.0184	
							(0.1305)	
$\log EDU_{jt}$							0.0451	
							(0.4897)	
$\log X_{ijt}$								0.2195***
								(0.0553)
$\log M_{ijt}$								-0.0546
								(0.1257)
$\log FDI_{ijt}$								0.0457
								(0.0449)
Constant	-0.1152	-21.2493	-12.9115***	1.6262	-59.4399	-12.9894***	0.8901	-44.7150
	(0.1309)	(18.3818)	(1.7130)	(0.7749)	(46.8354)	(1.7337)	(14.4675)	(45.5816)
Observations	620	620	620	620	620	620	620	620
Pseudo R-Squared	0.0015	0.1780	0.1093	0.1748	0.1788	0.1108	0.1776	0.1826
Panel Effects	Country i RE	Country i FE Country j FE Time FE	Pair ij RE	Country i FE Country j FE	Country i FE Country j FE Time FE	Pair ij RE	Country i FE Country j FE Time FE	Country i FE Country j FE Time FE
Hausman Test	0.6622	0.0001	0.2618	0.0000	0.0000	0.1555	0.0000	0.0004
Fischer Test	0.8417	0.0005	0.9319	0.9092	0.0000	0.8992	0.0001	0.0010

Source: author.

Note: Robust standard-errors are between parentheses. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

The number of patent collaborations generally significantly increases with European integration. Without taking into account other variables, the impact of European integration is significantly positive. Integrating other explanatory variables, the impact of European integration remains significantly positive except for the regression (B).

The impact of common border is now significantly positive under two cases while its impact on the probability of collaborations is not significant. The impact of the geographic distance is significantly negative under five cases. But it is no longer significant under regressions (F) and (H). Distance is no longer a significant determinant for the intensity of patent collaborations by integrating bilateral trade and FDI. The impact of each GDP is not significant. Patent collaborations significantly depend on populations. The effect of each country's population is significantly positive under regressions (B) and (F). The market size is a significant determinant for patent collaborations via populations. The human capital does not seem to be a significant determinant because the impacts of R&D expenditures, technological gap and public expenditures in education are not significant. The technological distance is not a significant determinant too. Finally, there is a significant and positive impact of emerging countries' exports again while the impacts of imports and FDI are not significant.

We also run conditional OLS/GLS estimations instead of Poisson. See Appendix B. The main changes are the following. First, with OLS/GLS estimations, the impact of common borders is always significantly positive while the effect is only significant under two cases with Poisson estimations. Second, with OLS/GLS estimations, we find one case where developed countries' population significantly reduces the intensity of collaborations. Third, emerging countries' R&D expenditures significantly increase collaborations under one case while the effect is never significant under Poisson estimations. The results generally hold, otherwise.

5.2. Total Estimations

Consider now the entire database by running total estimations. We integrate the cases where the number of patent collaborations equals to zero by implementing Poisson estimations. The explained variable is PAT_{ijt}. Table 6 illustrates the results. As under conditional estimations, the number of patent collaborations always increases with the European integration under each regression. There is a strong and positive impact of exports as in previous tables. The geographic distance still significantly reduces collaborations. Both populations are also significant and positive determinants. We do not find any case where developed countries' population significantly reduces the number of patent collaborations. The impact of GDP and income inequalities is not significant as under conditional estimations. The technological gap and the technological distance are now negative and significant determinants. The impact of the ratio r_{it}/r_{jt} is positive and significant, and the impact of the technological distance is now negative and significant. Another difference with respect to conditional estimations is that the common border is no longer a significant determinant for the number of patent collaborations.

Table 6 – Results under Poisson Total Estimations for Intensity of Patent Collaborations

PAT_{ijt}	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)
EU_{it}	0.3099***	0.2384*	0.3329***	0.2202*	0.3162***	0.2887***	0.2098*	0.3220***
	(0.0791)	(0.1256)	(0.0780)	(0.1225)	(0.1086)	(0.0804)	(0.1204)	(0.1138)
CB_{ij}		0.0024	0.4826	0.0018	0.0001	0.5011	0.0016	-0.1648
		(0.1093)	(0.4344)	(0.1090)	(0.1093)	(0.4365)	(0.1085)	(0.1139)
$\log DIST_{ij}$		-0.7765***	-1.1360***	-0.7770***	-0.7768***	-1.0490****	-0.7775***	-0.4597***
		(0.1204)	(0.2687)	(0.1203)	(0.1204)	(0.2680)	(0.1200)	(0.1489)
$\log Y_{it}$		-0.2416						
		(0.2385)						
$\log Y_{jt}$		0.5221						
		(0.7763)						
$\log POP_{it}$			0.7107***		3.2370	0.6843***		3.0309
			(0.0774)		(2.0912)	(0.0796)		(1.9616)
$\log POP_{jt}$			1.0563***		-0.8068	1.0496***		-2.6456
			(0.1152)		(2.3455)	(0.1158)		(2.2423)
$\log(y_{it}/y_{jt})$				-0.2940				
				(0.2137)				
$\log R_{it}$					0.1922			0.1376
					(0.1874)			(0.1885)
$\log R_{jt}$					0.3894			0.3669
					(0.5692)			(0.5522)
$\log(r_{it}/r_{jt})$						0.3182**		
						(0.1356)		
$\log TD_{ijt}$						-0.3046*		
						(0.1570)		
$\log EDU_{it}$							-0.2316	
							(0.1586)	
$\log EDU_{jt}$							0.0320	
							(0.5705)	
$\log X_{ijt}$								0.4005***
								(0.0657)
$\log M_{ijt}$								-0.0059
								(0.1276)
$\log FDI_{ijt}$								0.0550
								(0.0476)
Constant	0.7673***	-2.7972	-21.5217	4.3796***	-47.2896	-21.3344***	9.9823	-24.1735
	(0.2643)	(21.7444)	(2.3872)	(0.7779)	(55.0151)	(2.4040)	(16.8031)	(51.8154)
Observations	1,092	1,092	1,092	1,092	1,092	1,092	1,092	1,092
Pseudo R-Squared	0.0158	0.5996	0.4392	0.5997	0.6001	0.4414	0.5997	0.6094
Panel Effects	Country i RE Time FE	Country i FE Country j FE Time FE	Pair ij RE Time FE	Country i FE Country j FE Time FE	Country i FE Country j FE Time FE	Pair ij RE Time FE	Country i FE Country j FE Time FE	Country i FE Country j FE Time FE
Hausman Test	0.5113	0.0000	0.7452	0.0000	0.0000	0.7807	0.0000	0.0000
Fischer Test	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Source: author.

Note: Robust standard-errors are between parentheses. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

6. Summary and Discussion

Let us summarize and discuss the results.

- The European integration is a significant determinant for technology diffusion via patent collaborations. It especially increases the number of patent collaborations. The effect on the probability of patent collaborations is not significant by considering other explanatory variables. The European integration increases technological collaborations as compared to the case where emerging countries are not European members. Such a result means that the technology diffusion via patent collaborations is stronger under free trade and free human movements as compared to situations with trade and human barriers. Picci (2010) generally finds a positive impact of the European integration on internationalized patents. But he also finds a negative and significant impact under one case. The results in the empirical economic literature about the impact of policy instruments on technology diffusion are ambiguous as we said in the general introduction. Some papers show a positive impact of free trade. For example Bustos (2011) explains that the MERCOSUR integration has involved a technology upgrading in Argentina because firms have been encouraged to use new technologies. But other studies mention a positive impact of policy instrument (Jaffe and Stavins, 1995; Van Dijk and Szirmai, 2006).

- The geographic distance is also a significant determinant by reducing significantly both the number and the probability of patent collaborations. In spite of modern telecommunications, technological collaborations are complex when co-inventors are geographically distant. Nevertheless, the level of exports is more significant than the geographic distance. The economic literature also finds a significant negative impact of the geographic distance. Using an OLS estimation, Maggioni and al. (2007) also studies the European case and find an elasticity of -1 while our results illustrates that significant elasticities vary over [0.25,0.3] (See Appendix B).
- Sharing a common border significantly increases the number of patent collaborations under conditional estimations even by integrating the levels of trade and FDI. Potential co-inventors can work together more easily when their origin countries have a common border. The impact is stronger than the impact of distance in this case. But the effect on the probability of patent collaborations is not significant. A common border involves a large number of collaborations in Europe but does not influence the probability of collaborations. However, the results do not hold under Poisson total estimations. Guellec and Van Pottelsberghe de la Potterie (2001) always find a positive and significant effect of the common border by using TOBIT estimations. In our case of European transition economies, the positive effect is not systematically significant.
- Emerging countries' exports to developed countries are a strong determinant for both the number and the probability of patent collaborations while the effect of imports and FDI are not significant. These results relates to "learning-by-exporting" because exporters need to use modern technologies to be competitive. *"A domestic firm might through its exporting activity come into contact with foreign technology* [Keller, 2010, p. 817]*."* Previous studies demonstrate the existence of a "learning-by-exporting" effect (Rhee, Ross-Larson and Pursell, 1984; Bernard and Jensen, 1999). But other studies show that the effect is not significant (Clerides, Lach and Tybout, 1998).
- Our results illustrates that the role of imports and FDI is not significant while the economic literature shows that they are important channels for technology diffusion (Coe and Helpman, 1995; Eaton and Kortum, 2002; Keller, 2004; Keller, 2010). Nevertheless, Montobbio and Sterzi (2012) also find a non-significant impact of FDI on patent collaborations under Poisson estimations while the effect of trade is only significant for two cases over eight.
- Emerging countries' economic growth encourages inventors from developed countries to innovate with domestic partners but does not influence the number of collaborations. The impact of developed countries' GDP is never significant.
- The impact of population on both the probability and the number of collaborations is positive. Nevertheless, we find one case where developed countries' population significantly reduces the number of collaborations under OLS/GLS estimations. Inventors from developed countries may be encouraged to file patents in their domestic country instead of emerging countries when the market size is strong. Market sizes are significant determinants for technological collaborations, otherwise.
- Income inequalities significantly reduce the probability of patent collaborations because the impact of the ratio of GDP per capita is significantly positive under the LOGIT estimation. Technology diffusion occurs when countries are not economically distant. European Union has to reduce income inequalities between members to increase technology diffusion. But it does not significantly influence the number of collaborations.

- Emerging countries' R&D expenditures only significantly influence the number of patent collaborations under OLS/GLS conditional estimations. The impact of developed countries' R&D is not significant. There is a negative and significant impact of the technological gap on the intensity of collaborations under Poisson total estimations. The European Union should promote Easter Europe countries' R&D expenditures to reduce technological inequalities. Finally, emerging countries' public expenditures in education significantly increase the probability of patent collaborations. Then, the human capital is a significant determinant. But the effect on the intensity is not significant. The economic literature also illustrates a positive impact of the human capital (Eaton and Korturm, 1996; Xu, 2000).
- The impact of the technological distance is only significant under the Poisson total estimation. It significantly reduces the intensity of the patent collaborations. The impact is not significant under other estimations. Montobbio and Sterzi (2012) also found cases where the impact of the technological proximity is not significant.

Emerging countries' exports to developed countries seem to be the more significant determinant of technology diffusion via patent collaborations. Market sizes and geographic distance significantly influence the probability of collaborations. European integration, population and geographic distance significantly influence the intensity of patent collaborations. The impact of common border is only significant under conditional estimations.

7. Robustness: European Integration Length

Previously, we have studied the impact of the Easter Europe countries' European integration on the probability and the intensity of patent collaborations with Western Europe countries. The results show that the European integration has a significant and positive impact on the intensity of patent collaborations while the impact on the probability is not significant. Let us study now the impact of the number of years from the EU integration to 2011. We call such a number of years as "the European integration length." We denote as EUL_{it} the country i's European integration length. Since the first time of Eastern countries' European integration over 2000-2011 was in 2004. Then, we have: $EUL_{it} \in [0,8]$. We aim to verify whether or not the results hold by using such a quantitative variable instead of a dummy variable.

Appendix C illustrates the results of the regression H under LOGIT, OLS/GLS and Poisson estimations. The results generally hold by using the European integration length instead of the dummy variable. The effect on the probability is not significant but the impact on the intensity is still positive and significant. Nevertheless, the coefficients are lower than those by using the dummy variable. There is a new result. They are between 0.03 and 0.12 while they were always greater than 0.2 in previous sections. The signs of the impact of the European integration length and the impact of the dummy variable are the same. But the impact of the dummy variable is stronger. The accession to the European Union is a stronger determinant for technology diffusion via patent collaborations

About the impact of other explanatory variables, the common border significantly reduces the number of patent collaborations under the regression (H) with Poisson total estimations. Emerging countries' public expenditures in education significantly increases the intensity of collaborations by using OLS/GLS estimations. The ratio of R&D no longer significantly influences the intensity with Poisson total estimations. The technological distance significantly increases the intensity of patent collaborations under OLS/GLD estimations. The results generally hold, otherwise.

8. Concluding Remarks

In this paper, we aim to study the impact of potential determinants for technology diffusion via patent collaborations by running econometric estimations with panel data for Eastern and Western Europe countries (91 country pairs, over 2000-2011). First, we study the impact on the probability of patent collaborations by using LOGIT estimations. Then, we study the impact on the intensity of collaborations by using OLS/GLS and Poisson conditional estimations, and Poisson total estimations. We analyze whether or not the European integration has a significant and positive impact on collaborations. We also integrate other explanatory variables like the geographic distance, common borders, GDP, populations, income inequalities, exports, imports, FDI, R&D expenditures, technological gap, technological distance and public expenditures in education.

The results show that European is not a significant determinant for the probability of patent collaborations for emerging countries. But it significantly increases the intensity of patent collaborations. Then, there is an interest to join the European Union to benefit from stronger technology diffusion from other European countries. Then, free trade leads to technology diffusion. Such a European example means that both emerging and rich countries should liberalize their economies to enhance technology diffusion. Using the number of years from the European integration to 2011 instead of the dummy variable, the results hold.

There is also a crucial effect of exports from emerging to developed countries that relates to "learning-by-exporting" because exports lead to business relationships. Exporters may innovate and collaborate with foreign inventors owing to such relationships. Geographic distance and populations are significant determinants too.

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10. Appendix

A. Multi-Collinearity Tests: Variance Inflation Factors (VIF)

Table 7 – VIF with $P(PAT_{ijt} \geq 1)$

	(B)	(C)	(D)	(E)	(F)	(G)	(H)
EU_{it}	1.09	1.13	1.41	1.65	1.14	1.12	1.93
CB_{ij}	1.81	1.85	1.73	1.86	1.85	1.80	1.95
$\log DIST_{ij}$	2.07	2.19	1.96	2.33	2.44	2.10	3.37
$\log Y_{it}$	1.03						
$\log Y_{jt}$	1.25						
$\log POP_{it}$		1.21		3.54	1.52		4.57
$\log POP_{jt}$		1.19		6.50	1.26		8.06
$\log(y_{it}/y_{jt})$			1.65				
$\log R_{it}$				3.16			4.18
$\log R_{jt}$				6.89			7.67
$\log(r_{it}/r_{jt})$					1.05		
$\log TD_{ijt}$					1.45		
$\log EDU_{it}$						1.04	
$\log EDU_{jt}$						1.30	
$\log X_{ijt}$							8.44
$\log M_{ijt}$							9.26
$\log FDI_{ijt}$							3.39

Source: author.

Note: We consider that there is a multi-collinearity problem when at least one VIF is stronger than ten. These tests are implemented after OLS estimations.

Table 8 – VIF with $\log PAT_{ijt}/(PAT_{ijt} \geq 1)$

	(B)	(C)	(D)	(E)	(F)	(G)	(H)
EU_{it}	1.19	1.14	1.39	1.55	1.15	1.24	1.76
CB_{ij}	1.97	2.03	1.86	2.08	2.08	1.95	2.27
$\log DIST_{ij}$	2.74	3.16	2.17	3.29	3.37	2.77	4.20
$\log Y_{it}$	1.13						
$\log Y_{jt}$	1.40						
$\log POP_{it}$		1.54		4.01	1.79		4.58
$\log POP_{jt}$		1.45		6.63	1.55		8.51
$\log(y_{it}/y_{jt})$			1.65				
$\log R_{it}$				3.03			4.22
$\log R_{jt}$				6.55			7.66
$\log(r_{it}/r_{jt})$					1.05		
$\log TD_{ijt}$					1.32		
$\log EDU_{it}$						1.12	
$\log EDU_{jt}$						1.46	
$\log X_{ijt}$							6.21
$\log M_{ijt}$							7.70
$\log FDI_{ijt}$							3.75

Source: author.

Note: We consider that there is a multi-collinearity problem when at least one VIF is stronger than ten. These tests are implemented after OLS estimations.

Table 9 – VIF with PAT_{ijt}

	(B)	(C)	(D)	(E)	(F)	(G)	(H)
EU_{it}	1.09	1.13	1.41	1.65	1.13	1.12	1.93
CB_{ij}	1.81	1.85	1.73	1.86	1.85	1.80	1.95
$\log DIST_{ij}$	2.07	2.19	1.96	2.33	2.44	2.10	3.37
$\log Y_{it}$	1.03						
$\log Y_{jt}$	1.25						
$\log POP_{it}$		1.21		3.54	1.49		4.57
$\log POP_{jt}$		1.19		6.50	1.26		8.06
$\log(y_{it}/y_{jt})$			1.65				
$\log R_{it}$				3.16			4.18
$\log R_{jt}$				6.89			7.67
$\log(r_{it}/r_{jt})$					1.07		
$\log TD_{ijt}$					1.45		
$\log EDU_{it}$						1.04	
$\log EDU_{jt}$						1.30	
$\log X_{ijt}$							8.44
$\log M_{ijt}$							9.26
$\log FDI_{ijt}$							3.39

Source: author.

Note: We consider that there is a multi-collinearity problem when at least one VIF is stronger than ten. These tests are implemented after OLS estimations.

B. OLS/GLS Conditional Estimations for the Intensity of Patent Collaborations

Table 10 – Results of OLS/GLS Conditional Estimations for Intensity of Patent Collaborations

$\log PAT_{ijt}/PAT_{ijt} \geq 1$	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)
EU_{it}	0.2141***	0.2130**	0.2907***	0.2546***	0.2168**	0.2892***	0.2022*	0.2048**
	(0.0746)	(0.1077)	(0.0766)	(0.0776)	(0.1004)	(0.0771)	(0.1050)	(0.1022)
CB_{ij}		0.4347***	0.8316***	0.4327***	0.4338***	0.8352***	0.4347***	0.3158***
		(0.1157)	(0.2926)	(0.1140)	(0.1137)	(0.2977)	(0.1149)	(0.1178)
$\log DIST_{ij}$		-0.2723**	-0.1354	-0.2584**	-0.2749**	-0.1397	-0.2705**	-0.0827
		(0.1131)	(0.1514)	(0.1093)	(0.1139)	(0.1608)	(0.1130)	(0.1307)
$\log Y_{it}$		0.0319						
		(0.2299)						
$\log Y_{jt}$		0.6042						
		(0.6526)						
$\log POP_{it}$			0.3193***		3.2267*	0.3218***		2.8255*
			(0.0555)		(1.7952)	(0.0588)		(1.7174)
$\log POP_{jt}$			0.4557***		-3.8484	0.4570***		-4.3647*
			(0.0853)		(2.6232)	(0.0900)		(2.5327)
$\log(y_{it}/y_{jt})$				0.0599				
				(0.1027)				
$\log R_{it}$					0.3092*			0.2794
					(0.1678)			(0.1797)
$\log R_{jt}$					0.4079			0.4132
					(0.4412)			(0.4322)
$\log(r_{it}/r_{jt})$						0.0124		
						(0.0932)		
$\log TD_{ijt}$						0.0343		
						(0.1689)		
$\log EDU_{it}$							-0.0150	
							(0.1466)	
$\log EDU_{jt}$							0.3604	
							(0.5334)	
$\log X_{ijt}$								0.2252***
								(0.0493)
$\log M_{ijt}$								0.0305
								(0.1106)
$\log FDI_{ijt}$								0.0032
								(0.0357)
Constant	0.8728***	-14.3821	-11.4498***	2.0675***	-4.2005	-11.4599	-7.4255	4.5526
	(0.1199)	(18.1564)	(1.6147)	(0.6732)	(53.4929)	(1.6665)	(15.3694)	(51.3941)
Observations	620	620	620	620	620	620	620	620
R-Squared	0.0048	0.5977	0.3499	0.5891	0.6142	0.3505	0.6324	0.6163
Panel Effects	Country i RE	Country i FE Country j FE Time FE	Pair ij RE	Country i FE Country j FE	Country i FE Country j FE Time FE	Pair ij RE	Country i FE Country j FE Time FE	Country i FE Country j FE Time FE
Hausman Test	0.6884	0.0000	0.2618	0.0000	0.0000	0.1555	0.0000	0.0000
Fischer Test	0.7547	0.0000	0.5949	0.6462	0.0000	0.5359	0.0000	0.0000

Source: author.

Note: Robust standard-errors are between parentheses. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

C. European Integration Length

Table 11 – Results of LOGIT Estimations

$P(PAT_{ijt} \geq 1)$	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)
EUL_{it}	0.0344	0.0071	-0.0129	-0.0091	-0.0124	-0.0115	0.0130	-0.0165
	(0.0315)	(0.0162)	(0.0124)	(0.0107)	(0.0168)	(0.0200)	(0.0177)	(0.0177)
CB_{ij}		0.1307	0.1180	0.1183	0.1224	0.1185	0.1198	0.1441
		(0.5679)	(0.1302)	(0.1289)	(0.1321)	(0.1311)	(0.1303)	(0.1380)
$\log DIST_{ij}$		-0.4500***	-0.4411***	-0.4420***	-0.4488***	-0.4400***	-0.4487***	-0.1770*
		(0.1196)	(0.1198)	(0.1189)	(0.1201)	(0.1179)	(0.1198)	(0.0990)
$\log Y_{it}$		0.3531*						
		(0.1923)						
$\log Y_{jt}$		0.2516						
		(0.5005)						
$\log POP_{it}$			0.2986		1.0858	0.6074		1.2508
			(0.9685)		(1.1340)	(1.0773)		(1.1575)
$\log POP_{jt}$			4.0545		3.1048	2.6651		2.7717
			(1.6493)		(2.4547)	(2.4068)		(2.4896)
$\log(y_{it}/y_{jt})$				0.3039***				
				(0.0977)				
$\log R_{it}$					0.1738			0.1826
					(0.1166)			(0.1261)
$\log R_{jt}$					0.1535			0.0398
					(0.3375)			(0.3261)
$\log(r_{it}/r_{jt})$						0.0495		
						(0.1583)		
$\log TD_{ijt}$						0.1310		
						(0.1333)		
$\log EDU_{it}$							0.2451*	
							(0.1392)	
$\log EDU_{jt}$							-0.1402	
							(0.3791)	
$\log X_{ijt}$								0.1114**
								(0.0450)
$\log M_{ijt}$								0.0275
								(0.0743)
$\log FDI_{ijt}$								0.0332
								(0.0250)
Observations	1,092	1,092	1,092	1,092	1,092	1,092	1,092	1,092
Pseudo R-Squared	0.0001	0.3888	0.3774	0.3796	0.3892	0.3883	0.3886	0.3981
Panel Effects	Country i RE	Country i FE Country j FE Time FE	Country i FE Country j FE	Country i FE Country j FE	Country i FE Country j FE Time FE	Country i FE Country j FE Time FE	Country i FE Country j FE Time FE	Country i FE Country j FE Time FE
Hausman Test	0.6983	0.0000	0.0037	0.0000	0.0000	0.0050	0.0000	0.0003
Fischer Test	0.2661	0.0000	0.1088	0.4965	0.0000	0.0900	0.0000	0.0002

Source: author.

Note: Robust standard-errors are between parentheses. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Table 12 – Results of OLS/GLS Conditional Estimations

$\log PAT_{ijt}/PAT_{ijt} \geq 1$	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)
EUL_{it}	0.0437***	0.0878***	0.0618***	0.0467***	0.0557***	0.0623***	0.0953***	0.0544***
	(0.8859)	(0.0253)	(0.0148)	(0.0134)	(0.0199)	(0.0161)	(0.0277)	(0.0208)
CB_{ij}		0.4312***	0.4363***	0.4357***	0.4317***	0.4510***	0.4305***	0.3042***
		(0.1143)	(0.1123)	(0.1129)	(0.1132)	(0.1118)	(0.1139)	(0.1174)
$\log DIST_{ij}$		-0.2678**	-0.2552**	-0.2580**	-0.2692**	-0.2351**	-0.2673**	-0.0725
		(0.1134)	(0.1106)	(0.1105)	(0.1143)	(0.1105)	(0.1135)	(0.1317)
$\log Y_{it}$		0.4563						
		(0.2865)						
$\log Y_{jt}$		0.5783						
		(0.6473)						
$\log POP_{it}$			-0.1104		1.7259	0.0308		1.4248
			(1.7038)		(1.8985)	(1.7062)		(1.7939)
$\log POP_{jt}$			-2.1462		-3.6668	-2.2204		-4.1429*
			(1.9915)		(2.5959)	(2.0188)		(2.5091)
$\log(y_{it}/y_{jt})$				0.0758				
				(0.1073)				
$\log R_{it}$					0.2948*			0.2435
					(0.1688)			(0.1805)
$\log R_{jt}$					0.4382			0.4346
					(0.4403)			(0.4317)
$\log(r_{it}/r_{jt})$						-0.0295		
						(0.2156)		
$\log TD_{ijt}$						0.2574*		
						(0.1558)		
$\log EDU_{it}$							0.3437*	
							(0.2035)	
$\log EDU_{jt}$							0.3299	
							(0.5294)	
$\log X_{ijt}$								0.2130***
								(0.0509)
$\log M_{ijt}$								0.0644
								(0.1135)
$\log FDI_{ijt}$								0.0045
								(0.0359)
Constant	0.8859***	-24.3033	37.928	2.0938***	16.7570	36.8692	-16.0277	23.3863
	(0.1333)	(18.3652)	(48.6419)	(0.6696)	(53.7223)	(48.7420)	(15.5777)	(51.1759)
Observations	620	620	620	620	620	620	620	620
R-Squared	0.0105	0.6287	0.5905	0.6317	0.6283	0.6314	0.6288	0.6191
Panel Effects	Country i RE	Country i FE	Country i FE	Country i FE	Country i FE	Country i FE	Country i FE	Country i FE
		Country j FE	Country j FE	Country j FE	Country j FE	Country j FE	Country j FE	Country j FE
		Time FE			Time FE		Time FE	Time FE
Hausman Test	0.8376	0.0041	0.0000	0.0000	0.0185	0.0002	0.0006	0.0000
Fischer Test	0.8455	0.0000	0.1661	0.5469	0.0000	0.1513	0.0000	0.0000

Source: author.

Note: Robust standard-errors are between parentheses. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Table 13 – Results of Poisson Conditional Estimations

$\log PAT_{ijt}/PAT_{ijt} \geq 1$	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)
EUL_{it}	0.0373**	0.0774***	0.0503***	0.0398***	0.0511***	0.0506***	0.0833***	0.0526***
	(0.0159)	(0.0280)	(0.0157)	(0.0102)	(0.0181)	(0.0159)	(0.0299)	(0.0193)
CB_{ij}		0.1085	0.5167**	0.1134	0.1071	0.5459**	0.1086	0.0082
		(0.0926)	(0.2567)	(0.0924)	(0.0929)	(0.2572)	(0.0928)	(0.1019)
$\log DIST_{ij}$		-0.3584***	-0.2882*	-0.3531***	-0.3628***	-0.3003*	-0.3577***	-0.1925
		(0.1348)	(0.1751)	(0.1339)	(0.1356)	(0.1771)	(0.1354)	(0.1612)
$\log Y_{it}$		0.4072						
		(0.2784)						
$\log Y_{jt}$		0.8209						
		(0.6659)						
$\log POP_{it}$			0.3305***		0.4380	0.3394***		0.3557
			(0.0594)		(2.1080)	(0.0621)		(1.9898)
$\log POP_{jt}$			0.5193***		0.7071	0.5305***		-2.2710
			(0.0900)		(1.8750)	(0.0914)		(1.8467)
$\log(y_{it}/y_{jt})$				0.0675				
				(0.0747)				
$\log R_{it}$					0.2479			0.2139
					(0.1674)			(0.1778)
$\log R_{jt}$					0.7610			0.7320
					(0.5178)			(0.5063)
$\log(r_{it}/r_{jt})$						0.0435		
						(0.1275)		
$\log TD_{ijt}$						0.1469		
						(0.2428)		
$\log EDU_{it}$							0.3051	
							(0.2028)	
$\log EDU_{jt}$							0.0072	
							(0.4871)	
$\log X_{ijt}$								0.2076***
								(0.0568)
$\log M_{ijt}$								-0.0112
								(0.1302)
$\log FDI_{ijt}$								0.0464
								(0.0445)
Constant	-0.0965	-29.8856	-12.7050***	1.6515**	-38.6948	-12.9350	-6.5609	-26.4481
	(0.1256)	(18.6060)	(1.6898)	(0.7773)	(47.1551)	(1.8088)	(14.8502)	(45.3152)
Observations	620	620	620	620	620	620	620	620
Pseudo R-Squared	0.0105	0.1791	0.1104	0.1748	0.1793	0.1118	0.1787	0.1830
Panel Effects	Country i RE	Country i FE Country j FE Time FE	Pair ij RE	Country i FE Country j FE	Country i FE Country j FE Time FE	Pair ij RE	Country i FE Country j FE Time FE	Country i FE Country j FE Time FE
Hausman Test	0.8654	0.0000	0.8459	0.0000	0.0000	0.9131	0.0000	0.0000
Fischer Test	0.9021	0.0001	0.7614	0.7757	0.0000	0.7421	0.0000	0.0006

Source: author.

Note: Robust standard-errors are between parentheses. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Table 14 – Results of Poisson Total Estimations

PAT_{ijt}	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)
EUL_{it}	0.0875***	0.1176***	0.0897***	0.1077***	0.0924***	0.0835***	0.1195***	0.0990***
	(0.0143)	(0.0293)	(0.0142)	(0.0279)	(0.0203)	(0.0235)	(0.0314)	(0.0215)
CB_{ij}		0.0020	0.4942	0.0014	-0.0011	0.4835	0.0018	-0.1827*
		(0.1063)	(0.4314)	(0.1061)	(0.1063)	(0.4344)	(0.1063)	(0.1102)
$\log DIST_{ij}$		-0.7761***	-1.1012***	-0.7782***	-0.7765***	-1.0593***	-0.7775***	-0.4325***
		(0.1213)	(0.2654)	(0.1209)	(0.1207)	(0.2657)	(0.1214)	(0.1525)
$\log Y_{it}$		0.3899						
		(0.3090)						
$\log Y_{jt}$		0.4816						
		(0.7645)						
$\log POP_{it}$			0.7110***		0.8571	0.6905***		0.7361
			(0.0768)		(2.2309)	(0.0781)		(2.0691)
$\log POP_{jt}$			1.0514***		-0.7727	1.0425***		-2.1656
			(0.1141)		(2.2420)	(0.1146)		(2.1629)
$\log(y_{it}/y_{jt})$				0.2535				
				(0.2762)				
$\log R_{it}$					0.2575			0.1421
					(0.1880)			(0.1880)
$\log R_{jt}$					0.3561			0.3322
					(0.5666)			(0.5460)
$\log(r_{it}/r_{jt})$						0.1318		
						(0.1424)		
$\log TD_{ijt}$						-0.2512**		
						(0.1568)		
$\log EDU_{it}$							0.2639	
							(0.2299)	
$\log EDU_{jt}$							-0.0261	
							(0.5544)	
$\log X_{ijt}$								0.3670***
								(0.0679)
$\log M_{ijt}$								0.0983
								(0.1336)
$\log FDI_{ijt}$								0.0612
								(0.0470)
Constant	0.7673***	-17.4938	-21.6894***	5.0752***	-9.9857	-21.4841***	-1.4240	4.1869
	(0.2638)	(21.8895)	(2.3587)	(0.7789)	(55.8570)	(2.3708)	(16.9357)	(51.6949)
Observations	1,092	1,092	1,092	1,092	1,092	1,092	1,092	1,092
Pseudo R-Squared	0.0082	0.6022	0.4456	0.6019	0.6023	0.4488	0.6020	0.6115
Panel Effects	Country i RE Time FE	Country i FE Country j FE Time FE	Pair ij RE Time FE	Country i FE Country j FE Time FE	Country i FE Country j FE Time FE	Pair ij RE Time FE	Country i FE Country j FE Time FE	Country i FE Country j FE Time FE
Hausman Test	0.6578	0.0000	0.7282	0.0074	0.0000	0.2197	0.0000	0.0000
Fischer Test	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Source: author.

Note: Robust standard-errors are between parentheses. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

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