De Economist (2016) 164:109–123
DOI 10.1007/s10645-015-9269-5

Knowledge Migration: A Cross-National Analysis

Luigi Aldieri[1] · Concetto Paolo Vinci[2]

Published online: 19 December 2015

Abstract This study contributes to existing literature on the innovative activity of firms, examining how migration can be a channel for knowledge spillover. Indeed, the aim of the paper is to introduce a new variable, which is computed on the basis of the distribution of inventors across countries, according to patent data. The paper consists of a theoretical model and an empirical analysis, which is a cross-national analysis of the United States, Japan and Europe, based upon a new dataset of worldwide R&D-intensive manufacturing firms. We use data from all EU R&D investment scoreboard editions, which were issued every year from 2002 to 2010 by the JRC-IPTS. The empirical results suggest that the migration of inventors might enhance local innovation levels, by confirming the theoretical analysis propositions.

Keywords Knowledge spillovers · Innovation · Cross-national analysis

JEL Classification C23 · O33 · O4

1 Introduction

Literature about firms' innovation considers knowledge and its spillover as important drivers of competitiveness. The benefit of knowledge improves a firm's ability to create new knowledge and accrues to other firms by increasing the pool of knowledge to which they have access (Griliches 1992, 1998; Nadiri 1993; Coe and Helpman 1995).

✉ Luigi Aldieri
aldieri@uniparthenope.it

1 Department of Business and Economic Studies, University of Naples Parthenope, Naples, Italy

2 Department of Economic and Statistic Sciences, University of Salerno, Fisciano, Italy

Starting from previous studies, we assume that a firm's innovative output depends directly on its investment in R&D and physical capital, and indirectly on spillovers of innovation realized by other firms.

As discussed in Aldieri (2011a), the knowledge literature now considers a new series of studies that looks in more detail at the ways in which knowledge is transmitted from firm to firm and from public research to firms. There are two approaches: either researcher mobility across firms or countries brings with it the transmission of knowledge, or alternatively, researchers do not move, but their personal connections help knowledge to diffuse. Almeida and Kogut (1999) consider the patent citations of 18 regional clusters and find that the localization of patentable knowledge varies across regions (tacit or no-codified knowledge) and that ideas are transferred through labor markets. Maurseth and Verspagen (2002), using patent citations in Europe, examine whether geographical distance, national borders and language differences impede knowledge flow on this continent. The results show that geographical distance has a negative effect on knowledge flows, which are larger within countries than between regions located in separate countries, as well as within regions sharing the same language. Singh (2005) explores whether interpersonal networks help explain the geographic localization of knowledge flows and the concentration of knowledge flows within firm boundaries. By using patent citations, intraregional and intrafirm knowledge flows are found to be stronger than those across regional or firm boundaries. Using patent citations as a proxy for the influence of foreign technology on patents in French firms, MacGarvie (2006) finds that the inventions of importers are significantly more likely to be influenced by foreign technology than are the inventions of firms that do not import. On the basis of survey responses from 1547 patent inventors, Huang and Walsh (2010) analyze the impact of mobile inventors on information flow, values of patents in technical significance, and the propensity of commercialization. The results show that mobility from competing firms significantly contributes to higher values of the patent. In particular, they propose a new explanation: mobile inventors have the ability to change organizational routines. Singh and Agrawal (2010) find that hiring firms actually increase their use of prior inventions by new recruits. In this paper, we assume that spillovers are identified through the migration effect of inventors. Indeed, the paper offers a novel mechanism to explain why migration might be good or bad for innovation. In particular, we introduce a new variable, appropriate for exploring the knowledge diffusion issue. It is based on the distribution of inventors across countries using patent data. Empirical results suggest that the migration of inventors might enhance local innovation levels, depending on the level of knowledge capital of the migrants. The evidence contributes to a better understanding of how knowledge spillovers work, and has important implications for policy makers and practitioners in the US, Japan and Europe.

The remainder of the paper is as follows. The next section presents theoretical propositions. Section 3 presents data and empirical methods. Section 4 shows the empirical results. Finally, Sect. 5 discusses the policy implications and offers some concluding comments as well as some points deserving further research.

2 Theoretical Framework

This section will focus on an analysis of the knowledge exchange in the exercise of the diffusion of ideas that inventors have during their innovative process. Following a noteworthy strand of literature (Acemoglu 1996), we consider a simple non-overlapping generation model where each generation of two different types of agents are both normalized to one: people who collect physical capital, defined as entrepreneurs, and those who invest in R&D described as inventors. All of them, assumed to be risk-neutral and with an inter-temporal preference rate equal to zero, live for two periods. In the first period inventors choose their R&D capital level and entrepreneurs determine the physical capital, in the second one patents arise in the form of a partnership of one entrepreneur and one inventor. The benefits from the patent's consumption will be availed at the end of this second period, and then the agents die. The patent is created according to the following functional forms:

$$P_{i,j,t} = AK_{i,t}^{\alpha} K_{j,t}^{RD(1-\alpha)} \tag{1}$$

with $0 < \alpha < 1$, and where $P_{i,j,t}$ is the patent, $K_{i,t}$ is the physical capital of the i-th entrepreneur, and $K_{j,t}^{RD}$ the *R&D* capital of the j-th inventor. A stands for the technological context and other effects.[1] The assumption of randomness as far as concerns the agents' matching function, will entail that all the inventors (entrepreneurs) have the same probability of meeting each entrepreneur (inventor), and once a partnership has been formed that it is too costly to break it up in order to find a new partner for each agent. The randomness of the matching function will imply anonymity of contracts, in the sense that each inventor (entrepreneur) does not know the type of the entrepreneur (inventor) they are going to meet, and consequently their decisions will depend on the whole distribution of physical (*R&D*) capital across all the entrepreneurs (inventors).

The utility functions of the i-th entrepreneur and of the j-th inventor are given by the following:

$$U_{i,t} = P_{i,j,t}^{e} - \frac{\theta_i K_{i,t}^{(1+\gamma)}}{(1+\gamma)} \tag{2}$$

$$U_{j,t} = P_{i,j,t}^{e} - \frac{\lambda_j K_{j,t}^{RD(1+\gamma)}}{(1+\gamma)}, \tag{3}$$

where θ_i (λ_j) is a positive taste parameter which captures the disutility of accumulating physical (*R&D*) capital made in order to obtain patents. Equations. (2) and (3) may be rewritten as follows:

$$U_{i,t} = AK_{i,t}^{\alpha} \int K_{j,t}^{RD(1-\alpha)} dj - \frac{\theta_i K_{i,t}^{(1+\gamma)}}{(1+\gamma)} \tag{4}$$

[1] It is only for simplicity that we don't introduce parameters capturing the technological and geographical proximity.

$$U_{j,t} = AK_{j,t}^{RD(1-\alpha)} \int K_{i,t}^{\alpha} di - \frac{\lambda_j K_{j,t}^{RD(1+\gamma)}}{(1+\gamma)} \tag{5}$$

From the first order condition of the maximization process we may derive:

$$K_{i,t} = \left\{ \frac{A\alpha \int K_{j,t}^{RD(1-\alpha)} dj}{\theta_i} \right\}^{\frac{1}{\gamma+1-\alpha}} \tag{6}$$

$$K_{j,t}^{RD} = \left\{ \frac{A(1-\alpha) \int K_{i,t}^{\alpha} di}{\lambda_j} \right\}^{\frac{1}{\gamma+\alpha}} \tag{7}$$

from inspection of which it follows that the physical (*R&D*) capital will increase with the *R&D* (physical). As a result we can state the following:

Proposition 1 *Assuming* $\theta_i = \theta, \lambda_j = \lambda$*:*

1. *There exists a unique equilibrium, Pareto inefficient, given by:* $\left(K^*, K^{RD*}\right)$.
2. *There are social increasing returns in the sense that a small increase in the investments of all agents will make every one better off and when a small group of inventors (entrepreneurs) invest more in R&D (physical) capital, other agents will respond, and the equilibrium rate of return of all subjects will improve.*

Proposition 1 (proved in "Appendix 1") states that the equilibrium of this economy is unique, Pareto-inefficient and exhibits social increasing returns *a la Acemoglu* (1996). There will be a stronger form of increasing social returns in the sense that when a small group of inventors decide to make an investment in order to increase the number of patents, other agents respond by increasing their investments, and so the rates of returns of inventors who have not invested more will improve.

2.1 *R&D* Migration

We now consider an additional source of *R&D* capital accumulation: the immigration of inventors with a different talent for *R&D* capital accumulation. We assume two economies, the host and the source with a continuum of agents, living for two periods as before, and normalized to unity.

As regards the behavior of native inventors, the analysis will follow the previous line of reasoning; on the foreign inventors side, the decision related to investment in R&D capital is strictly related to the migration decision. This latter will depend on a comparison between the optimal utility levels derived from moving or otherwise. The utility functions of foreign inventors who decide, or not, to move, may be respectively written as follows[2]:

$$U_{j,t}^{f} = P_{i,j_f,t}^{e} - \frac{\delta_{j_f} K_{j_f,t}^{fRD(1+\gamma)}}{(1+\gamma)} \tag{8}$$

$$U_{j,t}^{o} = \left\{ P_{i,j_f,t}^{oe} - \frac{\delta_{j_f} K_{j_f,t}^{oRD(1+\gamma)}}{(1+\gamma)} \right\} \phi_{j_f}, \tag{9}$$

where ϕ_{j_f} is a positive taste parameter assumed to be greater than unity to capture the hypothesis of a preference for living in the origin country, different among inventors, and distributed, as in Carillo and Vinci (1999), according to a uniform cumulative distribution function $F(\phi)$ with parameter b. By maximizing the above utility functions (Eqs. 8 and 9) we may easily derive the following:

$$K_{j_f,t}^{fRD} = \left\{ \frac{A(1-\alpha)\int K_{i,t}^{\alpha} di}{\delta_{j_f}} \right\}^{\frac{1}{\gamma+\alpha}} \tag{10}$$

$$K_{j_f,t}^{oRD} = \left\{ \frac{A^{o}(1-\alpha)\int K_{i_f,t}^{\alpha} di_f}{\delta_{j_f}} \right\}^{\frac{1}{\gamma+\alpha}} \tag{11}$$

In order to decide whether or not to migrate, each inventor will compare the two maximum utility levels: U^{f*}, U^{o*}. We will assume that an inventor will move from the source country if and only if:

$$U^{f*} > U^{o*} \tag{12}$$

After simple algebraic substitutions, the migration condition decision (12) may be rewritten as follows:

$$\phi_{j_f} < \bar{\phi}, \quad \text{where } \bar{\phi} = \frac{P_{i,j_f,t}^{e} - \frac{\delta_{j_f} K^{*fRD(1+\gamma)}}{(1+\gamma)}}{P_{i,j_f,t}^{oe} - \frac{\delta_{j_f} K^{*oRD(1+\gamma)}}{(1+\gamma)}} \tag{13}$$

From inspection of the migration decision condition it may be noted that the number of inventors who decide to migrate will depend on the distribution function of the taste parameter ϕ_{j_f}, on the population, and on the parameters that determine the threshold value $\bar{\phi}$ that depend on economic conditions in both the source and destination country. Finally the share of moving inventors will be:

[2] Where f and o refer to foreign and origin countries.

$$\chi = \int_0^{\bar{\phi}} \frac{1}{b} d\phi_{jf} = \frac{\bar{\phi}}{b} \tag{14}$$

The entire population of inventors, native and immigrant will thus be: $(1 + \chi)$[3]. Normalizing the latter expression once again to unity, and labeling with β the percentage of native inventors, the share of foreign inventors in the host country is: $(1 - \beta) = \frac{\chi}{1+\chi} = \frac{\bar{\phi}}{b+\bar{\phi}}$.

At this point in the maximization process we can state the following.

Proposition 2 *We may distinguish two different cases: a) if the capital of foreign inventors R&D is higher than that of the natives, there are social increasing returns, and the immigration policies of inventors may be considered as a source of investment in R&D; b) in case of inventors with a lower level of R&D capital, increasing social returns may be reversed‘.*

Proposition 2 is proved in “Appendix 2”. In the following empirical section, we test for this last relevant result. Indeed, there are studies in the literature focusing on the effects of spillovers on innovation, measured by patents (Cincera 1997), while migration, as a potential channel for knowledge spillovers, has not received much attention. In the empirical section, we mainly analyze the migration of knowledge captured by inventors rather than the migration of R&D workers as in the theoretical model. Since inventors decide on R&D investments, as predicted by theoretical assumptions, we can assume that the migration of inventors and the migration of R&D capital levels produce the same effects.

3 Methodology

The dataset was constructed in order to set up a representative sample of the largest firms, at the international level, that report R&D expenditures. The information on company profiles and financial statements comes from all EU R&D investment scoreboard editions issued every year until 2011 by the JRC-IPTS (scoreboards).

R&D data from the scoreboards represents all R&D financed by the companies, regardless of the geographical localization of R&D activities. Scoreboard data is collected from audited financial accounts and reports[4]. For each firm, information is available for the annual capital expenditures (Cexp), annual R&D expenditures (RD), and the number of employees (L) to control for the a firm’s size and main industry sectors according to the Industrial Classification Benchmark (ICB) at the two digits level. The OECD, REGPAT database, January 2012[5,6] is the second source of information used in this study. This database includes patent applications to the European

[3] Since we are analyzing a context with no unmatched agent, we will assume an equal increase of entrepreneurs in destination country.

[4] See Moncada-Paternò-Castello et al. (2009) for more details.

[5] See Maraut et al. (2008) for the methodology used for the construction of REGPAT.

[6] Please contact Helene.DERNIS@oecd.org to download the REGPAT database.

Table 1 Average innovation flows across countries

	Europe (%)	Japan (%)	USA (%)
Europe	71.43	6.12	22.45
Japan	1.16	95.45	3.49
USA	6.82	3.03	90.15

Source: Own elaboration of REGPAT patent inventors data

Patent Office (EPO) including patents published up to December 2011. The matching procedure follows the same problems as in Aldieri and Vinci (2015).

Each monetary observation is converted into constant currency (in EUR) and prices[7]. It should be noted that data in the R&D scoreboards is already expressed in Euros and that a single scoreboard uses a fixed exchange rate for each currency in order to convert data into Euros for every period that it covers. Thus, we first convert the data into original currencies by using the exchange rates specific to each scoreboard. Second, data in the original currencies is converted into Euros using a fixed exchange rate[8].

Using national GDP price deflators with 2007 as the reference year, the data is transformed into constant prices[9]. The R&D and physical capital stocks (K and C, respectively) are constructed by using a perpetual inventory method (Griliches 1992), by considering a depreciation rate of 0.15 for R&D capital stock and 0.08 for physical capital stock, which is what is usually assumed in the literature. The growth rates that are used for the initial values in this study are the sample average growth rates of R&D and physical capital expenditures in each two-digit Industry Classification Benchmark (ICB) industry.

Once the firms with missing values for some variables in our sample were removed, we had 35 European[10], 82 Japanese and 122 American firms for the period 2002-2010. In order to identify the knowledge spillovers, we introduce a new index to track inventors across countries using patent data. In this way, we obtained a direct measure of spillovers related to migration[11].

Our indicator of innovation was captured by the Migration (MIG) variable computed as 1 minus the Herfindahl index of concentration across countries:

$$MIG_{it} = 1 - \sum_{k=1}^{K} s_{ikt}^2 \tag{15}$$

where s_{ikt} is the share of inventors with nationality k among all inventors of firm i in year t. This index is computed on the basis of the distribution of inventors across coun-

[7] Reference year is 2007. Source for exchange rates and deflators is EUROSTAT.

[8] We use the exchange rates in Eurostat for 2007.

[9] Eurostat GDP deflators.

[10] European area includes the following countries: Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Luxembourg, Spain, Sweden, Switzerland, The Netherlands and the United Kingdom.

[11] We thank an anonymous referee for theirs interesting suggestion about the direct measure of spillovers related to migration.

Table 2 Main factors affecting innovation

Variable	Mean	SD
PATi	2403.85 (min: 3; max: 23666)	3611.64
LnLi	9.96	1.369
LnCi	7.49	1.578
LnKi	7.16	1.458
MIGi	0.18	0.194

1587 observations

tries using patent data. The approach is similar to that of Niebuhr (2010). In Table 1, we summarize the average share of inventors of each economic area from abroad:

For example, 22.45 % of European patents derive from American innovation knowledge, through the migration effect.

The model that is estimated is the following:

$$PAT_i = f\,(LnCi, LnKi, LnLi, MIGi, Time\ dummies, Industry\text{-}dummies) \tag{16}$$

where PAT_i is the number of patents of firm i, Ci is physical capital of firm i, Ki is the R&D capital of firm i, *Li*is the number of employees of firm i, and MIG_i is the migration index, as described above. All continuous variables are considered in logarithmic terms (*Ln*). Time dummies refer to 2002-2010 period of time and industry dummies refer to two-digit ICB sectors (Oil & Gas, Chemicals, Basic Resources, Construction & materials, Manufacturing, Automobiles, Food & Beverages, Household goods, Health care, Retail, Travel & Leisure, Telecommunications, Utilities and High Technology). This approach is similar to papers by Keller and Yeaple (2009, 2013). In Table 2, we indicate the summary statistics of our sample.

Since the patents are count data and this is not normally distributed, OLS is not opportune (Greene 1994; Winkelmann and Zimmermann 1995). For this reason, we should implement the Poisson model corrected for heteroskedasticity, as in Aldieri (2011b).

As seen in the summary statistics table, first, the right tail of the distribution is very long. The overall mean is about 2403 and the maximum is 23666. Second, there are some very large values that contribute substantially to over dispersion. These two features make it difficult to specify a model with a conditional mean and variance that captures the main features of data. For this reason, we also compute the negative binomial estimates, with constant dispersion (NB1) and not constant dispersion (NB2)[12]. Finally, we compare Poisson, NB1 and NB2 estimates using AIC (*Akaike*'s information criterion) and BIC (*Bayesian*information criterion).

[12] See Cameron and Trivedi (2013) for a technical discussion of Poisson, NB1 and NB2 models.

Table 3 Full sample results

Poisson	All firms			NB1 All firms			NB2 All firms		
	Est[b].	ME[d]	SE[a,c]	Est.	ME	SE[a]	Est.	ME	SE[a]
LnLi	0.29*	420.46	(0.046)	0.16*	291.34	(0.034)	0.16*	226.88	(0.034)
LnCi	−0.14*	−197.36	(0.036)	−0.05***	−84.35	(0.028)	0.03	48.79	(0.034)
LnKi	0.52*	755.52	(0.034)	0.34*	611.24	(0.038)	0.39*	565.47	(0.032)
MIGi	1.12*	1622.26	(0.130)	1.34*	2389.89	(0.153)	2.19*	3139.10	(0.110)

[a], * Coefficient significant at the 1 %, *** Coefficient significant at the 10 %;
[b] 1587 observations. Time dummies and Industry dummies are included in the estimation procedure. 2002 is the Year Reference. Oil and Gas sector is the Industry Reference.
[c] SE are corrected for heteroskedasticity and autocorrelation.
[d] Marginal effect

Table 4 Comparison based on information criteria about the full sample

	All firms		
	Poisson	NB1	NB2
AIC	1546638.2	26511.4	25845.4
BIC	1546767.1	26645.7	25979.6

4 Results

In Table 3, we report the results of the analysis for the full sample of firms. As explained in the previous section, we compute Poisson, NB1 and NB2 estimates. In order to identify the best model, we take into account the AIC and BIC information criteria in Table 4. On the basis of this procedure, the NB2 model is preferred, due to the lower AIC and BIC. In addition to heteroskedasticity, we consider also autocorrelation[13] in our panel data. In particular, the Wooldridge autocorrelation test[14] rejects the null hypothesis of no autocorrelation.

We may note that the effect of own R&D capital stock on the innovation output, the patents, is always positive, as expected. Also the coefficient of knowledge spillovers through the migration effect is always positive. This result confirms the theoretical proposition about the migration effect: the migration of inventors might enhance local innovation levels. Lower Herfindahl concentration index and thus higher Migration index leads to a higher level of knowledge of the inventors abroad, and this determines a positive knowledge spillover effect.

In Table 5, we report the results of the analysis for each economic area. Also in this case, we compute Poisson, NB1 and NB2 estimates. In order to identify the best model, we take into account the AIC and BIC information criteria in Table 6. On the basis of this procedure, the NB2 model is preferred. The empirical result regarding the migration effect confirms the proposition in the theoretical section, also in this case. It is worth noting the results for Japan, which are higher than those for America and Europe. From Table 1, we can see that most of innovation knowledge comes from local inventors, and that the marginal effect of migration is then higher. This could explain our empirical results.

5 Policy Implications and Concluding Remarks

Since innovativeness is linked to productivity, and this in turn is vital for economic development, any policy measure supporting it, such as R&D subsidy, R&D tax credit, funding R&D and science and technology collaborations, could be justifiable. In order to make the innovation activity more efficient, policy makers should consider the relevance of geographic proximity, by attracting and agglomerating R&D companies in a given territory or space. Moreover, given the role of R&D activities to enhance the

[13] We thank one anonymous reviewer for the interesting suggestion about autocorrelation of data.

[14] Wooldridge test results are available from the authors upon request.

Table 5 Cross-national analysis

	EU firms			JP firms			US firm		
	Est[b].	ME[d]	SE[a,c]	Est.	ME	SE[a]	Est.	ME	SE[a]
Poisson									
LnLi	0.49*	1434.11	(0.095)	−0.14**	−232.4	(0.066)	0.13*	129.31	(0.035)
LnCi	−0.68*	−1983.39	(0.092)	0.14***	237.2	(0.081)	−0.03	−31.11	(0.032)
LnKi	0.97*	2832.29	(0.078)	0.47*	787.3	(0.069)	0.29*	301.99	(0.036)
MIGi	−0.39	−1129.31	(0.220)	2.46*	4125.0	(0.224)	2.24*	2297.51	(0.153)
NB1									
LnLi	0.40*	1184.57	(0.089)	−0.04	−63.61	(0.058)	0.12*	136.9	(0.030)
LnCi	−0.61*	−1803.38	(0.090)	0.09	156.49	(0.059)	−0.01	−15.8	(0.025)
LnKi	0.99*	2939.36	(0.072)	0.40*	691.29	(0.051)	0.16*	181.7	(0.031)
MIGi	−0.37	−1109.14	(0.240)	2.55*	4393.29	(0.234)	2.51*	2799.0	(0.123)
NB2									
LnLi	0.66*	1975.5	(0.137)	−0.06	−94.27	(0.056)	0.05	46.31	(0.032)
LnCi	−0.28**	−889.44	(0.152)	0.15*	235.45	(0.056)	0.16*	153.18	(0.040)
LnKi	0.46*	1369.14	(0.072)	0.47*	725.70	(0.057)	0.13*	129.70	(0.032)
MIGi	0.26	780.28	(0.245)	3.13*	4843.23	(0.162)	2.92*	2831.0	(0.139)

[a] , *** Coefficient significant at the 1 %, ** Coefficient significant at the 5 %, * Coefficient significant at the 10 %

[b] 215 observations for European firms; 478 observations for Japanese firms; 894 observations for American firms. Time dummies and Industry dummies are included in the estimation procedure. 2002 is the Year Reference. Oil & Gas sector is the Industry Reference

[c] Standard errors are corrected for heteroskedasticity and autocorrelation

[d] Marginal effect

Table 6 Comparison based on information criteria by economic area

	Poisson	NB1	NB2
EU firms			
AIC	81975.7	3652.9	3651.4
BIC	82046.5	3727.1	3725.6
JP firms			
AIC	180050.7	7619.1	7550.9
BIC	180138.2	7710.8	7642.7
US firms			
AIC	411053.4	13865.5	13726.9
BIC	411163.7	13980.6	13841.9

absorptive capacity of firms to identify, assimilate and exploit external knowledge, policies promoting this function of R&D, such as R&D subsidies or upgrading the skills of company's research personnel should be stimulated. In this paper, we realize a further step in terms of policy implications. Indeed, this study contributes to existing literature on a firm's innovative activity, examining how migration can be a relevant channel for knowledge spillovers. The aim of the paper is to introduce a new variable, which is computed on the basis of the distribution of inventors across countries according to patent data. The paper consists of a theoretical model and an empirical analysis, which is a cross-national analysis of the United States, Japan and Europe, based upon a new dataset of worldwide R&D-intensive manufacturing firms. We use data from all EU R&D investment scoreboards editions issued every year from 2002 to 2010 by the JRC-IPTS. Since in the literature there are studies focusing on the effects of spillovers on innovation, measured by the patents (Cincera 1997), while migration, as a potential channel for knowledge spillovers, has not received much attention, we try to test empirically for the migration effect of inventors. The empirical results evidence that the coefficient of knowledge spillovers through the migration effect is always positive: lower Herfindahl concentration index and thus higher Migration index leads to a higher level of knowledge of the inventors abroad, and this determines a positive knowledge spillover effect, by confirming the theoretical proposition about the migration effect.

We point out some limitations to our analysis, which can be addressed in future research. We account for the correlation between spillovers and innovation output, but it would be interesting to identify the causality of innovative process, through the implementation of a methodological procedure able to deal with the endogeneity of relevant variables. With this aim it would be reasonable to assume a time lag between the variables in order to move one step closer to causality.

In this paper we consider only an international patent system, the European Patent Data (EPO). It would be opportune to test for the robustness of our results by comparing them with those based on other patent systems, such as the US Patents and Trademarks Office data (USPTO). Finally, it would be interesting to consider firms in emerging countries in Asia, such as China, for new and interesting results.

Acknowledgments The authors are grateful to two referees whose comments greatly improved the quality of the paper. The results, conclusions, views or opinions expressed in this paper are only attributable to the authors.

Appendix 1 (Proof Proposition 1)

(1) By combining Eqs. (6) and (7) we obtain the equilibrium values:

$$K^{*} = A\left(\frac{\alpha}{\theta}\right)^{\frac{(\alpha+\gamma)}{(\gamma+1)}}\left[\frac{(1-\alpha)}{\lambda}\right]^{\frac{(1-\alpha)}{(\gamma+1)}} \tag{17}$$

$$K^{RD*} = A^{\frac{(\alpha+1)}{(\gamma+\alpha)}}\left(\frac{\alpha}{\theta}\right)^{\frac{\alpha}{(\gamma+1)}}\left[\frac{(1-\alpha)}{\lambda}\right]^{\frac{\gamma+1+\alpha(1-\alpha)}{(\gamma+1)(\gamma+\alpha)}} \tag{18}$$

In order to demonstrate Pareto inefficiency, we may write:

$$U^{*}_{i,t} = AK_t^{*\alpha}K_t^{*RD(1-\alpha)} - \frac{\theta K_t^{*(1+\gamma)}}{(1+\gamma)};$$

thus, considering small changes in the equilibrium values we will have:

$$dU^{*}_{i,t} = dK_t^{*}\left[\frac{A\alpha K_t^{*RD(1-\alpha)}}{K_t^{*(1-\alpha)}} - \theta K_t^{*\gamma}\right] + dK_t^{*RD}\left[\frac{A\,(1-\alpha)\,K_t^{*\alpha}}{K_t^{*RD\alpha}}\right], \tag{19}$$

from the inspection of which it is clear that the term multiplied by dK_t^{*} is zero, whereas the other term is positive. Similar reasoning may be applied to $dU^{*}_{j,t}$.

(2) From inspection of Eqs. (6) and (7). Furthermore, when a small group m of inventors experiment a reduction in λ to λ_1 we will have:

$$K^{RD*} = A^{\frac{(\alpha+1)}{(\gamma+\alpha)}}\left(\frac{\alpha}{\theta}\right)^{\frac{\alpha}{(\gamma+1)}}\left[\frac{(1-\alpha)}{\lambda}\right]^{\frac{\gamma+1+\alpha(1-\alpha)}{(\gamma+1)(\gamma+\alpha)}} \tag{20}$$

$$K^{1RD*} = A^{\frac{(\alpha+1)}{(\gamma+\alpha)}}\left(\frac{\alpha}{\theta}\right)^{\frac{\alpha}{(\gamma+1)}}\left[\frac{(1-\alpha)}{\lambda_1}\right]^{\frac{\gamma+1+\alpha(1-\alpha)}{(\gamma+1)(\gamma+\alpha)}}. \tag{21}$$

By dividing Eqs. (20) by (21), and substituting in Eq. (17) we may write:

$$K_{i,t} = \left\{\frac{A\alpha}{\theta}\right\}^{\frac{1}{(1+\gamma-\alpha)}}\left[mK^{1RD(1-\alpha)} + (1-m)\,K^{1RD(1-\alpha)}\left(\frac{\lambda_1}{\lambda}\right)^{\frac{(1-\alpha)[\gamma+1+\alpha(1-\alpha)]}{(\gamma+1)(\gamma+\alpha)}}\right]^{\frac{1}{(1+\gamma-\alpha)}} \tag{22}$$

from which $K_{i,t}$ increase in m.

Appendix 2 (Proof Proposition 2)

Evaluating the effects of small changes in K^*, K^{fRD*}, K^{oRD*} and β we may write:

$$\begin{aligned} dU^*_{i,t} &= dK^* \left\{ A\alpha K^{*(\alpha-1)} \left[(1-\beta)\, K^{fRD*(1-\alpha)} + \beta K^{RD*(1-\alpha)} \right] - \theta K^{*\gamma} \right\} \\ &\quad + dK^{fRD*} \left\{ \frac{A\,(1-\beta)\,(1-\alpha)\, K^{*\alpha}}{K^{fRD*\alpha}} \right\} + dK^{RD*} \left\{ \frac{A\beta\,(1-\alpha)\, K^{*\alpha}}{K^{RD*\alpha}} \right\} \\ &\quad + d\beta \left\{ AK^{*\alpha} \left[-K^{fRD*(1-\alpha)} + K^{RD*(1-\alpha)} \right] \right\} \end{aligned}$$

with uncertain sign.

References

Acemoglu, D. A. (1996). Microfoundation for social increasing returns in human capital accumulation. *The Quarterly Journal of Economics*, *111*(3), 779–804.

Aldieri, L. (2011a). *Three essays on knowledge diffusion and firms' economic performance*, Ph.D. Thesis, Université Libre de Bruxelles.

Aldieri, L. (2011b). Technological and geographical proximity Effects on knowledge spillovers: Evidence from the US patent citations. *Economics of Innovation and New Technology*, *20*(6), 597–607.

Aldieri, L., & Vinci, C. P. (2015). Technological spillovers through a patent citation analysis. *International Journal of Innovation Management*. doi:10.1142/S1363919616500286.

Almeida, P., & Kogut, B. (1999). Localization of knowledge and the mobility of engineers in regional networks. *Management Science*, *45*(7), 905–917.

Cameron, A. C., & Trivedi, P. K. (2013). *Regression analysis of count data* (2nd ed.). New York: Cambridge University Press.

Carillo, M. R., & Vinci, C. P. (1999). Social increasing returns and the effects of immigration on the host country economy. *Labour*, *13*(3), 623–645.

Cincera, M. (1997). Patents, R&D, and technological spillovers at the firm level: Some evidence from econometric count models for panel data. *Journal of Applied Econometrics*, *12*(3), 265–280.

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

European Commission (2011). The 2011 EU Industrial R&D Investment Scoreboard, JRC Scientific and Technical Research series. http://iri.jrc.ec.europa.eu/scoreboard.html.

Greene, W. R. (1994). Accounting for excess zeros and sample selection in poisson and binomial regression models, Working Paper 94–10, New York University.

Griliches, Z. (Ed.). (1992). *Introduction to output measurement in the service sectors*. In *output measurement in the service sectors* (1st ed.). *National Bureau of Economic Research Books*. Chicago: University of Chicago Press.

Griliches, Z. (Ed.). (1998). *Introduction to R&D and productivity: The econometric evidence*. In *R&D and productivity: The econometric evidence* (1st ed.). *National Bureau of Economic Research Books*. Chicago: University of Chicago Press.

Huang, Hsin-I, & Walsh, J. P. (2010). Mobile inventors. Are they stars, networks channels or problem solvers? working paper, Georgia Institute of Technology, May 10, 2010.

Keller, W., & Yeaple, S. R. (2009). Multinational enterprises, international trade, and productivity growth: Firm-level evidence from the United States. *The Review of Economics and Statistics*, *91*(4), 821–831.

Keller, W., & Yeaple, S. R. (2013). The gravity of knowledge. *American Economic Review*, *103*(4), 1414–1444.

MacGarvie, M. (2006). Do firms learn from international trade? *The Review of Economics and Statistics*, *88*(1), 46–60.

Maraut, S., Dernis, H., Webb, C., Spiezia, V., Guellec, D. (2008). The OECD REGPAT database: A presentation. OECD STI Working Papers, 2008/02.

Maurseth, P. B., & Verspagen, B. (2002). Knowledge spillovers in Europe: A patent citations analysis. *The Scandinavian Journal of Economics*, *104*(4), 531–545.

Moncada-Paternò-Castello, P., Ciupagea, C., Smith, K., Tübke, A., Tubbs, M. (2009). Does Europe perform too little corporate R&D. A comparison of EU and non-EU corporate R&D performance, Seville, Spain: IPTS Working Paper on Corporate R&D and Innovation, 11.

Nadiri, M.I. (1993). Innovations and technological spillovers, NBER Working Paper no. 4423, Washington D.C.

Niebuhr, A. (2010). Migration and Innovation: Does cultural diversity matter for regional R&D activity? *Papers in Regional Science*, *89*(3), 563–585.

Singh, J. (2005). Collaborative networks as determinants of knowledge diffusion patterns. *Management Science*, *51*(5), 756–770.

Singh, J., & Agrawal, A. (2011). Recruiting for ideas: How firms exploit the prior inventions of new hires. *Management Science*, *57*(1), 129–150.

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