Knowledge Flows, R&D Spillovers and Innovation *

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Abstract

Knowledge flows within and across countries should be carriers of important learning spillovers. We use data on 1.5 million patents and 4.5 million citations to analyze knowledge flows across 147 sub-national regions. We estimate that only 15% of average knowledge is learned outside the average region of origin, and only 9% outside the country of origin. However, knowledge in highly technological sectors flows substantially farther and knowledge generated by technological leaders does also. If compared to trade flows, knowledge flows reach much farther. Moreover, external accessible knowledge has very strong external impact on innovation for a panel of 113 European and North American regions over 22 years.

JEL Codes: F0, O3, R1

Key Words: Knowledge Flows, Gravity Equation, R&D Spillovers, Patent Citations, Regions.

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1 Introduction

What do we know about the flows of technological and scientific knowledge within and across countries? What do we know about the externalities of Research and Development (R&D from now on) within and across countries? Thanks to the attention devoted to these issues by economists in the last ten years we know a fair amount. Economists have improved their empirical methodology to analyze spillovers, they have sharpened their theoretical understanding of the phenomenon of innovation and, most of all, they have collected and made available for electronic use, large, detailed and comparable data set on Patents and R&D both for the U.S. and other OECD countries. However, the large number of studies has not yet produced a robust consensus on the quantitative assessment of knowledge flows and of R&D spillovers. Often different traditions and different methods of research seem somewhat at odds with each other and hard to reconcile.

Two strands of the literature have failed to share their insights and to compare each other on quantitative findings in part for lack of a common frame of analysis and in part for some hesitance in looking seriously at each other's data and methods. One branch of the literature that looks at knowledge flows and spillovers has focussed on data at the firm-level, considering in great detail few sectors within a country and has developed the analysis of spillovers in technological space. The roots of this literature were more in the empirical analysis than in the theoretical modelling and Zvi Griliches can be identified as the "father" of this line of research. We refer to this branch as the "micro-productivity" literature. Another branch has looked at flows and spillovers across large aggregate units such as countries or country-sectors emphasizing the geographical aspect of these flows. Differently from the other branch of research, the interest for international R&D spillovers was mainly generated by the theoretical analysis introduced by the "new growth" and the "trade and growth" literature. The idea of knowledge flows and R&D spillovers as key determinants of growth and international trade was developed and popularized by Krugman [48], Romer [56], Aghion and Howitt [2] and Grossman and Helpman [37]. Helpman had also a key role as initiator of the empirical literature. We call this branch the "trade-growth" literature. This paper, while more related to the trade-growth tradition, talks to both lines of analysis and establishes a bridge between those two approaches.

Both traditions agree on general statements such as "Knowledge flows are localized in space" (for some definition of technological or geographical space) or "R&D externalities are positive and significant". However, the large variance of estimates produced, the large variety of methods adopted and the large differences in assumptions make consensus on parameters' estimates hard to achieve. Our goal in this paper is to frame the issue of knowledge flows and R&D externalities in a simple empirical specification, acceptable both to the micro-productivity and to the trade-growth tradition. We use this empirical model to define and to estimate separately the intensity of knowledge flows on one hand and of R&D Spillovers on the other. Each of these two concepts corresponds to the estimates of some specific parameters.

We use a very large and very detailed data set on Patents in order to capture inventions and their linkages, the NBER Patent and Citations Data. These data have been hardly used at all by the trade-growth literature. However they have been extensively used and analyzed by the micro-productvity literature[1]. We aggregate the information from these patents into 147 sub-national regions covering the whole Western Europe and North America, and we merge these data with regional R&D and other regional data from OECD and national sources. This allows us to analyze sub-national regions as units and to obtain parameter estimates that are comparable to aggregate estimates of R&D spillovers from the trade-growth literature. However, the sub-national nature of our analysis and the detailed treatment of sectors and technological distance, as well as the use of patent data, allows us to compare results with cross-firms estimates from the micro-productivity literature as well.

The rest of the paper is organized as follows. Section 2 clarifies a key distinction between knowledge flows and R&D spillovers. Section 3 frames such distinction in a simple empirical specification. It also analyzes, in the light of this specification, the existing literature that is surveyed by grouping existing works into the "micro-productivity" literature and the "trade-growth" literature and distinguishing between estimates of "knowledge flows" and those of "R&D Externalities". Section 4 presents the data and discusses specification and measurement issues. In particular we consider R&D as input of the innovation process, patents as output of the innovation process and patents' citations as measure of knowledge flows. Section 5 presents the estimates of aggregate knowledge flows across the 147 European and North American regions. We qualify our results by looking at different sectors, different periods, different specifications and comparing localization-diffusion of knowledge flows to localization-diffusion of trade flows. Section 6 uses the estimates of "external accessible R&D" across regions to calculate its impact on aggregate innovative output. Section 7 concludes the paper.

2 Knowledge Flows and R&D Spillovers

It is useful, at this point, to introduce a distinction between what we call "Knowledge Flows" and what we call "R&D Spillovers". This distinction helps us to classify the recent developments of the micro-productivity and of the trade-growth literature. It also allows us to point out the innovative contribution of the present paper. In formal models knowledge flows (sometimes referred to as knowledge diffusion or flows of ideas) and "R&D spillovers" (sometimes referred to as externalities) are distinct phases of one phenomenon. They are two distinct steps in a sequence and should be analyzed separately, where possible. Knowledge flows

[1] More on this later.

are the first step and they take place whenever an idea generated by a certain institution is learned by another institution. These flows denote a process of learning from someone else's ideas. Learning creates a stock of so called "accessible knowledge" (Griliches [34]), or "borrowed knowledge". "R&D spillovers" (or externalities), however, are the second step and they exist only if this "accessible knowledge", learned through learning, has a positive impact on productivity. While knowledge flows are needed to generate R&D spillovers they do not automatically generate them. We may have a lack of R&D spillovers due to a lack of knowledge flows or due to an insignificant effect of accessible knowledge on productivity. Particularly, when we estimate quantitative parameters such as elasticities we need a precise distinction and estimation of each of these two phenomena. The present paper does exactly this by carefully decomposing these two steps: we analyze the process of R&D accumulation, the propagation of knowledge through learning and we estimate R&D spillovers. We do this by analyzing R&D spending in 113 sub-national regions of Western Europe and North America over 22 years (1975-1996). These regions cover about 50% of world GDP, 83% of world R&D and 85% of world patented innovation. We estimate the effect of R&D on innovation, we measure the flows of knowledge across 147 regions as revealed by patent to patent citation and we estimate the external effect of R&D (R&D spillovers).

The analysis of knowledge flows as defined above has been privileged by the micro-productivity literature. Researchers in this tradition have directed their attention to the understanding of learning relations in technological space. They constructed matrices of technological flows between sectors from input-output matrices (Terlecky [62], Wolf and Nadiri [63]), from invention-use matrices (Scherer [60]) or they defined concepts of angular distance between firms or regions (Jaffe [39]) based on their sector specialization. More recently this branch of literature has cleverly used data on patent to patent citations collected for the whole universe of U.S. patented discoveries granted between 1975 and 1999[2]. These citations provide an excellent piece of information tracking knowledge flows exactly as defined above. A citation establishes a link between the citing idea in firm r at time $t+n$ and the cited idea in firm s at time t. With some caveats, discussed later in detail, citations provide the "trail in the sand" left by the act of learning and can be used to assess its intensity.

The trade-growth literature on the other hand has been hesitant to incorporate information from the Patent citations data or to devote much attention to technological space in its analysis of international knowledge flows. Two alternatives have been preferred instead. Following Coe and Helpman [21], trade flows have been considered as a good proxy for knowledge flows (for instance Keller [47]). Alternatively, data on flows have been omitted altogether and R&D externalities have been inferred, jointly with knowledge flows , based on cross-countries or cross region productivity correlations (Keller [47], Bottazzi and Peri [7])

[2] These data are described and analyzed in detail in the recently published Jaffe and Trajtenberg [41]

or assuming a common pool of accessible R&D within a country across sectors or within a sector across countries (Frantzen [30]).

Interestingly, the theoretical trade-growth literature has emphasized in several influential studies the importance of analyzing international knowledge flows as channel of growth. Many theoretical studies have explicitly emphasized the deference between trade flows and knowledge flows, arguing that the second, rather than the first, are responsible for development and growth. Rivera Batiz and Romer [55] show that under some assumptions *"... trade in goods has no effect on the long-run rate of growth"* while *"...allowing flows of ideas* (i.e. knowledge flows) *results in a permanently higher growth rate"*. They go on stating that *"[f]lows of ideas deserve attention comparable to that devoted to flows of goods"*. Grossman and Helpman [37] in Chapter 9 of their very influential book "Innovation and Growth" point out that *"[T]he growth effect of knowledge spillovers and those of commodity trade are conceptually distinct"* and they develop models that show how *"the most important benefit to a country from participating in the international economy might be the access that such integration affords to the knowledge base in the world at large"*. Feenstra [27] argues that convergence in growth rates across countries takes place only if *"...trade occurs simultaneously with international diffusion of knowledge"* while if no diffusion of knowledge occurs trade could actually generate divergence. Moreover, scientific and technological knowledge has been recognized for a long time as an important factor of production on par with labor and capital (Solow [58]) and its growth regarded as the propellant of economic growth (Solow [59]).

Stimulated by these theoretical speculations one would think that the empirical trade-growth literature has made an effort to develop better measures of international knowledge flows, explicitly differentiating them from trade flows, and explicitly analyzing their effect on productivity growth. This has not happened in a significant way, yet. Certainly knowledge flows are hard to define, observe and measure and our understanding of knowledge flows is still in its infancy if compared to the analysis of trade flows. This is why it is extremely interesting to use the very large and detailed NBER patent citation data set, containing more than 2 million patents (1975-1999) and about 6 million citation links, to get information on regional flows of knowledge.

Large part of the skepticism within the trade-growth literature for the citation data comes from doubts on the real information contained in citation links. It is very important, therefore, to discuss and analyze extensively the estimates of knowledge flows generated by these data, comparing them across sectors, over time, across regions and with flows of goods. We do this in the first part of our paper. We also show the importance of accounting properly for differences in the technological specialization of regions even if our main concern is the diffusion of knowledge in space.

The second part of the paper uses the estimates of knowledge flows in order to construct measures of "accessible external R&D" for each of the considered regions. For a region j at time t this is the amount of R&D conducted elsewhere and filtered (weighted) by the flows of knowledge learned by region j from all other regions. "Own R&D" as well as "accessible external R&D" are treated as an input in an aggregate production function of innovation that is estimated at the regional level. In order to have a stringent analysis of learning externalities, without polluting it with problems of pecuniary externalities and price effects, we analyze the impact of external accessible knowledge on aggregate innovation, measured as weighted patent count. While the impact of knowledge flows on aggregate production is very important we leave it for further research and we concentrate here on spillovers on the innovative output. A host of other issues arises when we measure total factor productivity (TFP). In particular, the theoretically clean distinction between technological externalities, channeled by learning from others, and pecuniary (or rent) externalities channeled through input-output linkages, would be clouded by the difficulty of measuring prices precisely and adjusting them for quality improvements. Increased R&D in region i may generate increased TFP in region j because region i exports better quality of intermediate goods to j and the prices of intermediate goods and capital stock in region j do not properly adjust for quality improvements (Griliches [34]) or because imperfectly competitive prices fail to fully capture the marginal contribution of intermediate goods (Basu and Fernald [6]). As production of innovation (patents) does not require intermediate inputs and is not evaluated using prices but simply the quantity of patents, we minimize the role of pecuniary externalities.

3 Basic Framework and Existing Literature

Consider the measure Q_{it} as an index of the technological development of economic unit i at time t. Frequently in the literature some measure of total factor productivity has been used to capture Q_{it}. Total factor productivity determines how much output could be generated keeping the quantity and quality of labor and capital inputs constant. To avoid all the measurement issues of growth accounting and to keep our focus on knowledge flows and R&D externalities we use the measure of innovation activity of unit i at time t as our Q_{it}. In particular we use the (citation weighted) count of Patents granted to unit i as a measure of its innovative output. The units chosen are sub-national regions. Assuming that R&D activity is the main source of technological knowledge then the innovative output Q_{it} is produced as follows:

$$Q_{it} = (A_{it})^{\gamma} \, (A_{it}^{a})^{\mu} \tag{1}$$

A_{it} is the stock of past accumulated R&D resources invested yearly in region i (we indicate them as $R\&D_{it}$). A_{it}^{a} is the stock of past accumulated R&D resources invested in regions other than i and "accessible" (hence the a superscript) to region i at time t. The objective of our analysis is to construct a measure of the two stocks A_{it} and A^a_{it} for European and North-American regions and to estimate their impact, captured by γ and μ, on the regional innovative output. Equation (1) can be seen as the production function of innovation, whose inputs are A_{it} and A^a_{it}. The accumulation of A_{it} is simply described as $\Delta A_{it} = R\&D_{it} - \delta A_{it}$ where the depreciation rate of R&D capital is equal to δ. We apply such "perpetual inventory method" to calculate the value of such stock.

Our main focus and contribution, however, is on the construction of A^a_{it} and on the estimate of μ. In the presence of complete and immediate diffusion of knowledge from any region of origin into any other region the total external knowledge stock (or knowledge "pool" as defined by Griliches [34]) available in i would be $A^a_{it} = \sum_{j \neq i} A_{jt}$. However, considering less than perfect diffusion of knowledge across regions, total accessible knowledge in region i would be given by $A^a_{it} = \sum_{j \neq i} \phi_{ji} A_{jt}$. In this expression $\phi_{ji} \in [0, 1]$ is the percentage of knowledge stock generated in region j by time t and accessible to region i. Substituting this last expression for A^a_{it} into equation (1), taking logs on both sides and re-arranging we have the following equation:

$$\ln(Q_{it}) = \gamma \ln(A_{it}) + \mu \ln(\sum_{j \neq i} \phi_{ji} A_{jt}) \tag{2}$$

Expression (2) contains the key parameters that capture "R&D Externalities" and "Knowledge Flows". This equation says that the log level of innovative output $\ln(Q_{it})$, depends on the log level of the stock of regional knowledge $\ln(A_{it})$ and on the log level of the stock of external accessible knowledge $\ln(\sum_{j \neq i} \phi_{ji} A_{jt})$. If the stock of external accessible knowledge has a positive impact on productivity (i.e. if $\mu > 0$) then there are positive R&D Spillovers. However, in order to calculate the stock of external accessible knowledge A^a_{it} we need to estimate the intensity of knowledge flows (learning) between regions, captured by the parameters ϕ_{ji}. The above parametrization allows us to draw a very clear distinction between knowledge flows and R&D externalities. The parameters ϕ_{ji} capture the intensity of knowledge flows, they could depend on several bilateral characteristics of the regions, their technological differences, their location and so on. They should be estimated using the data on patent citations that reveal what part of knowledge generated in a region at some point in time has been learned in another region by some later point in time. The parameter μ, on the other hand, captures the R&D externalities, namely the impact of "accessible external research" on production. These two parameters are conceptually and empirically very different and separating them would be important for our understanding of the knowledge-productivity link as well as for our ability of prescribing policy implications. For instance finding a small effect of research in country j on productivity of country i could be due to little knowledge flows between the two countries (small ϕ_{ji}) or to a small impact of accessible external knowledge on productivity in country i (small μ). In the first case removing hurdles of communication between the two countries would result in higher innovative output of country i, in the second case it would not. While the above simple frame does not make justice of some more complex and structural approaches to the issue of knowledge flows and R&D Spillovers we can use it for a selective and limited, while still useful, review of the literature. We organize the review distinguishing between studies coming from the micro-productivity tradition and focusing on firms and studies within the trade-growth tradition focussing on international R&D spillovers.

3.1 The Micro-Productivity Literature

A little more than a decade ago Zvi Griliches ([34]) made the point and set the agenda of "the search for R&D spillovers". Several pieces of empirical research followed that seminal paper and improved our understanding of the process of knowledge diffusion and of R&D spillovers. In actuality, the micro-productivity studies were simply the continuation and the refinements of an empirical tradition that had analyzed R&D spillovers for a long time[3]. We consider here mostly work produced during the last ten years[4].

A first simple method used to proxy knowledge flows across firms assumed that only firms within the same "technological group" (for instance two or three digit SIC sector) have knowledge flows with each other. In this case $\phi_{ij} = 1$ for firms in the same group while $\phi_{ij} = 0$ for firms in different groups. This approach was used, for instance, by Bernstein and Nadiri [9], [10] for the U.S. high tech industries, Bernstien and Mohen [8] for U.S. and Japan, Bernstein and Yan [11] for Canada and Japan. Similar to this discrete type of weighting are also those methods that use geographical information to establish location of a firm within or outside a certain area. These studies impose $\phi_{ij} = 1$ for firms in the same county, region or within a certain radius of distance and $\phi_{ij} = 0$ outside that (see for instance Anselin et al. [4]).

More sophisticated measures of knowledge flows define technological distance as a truly bilateral concept and allow for different ϕ_{ij} for each pair of firms. Jaffe [39] describes each firm as the vector of shares of R&D (or innovative activity) of the firm in each sector. The flow ϕ_{ij} is calculated as the uncentered correlation coefficient between the vector of firm i and the vector of firm j. Perfect coincidence in the sectors' shares results in a correlation of 1 between firm i and j while perfect complementarity in R&D sectors would generate a value of 0 of the correlation coefficient. Using a similar methodology Branstetter [16] analyzes the impact of domestic and foreign R&D spillovers for U.S. and Japanese firms. Still trying to proxy ϕ_{ij} with some technological distance other authors have used "flows" connecting firms (or sectors) i and j. Among these Wolf and Nadiri [63] used input-output matrices, Terlecky [62] used flows of intermediate capital goods and Scherer [60] constructed a matrix of origin-use of patents. Recently Kaiser [43] has tried to establish

[3]Bresnahan ([17]), Griliches and Lichtenberg ([36]), Mansfield et al.([51]), Scherer([60]), Terlecky [62], Wolf and Nadiri ([63]) are some notable examples of earlier studies.

[4]Far from being a complete survey the present overview of the literature is meant to give a sense of the large body of work existing on this topic. Excellent surveys of the literature in the proper sense exist (notably Griliches[34], Mohnen [53], Branstetter [14], Cincera [20]).

some comparisons among the above described methods. Once ϕ_{ij} have been used to construct A^a_{it} most of the articles analyze the impact of the accessible stock of knowledge on total factor productivity or on the innovation output of firms. There is a wide range of estimates but most of the studies find an elasticity to external accessible R&D (μ) between one half and two times as large as the elasticity to own R&D (γ).

Finally and notably in the most recent years, thanks to the availability of new data, from the U.S. patent office and also from the European patent office, the parameters ϕ_{ij} have been estimated using patent citations. This method stands out because it is the only one in which "signs" of the presence of learning flows are actually observed in the data. Patent citations provide evidence on learning flows without making any a-priori assumption on their determinants (such as technological or geographical proximity). Using these data Jaffe et al. [40] test that distance matters for knowledge flows within the U.S., Jaffe and Trajtenberg ([41], Chapter 8 and 9), Adams [1] and Jozefowicz [42] compare knowledge flows originating in Universities, Federal Labs and or firms, Globerman et al. [32] analyze knowledge flows for Swedish firms, Maruseth and Verspagen [50] analyze knowledge flows across European regions and Jaffe and Trajtenberg ([41], Chapter 7) analyze knowledge flows across countries. While certainly more accurate and superior in estimating knowledge flows (ϕ_{ij}) these studies rarely use these estimates in order to assess the impact of these flows on productivity.

3.2 The Trade-Growth Literature

As already mentioned, large part of the tradition in the trade-growth literature followed the practice of Coe and Helpman [21] and measured ϕ_{ij} using trade (imports or exports) shares between country i and j. Several "improvements" to that paper followed. Keller [45] raised some doubts on the methodology of the Coe and Helpman [21] study, Edmond [25], Funk [31], Kao et al. [44] applied panel cointegration techniques to the analysis. Frantzen [29] added human capital and some estimation improvements. Coe et al. [22] extended the analysis of R&D spillovers to seventy-seven developing countries and Madden et al. [49] to six Asian countries. Most of these studies confirmed the original findings of strong R&D externalities (μ as large as γ) especially from developed to developing economies. A natural extension to the use of trade is to use flows of foreign direct investments to proxy for knowledge flows. FDI's have long been consider as a mean of technological transfer and imply movement of capital and know-how. Several studies such as Braconier and Sjoholm [13] find that FDIs facilitate spillovers (found within sectors across countries but not across sectors). Blomstrom and Kokko [12] review the main contributions of this literature. A distinctive line of analysis pursued by Eaton and Kortum [24] adopts a more complete and structural model of trade and growth across countries. They identify ϕ_{ij} using flows of cross-country patenting. In particular the share of inventions originated in country i and patented in country j is used to estimate ϕ_{ij} .

Finally, some recent studies on international R&D spillovers often do not use any information on flows in order to estimate ϕ_{ij} but they estimate it simultaneously with μ by exploiting the correlation structure of data on R&D, productivity and growth. Conley and Ligon [23] analyze the correlation across long-term growth rates and find that it positively depends on "economic distance" while Keller [47] identifies ϕ_{ij} and μ by estimating the effect on TFP of domestic R&D and R&D from the G5 countries. Identification relies on the specified functional form and on the dependence of ϕ_{ij} on geographical distance. Again, the overall message from this literature is that μ is positive, its estimates however, vary widely.

4 Specification, Measurement and Data

Our goal is to estimate the parameters ϕ_{ij} ,γ and μ. In particular we want to characterize ϕ_{ij} , the flow of knowledge between region i and j as depending on a host of bilateral characteristics. Then we use the estimated values of ϕ_{ij} to measure the accessible external R&D for each region, A^a_{it} and we include it as factor in the innovation function (2) to estimate the elasticity μ . In order to convince the reader that we are using appropriate data, that our specification is robust and that we are addressing adequately several measurement issues we describe and discuss each step of our procedure in some detail .

4.1 Knowledge Flows, Patents and Citations

We indicate the probability that a non-obsolete[5] idea generated in region i at time t_0 is learned in region j by time $t_1 = t_0 + \tau$ as $\phi_{ij}(\tau)$. This notation emphasizes the fact that such probability depends on characteristics of the couple of regions i, j, and on τ , the time elapsed between the invention and the act of learning. If there is a large number of ideas created in a region then, for the law of large numbers $\phi_{ij}(\tau)$ is the share of ideas learned in region j out of those generated in region i within interval τ since their invention. Inspired by what is done in the "micro-productivity" literature, in particular by Jaffe and Trajtenberg ([41] chapter 6 and 7) and by Caballero and Jaffe [18], we model the share $\phi_{ij}(\tau)$ as follows:

$$\phi_{ij}(\tau) = \varkappa e^{f(i,j)} \left(1 - e^{-\beta\tau}\right) \tag{3}$$

The term $1 - e^{-\beta\tau}$ captures the fact that ideas generated in region i become available in larger share to any other location j as time passes. If the event of learning an idea happens with a constant probability over time then this term captures the cumulative density of probability of learning the idea within τ years [6].

[5] Obsloescence of knowledge is incorporated in the depreciation used in calculating the stock of R&D of each region.

[6] If the event of learning of an idea has a Poisson distribution with hazard rate β then the CDF of the elapsed time before learning has the negative exponential form of expression 3.

However the term $e^{f(i,j)}$ where the function $f(i,j)$ depends on a whole set of bilateral regional characteristics, indicates that the intensity of learning from each sending region i to each receiving region j differ. The main simplifying assumption embedded in (3) is that the effect of bilateral characteristics $f(i,j)$ and the effect of time τ interact in a multiplicative way in determining knowledge diffusion. This implies that the relative flows of ideas across regions (not the absolute) does not depend on time elapsed τ , formally: $\phi_{ij}(\tau_0)/\phi_{kl}(\tau_0) = \phi_{ij}(\tau_1)/\phi_{kl}(\tau_1) = e^{f(i,j)-f(k,l)}$, for any i, j, k, l, τ_0 and τ $_1$. In words this means that, as time passes, more ideas that originated in region i are learned in any region, including itself, but such an increase is proportionally the same for any region so that the relative absorption of ideas originated from region i is constant over time. In our empirical analysis we experiment with different time intervals between generated and learned ideas $\tau = 2, 4, 6$ and 10.

Differently from the micro-productivity literature, in order to characterize diffusion of knowledge in a relatively simple form we do not parametrize excessively equation (3). In particular we assume that the share of ideas flowing from region i to j does not depend on the date (or cohort) of the sending (t_0) or of the receiving (t_1) idea. Again, we explore this dimension in the empirical analysis and we find that the assumption of constant flows for different calendar dates is supported by the data. We fix the same interval of time τ for all regions, we collect the constant terms (including those depending on τ) and we explicitly express the function $f(i,j)$ as depending on a host of geographical and technological characteristics and we obtain the following relation:

$$\begin{aligned}\phi_{ij} \quad = \quad & Ce^{f(i,j)} = \exp[a + b_1(out\_region)_{ij} + b_2(out\_next)_{ij} + b_3(out\_country)_{ij} \\ & +b_4(out\_lang)_{ij} + b_5(out\_trbl)_{ij} + b_6(dist)_{ij} + \underline{\gamma}(\underline{Controls})_{ij}]\end{aligned} \tag{4}$$

Equation (4) states that the (time-invariant) relative intensity of knowledge flows from region i to region j depends on an exponential function of several bilateral regional characteristics. We explicitly consider six geographic characteristics which we want to analyze in detail, while the others, concerning technological and productive characteristics of the regions are bundled in the vector of $\underline{Controls}$ and will be considered explicitly in the empirical sections. The bilateral characteristics considered here as determinants of the intensity of learning from i to j are mostly dummies. $(out\_region)_{ij}$ is a dummy which equals zero if i $= j$ and one otherwise and indicates whether ideas crossed one regional border. $(out\_next)_{ij}$ is equal to zero if $i = j$ or if region i and j share a border and 1 otherwise, it indicates whether ideas crossed two regional borders. $(out\_country)_{ij}$ is zero if the two regions belong to the same country and zero otherwise, it indicates whether ideas passed a national border. $(out\_lang)_{ij}$ is zero if the two regions speak the same language and 1 otherwise. It indicates whether ideas passed a linguistic border. $(out\_trbl)_{ij}$ is one if the two regions belong to the same trade block and one otherwise. It indicates whether ideas passed a trading-block border. Finally $(dist)_{ij}$ is simply the geographical distance between region i and region j. Estimates of the parameters b_1-b_6 and of $\underline{\gamma}$ would provide a detailed characterization of how geographic, technological and productive characteristics affect the flows of ideas across regions. While we do not observe ϕ_{ij} directly we do observe patents and citations between patents. We discuss in the remaining of this section how patents map into ideas and how citations map into flows of ideas.

There is a strict relation between the number of new ideas and the number of patents generated by a firm or a country. Following a long tradition we identify one patent with a bundle of ideas that fulfil the requirements of originality, non obviousness and economically profitable use. These are the standards of patentability as defined by the U.S. patent office and since the early work by Schmookler [61] many economists, such as Zvi Griliches, Ariel Pakes, Mark Shankerman and several others, have drawn from the large and rich pool of patent data, considering them a measure of "new ideas" (see Griliches [33] for a survey). As for assigning a patent to a region, we choose the region of residence of its first inventor. This method, as documented by Jaffe et al.[40], allows to locate each patent to the region where the idea was actually developed by its inventor(s) rather than to the region where the paperwork for the filing procedure was prepared (headquarters of the assignee company). The regions considered in our analysis are sub-national territorial units in eighteen countries in Europe and North America. They correspond to areas with some territorial unity and identity as well as administrative and policy autonomy. They are fifty federal states plus D.C., Puerto Rico, Guam and Virgin Islands for the U.S., ten federal provinces plus Yukon and Northwestern Territories for Canada and the so-called "NUTS 1[7]" regions within each of sixteen European countries (EU15 plus Switzerland) for a total of 147 regions covering the whole Western European and North American continents[8]. If each patent corresponded to one idea, the count of patents granted to region i (denoted as P_i.) would be equal to the number of ideas generated in that region (denoted as Υ_i). However different patents may have extremely different "importance" (see, for instance, Jaffe and Trajtenberg [41] Chapter 2). Counting all patents as containing one idea could generate distortions. This problem is much reduced in our study as we rely on a very large number of patents in each region (Total of 1.4 million of patents and almost 100,000 per region on average) and differences in value for single patents are of much smaller relevance for such large aggregates. However, we allow different regions to generate patents with different average "importance". Defining β_i (not observable) as the average number of ideas per patent generated in region i the relation between count of patents and number of ideas generated in region i is:

[7] Nomenclature Units Territorial Statistics, level 1.

[8] Names and distribution of these regions across countries are found in the Appendix.

$\Upsilon_i = \beta_i P_i$.

There is also a close relationship between learning of ideas (knowledge flows) and patent citations. Patent applicants are required to identify the "prior art" used in order to produce their innovative idea. They do so by including citations to previous patents that had some relevance in developing the idea. These citations inform us that the researcher knew about the cited idea and that such idea had some relevance in the research process leading to the new discovery. For our purposes if we had only the citations included by the authors of the patent we would have the best information available to establish the existence of knowledge flows[9]. What introduces noise for our use of citations is the fact that reviewers added citations to the patent. These added citations do not necessarily reveal ideas known to the author. Jaffe et al. [40] argue that the reviewers are expert in the area and they do a systematic search in the field so that these "added" citations should not have any (or much less of) geographical pattern. We assume that they simply add noise to the relation between knowledge flows and patent citations. A survey study (Jaffe and Trajtenberg [41], Chapter 12) confirms that while citations are not a perfect measure of the inventors' learned knowledge they contain a large amount of information about it. Again we rely on the extremely large amount of citation couples used (about 4.5 millions in total implying an average of about two hundreds citations for each regional couple) to reduce the random noise. We explicitly model, however, such random component. Defining as c_{ij} the count of citations from patent in region j to patents in region i and as Φ_{ij} the actual flow of ideas from region i to region j we assume the following relationship between citations frequency and knowledge flows:

$$c_{ij} = \psi_j \Phi_{ij} e^{\varepsilon_{ij}}. \tag{5}$$

As the total number of citations contained in a patent is not informative of any real characteristic of knowledge flows we include ψ_j to be a citing-region specific effect that allows the average number of citations to differ across citing regions. Φ_{ij} is the effective number of ideas flowed from region i to region j and $e^{\varepsilon_{ij}}$ is a randomly distributed disturbance where ε_{ij} is zero mean random noise. Using the relationship between patents and ideas and (5) we can derive the following relationship between the unobservable variable of interest ϕ_{ij} and the observable patent and citation counts:

$$\phi_{ij} = \frac{\Phi_{ij}}{\Upsilon_i} = \frac{c_{ij}}{\psi_j \beta_i P_i e^{\varepsilon_{ij}}} = Ce^{f(i,j)} \tag{6}$$

[9] Jaffe et al. [40] argue that citations not only establish a "learning" relation but also that they are limited to those ideas that had strict relevance to the development of the current innovation. This is because the inventors do not want to include irrelevant citations which would be dropped by the reviewer or would excessively restrict their claims on the use of the patent. For our purposes this restriction is not crucial. We only care that patents establish a learning relation between citing and cited idea. The fact that the cited idea was strictly relevant or not is not so crucial to us as we do not assume (but we estimate later) whether knowledge flows have positive effect in generating new ideas.

The first equality comes from the definition of ϕ_{ij}: the share of ideas learned in region j from region i is the number of ideas learned , Φ_{ij} relative to total ideas produced in i, Υ_i. The second equality derives from the relationship assumed between patents and ideas and between flows and citations, the last equality comes from the first part of equation (4). Substituting the second part of equation (4) in (6) and rearranging we obtain the following estimable specification:

$$\begin{aligned} c_{ij} \quad = \quad & \exp[\vartheta_i + \varphi_j + b_1(out\_region)_{ij} + b_2(out\_next)_{ij} + b_3(out\_country)_{ij} \\ & + b_4(out\_lang)_{ij} + b_5(out\_trbl)_{ij} + b_6(dist)_{ij} + \underline{\gamma}(\underline{Controls})_{ij} + \varepsilon_{ij}] \end{aligned} \tag{7}$$

This equation has an easy interpretation and some features that appeal both to the micro-productivity literature and to the trade-growth literature. The dependent variable is the count of citation links calculated for region j as citing region and region i as cited region. Such measure is clearly a proxy for the flow of ideas learned by region j from region i. However we allow for citing region fixed effects $\varphi_j = \ln(\psi_j)$ as well as cited region fixed effects $\vartheta_i = \ln(\beta_i P_i)$. The first set of effects controls for different propensity to cite across regions while the second set of controls cleans for different "importance" and number of potentially cited patents across regions. More in general the fixed effects control for any region-specific characteristics. Once we control for these effects and we allow for a random error ε_{ij}, we can estimate the parameters b_1-b_6 and $\underline{\gamma}$ as the other independent variables are all observable. Such regression is familiar to the micro-productivity literature and is often estimated using a non linear least squares regression (e.g. Jaffe and Trajtenberg [41], Chapter 7) or, more frequently, due to the count-data nature of citations, using the negative binomial regression (Branstetter [15]) or, given the mass of observation at 0, using a Tobit regression (e.g. Maruseth and Verspagen [50]).

On the other hand if we take logs on both sides of (7) we obtain a linear regression. Such regression is reminiscent of one that is heavily used in the trade-growth literature, mainly to analyze trade and is known as "gravity equation"[10]. In such equation a flow (of knowledge in this case) between region i and region j is regressed on "sending regions" and "receiving regions" characteristics and on a measure of distance between them as well as some other bilateral characteristics (such as belonging to the same country or sharing a border). Our specification is the most general form of a gravity equation as we control very generally for any sending and receiving regional fixed effect and we estimate parameters relative to the crossing of several geographical borders and relative to traveling geographic and technological distances. Typically, the trade literature estimates such equation using linear regression and omits (as logs are taken on both sides) the

[10] For a derivation of the gravity equation in the trade literature and a review of the main estimates obtained using it see Feenstra [28], Chapter 5.

couple of regions for which a zero trade link is present. In section 5 we estimate several variations of equation (7) using all the methods mentioned above. Luckily different estimation methods give very similar coefficient estimates.

4.2 Own R&D and Accessible External R&D Stock

While the analysis of the direction, intensity and determinants of knowledge flows is interesting in its own right we also use it to perform a further step. We can construct $\widehat{\phi}_{ij}$, the estimated share of knowledge flowing from i to j by substituting the estimated parameters b_1-b_6 and $\underline{\gamma}$ from regression (7) into equation (4). Such "weights" plus the measure of the stock of non-obsolete R&D capital in each region, A_{jt}, are used to construct the estimated stock of "accessible external R&D" for each region i: $A^a_{it} = \sum_{j\neq i} \widehat{\phi}_{ji} A_{jt}$. One standardization is needed in (4) to get rid of the constant a and we assume that $\widehat{\phi}_{ii} = 1$. By definition the non-depreciated stock of R&D generated in region i, A_{it} is fully accessible for learning to region i where it has been generated.

Estimation of equation (2) is performed using patent count as measure of Q_{it}. In particular in our preferred specification we use patents weighted by the citations received during the four years after they have been granted, in order to adjust for their relative importance. We construct the R&D stock A_{it} in each region for the period 1975-1996 by using the perpetual inventory method. R&D stocks are initialized for year 1975 assuming constant growth of R&D spending during the previous years. Specifically $A_{i1975} = (R\&D)_{i1975}/(\delta + g_i)$ where δ is the depreciation rate of R&D capital and g_i is the growth rate of R&D spending in the country to which region i belongs for the period 1975-80. For the following periods the recursive formula $A_{it} = (1-\delta)A_{it-1} + R\&D_{it}$ is applied. The value chosen for δ, the depreciation of R&D capital, is 10%, as preferred by most of the literature (see Keller [47]). Finally country by time fixed effects are allowed in the estimate. The exact form of the panel estimation for the innovation function is:

$$\ln(P_{it}) = D_{ct} + \gamma \ln(A_{it}) + \mu \ln(\sum_{j\neq i} \phi_{ji} A_{jt}) + u_{it} \qquad (8)$$

P_{it} is the citation weighted count of patents, D_{ct} are (country by time) dummies, A_{it} is the "own stock of R&D" $\sum_{j\neq i} \phi_{ji} A_{jt}$ is the "external accessible stock of R&D" and u_{it} are zero-mean random errors uncorrelated with the regressors.

4.3 Regional Data

The patent and citation data used are from the NBER Patent and Citation Dataset, which is publicly available and described in detail in Jaffe and Trajtenberg [41], Chapter 13. This data-set contains all the patents granted by the U.S. patent office and, since 1975, all the citations made by each patent. It includes information on the technological class of the patent and several data on the applicant and inventor. We choose the sample of patents granted between 1975-1996 whose inventor is resident of one of the eighteen countries considered and listed in the Appendix (all in Europe and North America). From the address of the first inventor we assigned patents to sub-national regions. While the data set contains a code to locate inventors in U.S. states it does not contain a code for regions in Canada or in European Countries. Using the city and the zip code of the residence of the inventor we manually located patents in Canadian Provinces and European NUTS1 regions with the help of Gazzetteers and of research assistants from each of the European countries that we considered. Our final sample contains about 1.5 million patents and about 4.5 million citation couples, distributed across 147 regions. We use all the bilateral relationships among the 147 regions (total of 21,609 pairs some of which with 0 citations) when we estimate the "gravity-like" equation (7). Table 1 reports some summary statistics at the regional level. Panel A shows average and standard deviation for the number of patents granted each year to residents of the 147 regions. The average region had 426 patents granted per year (clearly large variation over time is hidden in this table) but very large disparities across regions exist. The least innovative region was granted a patent every four years (0.27 yearly) and the most innovative was granted 6,434 patents per year. Panel B and C show the identity and some characteristics of the most and of the least innovative regions in our sample. The top innovator, with a very large lead on the second region, is California, that was granted more than 6,000 patents per year. High in the ranking are also some German, French and British regions (mostly the regions corresponding to large cities such as London, Paris and Hannover). They all have one thousand or more patents granted each year. The bottom of the list is taken by Greek, Spanish and East German regions that are granted one or less than one patent per year.

Data on R&D for the period 1975-1996 are not available for all regions. From national statistical agencies we obtain the share of total national R&D in the business sector that is performed in each region of 9 main countries. We then use the ANBERD data on business enterprise R&D intramural, measured in 1990 constant U.S. $ and we allocate the national aggregates according to the regional shares. This choice of data ensures the best comparability across countries. Missing years were filled by using interpolation. This method allows us to obtain a balanced panel for regions in all the main countries, namely the USA, United Kingdom, Canada, Germany, France, Italy, United Kingdom, Spain and the Netherlands. These countries count 113 regions altogether and all of the major innovators. Most of the countries we end up not considering in estimating equation (8) are countries made of a single region in the NUTS1 classification (Ireland, Norway, Portugal, Sweden, Luxemburg, Finland) or countries providing very small contribution to innovation (Greece, Austria). Again in terms of R&D intensity Table 1 shows that the regions we consider spend an average of 1.77% of their gross product in R&D but we have some regions spending a quarter of a percentage point (0.25%) and others spending more than 7% of their product in R&D. In general Panel B and C in Table 1 show that important innovators (top regions) spend between 2 and 4% of their GDP in business R&D, while the regions least active in innovation spend less than 1% in R&D. The last column of Panel B and C also show that innovation tends to be positively correlated with output per worker (data are yearly income in thousands of 1990 U.S. $) as output per worker in top-innovative regions is roughly twice as large as in regions at the bottom of the ranking.

Finally data on geographic distance among regions, are reported in the last row of Panel A of Table 1 and they are expressed in thousands of Km. These distances have been calculated as the shortest air distance between the capital cities of each region. The average distance among the sample of 147 regions is 4,400 Kilometers with maximum distance between Hawaii (USA) and Kriti (Greek Island) equal to 13,700 Km. The average distance between a region in Europe and one in North America (i.e. the average "transatlantic" distance) is about 6,000 Kilometers.

5 Estimates of Knowledge Flows

5.1 Aggregate Flows, Geographical Determinants

We present in this section the results of estimating the basic specification (7). At first we consider all patents together without differentiating across sectors. These estimates provide a measure of aggregate knowledge flows which could depend also on the sector- composition of regional ideas. We devote the following two sections to a detailed treatment of technological distance and of differences across technological categories. Specification I in Table 2 is the baseline regression for this section. We estimate equation (7) taking logs of both sides and using OLS with 147 citing-region and 147 cited-region fixed effects and we report the heteroskedasticity robust standard errors. The dependent variable is the log of the count of citation links, omitting self-citations[11], between patents of region i and patents of region j generated within the first 10 years since the cited patent is granted. In the notation of Section 4.1 we choose $t_0 = 10$. We are confident

[11] Self-Citations are citations between patents assigned to the same institution. Those citations denote, arguably, knowledge flows, but probably should not be included in the analysis of pure R&D externalities. Companies may reward their inventors for citing each other and for knowing about each other work. We estimated specifications including self-citations and the only difference is that the coefficient on "Crossing Region Border" is increased by roughly 10-15%.

that this time-span is long enough to capture the most relevant part of knowledge diffusion. If an idea has not been learned in ten years it is likely that it will not be very useful for innovation. However, we analyze flows also after 2, 6 years and after the longest available period in our sample (more on this below). As some regional couples have no citations, we simply drop those observations. This is why of the 21,609 possible couples (147 by 147) the first specification is only estimated on 15,839. The equation and the estimation method are akin to what the trade literature calls a "generalized " gravity equation used for trade flows. We choose this as basic specification for its simplicity and for the comparability of the coefficients to those obtained by the trade literature. Each coefficient captures the drop in knowledge flows as we move out of the region of origin and as we pass several borders. For instance the first coefficient says that in moving out of the region of origin average knowledge flows drop to $(e^{-1.9}) = 0.15$ of their initial level. Another way of saying it is that 85% of knowledge generated in the average region is not learned outside it but remains local. The second coefficient says that only $(e^{-0.43}) = 65\%$ of the 15% of knowledge flowing out of the regional border passes the next regional border. Only 9.75% (=15%*65%) of the initial knowledge, that is, flows outside the regions that share a border with the original one. Another 20% $(= 1 - e^{-0.20})$ is lost passing the country-border leaving about 8% of the initial knowledge. Crossing a trade block border has basically no effect, while passing a linguistic border further cuts the flow by 17%. On top of these effects, geographical distance adds a 5% decrease for each 1,000 kilometers traveled. Each coefficient is very precisely estimated, they are all very significantly negative (except for the effect of crossing a trade block border that is essentially zero) and extremely robust across specifications. The estimated drop in learning as consequence of geography is quite substantial. For instance only about 5% of the ideas generated in Connecticut are learned in Paris which is in a different region, country, linguistic area and 6,000 Km away. On the other hand, by far the most drastic drop takes place as we move out of the region itself, proving the very large local component of learning.

In order to gain confidence that the count-data nature of citations and the relatively large number of zeroes do not distort our linear estimates we use in column II and III the techniques that handle these issues explicitly. In Column II we report estimates of equation (7) in levels and using a negative binomial regression. The advantage of this method is that we include the zeroes and that, by assuming a generalized Poisson process as generating the data, we account for the fact that citations are "count data". The method used to estimate this model is maximum likelihood. Column III uses a Tobit regression. In particular, as there is a large mass of data at 0, we assume that log flows have a linear dependence on their geographical determinants but, for observation smaller than 0, we observe the variable truncated at 0. This specification is estimated using maximum likelihood. Column II and III of Table 2 show that these two methods of estimation deliver coefficient estimates almost identical to the simple log linear regression. In particular all coefficients are literally identical up to a 2% difference except for the first one (regional border effect) that is slightly higher in absolute value when estimated with the negative binomial regression (-2.1) or with the Tobit (-1.98). Even for this coefficient, however, both estimates are within two standard deviations of the linear one, and quantitatively they make very little difference[12]. We perform negative binomial estimates of our coefficients throughout the paper and when they are significantly different from OLS, due to the treatment of the zero observations, we report and prefer them. However it is normally the case that these estimates are rather similar to the OLS basic specification in which case we report only the OLS estimates.

Column IV in Table 2 investigates whether flows within a sector of technological innovation are more or less localized than flows across them. In this specification we select only citation links within the same 3-digit class (in the International Patent Classification code). These classes are rather specific, and there are about 400 of them[13]. We may think that diffusion of knowledge within a narrow field is farther reaching than diffusion across fields. Estimates of column IV are very similar to the baseline, providing evidence that diffusion of knowledge across fields does not exhibit significantly different localization pattern from diffusion within fields. Such feature was already pointed out by Jaffe, Trajtenberg and Henderson (see Jaffe and Trajtenberg [41] page175) when they found that within class citations do not have more tendency to be co-located than across-class citations.

Column V to VIII explore the robustness of our estimates when we allow shorter or longer interval of time between the citing and the cited patents. Column V and VI include citations within the first 2 years, column VII within the first 6 years, and column VIII all citations couples in the 1975-1996 period so that ideas generated early in the period include learning up to 20 years from their invention. Column VII and VIII show estimates basically identical to column I. Only for the 2-year interval there is some difference, which is probably driven by the larger number of zeroes omitted in the OLS regression, as the negative binomial regression is extremely similar to the 10-year one. In any case even the OLS estimates do not exhibit any important difference with the basic 10-year case, and certainly not stronger localization for the 2-year interval. Knowledge flows maintain their relative spatial distribution as time elapses, so that while knowledge of an invention becomes more available over time it does not become relatively more available far away than it is in the region. The pattern of regional diffusion within 2 years is pretty much representative of the overall pattern allowing for longer delays. The way we chose to model space and time diffusion keeping them multiplicatively interactive seems reasonably good to analyze our data. This is very fortunate as we can focus here on geographic diffusion without risking to have a very different analysis depending on the lag that we consider.

[12]The coefficient estimate using the Negative Binomial would imply 13% and the Tobit 14% of regional knowledge learned outside the region. This as opposed to 15% estimated using the linear regression.

[13]Some examples of these classes are "Robots" or "Distillation: Apparatus" or "Batteries"

Before moving to further specifications it is useful to summarize the results of this section using a couple of pictures. Figure 1 and 2 represent the estimated decay of knowledge flows as one moves from a region, out of it, out of its neighbor, out of the country, out of the linguistic area, out of the trade block and travels by steps of 1000 Km. In Figure 1 the total of knowledge generated in a region is standardized to 100. As we move from left to right the lines show the fall in knowledge flows as we pass borders and as we travel farther and farther. Six lines are reported and they correspond to the values obtained using estimates in column I, II, III, V, VI and VII of Table 2 respectively. What is clear is the predominance of the first drop (when moving out of the region) relative to all others and the extreme similarity of rate of decay estimated using any specification. In order to have a better visual sense of the further decay out of the region, in Figure 2 we simply consider only what we call "Exported Knowledge", i.e. knowledge flows once the own regional border has been crossed. We standardize that level to 100 and we track the decay from there on. Again we report six lines corresponding to the estimates I, II, III, V, VI and VII in Table 2. We can still appreciate the extreme similarity in patterns across different estimates. Now we see that out of the exported knowledge a very significant percentage (about one half of it) flows all the way out of the trade block.

5.2 Aggregate Flows, Technological Determinants

The estimates of the previous section provide a very interesting characterization of the effect of geography and borders on average knowledge flows, once we have controlled for citing and cited region effects. However, some important bilateral determinants of knowledge flows are missing. In particular, some measure of distance in technological space capturing the difference in technological fields of specialization and the difference in technological advancement should certainly be included. As we noted above the trade-growth literature has focused on aggregate flows and productivity and has not paid much attention to the relevance of technological space. However there is a huge body of evidence from the micro-productivity literature analyzing this issue. In particular, as regions with similar level of technological advancement and with similar technological fields of specialization could be located close to each other, failing to control for "technological distance' may result in overestimating the effect of geography. Table 3 shows the estimation of the basic specification with three proxies for technological differences added as control. The first two (introduced in specification I) are meant to capture differences in technological advancement. If it is easier to learn from regions at a similar level of technological development, rather than from regions much more or much less advanced, these indices should have a negative impact. The first index is simply the difference (in absolute value) of the log output per worker (average 1991-1996). This is a coarse measure of technological development. The second index is the difference (in absolute value) of log average real spending in R&D per worker (1991-1996). Only the second difference has significant impact on knowledge flows. The estimated coefficient implies that a difference in R&D per worker between two regions of 100% would reduce flows by 21%. Very similar estimates are obtained in Column IV that uses only citations within 2 years rather than within 10 years, as the baseline does. Technological advancement is relevant for knowledge flows, however the estimated coefficients on all the "geography" variables are very similar to the basic specification in Table 2. Interestingly, the difference in log output per worker has a significant effect when introduced by itself (regression not reported, coefficient of 0.15). As difference in R&D per worker is probably a much better measure of technological advancement, once we add that as a control, income differences have no further effect.

More striking is the impact of an index that proxies for technological distance. This index is constructed following Jaffe [39] and had a very large use in the micro-productivity literature. Specifically all patents granted to a region (call it region i) are grouped into 36 technological classes. These classes constitute specific areas of research, are defined following international patent classification and are reported in the appendix. The shares of regional patents (1975-1996) generated by region i in each technological class s is calculated. A vector of shares $\underline{Sh}_i = (sh_{i1}, sh_{i2}...sh_{i36})$ is then associated to each region. The uncentered correlation coefficient (or angular distance) between the vector of region i and j, calculated as$(TecCorr)_{ij} = (\underline{Sh}_i'\underline{Sh}_j)/\left[\sum_s (sh_{is})^2 \sum_s (sh_{js})^2\right]^{1/2}$ is a measure of "similarity" in technological space. Its value is between 0 and 1 and it is closer to one the larger is the "overlap" in technological classes of specialization. For perfect overlap the index is 1, for no overlap at all the index is 0. We use $(TecDis)_{ij} = 1 - (TecCorr)_{ij}$ as a control in specification II, III, V and VI of Table 3 as proxy of the technological distance between region i and region j.

The estimates of the effect of this variable is statistically and economically extremely significant. The OLS estimates for both the ten and two year delay specifications (Column II and V) produce similar results. The flow between two regions specialized in totally different areas is 87-90%[14] lower than the flow between two regions with identical technological specialization. As the standard deviation of $(TecDis)_{ij}$ is 0.17 increasing the difference in specialization by one standard deviation reduces learning by 31-33%. Even more dramatically, the negative Binomial estimates imply a decay of knowledge flows between 95 and 97% going from identical to completely different specialization. Moreover the inclusion of proxies of technological differences reduces the geographical effects. Particularly the effect of crossing the own region border and the next region border are reduced, respectively from 1.8-1.9 to 1.3-1.5 and from 0.4 to 0.3. About twenty percent of the previously estimated attrition in learning when moving out of the originating region and attributed to geographical factors is, in reality, the result of technological distance.

[14] $0.87 = (1 - e^{-2.01}), 0.90 = (1 - e^{-2.27})$.

5.3 Sectors, Periods and Continents

While our focus is on aggregate knowledge flows, as technological specialization plays an important role in determining what flows a region would get we analyze in greater detail here, the geographical behavior of flows dividing them in large technological sectors. Moreover, as we assumed stable behavior of these region to region flows over the years and across the two analyzed continents (Europe and North America) we explore here to what extent the data support such assumptions. Table 4 reports the estimates of distance and crossing borders on knowledge flows within each of six sectors. As we are only analyzing flows within a sector we omit the controls for differences in technological specialization. We choose only patents and citations within each sector (within ten years from the originating patent) and we perform OLS estimation including citing and cited region effects and we report heteroskedasticity-robust standard errors. The sector estimates are reported in column I to VI. Interestingly, the negative effect of the first two dummies (crossing regional border and crossing next region border)on knowledge flows grows in absolute value moving from Computers to "Other Sectors". The Computer sector exhibits by far the large geographical diffusion of knowledge. Close to 40% of computer-related knowledge generated in a region is learned outside of it and 25% of it flows all the way out of the country and linguistic area. In contrast the mechanical sector seems much more localized with only 18% of knowledge flowing out of the originating region and a slim 7% making it out of the country and linguistic area. Table 4 and Figure 3 (that represents graphically those estimates) provide a representation of the "degree of globalization" of each sector. If we think that the sector "Others" contains technological classes such as "Agriculture", "Apparel", "Furniture" and "Heating" we find that knowledge in "hotter" technological fields, such as Computers or Biotech (contained in the category Drugs) reaches further than knowledge in more "traditional" technologies, such as Mechanical or Chemical. Interestingly almost all of the geographical hurdles seem to cause a stronger attrition as we move from Computer to "Others". Of the "exported knowledge", i.e. of that share of knowledge learned outside the region of origin, fully 50% of computer-related knowledge reaches regions as far as 10,000 Kilometers out of the country and linguistic area. To the contrary for knowledge in "Other" sectors only 25% of the "exported knowledge" reaches 10,000 Km of distance outside the country and language area. While in the remainder of the work we analyze aggregate flows of knowledge the above discussed results make us aware that certainly the technological composition of knowledge affects the geographical reach of its flows.

As for the geographical reach of knowledge flows across different decades or in different continents (Europe versus North America) Table 5 provides us some reassurance that the assumption of stability of coefficients is reasonably good. All estimates use maximum likelihood negative binomial method because the handling of zeroes seems to make some difference in this case. Column I and II of Table 5 show estimates for knowledge flows (within 2 years) for the 1975-86 period and for the 1986-96 period, respectively. The only coefficients that are somewhat different across the two decades are the effect of crossing the own regional border (-1.33 versus -1.45) and the effect of crossing the country border (-0.12 versus -0.20). Let's remind the reader that the estimates in each subperiod, using fewer observations than the overall estimates, are less precise. Given that differences are not very significant and are in the direction of slightly larger localization of knowledge flows in the later period (while we would expect, if anything the opposite), we interpret the differences as due to noise and we confirm our assumption of basically identical effects. Column III and IV of Table 5 report the estimates of the effects of geographical characteristics on knowledge flows of the computer sector, also splitting the period between 1975-86 and 1986-96. The computer sector has been the one whose share of innovation has increased most in this period. The reader may be worried that if the geographical reach of knowledge flows for this sector has changed, this could affect the perspectives of knowledge flows and their future behavior. Although some small differences exist, there is no clear pattern of stronger localization in the earlier period. Even for this sector our simplifying assumption of similar geographical diffusion before and after 1986 seems reasonable. Finally Column V and VI compare the impact of geographical characteristics on knowledge flows in Europe and North America. As probably expected, there is a slightly stronger localization in Europe. Moving out of the region and its neighbors reduces learning flow by 83% of their initial value relative to a reduction of 79% for north American regions. However these differences are small, and it appears that linguistic borders play more of a role in Europe tan in North America[15]. On the other hand the effect of "technological distance" and of crossing a country border on learning flows appears larger for north American regions.

5.4 Flows from Leading Innovators

Our specification appears rather robust and effective in capturing knowledge flows across regions. So far, however, we have treated these flows as very symmetric across regions. We controlled for any region-specific factor that affects learning flows into and out of the region, we controlled for many bilateral characteristics that affect these flows and we analyzed differences across sectors. It is reasonable to think, however, that technological leaders not only generate larger flows overall (fully controlled for in the regional effect), but also generate flows with larger geographical reach, relative to other regions. When we analyze data on innovation and research across countries, as well as across regions, we notice a very large concentration of these activities: few regions are really main players and the others are much smaller actors. In our data, for instance, the top 20 regions (out of 147) perform 60% of total R&D in the sample (which is about 50% of the

[15]Notice that the Language Effect for North America is very imprecisely estimated as it is based on two regions only (Quebeck and Puerto Rico) that do not speak english.

world R&D) and California, the top innovator spends in R&D ten times what the Berlin region (Germany), which occupies a very respectable 25th place in R&D spending, does. The technological leaders, therefore, may serve as learning source for farther regions more than an average region does. To explore this aspect we focus on the top twenty regions in our sample, for R&D spending and we consider the learning flows from these regions to all the others. Using average real R&D spending in the period 1992-1996 we select the top twenty regions. Interestingly, while eleven of them are in the U.S. there are regions from many countries: four of them are in Germany, one is in Canada, one is in France, one in the United Kingdom, one in the Netherlands and one in Italy.

Table 6 shows the estimates of knowledge flows attrition considering only the top 20 R&D regions as source of learning (i.e. of cited patents)[16]. Column I to IV repeat the estimation using patents cited within a 2 year lag (I and II) or within a 10 year lag (III and IV), and for each of the two alternatives we report the OLS (column I and III) and the Negative Binomial Estimates (II and IV). Very consistently and robustly these estimates show much less geographic localization of knowledge. Ideas generated in leading regions travel much farther in space than average ideas. In particular the first two coefficients are much smaller than for the average knowledge specification. Even considering the most conservative estimate (Column I) we obtain that 46% of original knowledge flows out of the region and of its neighbors, up from an estimate of 16% for the average knowledge. Also differences in technological development (difference in R&D spending) play much less a role while, on the other hand, technological specialization has still a comparable effect to the one estimated for average knowledge flows. Knowledge generated by technological leaders may have a quality and importance that make it of use and relevant across the world and, for this reason, it travels further in space than other knowledge. To convince the reader that it is not some other characteristic of the chosen top 20 regions to drive the results, such as the fact that more than half of them are located in the U.S., we repeat the analysis, choosing as "sending regions" the top 20 innovators outside the U.S. While the effect of crossing the regional border and the country border increases slightly, the overall estimates confirm that these flows are much more far reaching than the average flows. Such finding strengthen our confidence in the idea that learning from technological leaders to other regions is probably a key phenomenon to understand R&D externalities. Finally we report the usual visual representation of learning decay as borders are crossed and distance is travelled in Figure 4. Estimates from specifications I, III and V in Table 6 are reported and the decay of learning from the technological leaders (top three lines) is represented vis a vis the decay of knowledge from the average region (lower line, estimated from Table 3 Column III). The visual impression confirms a strikingly broader reach of knowledge out of the technological leaders relative to the average region.

[16] We performed the same exercise using the top 15 and the top 25 regions and we obtained very similar results.

5.5 Comparison with Flows of Trade

Our frame provided us with several very robust estimates of the effect of geographical variables on knowledge flows. While our estimates reveal a high degree of localization of knowledge flows the reader may be wondering if such degree is reasonable. How localized are these flows, relative to trade flows that we know and understand much better? If our estimates reveal that knowledge flows are more geographically localized than trade flows we may be rather skeptical of their validity. Knowledge flows do not require movement of goods or people and therefore their lower cost should allow them to reach further. To our knowledge no one in the literature has performed an empirical comparison in the geographical scope of knowledge and trade flows.

The trade literature has extensively estimated the effect of geographical variables on total trade flows. In particular the effect of two variables has been studied in great detail: the effect of distance and the effect of crossing a country border. As we have precise estimates of these effects on learning flows too we concentrate on these two. The trade literature has used the "gravity" specification in order to estimate these effects and, as we noted above, our specification is similar and easy to compare to a gravity equation. Table 7 reports the estimates of the effect of distance and crossing the country border on knowledge flows. To ensure maximum comparability with the existing trade estimates we enter distance linearly (rather than exponentially) in equation (7), so that in the OLS estimates distance enters in logs as is commonly done in the trade specification. We omit citation linkages of the region with itself (as trade data do not have those links) and we include the whole set of citing and cited region fixed effects. Again to increase comparability we do not include other controls (such as proxies for technological distance) as they are normally not included in trade estimates. Column I, II and III show the estimates for knowledge flows considering the computer sector only, flows from the technological leaders and average flows respectively. Column IV and V report the estimates of border effect and distance on trade from recent estimates of the gravity equation. In particular equation IV uses the estimates from Anderson and Van Wincoop [3] and equation V from Feenstra [27]. These estimates are improvements, as they fully control for regional fixed effects, on the original Mc Callum [52] estimates that are reported in Column VI. Figure 5 shows what effect on decay of knowledge flows these estimates imply. While it is confirmed that knowledge flows from technological leaders and in the computer sector are significantly more mobile than average knowledge flows, the most evident feature from the picture is that all knowledge flows reach much farther than trade flows. According to the most recent estimates (defined as Trade I and II in figure 5) crossing a country border decreases trade by 80% while at 10,000 Km distance only 5-6% of the initial volume of trade is left. To the contrary fully 80% of original knowledge (85% for computer knowledge) is learned outside a country and 50% of it (65% for computers) is learned as far as 10,000 Km away. Both the effect of country borders and of distance are 4 to 5 times smaller on average knowledge flows than on trade flows and the effect on knowledge flows from the technological leaders is 40 to 50% smaller than for average knowledge.

5.6 Comparison with Existing Estimates of Knowledge Flows

Our estimates could be compared with some existing estimates of the geographical reach of knowledge flows. First we compare them to existing estimates that use same citation data in characterizing domestic (Jaffe et al. [40]) or international (Jaffe and Trajtenberg [41] Chapter 7) diffusion of knowledge. Then we compare them to similar estimates that use European Patent data (Maruseth and Verspagen [50]). Finally we compare them with important recent estimates in the trade-growth literature that use only productivity data and distance to infer R&D spillovers (Keller [47]).

The initial and influential work that assessed the degree of localization of knowledge flows using citations across patents was Jaffe et al. [40]. They used a much smaller sample limited to the U.S. and a very different method to estimate localization. However from the coefficients reported in their Table III we can recover some effects that could be compared to ours. Considering their sample without self-citations and with originating cohort 1980 (Column 4,5 and 6 in the "Matching by State" panel) they estimate a drop of citation flows moving out of the state[17] (corresponding to our "region" for the U.S.) of 50-60%. Our most comparable estimates (for North America only, column VI Table 5) give a drop of about 70% moving out of the region. For the country border effect, Jaffe et al. [40][18] estimate a drop by 12-15% of citation flows and our preferred estimate put that drop at 12% for the period 1975-1986 (Column I Table V) or 18-20% for the 75-96 period overall (Column III and VI, Table 3).

Jaffe and Trajtenberg [41] Chapter 7 reports some estimates of knowledge diffusion across US, UK, Germany, France and Japan. The authors insist on the interaction between geographical diffusion and citation lags and their estimates are hard to compare to ours and to reconcile to the "trade-growth" estimates in general. However their figures 2-6 (pages 221-223) provide some reassurance to our assumption. During the first 10 years after granting a patent, when the bulk of citation to a patent takes place, the relative frequency of citation to patents in different countries remains quite stable. All citation frequencies tend to peak at 3-4 year lag and then decrease but the relative ranking of citing countries for each cited country tends to remain remarkably stable. To a first degree of approximation the passing of time affects total frequency (i.e. total knowledge flows) but not the relative frequency of country to country citations.

The most comparable work to ours in terms of geographical units considered and methods is certainly

[17] We obtain this effect by comparing their matching fraction within SMSA relative to the matching fraction of the control group.

[18] Panel "Matching by Country", Column 3,4 and 5 of their table III

Maruseth and Verspaghen [50]. They use Citations between European-granted patents located in 112 European regions. From their Table 2, page 541, we read their estimated effects of (log) distance, of crossing a linguistic border and a country border. The first estimate ranges between 0.29 and 0.38, the second between 0.20 and 0.28 and the third between 1.53 and 1.56. The first two effects are rather similar to our estimates. We estimate the effect of Log distance (Column III, Table 5) on average knowledge flows at 0.20 and the effect of a linguistic border (Column III Table 3) at 0.18. To the contrary our estimate of the country-border effect is significantly smaller than theirs (ranging between 0.12 and 0.20). As their estimates of country border effects are as high as those estimated in the literature for trade flows (See our Table 7 column IV and V) we wonder if the process of patent revision at the European Patent Office generates an excessive own-country bias in the citation procedures. Confirming our worries, the authors warn us in their article that, contrarily to what is done in the U.S., the majority of citations are added by reviewers rather than by inventors in the European Patent Process[19].

Finally let us compare our estimates to an estimate of geographical reach of R&D spillovers from the recent trade-growth literature. Let us warn the reader that we are almost comparing apples and oranges here. We consider Keller [47] estimates of the effect of R&D in a G5 country on productivity in other 9 countries. Such method uses simply the correlation over time between sector productivity in a country and the stock of own and external R&D. Flows (of knowledge or trade) are not considered as carrier of externalities. Keller finds that the available external knowledge stock is reduced by 50% traveling 162 Kilometers in space. This effect should be compared to our country-border plus distance effect when we estimate a specification comparable with the trade estimates (Table 7). From Figure 4 we see that our estimates imply that only at 8,000 Km of distance from a region, the original knowledge is reduced by one half. Even the existing estimates of distance effect on trade imply a 50% decrease in flows only at 2,000 Km distance. Keller's estimates reveal a degree of spatial localization of external effects on productivity that seems much stronger than what characterizes knowledge and even trade flows. We may think that those estimates capture localization of other characteristics correlated to R&D and productivity (institutions or sectorial business cycles) or that diffusion of R&D spillovers is not really channeled by trade or knowledge flows but by some more localized process. In summary our estimates seem to reveal a degree of localization of learning consistent with what revealed by other studies of patent citation but significantly lower than localization of trade or localization of productivity levels.

[19] Maruseth and Verspaghen [50], page 534.

6 Estimates of R&D Spillovers

The final task of this article is to analyze R&D spillovers, i.e. the effect of external accessible knowledge on the generation of new ideas. We do this by estimating equation (8) after constructing the external accessible R&D (A^a_{it}) using the estimates of knowledge flows obtained in the previous section. To convince the reader of the robustness of our results and to best address some endogeneity issues we use four different specifications of A^a_{it} and two different panel estimation methods.

6.1 R&D Spillovers on Innovation

We showed that flows of knowledge out of the top 20 innovators reach substantially farther than average knowledge flows. We consider, therefore, as source of relevant spillovers these top 20 regions. Our basic specifications considers as accessible external knowledge only that flowed out of top 20 innovators. We use estimates of flows within 10 years as benchmark for long-run knowledge diffusion but we also consider flows within two years. In our first two estimates we use the following constructions as external accessible knowledge: $(A^a_{it})^{Top20}_{10yrs} = \sum_{j \in Top20}(\widehat{\phi}^{10yrs}_{ji} A_{jt})$ and $(A^a_{it})^{Top20}_{2yrs} = \sum_{j \in Top20}(\widehat{\phi}^{2yrs}_{ji} A_{jt-2})$. The first variable captures external accessible knowledge estimated using $\widehat{\phi}^{10yrs}_{ji}$ which are the weights obtained using coefficient in specification IV, Table 6. Alternatively the second variable uses $\widehat{\phi}^{2yrs}_{ji}$ which are the weights obtained using coefficient in specification II, Table 6. The only difference is that the first specification considers the intensity of knowledge flows as estimated after 10 years, while the second specification uses them after two years only. As we pointed out in the previous section the relative flows are not very different across years, however using flows in the "short run" (2 years) can be important when we identify the externality on the year to year variation of the innovation function. Table 8 reports the long run estimates of elasticities of innovation to own R&D and accessible external R&D measured as described above. In this analysis we are limited to 113 regions for the period 1975-1996. The regional composition of R&D spending can be recovered for the whole period only for regions of the U.S., U.K., Germany, France, Canada, Italy, the Netherlands and Spain. Moreover, in order to minimize endogeneity problems of the variable "accessible external R&D" we do not include the top 20 regions in the analysis as "receivers" of R&D spillovers. Estimates of Table 8 include innovation generated in the other 93 regions considering their own R&D and external accessible R&D from top 20 regions as inputs. The measure of innovation (dependent variable) is $\ln(P_{it})$ where P_{it} is the count of patents granted to region i in year t and weighted for the citations received during the first 4 years after granting for Column I and II while it is the simple count of patents for column III and IV. Weighting patents for citations received helps accounting for the "importance" of patents as new ideas (see Jaffe and Trajtenberg [41] Chapter 2), however the estimates are rather similar using weighted or unweightd patents.

We fully control for country by year fixed effects. This allows different countries to have different balanced growth paths in their "innovation function". We identify the parameters on the cross-regional differences within a country. Such method estimates what we can consider as "long run" elasticities of innovation to R&D, or "between" estimates.

Columns I to IV of table 8 show very similar elasticity estimates. The elasticity of innovation to own R&D is estimated between 0.60 and 0.64 while the elasticity of innovation to accessible external R&D is estimated at 0.94-0.97. The first estimate is extremely precise (robust standard errors around 0.01) while the externality is a bit less precisely estimated (robust standard errors are 0.10-10.11). The estimates of elasticity of innovation to R&D are similar to those found in Branstetter [16] (0.72), Pakes and Griliches [54] (0.61) and Bottazzi and Peri [7] (0.7-0.8). The estimates of the external effect of R&D are roughly 50% larger than the own effect. This value is roughly at the median of the existing estimates from the micro literature (see Griliches [34]). If we do a formal test the hypothesis that the elasticity to own R&D is smaller than elasticity to external R&D is not rejected by the data. As external accessible R&D originates in top innovating regions we may expect this larger effect to be due to higher quality of R&D in those regions.

Table 9 checks that limiting our attention to external R&D from top 20 regions is a very reasonable strategy. In Columns I to IV we include as external accessible R&D, flows of knowledge from all regions (not only top 20). Again we repeat the analysis for knowledge flows within 10 years (estimates Column I and III) and within 2 years (estimates in Column II and IV). The correlation of the measures of external R&D using all regions and using top 20 regions only is extremely large (0.99) confirming that flows from top regions capture most of the action. While the estimate of elasticity to own R&D increases somewhat (0.68-0.73), the estimate of externalities decreases slightly (0.70-0.84). Now we cannot reject the hypothesis that own and external accessible R&D have the same impact on innovation. The estimates of elasticity to external R&D using all regions confirm that learning from non-leaders does not play such a big role in generating R&D externalities, in fact including those regions "dilutes" the externality somewhat.

Table 10 shows estimates of our panel, controlling for region effects and year effects. Such estimates identify the "year to year" within region elasticity of innovation to own and external accessible R&D. We consider this as "short run" estimates of the elasticity of innovation to R&D. Given that the strategy focuses on year to year variation we only use the stock of available R&D constructed using the "short-run" knowledge flows (within 2 years). Column I and II present the estimates considering weighted patents as measure of innovation and externalities from the top 20 or from all regions. The short-run elasticity of innovation to R&D is 0.26-0.30. Such value is about a half of the long run elasticity and the external effect is around 0.45-0.5. Using the preferred specification in Column I, we have that external accessible knowledge stock from top 20 innovators has an impact on innovation 50% larger than own R&D. Moreover adding other regions as sources of external accessible knowledge (from column I to II) dilutes the estimated impact of accessible R&D (elasticity decreases from 0.49 to 0.43). It is a very common occurrence to find a much smaller effect of R&D on productivity or patenting when we consider the time-series variation rather than cross-sectional analysis. While some people include lagged values of R&D in order to capture lagged effects we use the present specification to provide an estimate of the short-run effect while we believe that our previous estimates of Tables 8 and 9 capture the long run effect. Column III and IV report the results obtained using unweighted patent count as measure of innovation. Probably the year to year variation of this variable is an extremely noisy measure of innovation. The estimates of R&D elasticity are slightly reduced and the external R&D effect is strongly reduced. However, considering the specification of flows out of the top 20 regions, we still have positive and significant effect of external R&D, of the same magnitude as the own R&D elasticity. As expected, these estimates based on the short run variation are less precise and more variable than the long run estimates. All specifications provide evidence or R&D externalities between the same level and 50% larger than the effect of own R&D.

6.2 Examples

The estimated elasticities provide evidence that external accessible knowledge is extremely important for innovation, that the role of top innovators in generating the relevant external knowledge is predominant. Our method of calculating knowledge flows and testing for R&D learning externalities confirms the existence and importance of these. Few examples of the effect of R&D on innovation would convince us that in spite of the large elasticity to external accessible R&D the impact of one region's R&D stock on innovation of another region is quite small. The only exception being California, which spends for R&D and patents overwhelmingly more than any other. Some examples will help to provide an idea of the magnitude of these effects. For instance if the stock of R&D in California, the largest innovator in our sample, were to double in year 1996 of our sample, innovation in California would increase by 30% immediately and by 71% in the long run. The region most affected by this change would be Arizona whose external accessible R&D would increase by 30% (calculated using estimates Column III, table 6) so its innovative activity would increase by 13% in the short run and by 36% in the long run in Arizona. The effect of such an increase on, say, the Berlin region (Germany) would be to increase accessible external knowledge by 12% and innovation by 5.2% in the short run and 8.5% in the long run. The effects are large, due to the overwhelming importance of California in the world R&D. Considering other important but not so prominent regions gives much smaller effects. A 100% increase of stock of R&D in a region like Paris (France) would increase external accessible R&D in, say, New York by only 3% and even in Berlin by only 7%, having a long-run impact on their innovation of 4.8% and 8.4% respectively.

7 Conclusions

The importance of R&D externalities has been recognized by the trade-growth literature for awhile, however, due to the lack of data on learning and knowledge flows trade has been considered as the international carrier of these externalities. We believe that there is much to be learned by using a very large and detailed data set on citations across patents, developed and used extensively by the micro-productivity literature. The present work uses data on 4.5 million citations across patents generated in Europe and North America to construct knowledge flows across 147 regions and to estimate how learning depends on geographical, technological and other regional characteristics. We obtain very robust estimates that show only 15% of average knowledge flowing out of the average region and being learned elsewhere. Moreover, another 36% drop in learning takes place when crossing the next regional border and a further 20% drop when passing the country border. If this is true, on average we find that technological specialization and development make a huge difference. First we find that "hotter" technologies such as Computer or Drugs, are learned much farther than the average. Second we find that technological leaders (top 20 regions in R&D) generate knowledge that is learned further and in larger shares. Third we find that differences in technological specialization are a huge hurdle to such knowledge flows. These features would be lost if we were to assimilate knowledge flows to trade flows.

The advantage of our approach is that knowledge flows are estimated using a gravity equation, very popular among trade economists and could be quantitatively compared to trade flows. It turns out that knowledge flows, although localized, are much less reduced by distance and country borders than trade flows. Finally, to confirm that the identified learning flows are relevant to regional innovative activity we estimate the impact of accessible external knowledge on innovation. We find that R&D spillovers from top 20 regions have an impact on innovation of regions often larger than own R&D stock in the short run as well as in the long run.

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A List of Regions

Austria: OSTOSTERREICH, SUDOSTERREICH, WESTOSTERREICH. **Belgium:** BRUXELLES, VLAAMS GEWEST, REGIONE WALLONNE. **Canada** (Provinces): NEW FOUNDLAND, PRINCE EDWARDS ISLAND, NOVA SCOTIA, NEW BRUNSWICH, QUEBECK, ONTARIO, MANITOBA, SASKATCHEWAN, ALBERTA, BRITISH COLUMBIA. **Denmark:** DENMARK. **Finland:** FINLAND. **France:** ILE DE FRANCE, BASSIN PARISIENNE, NORD-PAS DE CALAIS, ESTE, OUESTE, SUD-OUEST, CENTRE-EST, MEDITERRANEE. **Germany** (Landers)**:** BADEN-WURTTEMBERG, BAYERN, BERLIN, BRANDENBURG, BREMEN, HAMBURG, HESSEN, MECKLENBURG-VORPOMMERN, NIEDERSACHSEN, NORDRHINE-WESTFALIA, RHEINLAND-PFALZ, SAARLAND, SACHSEN, SACHSEN-ANHALT, SCHLESWIG-HOLSTEIN, TURINGEN. **Greece:** VORAIA ELLADA, KENTRIKI ELLADA, ATTIKI, NISIA AIGAIOU, KRITI. **Ireland:** IRELAND. **Italy:** NORD OVEST, LOMBARDIA, NORD-EST, EMILIA ROMAGNA, CENTRO, LAZIO, ABRUZZO-MOLISE, CAMPANIA, SUD, SICILIA, SARDEGNA. **Luxemburg:** LUXEMBURG. **Norway:** NORWAY. **Portugal:** PORTUGAL. **Spain:** NOROESTE, NORESTE, COMUNIDAD DE MADRID, CENTRO, ESTE, SUR, CANARIAS. **Sweden:** SWEDEN. **Switzerland:** REGIONE LEMANIQUE, ESPACE MITTELAND, NORTHWESTSCHWEITZ, ZURICH, OSTCHWEITZ, ZENTRALSCWEITZ, TICINO.**United Kingdom:** NORTH, YORKSHIRE AND THE HUMBER, EAST MIDLANDS, EAST ANGLIA, SOUTHEAST, SOUTHWEST, WEST MIDLANDS, NORTH WEST, WALES, SCOTLAND, NORTHERN IRELAND. **USA** (States): ALABAMA, ALASKA, ARIZONA, ARKANSAS, CALIFORNIA, COLORADO, CONNECTICUT, DELAWARE, D.C., FLORIDA, GEORGIA, HAWAII, IDAHO, ILLINOIS, INDIANA, IOWA, KANSAS, KENTUCKY, LOUISIANA, MAINE, MARYLAND, MASSACHUSSETS, MICHIGAN, MINNESOTA, MISSISSIPI, MISSOURI, MONTANA, NEBRASKA, NEVADA, NEW HAMPSHIRE, NEW JERSEY, NEW MEXICO, NEW YORK, NORTH CAROLINA, DAKOTA, OHIO, OKLAHOMA, OREGON, PENNSYLVANIA, RHODE ISLAND, SOUTH CAROLINA, SOUTH DAKOTA, TENNESSEE, TEXAS, UTAH, VERMONT, VIRGINIA, WASHINGTON, WEST VIRGINIA, WISCONSIN, WYOMING.

B List of Patent Categories

CHEMICAL {Agriculture, Food, Textile, Coating, Gas, Organic Compounds, Resins, Miscellaneous Chemicals}, COMPUTERS {Communications, Computers Hardware and Software, Computer Peripherals, Information Storage}, DRUGS {Drugs, Surgical and Medical Instruments, Biotechnology, Mischellaneous medical}, ELECTRONICS {Electrical Devices, Elactrical Lighting, Measuring and Testing, Nuclear and X-Rays, Power Systems, Semiconductors, Miscellaneous Electronics}, MECHANICAL {Material Processing and Handling, Metal Working, Motor and Engines, Optics, Transportations, Miscellaneous Mechanical}, OTHERS {Agriculture Husbandry and Food, Amusement Devices, Apparel, Earth Working and Wells, Furnitures, Heating, Pipes and Joints, Receptacles, Miscellaneous others}

C Patent and R&D Data

- **Europe:**

  Main Source for Data on R&D: Eurostat Regio Database

  (http://europa.eu.int/comm/eurostat)

For Italy, France and Germany we referred to national statistical agencies.As there were some missing values for some regions we interpolated existing values or we imputed regional values using the share of national R&D in the region from a previous year applied to the national Figure for the year. The following is the detailed description of the interpolated and imputed data:

France shares available from Eurostat 89-94;1975-1988: used regional shares from 1989. 1995-96:used regional shares from 1994

Germany's shares available from Eurostat 88,87,89,91,93. 1975-1984,1986: used regional shares from 1985

1988 used regional shares from 1987.1990used regional shares from 1989 1994-1996, used regional shares-from 1993

Spain's shares available From Eurostat 86-94; 1975-1985:used regional shares from 1986. 1995-96:used regional shares from 1994.

Italy's shares available from Eurostat 91-94 and from ISTAT 95-69;1975-1990:used regional shares from 1991

UK's shares available from Eurostat 93-95; 1975-1992: used regional shares from 1993. 1996 used regional shares from 1995

- **U.S.A.:**

Main Source: National Science Foundation/Division of Science Resources Studies, Survey of Industrial Research and Development: 1998.

- **Canada:**

Main Source: The document Cat No. 88F0006XIB01001" Estimates of Canadian Research and Development Expenditures(GERD), Canada, 1979 to 2000, and by Province 1979 to 1998." obtained from www.statcan.org.

For all regions we used the national data to determine for the available years the distribution within a country. We used then the ANBERD data on real business R&D spending 1975-96 and divided it across regions using the regional shares calculated as above.

Tables and Figures

Table 1
Descriptive statistics relative to 147 regions in Europe and North America

Panel A: Summary Statistics

Variable	Mean	Std. Deviation	Min	Max
Number of average yearly granted patents 1975-1996	426	830	0.27	6,434
Share of GDP spent in R&D Average 1975-1996	1.77%	1.23%	0.27%	7.69%
Number of total region to region citations without self, c(r,s)	171	1147	0	99,137
Geographical distance[b] (d_1)	4.44	3.22	0	13.70

Panel B: Top Patenting Regions in Top Countries

Region	Country	Yearly patents (average 75-96)	R&D spending (% GDP, 75-96)	GDP per worker, average 91-96
California (overall rank: 1)	USA	6434	3.86%	52,000
New York (overall rank: 2)	USA	3856	2.00%	59,200
New Jersey (overall rank: 3)	USA	2978	3.59%	59,200
NorthRhine Westfalia (overall rank: 10)	GER	1507	1.86%	63,900
Baden –Wurtenberg (overall rank: 11)	GER	1423	2.93%	63,600
Ile de France (overall rank: 16)	FRA	1104	3.51%	83,000
Southwest UK (overall rank: 17)	UK	976	3.45%	61,300

Panel C: Bottom Patenting Regions

Region	Country	Yearly patents (average 75-96)	R&D spending (% GDP, 75-96)	GDP per worker, average 91-96
Sachsen-Anhalt	GER	1.00	1.50%	30,200
Mecklenburg-Vorpommern	GER	0.91	1.14%	29,400
Prince-Edwards Island	CAN	0.86	0.71%	31,600
Centro Espana	SPA	0.64	0.44%	40,400
Kentriki Ellada	GRE	0.41	0.27%	28,500
Kriti	GRE	0.27	0.53%	28,000

Notes: Citation frequencies are calculated omitting self-citations, i.e. citations between patents whose first authors belong to the same company-institution.
a: Millions of 1993 U.S. $
b: Thousands of Kilometers

Table 2
Geographical Determinants of Average Knowledge Flows

Specification	I Baseline: Within 10 year	II Negative Binomial Within 10 year	III Tobit Within 10 year	IV Same 3-digit Within 10 year	V Within 2 years	VI Negative Binomial Within 2 years	VII Within 6 years	VIII All couples
Crossing Region Border	-1.91* (0.07)	-2.05* (0.04)	-1.98* (0.06)	-1.91* (0.02)	-1.80* (0.05)	-2.05* (0.05)	-1.91* (0.07)	-1.90* (0.07)
Crossing next-Region Border	-0.43* (0.02)	-0.45* (0.02)	-0.45* (0.03)	-0.44* (0.03)	-0.37* (0.03)	-0.40* (0.03)	-0.42* (0.02)	-0.43* (0.02)
Crossing Country Border	-0.19* (0.02)	-0.18* (0.01)	-0.19* (0.02)	-0.19* (0.02)	-0.21* (0.02)	-0.18* (0.02)	0.20* (0.02)	-0.20* (0.02)
Crossing Trade-Block Border	0.05 (0.03)	0.06* (0.03)	0.05 (0.03)	0.05 (0.03)	0.06 (0.03)	0.05 (0.03)	0.06 (0.03)	0.04 (0.03)
Crossing Linguistic Border	-0.19* (0.01)	-0.20* (0.01)	-0.19* (0.02)	-0.17* (0.02)	-0.11* (0.02)	-0.20* (0.02)	-0.18* (0.01)	-0.17* (0.01)
1000 Km farther	-0.05* (0.002)	-0.05* (0.001)	-0.05* (0.002)	-0.05* (0.002)	-0.05* (0.002)	-0.05* (0.002)	-0.05* (0.002)	-0.05* (0.002)
Citing Region Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Citied Region Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15378	21609	21609	14,395	12807	21609	14019	15839
Log-Likelihood		-65584.92						
R^2	0.91	na	na	0.89	0.86	na	0.89	0.92
Original Total Number of Citations	2,864,298	2,864,298	2,864,298	1,589,958	528,829	528,829	1,977,435	4,710,215

Notes: Citations are calculated omitting self-citations, i.e. citation within the same institution. Heteroskedasticity-robust standard errors in parenthesis.

*= significant at 1% confidence level.

Specification I: Dep. Variable ln(citations), Only citing-cited links less than 10 years apart (from citing to cited) are included. Citing years 1984-1996, Cited Years 1975-1996. Some region-couples have 0 citations links and they have been omitted from the regression. This is consistent with what done by the trade gravity model. Method of estimation: OLS with heteroskedasticity- robust std. errors.

Specification II: Dep var: number of citations. Only citing-cited links less than 10 years apart (from citing to cited) are included. Citing years 1984-1996, Cited Years 1975-1996. All couples of citing-cited regions in the period 1975-1996 were included. Method of estimation: Maximum Likelihood, negative binomial regression. Asymptotic standard errors in parenthesis.

Specification III: Dep. Var ln(citations+1), data as in Specification II. Method of Estimation is Maximum Likelihood Tobit with data censored at 0. Asymptotic standard errors in parenthesis.

Specification IV: Dep var: ln(citations). Same 3-digits Class couples of citing and -cited patents. Citing years 1984-1996, Cited Years 1975-1996. Some region-couples have 0 citations links and they have been omitted from the regression. This is consistent with what done by the trade gravity model. Method of estimation: OLS with heteroskedasticity- robust std. errors.

Specification V: Dep. Variable ln(citations), Only citing-cited links less than 2 years apart (from citing to cited) are included. Citing years 1976-1996, Cited Years 1975-1996. Some region-couples have 0 citations links and they have been omitted from the regression. This is consistent with what done by the trade gravity model. Method of estimation: OLS with heteroskedasticity- robust std. errors.

Specification VI: Dep var: number of citations. Only citing-cited links less than 2 years apart (from citing to cited) are included. Citing years 1976-1996, Cited Years 1975-1996. Method of estimation: Maximum Likelihood , negative binomial regression. Asymptotic standard errors in parenthesis.

Specification VII: Dep. Variable ln(citations), Only citing-cited links less than 6 years apart (from citing to cited) are included. Citing years 1982-1996, Cited Years 1975-1996. Some region-couples have 0 citations links and they have been omitted from the regression. This is consistent with what done by the trade gravity model. Method of estimation: OLS with heteroskedasticity- robust std. errors.

Specification VIII: Dep. Variable ln(citations), All citing-cited are included. Citing years 1974-1996, Cited Years 1975-1996. Some region-couples have 0 citations links and they have been omitted from the regression. This is consistent with what done by the trade gravity model. Method of estimation: OLS with heteroskedasticity- robust std. errors.

Table 3
Robustness Checks

Specification	I OLS Within 10 years	II OLS Within 10 years	III Neg. Bin. Within 10 years	IV OLS Within 2 years	V OLS Within 2 years	VI Neg. Bin. Within 2 years
Crossing Region Border	-1.80* (0.06)	-1.34* (0.06)	-1.50* (0.06)	-1.75* (0.06)	-1.30* (0.05)	-1.45* (0.06)
Crossing Next-Region Border	-0.40* (0.02)	-0.32* (0.02)	-0.32* (0.02)	-0.40* (0.02)	-0.29* (0.02)	-0.27* (0.02)
Crossing Country Border	-0.22* (0.02)	-0.22* (0.02)	-0.20* (0.02)	-0.20* (0.02)	-0.24* (0.02)	-0.19* (0.02)
Crossing Trade-Block Border	0.05 (0.04)	0.05 (0.03)	0.04 (0.02)	-0.05 (0.04)	0.05 (0.03)	0.04 (0.03)
Crossing Linguistic Border	-0.17* (0.02)	-0.16* (0.02)	-0.18* (0.01)	-0.15* (0.02)	-0.15* (0.02)	-0.17* (0.02)
1000 Km farther	-0.05* (0.002)	-0.05* (0.002)	-0.04* (0.002)	-0.05* (0.003)	-0.05* (0.002)	-0.05* (0.002)
Income Difference[a]	-0.01 (0.03)	-0.03 (0.03)	-0.06* (0.03)	-0.07 (0.04)	-0.01 (0.03)	-0.01 (0.03)
R&D Difference[b]	-0.21* (0.01)	-0.17* (0.01)	-0.10* (0.01)	-0.21* (0.01)	-0.20* (0.01)	-0.10* (0.01)
Technological Distance		-2.27* (0.06)	-2.86* (0.04)		-2.01* (0.07)	-3.10* (0.06)
Citing Region Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Citied Region Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,361	15,361	21,609	14,065	14,065	21,609
Log Likelihood			-56555.16			-36753.69
R^2	0.92	0.92	Na	0.85	0.87	Na

Notes: Citations are calculated omitting self-citations, i.e. citation within the same institution. Heteroskedasticity-robust standard errors in parenthesis.

*= significant at 1% confidence level.
a: difference in ln average real income per worker (1991-1996)
b: difference in ln average real R&D spending per worker (1991-1996)

Specification I: Dep. Variable ln(citations), Only citing-cited links less than 10 years apart (from citing to cited) are included. Citing years 1984-1996, Cited Years 1975-1996. Method of estimation: OLS with heteroskedasticity- robust std. errors.
Specification II: Dep. Variable ln(citations), Only citing-cited links less than 10 years apart (from citing to cited) are included. Citing years 1984-1996, Cited Years 1975-1996. Method of estimation: OLS with heteroskedasticity- robust std. errors.
Specification III: Dep. Variable: count of citations, Only citing-cited links less than 10 years apart (from citing to cited) are included. Citing years 1984-1996, Cited Years 1975-1996. Method of estimation: maximum likelihood, Negative Binomial .
Specification IV: Dep. Variable ln(citations), Only citing-cited links less than 2 years apart (from citing to cited) are included. Citing years 1976-1996, Cited Years 1975-1996. Method of estimation: OLS with heteroskedasticity- robust std. errors.
Specification V: Dep. Variable ln(citations), Only citing-cited links less than 2 years apart (from citing to cited) are included. Citing years 1976-1996, Cited Years 1975-1996. Method of estimation: OLS with heteroskedasticity- robust std. errors.
Specification VI: Dep. Variable: count of citations, Only citing-cited links less than 2 years apart (from citing to cited) are included. Citing years 1976-1996, Cited Years 1975-1996. Method of estimation: maximum likelihood, Negative Binomial .

Table 4
Knowledge Flows for six large technological sectors

Specification	I Computers 10 years	II Drugs 10 years	III Electronics 10 years	IV Chemical 10 years	V Mechanical 10 years	VI Others 10 years
Crossing Region Border	-1.00* (0.07)	-1.43* (0.06)	-1.50* (0.07)	-1.61* (0.06)	-1.67* (0.05)	-1.82* (0.06)
Crossing next-Region Border	-0.17* (0.04)	-0.10* (0.03)	-0.25* (0.03)	-0.33* (0.03)	-0.38* (0.03)	-0.44* (0.03)
Crossing Country Border	-0.16* (0.03)	-0.21* (0.03)	-0.21* (0.02)	-0.12* (0.03)	-0.13* (0.03)	-0.20* (0.02)
Crossing Trade-Block Border	0.06 (0.03)	0.01 (0.03)	0.06 (0.04)	0.05 (0.04)	0.04 (0.04)	0.06 (0.04)
Crossing Linguistic Border	-0.07* (0.02)	-0.04* (0.02)	-0.07* (0.02)	-0.12* (0.02)	-0.08* (0.02)	-0.12* (0.02)
1000 Km farther	-0.04* (0.002)	-0.04* (0.003)	-0.04* (0.003)	-0.04* (0.003)	-0.05* (0.002)	-0.06* (0.02)
Citing Region Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Citied Region Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,173	8,662	9,573	10,446	11,231	11,842
R^2	0.80	0.79	0.83	0.81	0.83	0.84
Original Number of Citations	243,563	243,902	333,637	342,572	356,614	486,513

Notes: Citations are calculated omitting self-citations, i.e. citation within the same institution. Heteroskedasticity-robust standard errors in parenthesis.
*= significant at 1% confidence level.
Specification I: Dependent Variable: log of citations between patents in Computer Class with citing and -cited patents less than 10 years apart. Citing Patent in the period 1985-1996, cited Patents in the period 1975-1996 were included. Some region-couples have 0 citations links and are dropped. Method of estimation: OLS with heteroskedasticity-robust standard errors.
Specification II: Dependent Variable: log of citations between patents in Drugs Class with citing and -cited patents less than 10 years apart. Citing Patent in the period 1985-1996, cited Patents in the period 1975-1996 were included. Some region-couples have 0 citations links and are dropped. Method of estimation: OLS with heteroskedasticity-robust standard errors.
Specification III: Dependent Variable: log of citations between patents in Electronics Class with citing and -cited patents less than 10 years apart. Citing Patent in the period 1985-1996, cited Patents in the period 1975-1996 were included. Some region-couples have 0 citations links and are dropped. Method of estimation: OLS with heteroskedasticity-robust standard errors
Specification IV: Dependent Variable: log of citations between patents in Chemical Class with citing and -cited patents less than 10 years apart. Citing Patent in the period 1985-1996, cited Patents in the period 1975-1996 were included. Some region-couples have 0 citations links and are dropped. Method of estimation: OLS with heteroskedasticity-robust standard errors
Specification V: Dependent Variable: log of citations between patents in Mechanical Class with citing and -cited patents less than 10 years apart. Citing Patent in the period 1985-1996, cited Patents in the period 1975-1996 were included. Some region-couples have 0 citations links and are dropped. Method of estimation: OLS with heteroskedasticity-robust standard errors
Specification VI: Dependent Variable: log of citations between patents in Other Classes with citing and -cited patents less than 10 years apart. Citing Patent in the period 1985-1996, cited Patents in the period 1975-1996 were included. Some region-couples have 0 citations links and are dropped. Method of estimation: OLS with heteroskedasticity-robust standard errors
Specification VII: Dependent Variable: log of citations between patents in Computer Class with citing and -cited patents less than 4 years apart. Citing Patent in the period 1980-1996, cited Patents in the period 1975-1996 were included. Some region-couples have 0 citations links and are dropped. Method of estimation: OLS with heteroskedasticity-robust standard errors

Table 5
Knowledge Flows in different decades and different Continents

Specification	I Average Flows 2 years lag 1975-1986 Negative Binomial	II Average Flows 2 years lag 1986-1996 Negative Binomial	III Computers 2 years lag 1975-1986 Negative Binomial	IV Computers 2 years lag 1986-1996 Negative Binomial	V Average Sector 10 years lag Europe Negative Binomial	VI Average Sector 10 years lag North America 10 years Negative Binomial
Crossing Region Border	-1.33* (0.10)	-1.49* (0.10)	-0.85* (0.09)	-0.94* (0.08)	-1.50* (0.10)	-1.30* (0.13)
Crossing next-Region Border	-0.28* (0.03)	-0.26* (0.03)	-0.18* (0.04)	-0.07* (0.04)	-0.26* (0.04)	-0.23* (0.03)
Crossing Country Border	-0.12* (0.03)	-0.20* (0.03)	-0.06 (0.04)	-0.14* (0.04)	-0.30* (0.04)	-0.41* (0.05)
Crossing Trade-Block Border	0.07 (0.04)	0.05 (0.03)	0.04 (0.04)	0.04 (0.04)		
Crossing Linguistic Border	-0.20* (0.02)	-0.19* (0.02)	-0.06 (0.04)	-0.05 (0.04)	-0.18* (0.02)	-0.08 (0.07)
1000 Km farther	-0.05* (0.003)	-0.05* (0.002_	0.04* (0.005)	-0.05* (0.005)	-0.04* (0.01)	-0.05* (0.01)
R&D Difference	-0.12* (0.01)	-0.09* (0.01)			-0.04* (0.02)	-0.09* (0.02)
Technological Distance	-3.3* (0.11)	-3.2* (0.10)			-2.67* (0.06)	-4.01* (0.14)
Citing Region Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Citied Region Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,845	19,845	4062	4350	16,709.44	3,798
Log Likelihood	-23006.902	-27615.223	-24023.902	-23615.253	-44318.62	-13798.08

Notes: Citations are calculated omitting self-citations, i.e. citation within the same institution. Heteroskedasticity-robust standard errors in parenthesis.
*= significant at 1% confidence level.

Specification I: Dependent variable: number of citations. Only citing-cited links less than 2 years apart (from citing to cited) are included. Citing years 1976-1986, Cited Years 1975-1986. Method of estimation: Maximum Likelihood, negative binomial regression. Asymptotic standard errors in parenthesis.
Specification II: Dependent variable: number of citations. Only citing-cited links less than 2 years apart (from citing to cited) are included. Citing years 1986-1996, Cited Years 1985-1996. Method of estimation: Maximum Likelihood, negative binomial regression. Asymptotic standard errors in parenthesis.
Specification III: : Dep var: number of citations between patents in the Computer Class Only. Only citing-cited links less than 2 years apart (from citing to cited) are included. Citing years 1976-1986, Cited Years 1975-1986. Method of estimation: Maximum Likelihood, negative binomial regression. Asymptotic standard errors in parenthesis.
Specification IV: Dependent variable: number of citations between patents in the Computer Class Only. Only citing-cited links less than 2 years apart (from citing to cited) are included. Citing years 1986-1996, Cited Years 1985-1996. Method of estimation: Maximum Likelihood, negative binomial regression. Asymptotic standard errors in parenthesis.
Specification V: : Dependent variable: number of citations between European Region only. Only citing-cited links less than 10 years apart (from citing to cited) are included. Citing years 1984-1996, Cited Years 1975-1996. All couples of citing-cited regions in the period 1975-1996 were included. Method of estimation: Maximum Likelihood, negative binomial regression. Asymptotic standard errors in parenthesis.
Specification VI: Dependent variable: number of citations between North-American Regions only. Only citing-cited links less than 10 years apart (from citing to cited) are included. Citing years 1984-1996, Cited Years 1975-1996. All couples of citing-cited regions in the period 1975-1996 were included. Method of estimation: Maximum Likelihood, negative binomial regression. Asymptotic standard errors in parenthesis.

Table 6
Knowledge Flows from the 20 World Technological Leaders

Specification	**I** **2 years** **Top 20** **World R&D** **OLS**	**II** **2 years** **Top 20** **World R&D** **Negative Binomial**	**III** **10 years** **Top 20** **World R&D** **OLS**	**IV** **10 years** **Top 20** **World R&D** **Negative Binomial**	**V** **10 years** **Top 20** **non-US** **world R&D** **OLS**	**VI** **10 years** **Top 20** **non-US** **world R&D** **Negative Binomial**
Crossing Region Border	-0.60* (0.08)	-0.59* (0.09)	-0.54* (0.07)	-0.50* (0.07)	-0.77* (0.12)	-0.77* (0.12)
Crossing next-Region Border	-0.17* (0.04)	-0.15* (0.03)	-0.15* (0.04)	0.14* (0.04)	-0.14* (0.06)	-0.13* (0.05)
Crossing Country Border	-0.15* (0.04)	-0.11* (0.03)	-0.11* (0.04)	0.11* (0.04)	-0.21* (0.03)	-0.22* (0.05)
Crossing Trade-Block Border	0.05 (0.04)	0.05 (0.04)	0.06 (0.04)	0.05 (0.04)	0.02 (0.03)	0.03 (0.04)
Crossing Linguistic Border	-0.20* (0.04)	-0.25* (0.03)	-0.24* (0.04)	-0.24* (0.04)	-0.23* (0.03)	-0.20* (0.03)
1000 Km farther	-0.03* (0.004)	-0.03* (0.003)	-0.03* (0.004)	-0.03* (0.003)	-0.03* (0.006)	-0.03* (0.005)
R&D Difference	-0.04 (0.03)	-0.04* (0.02)	-0.04 (0.03)	-0.05 (0.03)	-0.03 (0.03)	-0.03 (0.02)
Technological Distance	-2.65* (0.12)	-3.11* (0.10)	-2.58* (0.10)	-2.81* (0.10)	2.48* (0.14)	-2.65* (0.11)
Citing Region Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Citied Region Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2556	2961	2784	2961	1651	1833
Log Likelihood	na	-9822.51	na	-14505.51	na	-7769.89
R^2	0.96	na	0.98	na	0.94	na

Notes: Citations are calculated omitting self-citations, i.e. citation within the same institution. Heteroskedasticity-robust standard errors in parenthesis.
*= significant at 1% confidence level
Specification I: Dep. Variable ln(citations), Only citing-cited links less than 2 years apart (from citing to cited) are included. Citing years 1976-1996, Cited Years 1975-1996. Only top 20 regions for R&D spending included as "cited regions". Method of estimation: OLS with heteroskedasticity- robust std. errors.
Specification II: Dep. Variable: count of citations, Only citing-cited links less than 2 years apart (from citing to cited) are included. Citing years 1976-1996, Cited Years 1975-1996. Only top 20 regions for R&D spending included as "cited regions". Method of estimation: maximum likelihood, Negative Binomial .
Specification III: Dep. Variable ln(citations), Only citing-cited links less than 10 years apart (from citing to cited) are included. Citing years 1986-1996, Cited Years 1975-1996. Only top 20 regions for R&D spending included as "cited regions". Method of estimation: OLS with heteroskedasticity- robust std. errors.
Specification IV: : Dep. Variable: count of citations, Only citing-cited links less than 10 years apart (from citing to cited) are included. Citing years 1986-1996, Cited Years 1975-1996. Only top 20 regions for R&D spending included as "cited regions". Method of estimation: maximum likelihood, Negative Binomial .
Specification V:. Dep. Variable ln(citations), Only citing-cited links less than 10 years apart (from citing to cited) are included. Citing years 1986-1996, Cited Years 1975-1996. Only top 20 regions. for R&D spending outside the U.S included as "cited regions". Method of estimation: OLS with heteroskedasticity- robust std. errors.
Specification VI:. Dep. Variable: count of citations, Only citing-cited links less than 10 years apart (from citing to cited) are included. Citing years 1986-1996, Cited Years 1975-1996. Only top 20 regions for R&D spending outside the U.S included as "cited regions". Method of estimation: maximum likelihood, Negative Binomial .

Table 7

Flows of Knowledge and Flows of Goods: Distance and Border effects

Specification	I Computers' Knowledge Flows: 10 years	II Knowledge Flows from Top 20 Technological leaders 10 years	III Average Knowledge Flows: 10 years	IV Trade Flows Estimate I	V Trade Flows Estimate II	VI Trade Flows: Estimate III
Crossing Country Border	-0.16* (0.03)	-0.17* (0.03)	-0.22* (0.02)	-1.65* (0.08)	-1.55* (0.08)	-3.09* (0.04)
Ln(distance)	-0.10* (0.01)	-0.14* (0.01)	-0.19* (0.01)	-0.79* (0.03)	-1.25* (0.03)	-1.42* (0.08)
Sending Region Fixed Effects	Yes	Yes	Yes	No	Yes	No
Receiving Region Fixed Effects	Yes	Yes	Yes	No	Yes	No
Percentage of Flows passing the Country Border	85%	84%	80%	19%	21%	4.5%
Observations	7075	2851	14395	1511	1511	683
R^2	0.80	0.96	0.90	n.a.	0.66	0.81

Notes: Citations are calculated omitting self-citations, i.e. citation within the same institution. Heteroskedasticity-robust standard errors in parenthesis.
*= significant at 1% confidence level.
Specification I: Dependent Variable: log of Region to Region Citations between patents in the class of "Computers and Communications" with citing patent and cited patent within 10 years. Citing 1975-84, Cited 1974-1996. Regions with 0 citations are dropped.
Specification II: Dependent Variable: log of Region to Region Citations between patents within 10 years. Citing regions are all regions for the period 1975-84, Cited regions are the top 20 innovators only for the period 1974-1996. Regions with 0 citations are dropped.
Specification III: Dependent Variable: log of Region to Region Citations between patents in the same class with citing patent and cited patent within 10 years. Citing 1975-84, Cited 1974-1996. Regions with 0 citations are dropped.
Specification III: Estimates of Border and Distance Effect from a gravity equation for trade, from Andreson and Van Wincoop (2001)
Specification IV: Estimates of Border and Distance Effect from a gravity equation for trade from Feenstra (2003)
Specification VI: Estimates of Border and Distance Effect from a gravity equation for trade from McCallum (1995)

Table 8
Estimates of R&D Externalities from Top Innovators in the Long Run

Specification	**I** **Flows from Top 20 Innovators, 10 years**	**II** **Flows from Top 20 Innovators, 2 years**	**III** **Flows from Top 20 Innovators, 10 years**	**IV** **Flows from Top 20 Innovators, 2 years**
Dependent Variable	**Citation-Weighted Patent Count**		**Unweighted Patent Count**	
$\ln(A_{it})$, Own R&D	0.64* (0.01)	0.65* (0.01)	0.60* (0.01)	0.60* (0.01)
$\ln(A^{a}_{it})$, External Accessible R&D	0.97* (0.11)	0.95* (0.10)	0.96* (0.10)	0.94* (0.10)
Country x Time Effects	Yes	Yes	Yes	Yes
Region Effects	No	No	No	No
Time effects	No	No	No	No
Period	1975-1993	1977-1993	1975-1996	1977-1996
R^2	0.84	0.84	0.83	0.83
Observations	1674	1488	2024	1840

Heteroskedasticity-Robust standard errors in parentheses.
*= significant at 1% confidence level.
Specification I: Dependent Variable: log of patents weighted by citation in first 4 years since granted. External Accessible R&D constructed using the estimated intensity of knowledge flows from Table 6 Column II. These estimates capture geographical flows of knowledge within 10 years (long run). Only the Top 20 world innovators were included as “senders”. Only the remaining 93 regions were included as “receivers”. Countries covered: USA, West Germany, UK, Italy, Spain, France, the Netherlands and Canada.
Specification II: Dependent Variable: log of patents weighted by citation in first 4 years since granted. External Accessible R&D constructed using the estimated intensity of knowledge flows from Table 6 Column IV. These estimates capture geographical flows of knowledge within 2 years (short run). Only the Top 20 world innovators were included as “senders”. Only the remaining 93 regions were included as “receivers”. Countries covered: USA, West Germany, UK, Italy, Spain, France, the Netherlands and Canada.
Specification III: Dependent Variable: log of count of patents. External Accessible R&D constructed using the estimated intensity of knowledge flows from Table 6 Column II. These estimates capture geographical flows of knowledge within 10 years (long run). Only the Top 20 world innovators were included as “senders”. Only the remaining 93 regions were included as “receivers”. Countries covered: USA, West Germany, UK, Italy, Spain, France, the Netherlands and Canada.
Specification IV: Dependent Variable: log of count of patents. External Accessible R&D constructed using the estimated intensity of knowledge flows from Table 6 Column IV. These estimates capture geographical flows of knowledge within 2 years (short run). Only the Top 20 world innovators were included as “senders”. Only the remaining 93 regions were included as “receivers”. Countries covered: USA, West Germany, UK, Italy, Spain, France, the Netherlands and Canada.

Table 9
Estimates of R&D Externalities from all regions in the Long Run

Specification	**I** **Flows from All regions** **10 years**	**II** **Flows from All regions,** **2 years**	**III** **Flows from All regions,** **10 years**	**IV** **Flows from All regions,** **2 years**
Dependent Variable	**Citation-Weighted Patent Count**		**Unweighted Patent Count**	
$\ln(A_{it})$, Own R&D	0.72* (0.01)	0.73* (0.01)	0.68* (0.01)	0.68* (0.01)
$\ln(A^{a}_{it})$, External Accessible R&D	0.84* (0.09)	0.83* (0.09)	0.73* (0.08)	0.70* (0.09)
Country x Time Effects	Yes	Yes	Yes	Yes
Region Effects	No	No	No	No
Time effects	No	No	No	No
Period	1975-1993	1977-1993	1975-1996	1977-1996
R^2	2034	1808	2373	2147
Observations	0.88	0.88	0.87	0.87

Heteroskedasticity-Robust standard errors in parentheses.
*= significant at 1% confidence level.
Specification I: Dependent Variable: log of patents weighted by citation in first 4 years since granted. External Accessible R&D constructed using the estimated intensity of knowledge flows from Table 3 Column III. These estimates capture geographical flows of knowledge within 10 years (long run) from all regions. All 113 regions included as "senders" as well as "receivers". Countries covered: USA, West Germany, UK, Italy, Spain, France, the Netherlands and Canada.
Specification II: Dependent Variable: log of patents weighted by citation in first 4 years since granted. External Accessible R&D constructed using the estimated intensity of knowledge flows from Table 3 Column VI. These estimates capture geographical flows of knowledge within2 years (short run) from all regions. All 113 regions included as "senders" as well as "receivers". Countries covered: USA, West Germany, UK, Italy, Spain, France, the Netherlands and Canada.
Specification III: Dependent Variable: log of patents' count. External Accessible R&D constructed using the estimated intensity of knowledge flows from Table 3 Column III. These estimates capture geographical flows of knowledge within 10 years (long run) from all regions. All 113 regions included as "senders" as well as "receivers". Countries covered: USA, West Germany, UK, Italy, Spain, France, the Netherlands and Canada.
Specification IV: Dependent Variable: log of patents' count. External Accessible R&D constructed using the estimated intensity of knowledge flows from Table 3 Column VI. These estimates capture geographical flows of knowledge within2 years (short run) from all regions. All 113 regions included as "senders" as well as "receivers". Countries covered: USA, West Germany, UK, Italy, Spain, France, the Netherlands and Canada.

Table 10
Estimates of R&D Externalities on Innovation in the Short Run

Specification	I Flows from Top 20 Innovators, 2 years	II Flows from All Regions 2 years	III Flows Top 20 innovators, 2 years	IV Flows from all regions, 2 years
Patent Count (Dependent Variable)	**Citation Weighted**		**Unweighted**	
$\ln(A_{it})$, Own R&D	0.26* (0.08)	0.30* (0.07)	0.21* (0.06)	0.24* (0.06)
$\ln(A^{a}_{it})$, External Accessible R&D	0.49* (0.08)	0.43* (0.07)	0.17* (0.06)	0.10* (0.05)
Country x Time Effects	No	No	No	No
Region Effects	Yes	Yes	Yes	Yes
Time Effect	Yes	Yes	Yes	Yes
Period	1977-1993	1977-1993	1977-1996	1977-1996
R^2	0.95	0.96	0.96	0.96
Observations	1472	1808	1472	2147

Heteroskedasticity-Robust standard errors in parentheses.
Specification I: Dependent Variable: log of citation-weighted patent count. Weight= citations in the 4 years after the patent was granted. External Accessible R&D constructed using the estimated intensity of knowledge flows from Table 6 Column II. These estimates capture geographical flows of knowledge within 2 years from the generation of ideas.). Only the Top 20 world innovators were included as "senders". Only the remaining 93 regions were included as "receivers". Countries covered: USA, West Germany, UK, Italy, Spain, France, the Netherlands and Canada.
Specification II: Dependent Variable: log of citation-weighted patent count. Weight= citations in the 4 years after the patent was granted. External Accessible R&D constructed using the estimated intensity of knowledge flows from Table 3 Column VI. These estimates capture geographical flows of knowledge within 2 years from the generation of ideas. All 113 regions considered as "senders" as well as "receivers". Countries covered: USA, West Germany, UK, Italy, Spain, France, the Netherlands, Canada.
Specification III: Dependent Variable: log of citation count. External Accessible R&D constructed using the estimated intensity of knowledge flows from Table 6 Column II. These estimates capture geographical flows of knowledge within 2 years from the generation of ideas. Only the Top 20 world innovators were included as "senders". Only the remaining 93 regions were included as "receivers". Countries covered: USA, West Germany, UK, Italy, Spain, France, the Netherlands and Canada.
Specification IV: Dependent Variable: log of citation count. External Accessible R&D constructed using the estimated intensity of knowledge flows from Table 3 Column VI. These estimates capture geographical flows of knowledge within 2 years from the generation of ideas. All 113 regions considered as "senders" as well as "receivers". Countries covered: USA, West Germany, UK, Italy, Spain, France, the Netherlands and Canada.

Figure 1

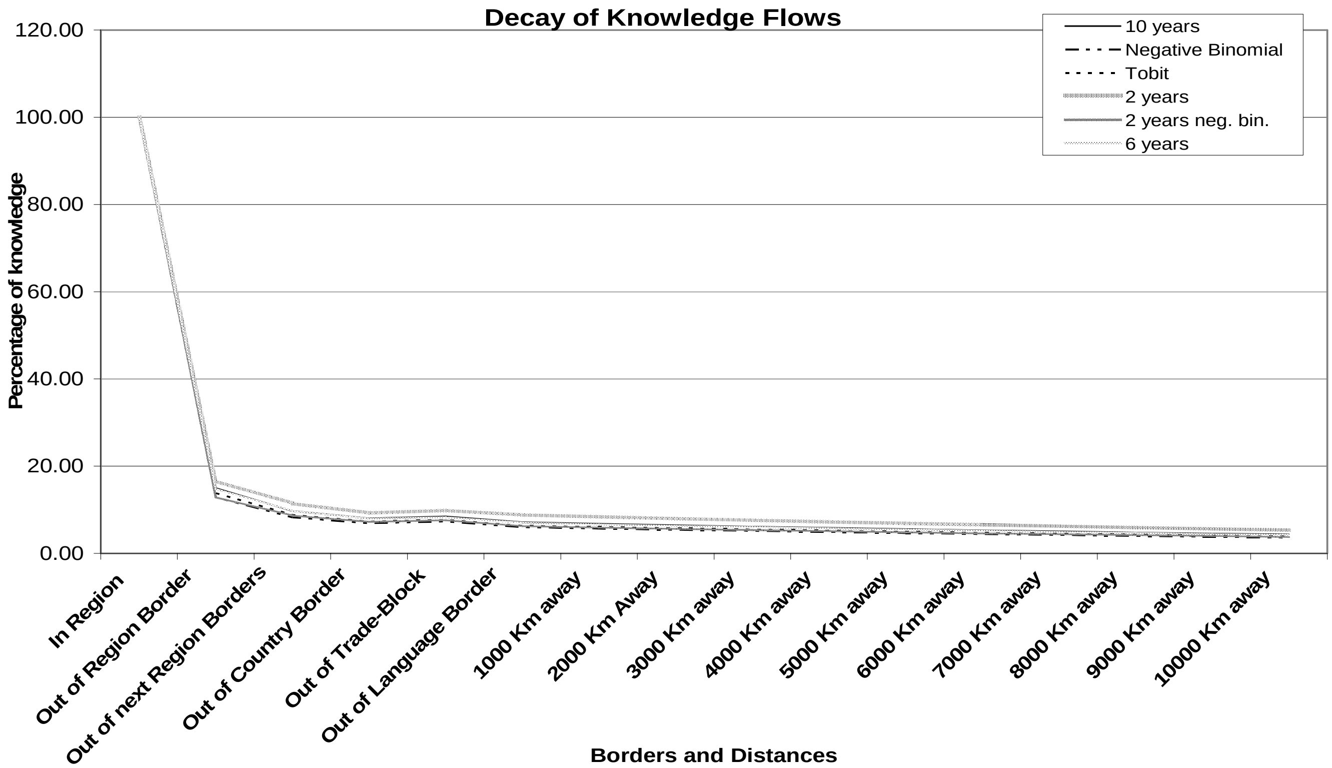


Figure 2

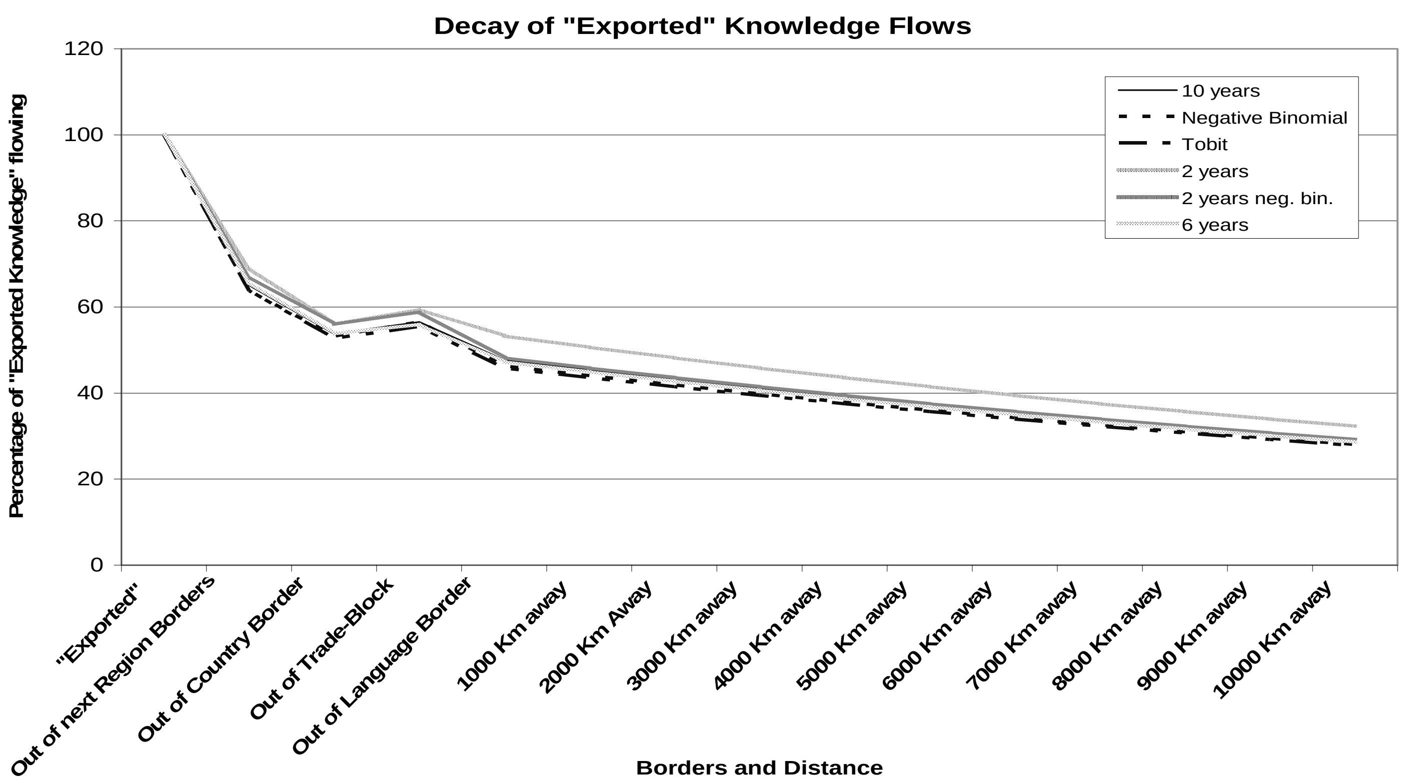


Figure 3

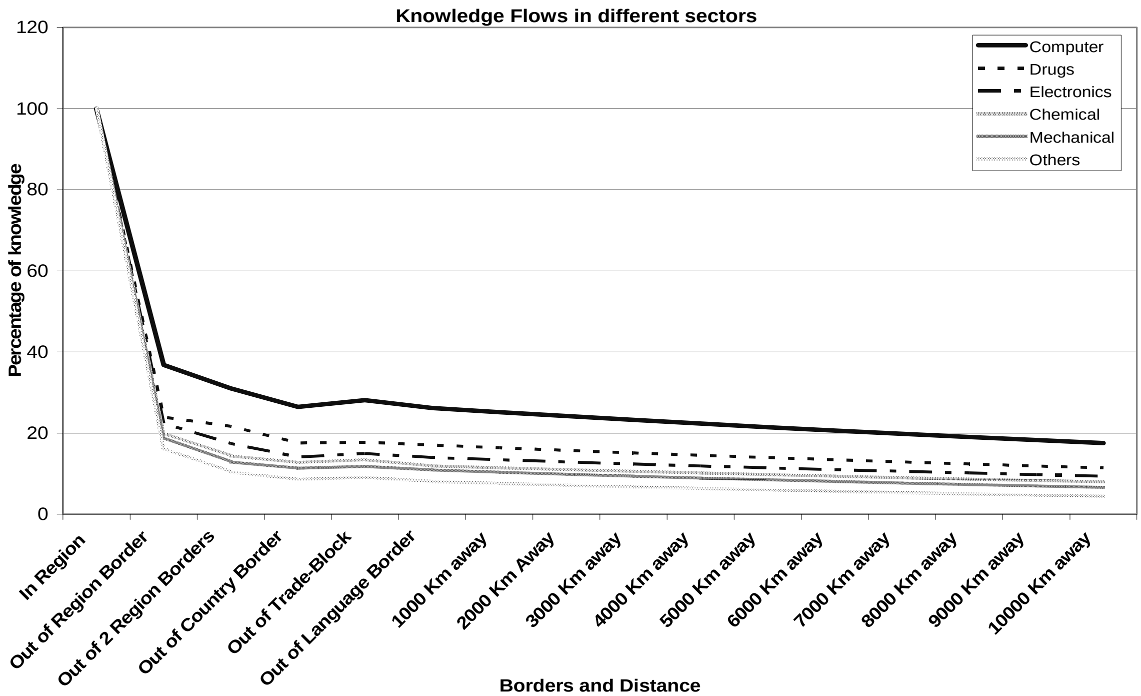


Figure 4

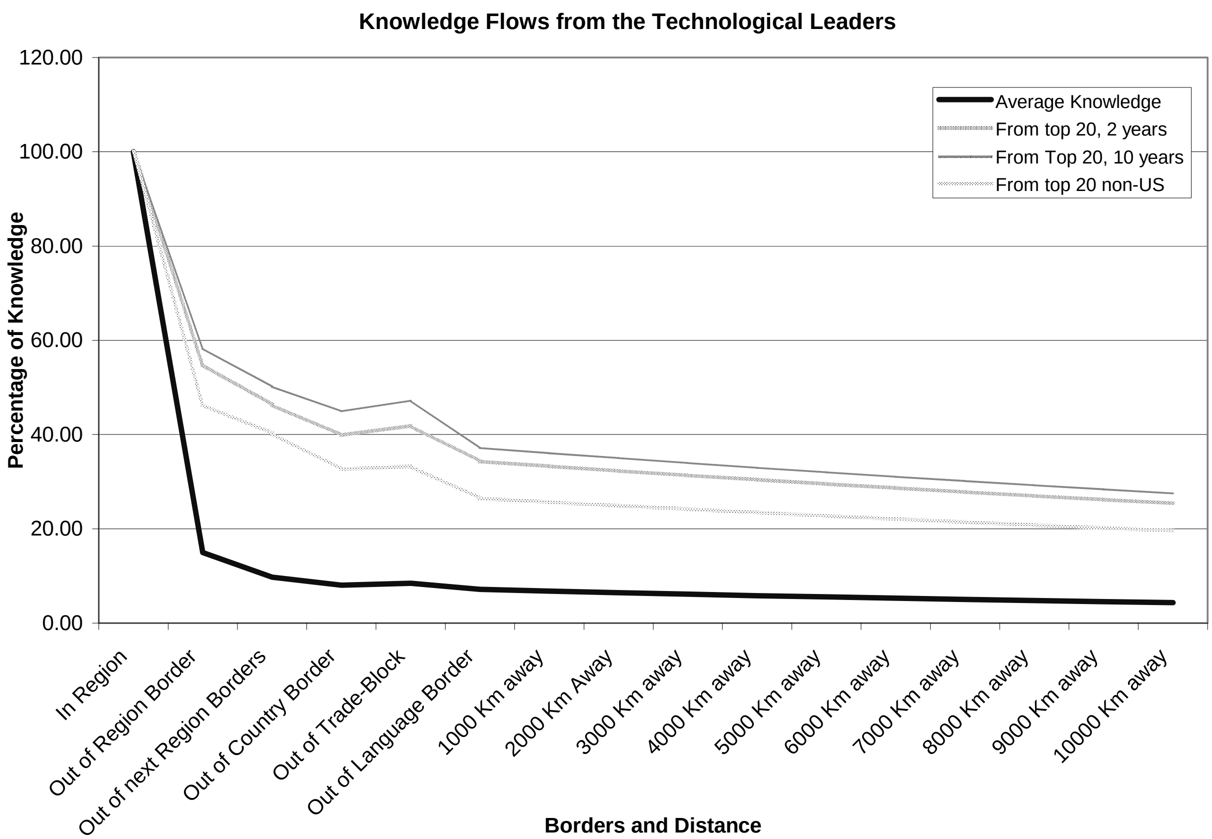
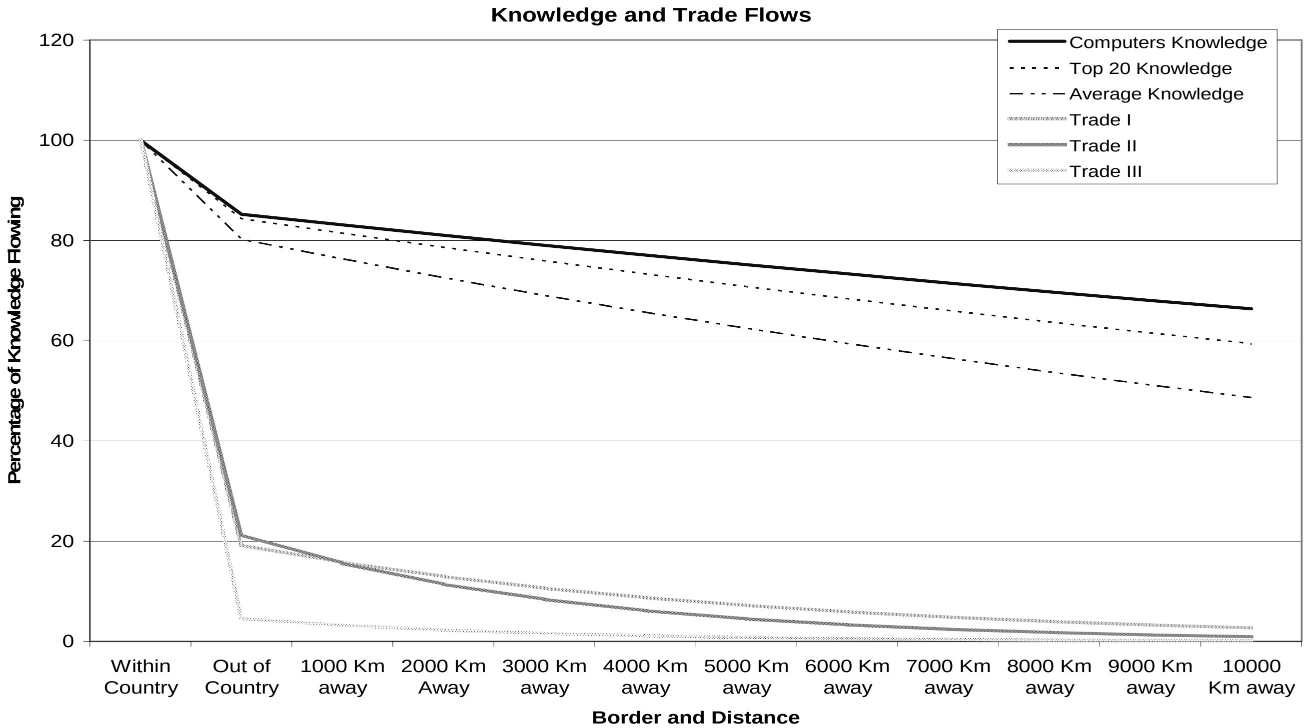


Figure 5



Knowledge and Trade Flows
Computers Knowledge
Top 20 Knowledge
Average Knowledge
Trade I
Trade II
Trade III
Percentage of Knowledge Flowing
120
100
80
60
40
20
0
Within Country
Out of Country
1000 Km away
2000 Km Away
3000 Km away
4000 Km away
5000 Km away
6000 Km away
7000 Km away
8000 Km away
9000 Km away
10000 Km away
Border and Distance