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# **Do labour mobility and networks foster geographical knowledge diffusion? The case of European regions**

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## **Abstract**

The goal of this paper is twofold: first, we aim to assess the role played by inventors' cross-regional mobility and networks of collaboration in fostering knowledge diffusion across regions and subsequent innovation. Second, we intend to evaluate the feasibility of using mobility and networks information to build cross-regional interaction matrices to be used within the spatial econometrics toolbox. To do so, we depart from a knowledge production function where regional innovation intensity is a function not only of the own regional innovation inputs but also external accessible R&D gained through interregional interactions. Differently from much of the previous literature, cross-section gravity models of mobility and networks are estimated to use the fitted values to build our 'spatial' weights matrices, which characterize the intensity of knowledge interactions across a panel of 269 regions covering most European countries over 6 years.

**Key words:** inventors' spatial mobility, co-patenting, gravity models, weights matrix, knowledge production function

**JEL:** C8, J61, O31, O33, R0

## **1. Introduction and motivation**

Knowledge diffusion and creation have been core elements not only within the geography of innovation literature in the past two decades, but also within other related streams, such as new growth economics, regional science, or innovation studies. In large part, this relevance lies in the belief that the combination and recombination of previously unconnected ideas lead to new knowledge production, subsequent technological innovations, and ensuing economic growth and well-being (Aghion and Howitt, 1998; Jones, 1995). Further, knowledge diffusion in the form of knowledge spillovers is central to this literature as a cause of endogenous growth (Romer, 1986, 1990). Still, despite the prominent role conferred to knowledge spillovers, measuring the actual channels through which knowledge is transmitted is far from straightforward.

This paper follows this avenue of reasoning, and aims to assess the role played by the geographical mobility of skilled workers and their networks of research collaboration on the dissemination and creation of technical knowledge across a large panel of European regions, using a Knowledge Production Function (KPF hereafter) framework with ‘spatial’ effects. A second contribution of this paper is more methodological. As it is well known in the spatial econometrics literature, one of the main weaknesses within related studies concerns the arbitrary choice of the weights matrix to characterize knowledge interactions across regions. The present inquiry aims to develop a refinement of the typical matrices based on purely geographical definitions precisely exploiting information on this cross-regional mobility of inventors and their collaborative ties. As it is customary assumed in the literature, distance matters so as the interdependences between units are stronger if they are closer in the space (Rincke, 2010). Our tenet in this paper states, however, that distance matters precisely because labour mobility of skills and interpersonal formal networks tend to be regional in nature (Breschi and Lissoni, 2004, 2009; Singh, 2005; Zucker et al., 1998). With this idea in mind, we estimate a series of gravity models to explain both mobility and networking phenomena, using a set of geographical, administrative and cognitive variables. In so doing, a thorough analysis to choose the adequate estimation method is performed. Afterwards, the fitted values of these estimations are used to build our weights matrices to characterize cross-regional R&D diffusion patterns, which explain a sizeable part of patent production heterogeneity across regions.

The 1990s and early 2000s witnessed an overwhelming emphasis given to knowledge spillovers to explain both increasing returns to scale, marked spatial disparities in regional economic growth and the agglomeration of technological activities in space (Audretsch and Feldman, 1996, 2004; Jaffe et al., 1993). This avenue of research underscored the critical role played by spatial proximity to access these technological and knowledge advantages (Capello and Lenzi, 2012). The advent of spatial econometric techniques (Anselin, 1988; Cliff and Ord, 1973) and the use of the regional KPF with spatial interactions between units (most notably, Acs et al., 1994; Anselin, 2000; Anselin et al., 1997; Bottazzi and Peri, 2003) featured a critical inflexion point among the related studies. Indeed, as stated by prominent scholars, there is no reason to assume that knowledge stops flowing because of regional borders (Audretsch and Feldman, 2004; Krugman, 1991). Therefore, spatial econometrics techniques and the spatial weight matrix notably improved the way in which such externalities were measured (Autant-Bernard and Massard, 2009).

Soon this oversimplified approach was overtaken and different concepts of proximity were also highlighted (Boschma, 2005; Capello, 2009; Capello and Lenzi, 2012; Rallet and Torre, 1995). Thus, an increasing number of scholars pointed out that, even at close spatial proximity, knowledge flows are not automatically received just by 'being there'. Rather, knowledge flows follow specific transmission channels, which are mainly based on market interactions and pecuniary externalities (Breschi and Lissoni, 2001a,b).

Economists have long suspected that mobility of skilled employees transmits knowledge across organizations. This literature draws, among others, on earlier contributions such as Arrow (1962), Rosen (1972) or Stephan (1996), who pioneering stated that mobility of personnel between firms provides a principal way of spreading information. Indeed, mobility of skills across firms and institutions is likely to diffuse knowledge. When they move, skilled workers take their embodied knowledge with them. Hence, firms learn about other firms' research after employing innovators who work or have worked in competing labs. In return, mobile employees acquire knowledge from their new colleagues and, in general, promote new combinations of

knowledge (Laudel, 2003; Trippi and Maier 2010).<sup>1</sup> Further, when skilled workers move from place to place, their knowledge and skills move as well (Breschi et al., 2010; Coe and Bunnell, 2003) and hence, may constitute a central way to establish cross-regional linkages and spread knowledge and information across the space (in this later regard, see empirical applications by Boschma et al., 2009, and Simonen and McCann, 2008).

Besides, networks are critical for innovation. Cross-pollination of ideas, barter of tacit knowledge or the division of labour, have been regarded to be the underlying forces heading to network formation (Katz and Martin, 1997). In some instances, actors in regions build ‘pipelines’ in the form of alliances to benefit from knowledge hotspots around the world (Bathelt et al. 2004; Owen-Smith and Powell 2004). Although research collaboration can be considered as co-production of knowledge where inputs are transformed into outputs (Ponds et al, 2010), knowledge diffusion will occur as a by-product of such processes.

In light of these arguments and the abovementioned literature, as well as the weaknesses of the typical weights matrix formerly referenced, in the following subsections we model and estimate a regional KPF with ‘neighbouring’ effects built using meaningful data, such as, precisely, mobility and networks information, to construct such matrices. We acknowledge that this approach is, however, not new. Moreno et al. (2005a) and Parent and LeSage (2008), among others, have exploited the concept of technological proximity between regions vis-à-vis spatial proximity in estimates of cross-regional externalities. Their underlying logic lies on the idea that knowledge externalities flow easily among members of epistemic communities of scientists and technicians in highly specialized technological fields, irrespective of their geographical location, due to the fact that they share a specific knowledge background and common jargon and codes. Similarly, Kroll (2009) and Ponds et al. (2010) have built weight matrices that display the intensity of pair-wise relationships using collaborative research data across regions to proxy the social distance between them at the aggregate level. In this way, they show the importance of reflecting non-spatial, more meaningful measures of proximity across

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<sup>1</sup> Several empirical applications on the topic include, among others: Almeida and Kogut (1999), Corredoria and Rosenkopf (2010), Crespi et al. (2007), Fallick et al. (2006), Kim et al. (2006), Power and Lundmark (2004), Singh and Agrawal (2011) or Song et al. (2003).

regions in estimating the effects of cross-regional knowledge flows on regional innovative performance. Maggioni et al. (2007) follows a similar approach, as spatial effects vis-à-vis network effects in the form of research collaborations are estimated in a spatial KPF framework. However, their approach reveals that when the spatial weight matrix is subtracted from the network matrix and a pure social matrix is considered on its own, important spatial effects remain unaccounted. Further examples include Morrocu et al. (2011a,b), who build a set of different weights matrices using various dimensions of proximity put to the forefront in the literature (see Boschma, 2005, as well as the French School of Proximity – Carrincazeaux et al., 2008).<sup>2</sup>

A main concern when using these meaningful matrices, however, is as follows: geography-based matrices are suitable to introduce exogenous variation into the models, allowing the identification of both endogenous and exogenous effects (Corrado and Fingleton, 2012). Contrariwise, the necessary exogeneity of the r.h.s. variables might be compromised if weights matrices built with meaningful data are used (Harris et al., 2011). To the best of our knowledge, Peri (2005) is the most known work that, in a KPF framework, has tried to deal with this drawback. In his study, Peri (2005) utilizes gravitational models to estimate cross-regional citation flows and plug the estimated fitted values into a pseudo-weights matrix, which characterize knowledge flows across a set of European and North-American regions. Our own paper builds partially on Peri's contribution. Different from him, however, we rely on the weights matrix taken from the spatial econometrics toolkit to characterize pair-wise cross-regional interactions. In addition, our analysis relies on the actors more involved in innovation, namely, the inventors, and their mobility and networking practices.

The outline of the paper is as follows. In section 2 we offer the theoretical framework for the analysis of regional patent intensity, as well as the determinants of mobility and networks across the space. Section 3 describes the data sources, variables construction and econometric issues, and section 4 provides the main results. Finally we conclude in section 5.

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<sup>2</sup> Other studies have estimated models with meaningful data to characterise the weights matrix, beyond the KPF framework. It is not our intention to review them all here, but a selection of the most outstanding ones can be found in Corrado and Fingleton (2012), Harris et al. (2011) or Pinske and Slade (2010).

## 2. Framework of analysis

### A model of regional innovation and external accessible knowledge

This section sketches a formal model of knowledge production of firms in regions which benefit from accessing extra-regional pools of ideas by means of workers' mobility and networks. Our point of departure is the simplest specification of the knowledge production function of a representative firm<sup>3</sup>  $k$  of region  $i$ :

$$Y_{kit} = A_{it} \cdot f(K_{kit}, L_{kit}) \quad (1)$$

where  $Y$  denotes innovation outputs,  $K$  denotes R&D inputs and  $L$  the skilled labour force of a representative firm  $k$  in region  $i$  at time  $t$ .

Moreover, the firms' innovation output is allowed to depend on an R&D productivity index specific to each region,  $A$ . For simplicity, it is assumed that the KPF follows a Cobb-Douglas functional form:

$$Y_{kit} = A_{it} \cdot K_{kit}^{\beta} \cdot L_{kit}^{\alpha}, \quad 0 < \alpha < 1, \quad 0 < \beta < 1, \quad \alpha + \beta = 1 \quad (2)$$

Aggregating all over firms in region  $i$  yields to

$$Y_{it} = e^C \cdot A_{it} \cdot K_{it}^{\beta} \cdot L_{it}^{\alpha}, \quad (3)$$

where  $Y_{it}$  denotes now the aggregated innovation output of region  $i$ ,  $K_{it}$  the aggregated R&D expenditures,  $L_{it}$  the sum of scientists and technologists across all the organizations, and  $e^C$  denotes the constant term capturing the impact of all common factors affecting innovation across all the sample of regions. In order to guarantee reliable results in the estimations, the regional observations need to be comparable in size: equation (3) is pre-multiplied by a factor of  $1/N$ , where  $N$  is the total population of each region. That is,

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<sup>3</sup> In our theoretical exposition, we mainly talk about firms, though research centres and universities could also be included as central innovative agents of regions.

$$y_{it} = e^C \cdot A_{it} \cdot k_{it}^\beta \cdot l_{it}^\alpha \quad (4)$$

where  $y=Y/N$ ,  $k=K/N$ , and  $l=L/N$ . In this way, the innovative intensity of regions depends on R&D expenditures per capita and the number of scientists and technologists as a proportion of the total population.

The R&D productivity index,  $A_{it}$ , is assumed to depend on local interactions giving firms' access to knowledge from their immediate vicinity – networks, technological spillovers, local labour mobility – as well as from more distant pools of ideas. Our focus on cross-regional interactions as well as the macro data at hand precludes us to observe the effect of micro-interactions at the local level and their effect on firms' performance. In consequence, the R&D productivity index is assumed to depend on the external-to-the-region stock of knowledge available for firm  $i$  at time  $t$ , and some general locational advantages of region  $i$ , proxied by a regional fixed-effect,  $e^{\delta_i}$ .

Let us denote SK as the stock of knowledge accumulated in regions other than  $i$  and accessible to all the firms in region  $i$  at time  $t$ . If knowledge accessible in one region was perfectly and immediately diffusible to all other regions, we would consider the external stock of knowledge accessible to region  $i$  simply as the sum of the knowledge stocks in all other regions. However, since diffusion is not perfect and, as we discussed, follow specific channels based on market mechanisms and embodied in individuals – such as labour mobility of skilled individuals and networks of research collaboration, we assume that there is only a part of the stock generated in region, say,  $j$  that is accessible to region  $i$ , which will depend upon the strength of the  $ij$ -interactions in time  $t$ , that is

$$SK_{it} = \left( \prod_{\substack{j=1 \\ j \neq i}}^L SK_{jt}^{\rho^m \omega_{ij,t}^m} \right) \left( \prod_{\substack{j=1 \\ j \neq i}}^L SK_{jt}^{\rho^n \omega_{ij,t}^n} \right) \quad (5)$$

where  $\omega_{ij,t}^m$  and  $\omega_{ij,t}^n$  are bilateral weights that measure the strength of the interactions between region  $i$  and region  $j$  by means of, respectively, spatial mobility of the skilled

labour force and geographical networks of collaboration.  $\rho^m$  and  $\rho^n$  are the output elasticities of the potential of, respectively, mobility and networks to spread R&D stocks across European regions and therefore constitute the parameters of interest to be estimated in the present paper.

Next, expressing (5) in logs and substituting it into the log-transformation of (4), yields to

$$\ln y_{it} = c + \beta \ln k_{it} + \alpha \ln l_{it} + \rho^m \cdot \sum_{j \neq i} \omega_{ij,t}^m \ln SK_{jt} + \rho^n \cdot \sum_{j \neq i} \omega_{ij,t}^n \ln SK_{jt} + \delta_i + \varepsilon_{it} \quad (6)$$

where a well-behaved error term is now added,  $\varepsilon_{it}$ .

As can be observed in (6), we need to measure the intensity of bilateral linkages in the form of bilateral mobility of skilled workers and technological collaborations,  $\omega_{ij,t}^m$  and  $\omega_{ij,t}^n$  respectively, for each regional pair, in order to calculate the stock of external accessible R&D.

Hence, as we will show in the empirical section, our framework of analysis encompasses two stages: we first estimate the magnitude of the interactions for each pair of regions ( $\omega_{ij,t}^m$  and  $\omega_{ij,t}^n$ ) using data both on mobility and co-patenting across regions as a function of a set of explanatory bilateral variables; and secondly we use the fitted values of these estimations to infer the impact of the external knowledge in equation (6) through the parameters  $\rho^m$  and  $\rho^n$ . Thus, one main contribution of the present paper is to let the intensity of these linkages to be estimated by a number of bilateral characteristics of the regions that affect the decision of a utility maximization agent in his choice on where to migrate or with whom to collaborate, to which we turn next.

## Knowledge interactions across-regions: a gravity approach

### *Knowledge interactions and mobility of inventors*

Our primary interest lies on a linear utility model where the inventor's utility of working and living in a location  $i$  has a deterministic part common to all the inventors,  $u$ , and an individual-specific stochastic component,  $\varepsilon_i^k$ . Specifically,  $k$ 's utility of working in location  $i$  can be expressed as

$$U_i^k = u(E_i) + \varepsilon_i^k \quad (7)$$

Define the deterministic part  $u$  as a function of a vector of amenities and economic variables ( $E_i$ ) of the  $i$ -th region affecting  $k$ -th utilities of that region. Individuals are rational, so their decision to move from one location to an alternative one will be based on a comparison between the expected utilities of the two locations. An individual will decide to migrate from location  $i$  to location  $j$  if the expected utility on the destination location is greater than the expected utility at the origin location minus the costs of relocating, which depend upon a set of geographical, administrative and cognitive distances,  $D_{ij}$ :

$$E(U_j^k) > E(U_i^k) + C(D_{ij}) \quad (8)$$

When condition (8) holds, we define a variable  $M_{ij}^k$  being equal to 1, and 0 otherwise. Thus, for individual  $k$  to migrate from location  $i$  to location  $j$  (and not to any other location  $r$ ), the move must lead to higher expected utility and must mean that there were no alternative moves that would have provided a larger improvement. By aggregating individual movements by region and employing a very general gravity-type model specification, we can write:

$$M_{ij} = f(E_i, E_j, D_{ij}) \quad (9)$$

where  $D_{ij}$  is a set of bilateral distance variables widely applied in gravity models of immigration. More specifically,

$$D_{ij} = G_{ij} \cdot e^{\nu_{ij}} \cdot T_{ij} \cdot e^{\gamma_{ij}} \quad (10)$$

where  $G_{ij}$  is the euclidean distance between the  $i$ -th and the  $j$ -th centroids, which is likely to negatively affect bilateral inventors' mobility because, among other reasons: (i) information on the destination location is more imperfect as the physical distance increases, (ii) transportation costs are likely to be larger, and (iii) regular encounters with family, friends and former colleagues will be more sparse in time at larger geographical distances. However, these effects are less likely to dominate in contiguous regions, and so, a dummy denoting the regions sharing a common border is also included,  $e^{\nu_{ij}}$ . On the other hand, technological proximity,  $T_{ij}$ , is included in order to proxy to what extent cognitive similarity (a shared, related, and complementary knowledge base) explains mobility across physically distant epistemic communities. Finally, a dummy variable indicating whether two regions belongs to the same country,  $e^{\gamma_{ij}}$ , is also introduced, in order to control for institutional, cultural or linguistic effects in the mobility decisions of inventors.

Next, since the set of push and pull region-specific variables possibly influencing cross-regional mobility,  $E_i$  and  $E_j$ , is likely to be large, we introduce origin and destination fixed-effects,  $e^{\delta_i}$  and  $e^{\delta_j}$ , and focus only on the abovementioned bilateral variables. As shown by Anderson and van Wincoop (2003), the inclusion of origin and destination fixed-effects in gravity models accords with theoretical concerns regarding the correct specification of these models, which translates into more consistent estimations. Thus, introducing origin and destination fixed effects in equation (10), we obtain our basic gravity model:

$$M_{ij} = e^{\beta_0} \cdot G_{ij} \cdot e^{\nu_{ij}} \cdot T_{ij} \cdot e^{\gamma_{ij}} \cdot \prod_{i=1}^I e^{\delta_i} \cdot \prod_{j=1}^J e^{\delta_j} \cdot \varepsilon_{ij} \quad (11)$$

where  $e^{\beta_0}$  is a constant term capturing the impact of all common factors affecting mobility across all the sample of regions and  $\varepsilon_{ij}$  a well-behaved error term.

### *Knowledge interactions and co-patenting networks*

As it is customary in the recent literature on network formation (Autant-Bernard et al., 2007; Cassi and Plunket, 2010; Mariani, 2004; Paier and Scherngell, 2011; Ter Waal, 2011), we base our estimation framework on the utility-maximizing individuals' decision to engage in a partnership with inventors located in other regions – in our specific case, co-patents. For each pair of inventors,  $k$  and  $h$ , a link is formed if and only if the associated payoffs of collaborating are expected to be positive,  $\pi^{kh} > 0$ . Hence, the payoffs of collaborating would depend upon  $k$ 's and  $h$ 's observable characteristics,  $X^k$  and  $X^h$ :

$$\pi^{kh} = f(X^k, X^h) + \varepsilon^{kh} \quad (12)$$

where  $\varepsilon^{kh}$  is a pair-wise specific stochastic term.  $X^k$  and  $X^h$  may refer to  $k$ 's and  $h$ 's talent, productivity or willingness to collaborate, but they may also refer to the features of the institution, city or region where they work that may affect their common likelihood to collaborate with each other. An individual  $h$  will decide to collaborate with individual  $k$ , and vice-versa, when the associated payoffs of collaborating are greater than the costs of doing so,  $C(D^{kh})$ ,

$$\pi^{kh} > C(D^{kh}) \quad (13)$$

When condition (13) holds, we define a variable  $N_{ij}^{kh}$  being equal to 1, and 0 otherwise. By aggregating all individual decisions by pairs of regions, we end up specifying a gravity model of regional collaboration in the form of

$$N_{ij} = f(X_i, X_j, D_{ij}) \quad (14)$$

where  $N_{ij}$  is the sum of individual choices of inventors from region  $i$  collaborating with someone from region  $j$ , which depends on the characteristics of a representative inventor of region  $i$  ( $X_i$ ) and the characteristics of a representative inventor of region  $j$  ( $X_j$ ). For the same reasons abovementioned, the features of representative inventors in the  $i$ -th and the  $j$ -th regions are proxied by origin and destination fixed-effects,  $e^{\delta_i}$  and  $e^{\delta_j}$ , while focusing only on  $D_{ij}$ , which is again a set of bilateral distance variables widely applied in gravity models of spatial interactions. More specifically,

$$D_{ij} = G_{ij} \cdot e^{\nu_{ij}} \cdot T_{ij} \cdot e^{\gamma_{ij}} \quad (15)$$

where  $G_{ij}$  is the euclidean distance between the  $i$ -th and the  $j$ -th centroids, which is likely to negatively affect inventors' collaborations. Arguably, spatial proximity enables the formation of formal networks: it facilitates the screening of potential partners (Storper and Venables, 2004), ease the managing and administration of the common project, and smoothes monitoring of partners' fulfillments. A dummy denoting the regions sharing a common border is also included,  $e^{\nu_{ij}}$ . Technological proximity,  $T_{ij}$ , is introduced in order to proxy to what extent cognitive similarity (a shared, related, and complementary knowledge base) explains co-patenting across physically distant epistemic communities. Finally, again, a dummy variable indicating whether two regions belongs to the same country or not,  $e^{\gamma_{ij}}$ , is also introduced. All in all, the following gravity-type model for the case of cross-regional collaborations is also going to be estimated:

$$N_{ij} = e^{\beta_0} \cdot G_{ij} \cdot e^{\nu_{ij}} \cdot T_{ij} \cdot e^{\gamma_{ij}} \cdot \prod_{i=1}^I e^{\delta_i} \cdot \prod_{j=1}^J e^{\delta_j} \cdot \varepsilon_{ij} \quad (16)$$

where  $e^{\beta_0}$  is a constant term capturing the impact of all common factors affecting collaboration across all the sample of regions and  $\varepsilon_{ij}$  a well-behaved error term.

### 3. Empirical application

#### Data and variables construction

Patent data per million population, from the REGPAT database (January 2010 edition), is used to proxy regional innovative intensity (in particular, EPO<sup>4</sup> patents, fractional counting) – patent data correspond to the years 2000 to 2005. In spite of their shortcomings (Griliches, 1991; Verspagen and Schoenmakers, 2004), patent data have proved reasonably useful for proxying inventive activity. Since these data are prone to exhibit lumpiness from year to year, we have averaged out patent figures. Thus, a three-year moving average is computed for every observation, thereby mitigating the effects of annual fluctuations in this variable, especially in those less populated areas.<sup>5</sup>

Proxies for the two main inputs of the regional KPF are also elaborated. R&D expenditures per capita are computed by CRENoS. Specifically, data were collected from Eurostat and some National Statistical Offices, with some elaboration for regions in specific countries (Belgium, Greece, Netherlands, Switzerland). Human capital is measured as the population with tertiary education (population aged 15 and over by ISCED level of education attained) over overall regional population and is again elaborated by CRENoS, collected from Eurostat. The stock of R&D of each region, which will be used to compute the available external stock of knowledge, is proxied using R&D data. The accumulation of R&D is described as  $\Delta R\&D = R\&D_t - \delta R\&D_{t-1}$  – see Peri (2005) – where  $\delta$  is an arbitrary depreciation rate set at 5%. Other depreciation rates, however, do not alter the results. The initial stock of R&D has been calculated using the perpetual inventory method,  $R\&D_0 = R\&D_{t-n} / (g + \delta)$ , where  $R\&D_{t-n}$  is the first year for which the data were available, and  $g$  is the geometric average annual growth rate of R&D expenditure between 1996 and 1998. All the variables, as well as the remaining controls, are lagged one period in order to lessen endogeneity problems due to system feedbacks. Other controls include population density and population density squared, and specialization and concentration indexes –

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<sup>4</sup> EPO stands for European Patent Office.

<sup>5</sup> Thus, the 2000 observations include averaged data from 2000 to 2002, whereas the 2005 observations include data from 2005 to 2007.

computed using patent data broken down into technological sectors (Schmoch, 2008), aside from regional fixed-effects, which allow us to control for important time-invariant confounders that might have biased previous estimates of the regional KPF.

Data to build our ‘weights’ matrices and the dependent variables of the gravity models come also from EPO patents retrieved from the REGPAT database (January 2010 edition). Three-year moving time-windows are computed, and are lagged one period with respect to the stock of regional R&D. This way, if per capita patent data are computed gathering data from  $t$  to  $t+2$ , the stock of R&D corresponds to the year  $t-1$ , whereas the mobility and network weights matrices are computed using three-year time-windows from  $t-4$  to  $t-2$ .<sup>6</sup> These time lags are introduced again to minimize endogeneity and reverse causality problems. Whereas purely geographical weights matrices can be assumed to be clearly exogenous, our matrices are not, as the structure of collaborations and mobility is likely to be related to patterns of patenting. Clearly, however, our weights matrices have the advantage of bearing a direct relation with the theoretical conceptualization of the structure of spatial dependence, rather than an ad-hoc description of a spatial pattern based on geography. In addition, exogenous variables are used in our gravity-type estimations to capture, to some extent, the exogenous component of both mobility and networks and plug it into both weights matrices. We turn next to the description of the gravity variables.

Our model of geographical mobility of inventors is estimated year by year, from 1996 to 2001 (both inclusive). The dependent variable is built by full-counting the movements of inventors crossing regional borders, data computed within 3-year time-windows.<sup>7</sup> We therefore construct mobility asymmetrical matrices of 269 rows and 269 columns for each time window, where each of the elements in the matrix is the number of inventors moving from region  $i$  to region  $j$ . If an inventor moves more than once, or if she returns to her former region, we compute these movements as separate and independent. By definition movements from region  $i$  to region  $i$  do not exist and

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<sup>6</sup> As it will be explained later on, the technological distance used as one of the r.h.s. variables of the gravity models is computed using 3-year time windows as well. Again, the windows are time-lagged, and, continuing with our example, they correspond to the years  $t-7$  to  $t-5$ . Note, therefore, that the sets of variables corresponding to each estimation step never overlap in time.

<sup>7</sup> Note, therefore, that the 1996-window corresponds to data from 1996 to 1998, whilst the 2001-window corresponds to data from 2001 to 2003.

therefore the diagonal elements of the matrix are always zero. Mobility is computed through the changes observed in the region of residence reported by the inventor in patent documents from the EPO. Of course, in this way we only capture mobility if the inventor applies for a patent before and after the move, and so we probably underestimate real mobility. We compute each movement exactly in between the origin and the destination patents, but only if there is a maximum time lapse of five years between them.

A thorough disambiguation process of the names of the inventors in patents was carried out in order to track their mobility patterns, as it is done in Miguélez and Gómez-Miguélez (2011), among others. In brief, we first clean, harmonize and code all the inventors' names and surnames. Afterwards, we test whether each pair of names belong to the same individual, using a wide range of characteristics, such as their address, the applicants and groups of applicants of their patents, their self-citations, or the technological classes to which their patents belong – up to 15 different tests were run.

The gravity network model is also estimated year by year, and cross-regional networks are computed within 3-year time-windows as well. EPO co-patents between inventors residing, at the time of the patent application, in different NUTS2 region, are used as a proxy for regional bilateral collaboration. Obviously, the underlying assumption is that co-patents reflect inventors' collaborative practices between non-co-located peers. Based on the addresses of the inventors appearing in the patent document, we compute the pair-wise number of collaborations between each pair of regions, and a matrix of 269 rows and 269 columns for each time window was also constructed. The elements of these matrices, and therefore the dependent variable of our gravity models, is simply the number of all technological collaborations within a given time window between two regions  $i$  and  $j$ , irrespective of the number of inventors listed in each patent, being the diagonal elements of the matrix, again, always zeros. Because of the nature of a collaboration, the matrices are symmetrical by definition, meaning that the final number of observations reduces to  $(N*N-1)/2$ .

The explanatory variables of the gravity models coincide in both cases. These include: (i) the Euclidean distance between the regions' centroids, (ii) a dummy variable indicating whether the two region share a common border, and (iii) a dummy variable

indicating whether the two regions belong to the same country or not. In addition, cognitive proximity is proxied by an index of technological similarity (in our case, 1 minus technological similarity), measured as the uncentred correlation between regional vectors of technological classes of patents (Jaffe 1986).

Note, importantly, that our sample of 269 European NUTS2 regions is relatively large compared to previous studies and covers a high number of countries (EU-27 plus Norway and Switzerland).<sup>8</sup> Table 1 provides summary statistics of the variables used for the KPF estimation, whereas tables 2 and 3 provide yearly figures for the mobility and networking dependent variables.

[Insert Tables 1, 2 and 3 about here]

Table 4 provides the correlation matrix corresponding to the KPF estimations. Arguably, some pairs of variables show relatively large correlation coefficients (though “only” around 0.7). Introducing alternatively in the KPF estimations one or the other variable of each pair does not change to a large extent the quantitative results, though – results provided upon request. The correlation among the remaining independent variables is, in general, sufficiently small and collinearity does not pose a significant problem in our estimations. Note, importantly, that the correlation between the R&D stocks weighted either by mobility or by networks is not particularly large, which was a potential concern when introducing both variables at the same time in the estimations.

[Insert Table 4 about here]

### **Econometric issues**

A natural way to estimate the gravity models, equations (11) and (16), would be to apply a logarithmic transformation and OLS techniques. Santos Silva and Tenreyro (2006, 2010) show, however, that this standard procedure in a gravity model may

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<sup>8</sup> We have omitted the regions of Las Canarias, Ceuta, Melilla, Madeira, Açores, Guadeloupe, Martinique, Guyane and Reunion, as well as Malta and Cyprus, due to their distance from continental Europe. In addition, four Greek regions filed no patent applications in our period of analysis and so were removed from the study. We do not expect this omission to alter our results significantly.

induce a form of heteroskedasticity of the error term because of the log transformation of the data, and OLS would be inconsistent. In addition to this, the number of zeros in the dependent variables is relatively large, making a logarithmic transformation of these variables impossible. To address these issues, Santos Silva and Tenreyro (2006, 2010) suggest estimating the multiplicative form of the model by Poisson pseudo-maximum likelihood.

Further, their suggested estimators are particularly suitable in our case because our response variables are discrete, with a distribution that places the probability mass at non-negative integer values only, with data concentrated in a few small discrete values skewed to the left and intrinsically heteroskedastic, with variance increasing with the mean (Cameron and Trivedi, 1998). Again, count data models are more suitable in this framework.

The most basic type of count data model is derived from the Poisson distribution. However, the Poisson distribution assumes equidispersion – that is, the conditional variance equals the conditional mean. But the conditional variance often exceeds the conditional mean (Burger et al., 2009; Long, 1997), which is a clear symptom of overdispersion. As a result, the Poisson regression may lead to consistent but inefficient estimates (Burger et al., 2009), with standard errors biased downward (Cameron and Trivedi, 1998; Long, 1997). Over-dispersion tests, based on the significance of  $\alpha$ , the dispersion parameter, can be performed to guide our model choice.

An important issue is related to the disproportionate number of zero that our dependent variables contain. Although count data models are explicitly designed to deal with the presence of zeros, these zeros may come from different data generating processes. Specific estimation techniques might be therefore required, such as the use of zero-inflated models. In these models, the estimation process includes two parts: first the probability of observing mobility from  $i$  to  $j$ ,  $\varphi$ , is estimated by means of a probit or logit model, which is a function of certain characteristics – a set of covariates that predict the probability of belonging to the strictly-zero group; and second, the count data model is estimated for the probability of each count for the group that has non-zero probability.

In the following section, we thoroughly compare the performance of various types of count data models in order to choose the most appropriate estimation technique.

#### 4. Results

Our empirical analysis consists of two differentiated parts. First, in the following subsection we present the results of estimating the weights matrices  $\omega_{ij}^m$  and  $\omega_{ij}^n$  using data on mobility of skilled workers and networks of technical collaborations between regions, and the selection criteria used among different count data models. Afterwards, we use these estimated values along with data on regional R&D to estimate the elasticities  $\rho_m$  and  $\rho_n$  in equation (6).

##### Estimation of knowledge interactions

Model (i) in table 5 shows the OLS estimations of the gravity model of cross-regional mobility, included for comparison purposes, for the case of the time window 2001-2003. Besides, columns (ii) to (v) show, respectively, the Poisson Pseudo-Maximum Likelihood estimation (PPML), the Negative Binomial Pseudo-Maximum Likelihood (NBPML), the Zero Inflated Poisson Pseudo-Maximum Likelihood (ZIPML) and the Zero-Inflated Negative Binomial Pseudo-Maximum Likelihood (ZINBPML), thereby controlling for the presence of zeros in the dependent variable, over-dispersion and excess of zeros. In particular, column (ii) controls for the presence of zeros, whilst column (iii) also controls for over-dispersion. Finally, columns (iv) and (v) take also on board the disproportionate presence of zeros in the dependent variable for, respectively, the Poisson and negative binomial estimations. As a general conclusion, we observe that apart from the OLS estimation, the coefficient estimates are very similar for the rest of the cases in terms of significance and sign. The geographical distance and the technological/cognitive distance are negative, as expected, and strongly significant. We find that both greater geographical as well as cognitive distances between two regions tend to hamper knowledge workers mobility. The results are in line to what is found in the regional migration literature at the European level (Crozet, 2004) as well as the results for the specific case of inventors (Miguelez and Moreno, 2012). In general, since the covariates are expressed in logarithmic form, the estimated coefficients can be

interpreted as elasticities (Cameron and Trivedi, 1998). Meanwhile, sharing a common border and belonging to the same country foster the inter-exchange of inventors, as expected. Note, importantly, that geographical and cognitive distance tend to show smaller coefficient estimates in zero-inflated models, which might be a symptom of the upward bias introduced in their non-zero-inflated counterparts. We discuss this issue shortly.

[Insert Table 5 about here]

Being the OLS estimation disregarded in theoretical grounds, a first graphical way to assess the different performance of count data models and to help choosing the most suitable one is to look at the probability distribution and compare the expected probabilities to the observed probabilities. Figure 1 shows this. The points above the horizontal axis indicate an over-prediction of the probability of observing mobility, whilst points below the axis indicate under-prediction. Clearly, ZIPPML (labelled 'zip' in the graph) and ZINBPML ('zinb') seem to perform the best, as the difference between expected and observed probabilities tends to be lower for all the cases. Note, however, that the ZINBPML ('zinb') seems to slightly under-predict the zeros whilst the ZIPPML ('zip') seems to slightly over-predict the ones. In order to choose between these two estimation methods, more formal statistical tests can also be used, to which we turn next.

[Insert Figure 1 about here]

Broadly speaking, the ZIPNBML presents a lower AIC and a higher log-likelihood value (OLS set aside), which seems to indicate its superiority over the other methods in terms of fit. In addition to this, both over-dispersion tests and Vuong statistics (bottom of table 5) seem to clearly point to the use of ZINBPML to the detriment of the other estimation methods.

Table 6 presents the gravity estimations of the cooperative networks across regions in Europe, same period as before, same estimation techniques. Again, aside from the case of the OLS estimations, included for comparison purposes but disregarded on theoretical grounds, the coefficient estimates are comparable among estimation

methods – it is worth noting, however, important differences in their magnitudes. In general, the results found accord with previous empirical findings in similar contexts (Hoekman et al, 2009; Maggioni et al., 2007).

[Insert Table 6 about here]

As before, the difference between the expected probabilities to the observed probabilities is plotted in figure 2. As can be seen, the conclusions for the case of cross-regional cooperation slightly differ from before. All the models seem to over-predict the number of zeros, though ZIPPM (labelled ‘zip’) and ZINBPML (‘zinb’) largely outperforms PPML (‘poisson’) and NBPML (‘nbreg’). Meanwhile, all the models seem to under-predict ones, being, in this order, ZIPPM (‘zip’) and ZINBPML (‘zinb’) outperforming the other methods. It seems, therefore, that ZIPPM (‘zip’) would be the chosen model based on the graphical representation of expected probabilities. We next turn to examining additional statistical tests in order to clarify this extreme and take a final decision.

[Insert Figure 2 about here]

Despite the former graphical results, statistical tests seem to point to the use of the ZINBPML again – see bottom of table 6, according to the AIC criteria, the value of the log-likelihood and the over-dispersion and Vuong statistics. In order to be as consistent as possible with the mobility case, we chose to estimate the gravity models of collaboration by means of ZINBPML, but we present robustness checks of the KPF estimation with ZIPPM estimations of both gravitational models, in order to study the stability and significance of the estimated parameters.

Finally, tables 7 and 8 show the ZINBPML estimations, respectively, for the case of mobility and networks, and from 1996 to 2001 (from the time window 1996-1998 to the time window 2001-2003). Interestingly enough, the coefficients barely change over

time, though somehow the different estimations partially overlap so as to observe big differences between them.<sup>9</sup>

[Insert Table 7 and 8 about here]

### **The impact of external accessible knowledge on innovation production**

Table 9 presents the results of the pooled OLS as well as the random and fixed effects estimation of the regional KPF, including the stock of knowledge in the external regions, weighted both by fitted mobility values and fitted networking values.<sup>10</sup> At first sight results are consistent across methods of estimation in relation to the significance and sign of the core variables, namely R&D and human capital, as well as our focus variables. This is so irrespective of the consideration of control variables (columns (iv) to (vi)). However, the magnitude of their impact differs substantially from one method to another.<sup>11</sup> Clearly, the point estimates of most of the variables are dramatically changed when regional fixed-effects are included, signalling the importance of time-invariant unobserved heterogeneity. With the aim of using the most adequate model for the interpretation of our results, we use the Hausman test, which rejects the null hypothesis that individual effects are uncorrelated with the independent variables. This points to the preference of the fixed effect model – columns (iii) and (vi) – to the expense of the random-effects.

The elasticity of patents with respect to R&D expenditures when the fixed-effects estimations are carried out presents significant values (around 0.21), which is in line with the value obtained in the literature (Acs et al., 1994; Bottazzi and Peri, 2003; Jaffe,

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<sup>9</sup> Although origin and destination fixed effects fairly control for origin and destination important features in a cross-sectional setting, they do not so in a longitudinal framework. Thus, when a panel gravity model is estimated and origin, destination, and pair-wise fixed-effects are included, important time-variant origin and destination variables need also to be included. This would imply including variables such as GDP per capita and other economic variables, amenities, and the like. Unfortunately, this kind of variables covering the whole sample of regions is not readily available. For that reason, we prefer to estimate separate cross-sections and get the fitted values separately to plug them into our knowledge interaction matrices.

<sup>10</sup>  $\omega_{ij}^m$  and  $\omega_{ij}^n$  have been row-standardized, as it is usually done in the spatial econometrics literature.

<sup>11</sup> In principle, again, the coefficients can be interpreted as elasticities, since the variables in the regression are expressed in natural logarithmic form: the proportional increase in patenting activity in response to a 1% increase in a given explanatory variable.

1989). Additionally, the human capital parameter is significant and with the expected positive sign, with similar values to those reported elsewhere (around 0.19 as in Bottazzi and Peri, 2003).

Column (vi) further includes additional control variables: population density, population density squared, and specialization and concentration indices. Population density is significantly positive, pointing to the presence of agglomeration and urbanization economies, and its quadratic form is also included, being negative. These results would indicate evidence that overly dense areas suffer several costs related to congestion effects of agglomeration (negative externalities). On the other hand, the specialization index is positive whereas concentration seems to affect negatively the innovative activity.

More important for our purposes are the significant and positive parameters obtained for the two variables proxying the available stock of knowledge from other regions. The elasticity of patenting activity with respect to R&D stocks in the rest of the European regions, weighted by the mobility of researchers between each pair of regions, presents a significant value of 0.012. Also positive, although of a greater magnitude, is the elasticity of patenting with respect to R&D stocks in the rest of European regions weighted by the intensity of collaborative networks across regions, with a value of 0.037. These results seem to confirm that the production of knowledge in regions depends not only on its own research efforts and internal factors, but also on the knowledge available in other regions, accessible through mobile inventors and co-patent networks. In addition, it seems that among the two mechanisms through which knowledge diffuses and which we have explicitly considered in this paper, regions benefit more from external knowledge stocks when the transmission is through networks of collaboration than through the movement of highly skilled workers. The impact of the later is one third of the former.

In short, the empirical analysis undertaken here support the hypothesis concerning the importance of collaborative networks and, to a lesser extent, of labour mobility as the means fostering the geographical diffusion of knowledge. However, several extensions to this initial approach can next be made.

## **Robustness checks**

In this section we summarize several robustness checks performed to study the stability and significance of the estimated parameters, and the results encountered so far. The initial checks refer to the way of constructing the two variables proxying the stock of R&D in external regions. Column (i) estimates our main equation with fitted values from previous gravity models for mobility and collaboration networks that have been estimated using the ZIPML method. The coefficients and resulting conclusions are virtually unchanged. The same occurs when the actual values of networks and mobility, instead of the fitted ones, are used for the weights of the stock of R&D in external regions (column (ii)).

The remaining robustness checks are related to the role of physical proximity per se in the transmission of knowledge. In column (iii) we allow the production of knowledge in a region to depend not only on its own research efforts and internal factors, but also on the knowledge available in the physically close neighbouring regions. The latter is proxied by the sum of the R&D stocks in the regions sharing a border, where each stock is divided by the number of contiguous regions (row-standardized weight matrix), as it is customary done in the related literature. As it is shown, the impact exerted by the knowledge available in the physically neighbouring regions is significantly positive and clearly of a much higher magnitude than that exerted thanks to the knowledge transmitted through networks of collaboration or mobility of inventors. In general, the related studies tend to interpret the estimates of cross-regional spatial effects as evidence of geographical knowledge spillovers (among many others, see: Bottazzi and Peri, 2003; Moreno et al., 2005a, 2005b). In the present inquiry we follow this same simple route of interpretation and understand our coefficient estimates as evidence of interregional spillovers influencing the innovative activity of European regions. Nevertheless, we claim that an important part of knowledge diffusion across regions in the knowledge production process are driven by networks of research collaborations and labour mobility. Column (iv) includes the three variables at a time, that is, the stock of knowledge in the remaining regions weighted by mobility, networks and spatial contiguity. In principle, one would expect the values of the parameter of the stock of R&D in the contiguous neighbouring regions to fall significantly when the other two variables are included in the regressions. This appears not to be true, since the

parameter decreases but only slightly (from 0.52 to 0.47). It is worth mentioning though that our focal variables remain strongly significant even when purely spatial effects are introduced – though with slightly smaller coefficient estimates, as it is the case of the spatial R&D variable. It seems, therefore, that the three variables partially overlap. This points to the need to undertake further research to investigate the additional actual channels by which knowledge diffuses over the space, beyond contiguity and physical proximity per se. Finally, column (v) repeats our main estimation but including the regional stock of R&D per capita instead of the R&D expenditures per capita. In this case, the own R&D parameter is considerably larger, though the conclusions and main results regarding the remaining parameters are maintained.

## **5. Concluding remarks**

Although knowledge and innovation are well recognized as critical pillars of ‘smart growth’ in Europe, the right strategies that can help the continent to move in this direction are not so evident. Arguably, a pivotal element to ensure regional economic growth lies in accessing external sources of knowledge and facilitating interactive learning and interaction in innovation. This knowledge diffusion can take place through diffusive patterns based on knowledge externalities, that rely on informal transmission channels, relatively bounded in space, but also through intentional relations such as spatial mobility of skilled employees and geographical networks of research collaboration (Moreno and Miguelez, 2012; ESPON, 2012)

The present inquiry is a first step in this direction and estimates a KPF where geographical interactions occurring across regions in the production of knowledge are introduced. Specifically, a more meaningful modelling of these interactions through inventors’ mobility and co-patenting data has been considered when building weights matrix to describe the strength of bilateral knowledge relations across European regions. We acknowledge that a thorough spatial econometric analysis needs to be performed. Inventors’ mobility and networking data, and the approach we have suggested here – the gravity estimations, could be used to build weights matrices to estimate spatial lag models and spatial error models (Anselin, 1988). Our own future research will definitely go in this direction.

We find that both collaboration networks and, to a lesser extent, mobility, foster knowledge diffusion across European regions. Hence, from a policy perspective, these results illustrate that, not only R&D and human capital efforts are important to generate innovations at the regional level, but also the degree of connectivity of agents with the outside world, which give them access to global knowledge hotspots useful for innovation. Such idea of connectivity, among others, is precisely in the core of the ‘smart specialisation’ strategy recently launched by the European Commission (McCann and Ortega-Argilés, 2011).

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**Table 1. Summary statistics knowledge production function**

	Obs.	Mean	St.Dev.	Min.	Max.
ln(PAT)p.c.	1,614	3.61	1.91	-3.93	6.77
ln(R&D)p.c.	1,614	-1.79	1.53	-6.55	1.06
lnHK	1,614	-9.31	0.50	-11.83	-8.29
$W^{colls*} \ln StockR\&D$	1,614	8.39	1.70	0.00	10.31
$W^{mob*} \ln StockR\&D$	1,614	7.05	3.57	0.00	10.63
ln(population density)	1,614	4.93	1.20	1.12	9.12
Special. Index	1,614	6.06	2.95	2.06	21.14
Concen. Index	1,614	0.10	0.12	0.00	1.00

Note: The 1,614 observations correspond to 269 regions over 6 periods.

**Table 2. Summary statistics, mobility. 3-year time windows: 1996-2001**

All links	Obs.	Mean	St.Dev.	Min.	Max.
Mobility1996	72,361	0.11	1.19	0	59
Mobility1997	72,361	0.12	1.37	0	79
Mobility1998	72,361	0.14	1.61	0	134
Mobility1999	72,361	0.15	1.92	0	207
Mobility2000	72,361	0.16	2.27	0	254
Mobility2001	72,361	0.16	2.60	0	275
Positive links	Obs.	Mean	St.Dev.	Min.	Max.
Mobility1996	2,319	3.28	5.84	1	59
Mobility1997	2,588	3.37	6.43	1	79
Mobility1998	2,817	3.53	7.40	1	134
Mobility1999	2,899	3.67	8.89	1	207
Mobility2000	2,948	3.83	10.60	1	254
Mobility2001	2,903	3.89	12.42	1	275

Note: The variables on mobility and collaborations are build summing up within time windows of three years. Thus, for instance, mobility1996 corresponds to all the movements observed in 1996, 1997 and 1998.

**Table 3. Summary statistics, collaborations. 3-year time windows: 1996-2001**

All links	Obs.	Mean	St.Dev.	Min.	Max.
Collab.1996	36,315	1.33	15.32	0	1,355
Collab.1997	36,315	1.52	16.67	0	1,449
Collab.1998	36,315	1.75	18.73	0	1,622
Collab.1999	36,315	1.90	20.04	0	1,701
Collab.2000	36,315	1.99	21.23	0	1,711
Collab.2001	36,315	2.01	21.27	0	1,642
Positive links	Obs.	Mean	St.Dev.	Min.	Max.
Collab.1996	5,291	9.159	39.228	1	1,355
Collab.1997	5,638	9.818	41.326	1	1,449
Collab.1998	6,074	10.445	44.79	1	1,622
Collab.1999	6,399	10.78	46.718	1	1,701
Collab.2000	6,678	10.848	48.54	1	1,711
Collab.2001	6,755	10.808	48.34	1	1,642

Note: The variables on mobility and collaborations are build summing up within time windows of three years. Thus, for instance, mobility1996 corresponds to all the movements observed in 1996, 1997 and 1998.

**Table 4. Correlation matrix, knowledge production function**

	1	2	3	4	5	6	7	8
1. ln(PAT)p.c.	1							
2. ln(R&D)p.c.	0.90	1						
3. lnHK	0.52	0.56	1					
4. $W^{colls*} \ln StockR\&D$	0.55	0.54	0.26	1				
5. $W^{mob*} \ln StockR\&D$	0.78	0.73	0.40	0.51	1			
6. ln(population density)	0.26	0.29	0.19	0.09	0.23	1		
7. Special. Index	-0.75	-0.72	-0.40	-0.51	-0.73	-0.34	1	
8. Concen. Index	-0.51	-0.49	-0.28	-0.55	-0.49	-0.22	0.66	1

**Table 5. Gravity estimations – mobility (2001-2003), various techniques.**

	(i)	(ii)	(iii)	(iv)	(v)
	OLS	ppml	nbpml	zippl	zinbpl
	$\ln(M_{ij} + 1)$				
Ln(Geographic distance)	-0.003 (0.002)	-0.975*** (0.134)	-0.916*** (0.049)	-0.690*** (0.120)	-0.704*** (0.055)
Contiguity dummy	0.488*** (0.027)	0.774*** (0.133)	1.075*** (0.077)	0.885*** (0.121)	1.208*** (0.076)
Ln(Cognitive distance)	-0.063*** (0.004)	-0.331*** (0.096)	-0.404*** (0.052)	-0.224*** (0.087)	-0.263*** (0.057)
Same country dummy	0.307*** (0.009)	1.713*** (0.156)	2.176*** (0.062)	0.780*** (0.150)	1.417*** (0.079)
Constant	-0.139*** (0.024)	0.524 (1.437)	-0.329 (0.872)	-0.072 (1.298)	-0.761 (0.910)
Origin F.E.	yes	yes	yes	yes	yes
Destination F.E.	yes	yes	yes	yes	yes
Overdispersion			0.270*** (0.068)		-0.221*** (0.052)
LR of $\alpha=0$					4466.65***
p-value					0.000
Vuong				5.97***	6.90***
p-value				0.000	0.000
Observations	72,088	50,401	50,401	50,401	50,401
Adjusted R2	0.309				
BIC	-8,076.42	33,495.29	25,850.41	29,990.54	25,534.72
AIC	-13,045.85	29,496.31	21,842.60	25,947.43	21,482.78
Log-likelihood	7,063.92	-14,295.15	-10,467.30	-12,515.71	-10,282.39
McFadden djusted-R2	0.309	0.694	0.343	0.519	0.354

Robust standard errors in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. Overdispersion tests largely reject the null hypothesis of no overdispersion. Vuong statistics (Vuong, 1989), are also performed and reported at the bottom of each regression. The tests performed point to the need of the zero-inflated models to accommodate our estimations to the excess of zeros. 'ppml' stands for poisson pseudo-maximum likelihood; 'nbpml' stands for negative binomial pseudo-maximum likelihood; 'zippl' stands for zero-inflated Poisson pseudo-maximum likelihood; and 'zinbpl' stands for zero-inflated negative binomial pseudo-maximum likelihood. Due to the inclusion of fixed effects, pseudo-maximum likelihood estimations do not converge unless we drop the regional fixed-effects (and their corresponding observations) for which the region has zero recorded inventors' flows to every other region in the sample. This explains the smaller number of observations used in these estimations (see Santos Silva and Tenreiro, 2010). For the case of 'zippl' and 'zinbpl', the logit part is not shown here but can be provided upon request.

**Table 6. Gravity estimations – collaborations (2001-2003), various techniques.**

	(i)	(ii)	(iii)	(iv)	(v)
	OLS				
	$\ln(N_{ij} + 1)$	ppml	nbpml	zipplml	zinbplml
Ln(Geographic distance)	-0.116*** (0.007)	-0.902*** (0.044)	-0.815*** (0.028)	-0.837*** (0.046)	-0.762*** (0.034)
Contiguity Dummy	0.856*** (0.057)	0.869*** (0.061)	1.022*** (0.061)	0.925*** (0.061)	1.029*** (0.059)
Ln(Cognitive distance)	-0.194*** (0.010)	-0.197*** (0.049)	-0.363*** (0.034)	-0.165*** (0.052)	-0.222*** (0.035)
Same country dummy	1.188*** (0.023)	1.666*** (0.079)	2.097*** (0.045)	1.403*** (0.080)	1.930*** (0.049)
Constant	0.329*** (0.079)	1.723*** (0.598)	0.531 (0.523)	1.754*** (0.599)	0.553 (0.533)
Origin F.E.	yes	yes	yes	yes	yes
Destination F.E.	yes	yes	yes	yes	yes
Overdispersion			-0.313*** (0.041)		-0.601*** (0.048)
LR of $\alpha=0$				12.33	1200
p-value				0.000	0.000
Vuong					6.21
p-value					0.000
Observations	36,044	33,674	33,674	33,674	33,674
Adjusted-R2	0.608				
BIC	52,528.863	66,509.488	52,004.326	63,699.906	51,837.742
AIC	47,934.423	62,103.485	47,589.898	59,251.779	47,381.192
Log-likelihood	-23,426.211	-30,528.742	-23,270.949	-29,097.890	-23,161.596
McFadden djusted-R2	0.602	0.875	0.327	0.800	0.329

Robust standard errors in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. Overdispersion tests largely reject the null hypothesis of no overdispersion. Vuong statistics (Vuong, 1989), are also performed and reported at the bottom of each regression. The tests performed point to the need of the zero-inflated models to accommodate our estimations to the excess of zeros. 'ppml' stands for poisson pseudo-maximum likelihood; 'nbpml' stands for negative binomial pseudo-maximum likelihood; 'zipplml' stands for zero-inflated Poisson pseudo-maximum likelihood; and 'zinbplml' stands for zero-inflated negative binomial pseudo-maximum likelihood. Due to the inclusion of fixed effects, pseudo-maximum likelihood estimations do not converge unless we drop the regional fixed-effects (and their corresponding observations) for which the region has zero recorded inventors' flows to every other region in the sample. This explains the smaller number of observations used in these estimations (see Santos Silva and Tenreiro, 2010). For the case of 'zipplml' and 'zinbplml', the logit part is not shown here but can be provided upon request.

**Table 7. Gravity estimations – mobility. Zero-inflated negative binomial, 1996-2001**

	(i)	(ii)	(iii)	(iv)	(v)	(vi)
	1996	1997	1998	1999	2000	2001
Ln(Geographic distance)	-0.654*** (0.055)	-0.702*** (0.056)	-0.758*** (0.055)	-0.733*** (0.056)	-0.738*** (0.056)	-0.704*** (0.055)
Contiguity Dummy	1.253*** (0.081)	1.187*** (0.077)	1.114*** (0.073)	1.159*** (0.072)	1.159*** (0.075)	1.208*** (0.076)
Ln(Cognitive distance)	-0.308*** (0.068)	-0.234*** (0.069)	-0.143** (0.063)	-0.116** (0.057)	-0.181*** (0.057)	-0.263*** (0.057)
Same country dummy	1.579*** (0.096)	1.558*** (0.094)	1.524*** (0.087)	1.458*** (0.079)	1.435*** (0.077)	1.417*** (0.079)
Constant	-1.137 (0.800)	-1.043 (0.862)	-0.853 (0.920)	-0.248 (0.795)	-0.632 (0.858)	-0.761 (0.910)
Origin F.E.	yes	yes	yes	yes	yes	yes
Destination F.E.	yes	yes	yes	yes	yes	yes
LR of $\alpha=0$	1,783.67	2,082.29	2,236.44	2,647.52	3,608.57	4,466.65
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Vuong	6.45	6.31	6.47	7.22	7.05	6.90
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Observations	43,062	44,321	45,591	46,879	47,966	50,401
Non-zero obs.	2,319	2,588	2,817	2,899	2,948	2,903
BIC	20,704.10	22,506.88	24,174.98	24,845.37	25,553.64	25,534.72
AIC	17,019.18	18,757.52	20,361.08	20,966.76	21,620.99	21,482.78
Log-likelihood	-8,084.59	-8,947.76	-9,743.54	-10,040.38	-10,362.49	-10,282.39
Adjusted-R2	0.356	0.357	0.356	0.358	0.353	0.354

Robust standard errors in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. Overdispersion tests largely reject the null hypothesis of no overdispersion. Vuong statistics (Vuong, 1989), are also performed and reported at the bottom of each regression. The tests performed point to the need of the zero-inflated models to accommodate our estimations to the excess of zeros.

**Table 8. Gravity estimations – collaborations. Zero-inflated negative binomial, 1996-2001**

	(i)	(ii)	(iii)	(iv)	(v)	(vi)
	1996	1997	1998	1999	2000	2001
Ln(Geographic distance)	-0.677*** (0.033)	-0.657*** (0.033)	-0.683*** (0.034)	-0.696*** (0.033)	-0.724*** (0.034)	-0.762*** (0.034)
Contiguity Dummy	1.043*** (0.058)	1.065*** (0.058)	1.071*** (0.056)	1.067*** (0.057)	1.063*** (0.057)	1.029*** (0.059)
Ln(Cognitive distance)	-0.264*** (0.041)	-0.227*** (0.039)	-0.247*** (0.037)	-0.267*** (0.038)	-0.243*** (0.036)	-0.222*** (0.035)
Same country dummy	2.119*** (0.052)	2.144*** (0.051)	2.032*** (0.049)	2.024*** (0.049)	1.929*** (0.048)	1.930*** (0.049)
Constant	1.133 (0.771)	1.011 (0.790)	0.777 (0.609)	0.476 (0.521)	0.879* (0.519)	0.553 (0.533)
Origin F.E.	yes	yes	yes	yes	yes	yes
Destination F.E.	yes	yes	yes	yes	yes	yes
Overdispersion	7,332.72	8,301.07	9,695.56	12,000	12,000	12,000
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Vuong	6.51	7.09	7.41	6.66	6.75	6.21
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Observations	30,034	30,043	30,281	32,003	32,902	33,674
Non-zero obs.	5,291	5,638	6,074	6,399	6,678	6,754
BIC	40,702.82	43,446.34	46,850.60	49,120.99	51,391.51	51,837.74
AIC	36,547.78	39,291.15	42,674.83	44,800.22	46,997.64	47,381.19
Log-likelihood	-17,773.89	-19,145.57	-20,835.41	-21,884.11	-22,975.82	-23,161.59
Adjusted-R2	0.342	0.335	0.327	0.331	0.327	0.329

Robust standard errors in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. Overdispersion tests largely reject the null hypothesis of no overdispersion. Vuong statistics (Vuong, 1989), are also performed and reported at the bottom of each regression. The tests performed point to the need of the zero-inflated models to accommodate our estimations to the excess of zeros.

**Table 9. Main estimation results. Dep. Var.: lnPATpc, KPF 1999-2004**

	(i)	(ii)	(iii)	(iv)	(v)	(vi)
	Pooled OLS	RE	FE	Pooled OLS	RE	FE
ln(R&D)p.c.	0.838*** (0.021)	0.744*** (0.027)	0.204*** (0.038)	0.805*** (0.022)	0.737*** (0.028)	0.210*** (0.038)
lnHK	0.120*** (0.045)	0.115*** (0.038)	0.187*** (0.036)	0.171*** (0.044)	0.116*** (0.038)	0.188*** (0.036)
W <sup>mob</sup> *lnStockR&D	0.133*** (0.008)	0.023*** (0.005)	0.011** (0.005)	0.105*** (0.008)	0.023*** (0.005)	0.012*** (0.005)
W <sup>colls</sup> *lnStockR&D	0.058*** (0.013)	0.043*** (0.007)	0.039*** (0.007)	0.046*** (0.014)	0.040*** (0.008)	0.037*** (0.007)
ln(population density)				0.373*** (0.073)	0.335* (0.177)	4.943** (2.307)
ln(population density)^2				-0.040*** (0.007)	-0.022 (0.017)	-0.438* (0.229)
Special. Index				-0.079*** (0.011)	0.003 (0.009)	0.031*** (0.008)
Concen. Index				0.253 (0.222)	-0.172 (0.114)	-0.360*** (0.102)
Constant	4.798*** (0.416)	5.488*** (0.368)	5.320*** (0.343)	5.159*** (0.440)	4.430*** (0.569)	-7.903 (5.837)
Hausman test		413.07***			444.62***	
AIC	3,628.26		-177.098	3,539.652		-197.111
BIC	3,655.192		-150.1656	3,588.13		-148.6328
Observations	1,614	1,614	1,614	1,614	1,614	1,614
Adjusted R2	0.848			0.856		
R2 within		0.0788	0.0996		0.0816	0.1151
R2 between		0.8503	0.8415		0.8461	0.0896
R2 overall		0.8320	0.8158		0.8284	0.0894
Number of periods	6	6	6	6	6	6
Number of regions	269	269	269	269	269	269

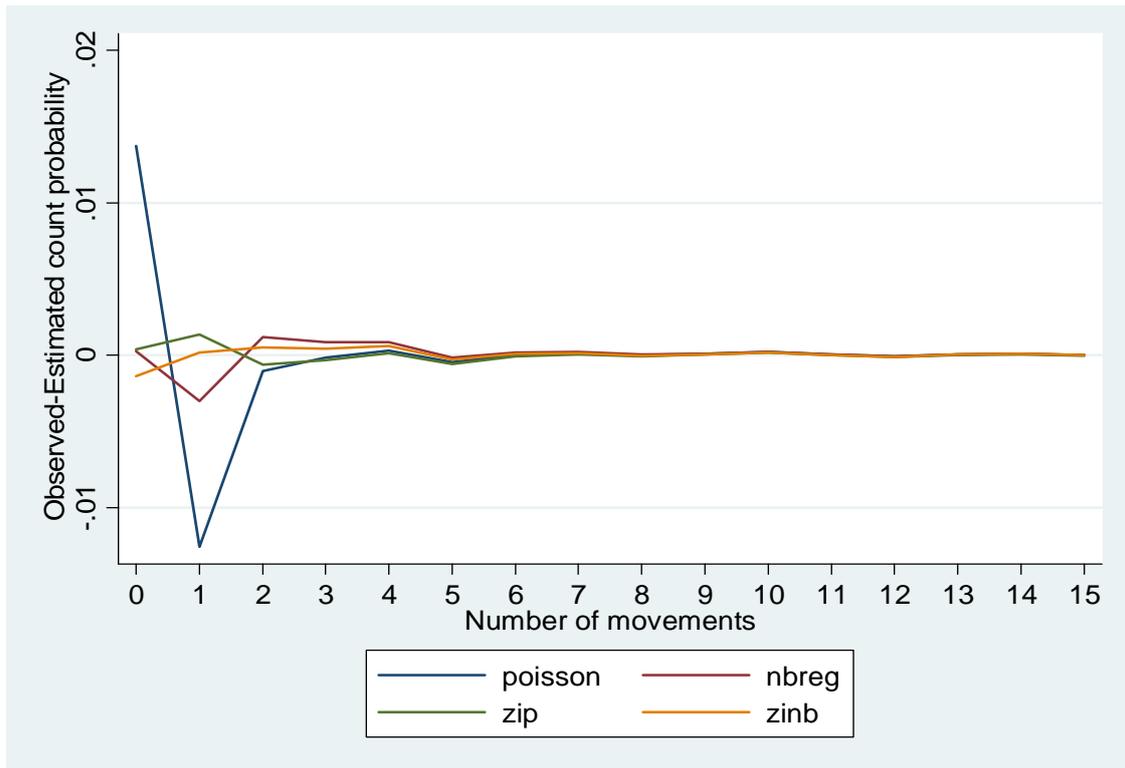
Standard errors in parentheses \*\*\* p&lt;0.01, \*\* p&lt;0.05, \* p&lt;0.1

**Table 10. Robustness checks. Dep. Var.: lnPAtpc**

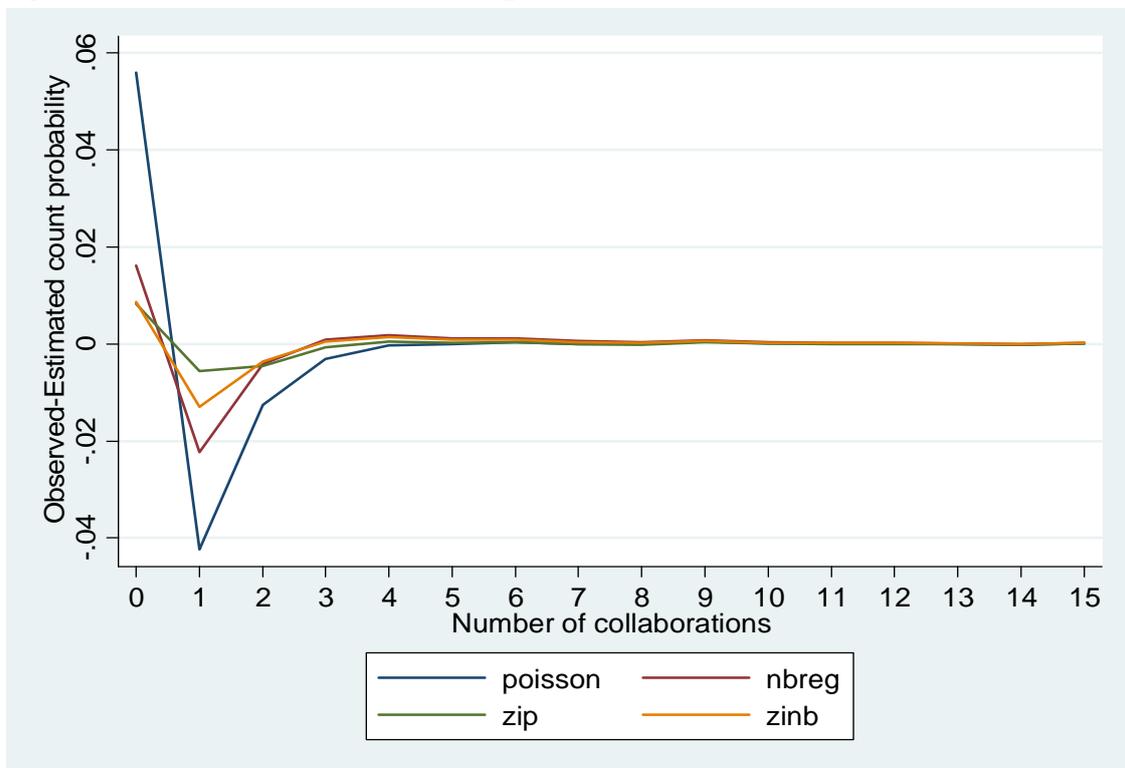
	(i)	(ii)	(iii)	(iv)	(v)
	zipplml	Actual values	Spatial R&D	Spatial R&D	StockR&Dpc
	FE	FE	FE	FE	FE
ln(R&D)p.c.	0.210*** (0.038)	0.206*** (0.038)	0.090** (0.039)	0.090** (0.039)	0.398*** (0.045)
lnHK	0.190*** (0.036)	0.191*** (0.036)	0.071* (0.038)	0.062 (0.038)	0.108*** (0.038)
W <sup>mob</sup> *lnStockR&D	0.012*** (0.005)	0.014*** (0.004)		0.009** (0.004)	0.008* (0.005)
W <sup>colls</sup> *lnStockR&D	0.036*** (0.007)	0.034*** (0.007)		0.024*** (0.007)	0.029*** (0.007)
W <sup>contig</sup> *lnStockR&D			0.522*** (0.053)	0.470*** (0.054)	
ln(population density)	4.939** (2.310)	4.510* (2.303)	4.523** (2.250)	5.174** (2.245)	4.835** (2.268)
ln(population density) <sup>2</sup>	-0.438* (0.229)	-0.396* (0.229)	-0.589*** (0.225)	-0.621*** (0.224)	-0.513** (0.225)
Special. Index	0.031*** (0.008)	0.031*** (0.008)	0.037*** (0.008)	0.038*** (0.008)	0.039*** (0.008)
Concen. Index	-0.366*** (0.102)	-0.374*** (0.102)	-0.440*** (0.097)	-0.368*** (0.099)	-0.396*** (0.100)
Constant	-7.847 (5.846)	-6.827 (5.822)	-6.672 (5.680)	-9.060 (5.681)	-6.511 (5.741)
Hausman test	443.78***	447.43***	356.04***	351.68***	127.56***
AIC	-193.6534	-196.5001	-269.3157	-284.8043	-252.792
BIC	-145.1752	-148.0218	-226.224	-230.9396	-204.3137
Observations	1,614	1,614	1,614	1,614	1,614
R2 within	0.1132	0.1148	0.1528	0.1630	0.1451
R2 between	0.0889	0.1063	0.0004	0.0036	0.0535
R2 overall	0.0887	0.1060	0.0005	0.0038	0.0539
Number of periods	6	6	6	6	6
Number of regions	269	269	269	269	269

Standard errors in parentheses \*\*\* p&lt;0.01, \*\* p&lt;0.05, \* p&lt;0.1

**Figure 1. Observed versus estimated probability of the number of movements.**



**Figure 2. Observed versus estimated probability of the number of collaborations.**





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(Desembre 2006)



**CREAP2006-13**

**Royuela, V.** (AQR-IREA); **Lambiri, D.**; **Biagi, B.**

"Economía urbana y calidad de vida. Una revisión del estado del conocimiento en España"  
(Desembre 2006)

**CREAP2006-14**

**Camarero, M.**; **Carrion-i-Silvestre, J.LL.** (AQR-IREA); **Tamarit, C.**

"New evidence of the real interest rate parity for OECD countries using panel unit root tests with breaks"  
(Desembre 2006)

**CREAP2006-15**

**Karanassou, M.**; **Sala, H.** (GEAP); **Snower, D. J.**

"The macroeconomics of the labor market: Three fundamental views"  
(Desembre 2006)

**2007**

**XREAP2007-01**

**Castany, L.** (AQR-IREA); **López-Bazo, E.** (AQR-IREA); **Moreno, R.** (AQR-IREA)

"Decomposing differences in total factor productivity across firm size"  
(Març 2007)

**XREAP2007-02**

**Raymond, J. Ll.** (GEAP); **Roig, J. Ll.** (GEAP)

"Una propuesta de evaluación de las externalidades de capital humano en la empresa"  
(Abril 2007)

**XREAP2007-03**

**Durán, J. M.** (IEB); **Esteller, A.** (IEB)

"An empirical analysis of wealth taxation: Equity vs. Tax compliance"  
(Juny 2007)

**XREAP2007-04**

**Matas, A.** (GEAP); **Raymond, J.Ll.** (GEAP)

"Cross-section data, disequilibrium situations and estimated coefficients: evidence from car ownership demand"  
(Juny 2007)

**XREAP2007-05**

**Jofre-Montseny, J.** (IEB); **Solé-Ollé, A.** (IEB)

"Tax differentials and agglomeration economies in intraregional firm location"  
(Juny 2007)

**XREAP2007-06**

**Álvarez-Albelo, C.** (CREB); **Hernández-Martín, R.**

"Explaining high economic growth in small tourism countries with a dynamic general equilibrium model"  
(Juliol 2007)

**XREAP2007-07**

**Duch, N.** (IEB); **Montolio, D.** (IEB); **Mediavilla, M.**

"Evaluating the impact of public subsidies on a firm's performance: a quasi-experimental approach"  
(Juliol 2007)

**XREAP2007-08**

**Segarra-Blasco, A.** (GRIT)

"Innovation sources and productivity: a quantile regression analysis"  
(Octubre 2007)

**XREAP2007-09**

**Albalade, D.** (PPRE-IREA)

"Shifting death to their Alternatives: The case of Toll Motorways"  
(Octubre 2007)

**XREAP2007-10**

**Segarra-Blasco, A.** (GRIT); **García-Quevedo, J.** (IEB); **Teruel-Carrizosa, M.** (GRIT)

"Barriers to innovation and public policy in catalonia"  
(Novembre 2007)



**XREAP2007-11**

**Bel, G.** (PPRE-IREA); **Foote, J.**

“Comparison of recent toll road concession transactions in the United States and France”  
(Novembre 2007)

**XREAP2007-12**

**Segarra-Blasco, A.** (GRIT);

“Innovation, R&D spillovers and productivity: the role of knowledge-intensive services”  
(Novembre 2007)

**XREAP2007-13**

**Bermúdez Morata, Ll.** (RFA-IREA); **Guillén Estany, M.** (RFA-IREA), **Solé Auró, A.** (RFA-IREA)

“Impacto de la inmigración sobre la esperanza de vida en salud y en discapacidad de la población española”  
(Novembre 2007)

**XREAP2007-14**

**Calaeys, P.** (AQR-IREA); **Ramos, R.** (AQR-IREA), **Suriñach, J.** (AQR-IREA)

“Fiscal sustainability across government tiers”  
(Desembre 2007)

**XREAP2007-15**

**Sánchez Hugalbe, A.** (IEB)

“Influencia de la inmigración en la elección escolar”  
(Desembre 2007)

**2008**

**XREAP2008-01**

**Durán Weitkamp, C.** (GRIT); **Martín Bofarull, M.** (GRIT) ; **Pablo Martí, F.**

“Economic effects of road accessibility in the Pyrenees: User perspective”  
(Gener 2008)

**XREAP2008-02**

**Díaz-Serrano, L.;** **Stoyanova, A. P.** (CREB)

“The Causal Relationship between Individual’s Choice Behavior and Self-Reported Satisfaction: the Case of Residential Mobility in the EU”  
(Març 2008)

**XREAP2008-03**

**Matas, A.** (GEAP); **Raymond, J. L.** (GEAP); **Roig, J. L.** (GEAP)

“Car ownership and access to jobs in Spain”  
(Abril 2008)

**XREAP2008-04**

**Bel, G.** (PPRE-IREA) ; **Fageda, X.** (PPRE-IREA)

“Privatization and competition in the delivery of local services: An empirical examination of the dual market hypothesis”  
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**Matas, A.** (GEAP); **Raymond, J. L.** (GEAP); **Roig, J. L.** (GEAP)

“Job accessibility and employment probability”  
(Maig 2008)

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**Basher, S. A.;** **Carrión, J. Ll.** (AQR-IREA)

Deconstructing Shocks and Persistence in OECD Real Exchange Rates  
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**Sanromá, E.** (IEB); **Ramos, R.** (AQR-IREA); **Simón, H.**

Portabilidad del capital humano y asimilación de los inmigrantes. Evidencia para España  
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**XREAP2008-08**

**Basher, S. A.;** **Carrión, J. Ll.** (AQR-IREA)

Price level convergence, purchasing power parity and multiple structural breaks: An application to US cities  
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**XREAP2008-09**

**Bermúdez, Ll.** (RFA-IREA)

A priori ratemaking using bivariate poisson regression models  
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**XREAP2008-10**

**Solé-Ollé, A.** (IEB), **Hortas Rico, M.** (IEB)

Does urban sprawl increase the costs of providing local public services? Evidence from Spanish municipalities  
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**Teruel-Carrizosa, M.** (GRIT), **Segarra-Blasco, A.** (GRIT)

Immigration and Firm Growth: Evidence from Spanish cities  
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**Duch-Brown, N.** (IEB), **García-Quevedo, J.** (IEB), **Montolio, D.** (IEB)

Assessing the assignation of public subsidies: Do the experts choose the most efficient R&D projects?  
(Novembre 2008)

**XREAP2008-13**

**Bilotkach, V., Fageda, X.** (PPRE-IREA), **Flores-Fillol, R.**

Scheduled service versus personal transportation: the role of distance  
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**Albalate, D.** (PPRE-IREA), **Gel, G.** (PPRE-IREA)

Tourism and urban transport: Holding demand pressure under supply constraints  
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**2009**

**XREAP2009-01**

**Calonge, S.** (CREB); **Tejada, O.**

“A theoretical and practical study on linear reforms of dual taxes”  
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**Albalate, D.** (PPRE-IREA); **Fernández-Villadangos, L.** (PPRE-IREA)

“Exploring Determinants of Urban Motorcycle Accident Severity: The Case of Barcelona”  
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**Borrell, J. R.** (PPRE-IREA); **Fernández-Villadangos, L.** (PPRE-IREA)

“Assessing excess profits from different entry regulations”  
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**Sanromá, E.** (IEB); **Ramos, R.** (AQR-IREA), **Simon, H.**

“Los salarios de los inmigrantes en el mercado de trabajo español. ¿Importa el origen del capital humano?”  
(Abril 2009)

**XREAP2009-05**

**Jiménez, J. L.;** **Perdiguero, J.** (PPRE-IREA)

“(No)competition in the Spanish retailing gasoline market: a variance filter approach”  
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**Álvarez-Albelo, C. D.** (CREB), **Manresa, A.** (CREB), **Pigem-Vigo, M.** (CREB)

“International trade as the sole engine of growth for an economy”  
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**Callejón, M.** (PPRE-IREA), **Ortún V, M.**

“The Black Box of Business Dynamics”  
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**Lucena, A.** (CREB)

“The antecedents and innovation consequences of organizational search: empirical evidence for Spain”  
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**Domènech Campmajó, L.** (PPRE-IREA)

“Competition between TV Platforms”  
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**Solé-Auró, A.** (RFA-IREA), **Guillén, M.** (RFA-IREA), **Crimmins, E. M.**

“Health care utilization among immigrants and native-born populations in 11 European countries. Results from the Survey of Health, Ageing and Retirement in Europe”  
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**Segarra, A.** (GRIT), **Teruel, M.** (GRIT)

“Small firms, growth and financial constraints”  
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**Matas, A.** (GEAP), **Raymond, J.Ll.** (GEAP), **Ruiz, A.** (GEAP)

“Traffic forecasts under uncertainty and capacity constraints”  
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**Sole-Ollé, A.** (IEB)

“Inter-regional redistribution through infrastructure investment: tactical or programmatic?”  
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**Del Barrio-Castro, T.**, **García-Quevedo, J.** (IEB)

“The determinants of university patenting: Do incentives matter?”  
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**Ramos, R.** (AQR-IREA), **Suriñach, J.** (AQR-IREA), **Artís, M.** (AQR-IREA)

“Human capital spillovers, productivity and regional convergence in Spain”  
(Novembre 2009)

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**Álvarez-Albelo, C. D.** (CREB), **Hernández-Martín, R.**

“The commons and anti-commons problems in the tourism economy”  
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**García-López, M. A.** (GEAP)

“The Accessibility City. When Transport Infrastructure Matters in Urban Spatial Structure”  
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**García-Quevedo, J.** (IEB), **Mas-Verdú, F.** (IEB), **Polo-Otero, J.** (IEB)

“Which firms want PhDs? The effect of the university-industry relationship on the PhD labour market”  
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**Pitt, D.**, **Guillén, M.** (RFA-IREA)

“An introduction to parametric and non-parametric models for bivariate positive insurance claim severity distributions”  
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**Bermúdez, Ll. (RFA-IREA), Karlis, D.**

“Modelling dependence in a ratemaking procedure with multivariate Poisson regression models”  
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**XREAP2010-05**

**Di Paolo, A. (IEB)**

“Parental education and family characteristics: educational opportunities across cohorts in Italy and Spain”  
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**Simón, H. (IEB), Ramos, R. (AQR-IREA), Sanromá, E. (IEB)**

“Movilidad ocupacional de los inmigrantes en una economía de bajas cualificaciones. El caso de España”  
(Juny 2010)

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**Di Paolo, A. (GEAP & IEB), Raymond, J. Ll. (GEAP & IEB)**

“Language knowledge and earnings in Catalonia”  
(Juliol 2010)

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**Bolancé, C. (RFA-IREA), Alemany, R. (RFA-IREA), Guillén, M. (RFA-IREA)**

“Prediction of the economic cost of individual long-term care in the Spanish population”  
(Setembre 2010)

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**Di Paolo, A. (GEAP & IEB)**

“Knowledge of catalan, public/private sector choice and earnings: Evidence from a double sample selection model”  
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**Coad, A., Segarra, A. (GRIT), Teruel, M. (GRIT)**

“Like milk or wine: Does firm performance improve with age?”  
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**Di Paolo, A. (GEAP & IEB), Raymond, J. Ll. (GEAP & IEB), Calero, J. (IEB)**

“Exploring educational mobility in Europe”  
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**Borrell, A. (GiM-IREA), Fernández-Villadangos, L. (GiM-IREA)**

“Clustering or scattering: the underlying reason for regulating distance among retail outlets”  
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**Di Paolo, A. (GEAP & IEB)**

“School composition effects in Spain”  
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**XREAP2010-14**

**Fageda, X. (GiM-IREA), Flores-Fillol, R.**

“Technology, Business Models and Network Structure in the Airline Industry”  
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**XREAP2010-15**

**Albalade, D. (GiM-IREA), Bel, G. (GiM-IREA), Fageda, X. (GiM-IREA)**

“Is it Redistribution or Centralization? On the Determinants of Government Investment in Infrastructure”  
(Desembre 2010)

**XREAP2010-16**

**Oppedisano, V., Turati, G.**

“What are the causes of educational inequalities and of their evolution over time in Europe? Evidence from PISA”  
(Desembre 2010)



**XREAP2010-17**

**Canova, L., Vaglio, A.**

“Why do educated mothers matter? A model of parental help”  
(Desembre 2010)

**2011**

**XREAP2011-01**

**Fageda, X.** (GiM-IREA), **Perdiguero, J.** (GiM-IREA)

“An empirical analysis of a merger between a network and low-cost airlines”  
(Maig 2011)

**XREAP2011-02**

**Moreno-Torres, I.** (ACCO, CRES & GiM-IREA)

“What if there was a stronger pharmaceutical price competition in Spain? When regulation has a similar effect to collusion”  
(Maig 2011)

**XREAP2011-03**

**Miguélez, E.** (AQR-IREA); **Gómez-Miguélez, I.**

“Singling out individual inventors from patent data”  
(Maig 2011)

**XREAP2011-04**

**Moreno-Torres, I.** (ACCO, CRES & GiM-IREA)

“Generic drugs in Spain: price competition vs. moral hazard”  
(Maig 2011)

**XREAP2011-05**

**Nieto, S.** (AQR-IREA), **Ramos, R.** (AQR-IREA)

“¿Afecta la sobreeducación de los padres al rendimiento académico de sus hijos?”  
(Maig 2011)

**XREAP2011-06**

**Pitt, D., Guillén, M.** (RFA-IREA), **Bolancé, C.** (RFA-IREA)

“Estimation of Parametric and Nonparametric Models for Univariate Claim Severity Distributions - an approach using R”  
(Juny 2011)

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**Guillén, M.** (RFA-IREA), **Comas-Herrera, A.**

“How much risk is mitigated by LTC Insurance? A case study of the public system in Spain”  
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**Ayuso, M.** (RFA-IREA), **Guillén, M.** (RFA-IREA), **Bolancé, C.** (RFA-IREA)

“Loss risk through fraud in car insurance”  
(Juny 2011)

**XREAP2011-09**

**Duch-Brown, N.** (IEB), **García-Quevedo, J.** (IEB), **Montolio, D.** (IEB)

“The link between public support and private R&D effort: What is the optimal subsidy?”  
(Juny 2011)

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**Bermúdez, Ll.** (RFA-IREA), **Karlis, D.**

“Mixture of bivariate Poisson regression models with an application to insurance”  
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**XREAP2011-11**

**Varela-Irimia, X-L.** (GRIT)

“Age effects, unobserved characteristics and hedonic price indexes: The Spanish car market in the 1990s”  
(Agost 2011)

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**Bermúdez, Ll.** (RFA-IREA), **Ferri, A.** (RFA-IREA), **Guillén, M.** (RFA-IREA)

“A correlation sensitivity analysis of non-life underwriting risk in solvency capital requirement estimation”  
(Setembre 2011)



**XREAP2011-13**

**Guillén, M.** (RFA-IREA), **Pérez-Marín, A.** (RFA-IREA), **Alcañiz, M.** (RFA-IREA)

“A logistic regression approach to estimating customer profit loss due to lapses in insurance”  
(Octubre 2011)

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**Jiménez, J. L., Perdiguero, J.** (GiM-IREA), **García, C.**

“Evaluation of subsidies programs to sell green cars: Impact on prices, quantities and efficiency”  
(Octubre 2011)

**XREAP2011-15**

**Arespa, M.** (CREB)

“A New Open Economy Macroeconomic Model with Endogenous Portfolio Diversification and Firms Entry”  
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**Matas, A.** (GEAP), **Raymond, J. L.** (GEAP), **Roig, J.L.** (GEAP)

“The impact of agglomeration effects and accessibility on wages”  
(Novembre 2011)

**XREAP2011-17**

**Segarra, A.** (GRIT)

“R&D cooperation between Spanish firms and scientific partners: what is the role of tertiary education?”  
(Novembre 2011)

**XREAP2011-18**

**García-Pérez, J. I., Hidalgo-Hidalgo, M., Robles-Zurita, J. A.**

“Does grade retention affect achievement? Some evidence from PISA”  
(Novembre 2011)

**XREAP2011-19**

**Arespa, M.** (CREB)

“Macroeconomics of extensive margins: a simple model”  
(Novembre 2011)

**XREAP2011-20**

**García-Quevedo, J.** (IEB), **Pellegrino, G.** (IEB), **Vivarelli, M.**

“The determinants of YICs’ R&D activity”  
(Desembre 2011)

**XREAP2011-21**

**González-Val, R.** (IEB), **Olmo, J.**

“Growth in a Cross-Section of Cities: Location, Increasing Returns or Random Growth?”  
(Desembre 2011)

**XREAP2011-22**

**Gombau, V.** (GRIT), **Segarra, A.** (GRIT)

“The Innovation and Imitation Dichotomy in Spanish firms: do absorptive capacity and the technological frontier matter?”  
(Desembre 2011)

**2012**

**XREAP2012-01**

**Borrell, J. R.** (GiM-IREA), **Jiménez, J. L., García, C.**

“Evaluating Antitrust Leniency Programs”  
(Gener 2012)

**XREAP2012-02**

**Ferri, A.** (RFA-IREA), **Guillén, M.** (RFA-IREA), **Bermúdez, Ll.** (RFA-IREA)

“Solvency capital estimation and risk measures”  
(Gener 2012)

**XREAP2012-03**

**Ferri, A.** (RFA-IREA), **Bermúdez, Ll.** (RFA-IREA), **Guillén, M.** (RFA-IREA)

“How to use the standard model with own data”  
(Febrer 2012)



**XREAP2012-04**

**Perdiguero, J.** (GiM-IREA), **Borrell, J.R.** (GiM-IREA)

“Driving competition in local gasoline markets”

(Març 2012)

**XREAP2012-05**

D’Amico, G., **Guillen, M.** (RFA-IREA), Manca, R.

“Discrete time Non-homogeneous Semi-Markov Processes applied to Models for Disability Insurance”

(Març 2012)

**XREAP2012-06**

**Bové-Sans, M. A.** (GRIT), Laguado-Ramírez, R.

“Quantitative analysis of image factors in a cultural heritage tourist destination”

(Abril 2012)

**XREAP2012-07**

**Tello, C.** (AQR-IREA), **Ramos, R.** (AQR-IREA), **Artís, M.** (AQR-IREA)

“Changes in wage structure in Mexico going beyond the mean: An analysis of differences in distribution, 1987-2008”

(Maig 2012)

**XREAP2012-08**

**Jofre-Monseny, J.** (IEB), **Marín-López, R.** (IEB), **Viladecans-Marsal, E.** (IEB)

“What underlies localization and urbanization economies? Evidence from the location of new firms”

(Maig 2012)

**XREAP2012-09**

**Muñiz, I.** (GEAP), **Calatayud, D.**, **Dobaño, R.**

“Los límites de la compacidad urbana como instrumento a favor de la sostenibilidad. La hipótesis de la compensación en Barcelona medida a través de la huella ecológica de la movilidad y la vivienda”

(Maig 2012)

**XREAP2012-10**

**Arqué-Castells, P.** (GEAP), **Mohnen, P.**

“Sunk costs, extensive R&D subsidies and permanent inducement effects”

(Maig 2012)

**XREAP2012-11**

**Boj, E.** (CREB), **Delicado, P.**, **Fortiana, J.**, **Esteve, A.**, **Caballé, A.**

“Local Distance-Based Generalized Linear Models using the dbstats package for R”

(Maig 2012)

**XREAP2012-12**

**Royuela, V.** (AQR-IREA)

“What about people in European Regional Science?”

(Maig 2012)

**XREAP2012-13**

**Osorio A. M.** (RFA-IREA), **Bolancé, C.** (RFA-IREA), **Madise, N.**

“Intermediary and structural determinants of early childhood health in Colombia: exploring the role of communities”

(Juny 2012)

**XREAP2012-14**

**Míguelz, E.** (AQR-IREA), **Moreno, R.** (AQR-IREA)

“Do labour mobility and networks foster geographical knowledge diffusion? The case of European regions”

(Juliol 2012)



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