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**PRELIMINARY VERSION NOT FOR QUOTATION**

# Moving People with Ideas
# Does inventors' mobility foster firms' innovative performance?

*(Provisional title)*

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**Abstract**

The mobility of knowledgeable individuals is the target of regional development policies at the European, national and local level. This paper aims to explore the impact of the inflows of inventors (as captured by patent data) on the innovative performance of firms (on the basis of UK-CIS data) located in recipient areas. The analysis is based on firm level (UK-CIS) data and looks at the inflows of inventors – as proxy for the internal mobility of knowledgeable individuals otherwise impossible to capture – in local labour markets. The standard firm level knowledge production function is extended in order to consider both firm level and area level characteristics. Estimations are based on a robust identification strategy that accounts for the potential endogeneity of inventors' inflows. The analysis suggests that the geographical relocation of knowledgeable individuals per se has no impact on firms' innovation. The availability of novel information coming from the mobility of knowledgeable individuals exerts a positive impact on innovation only after firm-level capabilities to exploit new sources of locally available knowledge are fully accounted for. Only those firms complementing internal sources of information with external flows are able to benefit from the increased availability of "innovative" individuals in the local economy. This suggests that policies targeting the spatial mobility of skilled individuals should be complemented by measures reinforcing the "receptiveness" of local firms.

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**Disclaimer**

## Introduction

Human capital is traditionally considered a key input in the generation of an innovative outcome because the production of new ideas is function of the number of ideas developed by each individual (*Lucas, 1988*). Human capital enhances the knowledge base of the economy stimulating the recombination of new and preexistent knowledge. As far as the micro level is concerned human capital is simultaneously a crucial input for firms' innovation process and an essential asset for the assimilation and productive use of external knowledge. This further implies that human capital accumulation has both a direct effect on micro level productivity and a positive effect on local aggregate productivity through externalities (*Moretti, 2004a*).

The individually embodied nature of human capital is a key aspect in understanding the rationale behind the spatial distribution of innovation. Once we account for the fact that "knowledge tends to travel along with people who master it" (*Breschi and Lissoni, 2001*) mobility in itself becomes a crucial input in the generation of innovative outcomes. The characteristics and intensity of these movements shape the geography of innovation and determine the patterns of winners and losers at both the macro-regional and micro-firm level.

Although there is a broad consensus on the positive correlation between the stock of available human capital and the generation of innovation, the mechanisms driving this effect remained relatively underexplored. In particular the empirical evidence on the role of spatial mobility of knowledgeable individuals - the primary channel for the diffusion of knowledge over space and accumulation/decumulation of human capital - is still mixed. Even if some authors found a positive impact of mobility of knowledgeable individuals on innovation (*Peri, 2005 2007, Chellaraj et al, 2008, Ozgen et al., 2011, Hunt et al, 2008*), others argued that this effect, more than being relevant per se, is substantially dependent on either the individual capability to recreate new networks relations in the host countries (*Breschi et al, 2010*) or on the organizational routines characterizing the firms operating in a certain geographical context (*Becker et al., 2005*).

The lack of univocal predictions is partly due to the fact that the empirical research on the link between mobility and innovation is recent and still affected by methodological flaws and limited data availability.
Existing studies look predominantly on the USA (*Ozgen et al, 2011*) and with the exception of a few recent contributions (*Miguelez and Moreno, 2010, Faggian and McCann, 2006, 2009, Gagliardi, 2011*) the issue remains largely unexplored in the

European context. In addition different studies focused upon different typologies of mobility (international vs. intra-national) and movers (recent graduates or highly skilled individuals or inventors) making any cross studies comparison of their results extremely difficult.

This paper looks at the internal mobility of inventors as a proxy for the mobility of "innovative", highly skilled individuals (otherwise impossible to capture with traditional data) and aims to assess its impact on the innovative performance of local firms in recipient regions. The focus on inventors' mobility makes it possible to disentangle the impact of a specific typology of movers that goes beyond the simple category of highly skilled individuals (in terms of formal educational achievements) and account for the effective capability to transform knowledge in economically valuable innovation. In addition the focus of the analysis on internal mobility across local labour markets make it possible to minimize the impact on the outcome of interest of any potential confounding factors such as the effect of an increase in ethnic and cultural diversity due to international migration migration.

The paper is organized as follows: the next session presents the theoretical background. Section 2 discusses the main methodological challenges in tracing mobility using patents data while section 3 analyses the spatial issues associated to the link of mobility and firms' innovative performance. Section 4 describes the main data sources and the procedure used to construct the key variables while section 5 discusses the methodological challenges related to the estimation of the effect of mobility on innovation. Section 6 reports the main results and section 7 concludes.

**Background**

The accumulation of human capital is fundamental to enhance regional productivity and innovative performance (*Lucas, 1988, Florida, 2002, Miguelez et al 2010*). People are the repositories of ideas and skills implying that their physical mobility over space is a primary channel of knowledge diffusion (*Herrera et al, 2010*). Countries, regions and cities are systematically competing for attracting knowledgeable individuals because within each geographical context the positive effect of human capital on local economic and innovative performance is significantly dependent on the possibility of accessing and using knowledge that spills over from other co-located actors (*D'Este et al., 2011*). This further implies that the positive effect associated to an increase in the availability of qualified human capital goes beyond the benefit internalized by each economic actor and it is magnified by the externalities associated to human capital accumulation (*Moretti, 2004a, Duranton, 2007, Gagliardi, 2011*).

The mobility of these individuals becomes the mechanism driving the competitiveness of different territories and shaping the geography of innovation. Those areas succeeding in developing themselves as "agglomeration centers for knowledge flows" (*Miguelez et*

*al, 2010*) represent the winners of the new economic landscape. Within these geographical contexts the knowledge holders engage with each other and with the local production system stimulating the exchange of new ideas and the exploitation of their economic potential in terms of firms' product and process innovation.
Firms, as key actors of the innovative process, take advantage of the availability of a qualified labour force and of the existence of a "contextually – enabling environment" for innovativeness (*Gleaser et al, 2010*). These dimensions, alongside with the peculiar characteristics and innovative attitude of each firm, significantly affect their likelihood of innovation.
This explains why the positive effect associated to the mobility of knowledgeable individuals goes beyond the standard learning by hiring mechanism (*Song et al, 2003, Lewis and Yao, 2006*), that allows the local production system to internalize human capital externalities through the labour market, exploiting those localization economies that Marshall (1890) primary associated to the "knowledge is in the air" paradigm.

Despite the broadly accepted rationale building on the potential transfer of skills and ideas accompanying the geographical relocation of knowledgeable individuals, the effect of mobility on innovation is far from being obvious and the possibility to recover reliable findings has to take into account the multiple processes that the mobility event involves and generates.
Human capital inflows tend to boost innovation transforming and enriching the local labour force (*Ozgen et al, 2011*) as well as generating valuable knowledge externalities coming from the exchange of ideas and skills among individuals.
On the other hand the effect of mobility on the skills' composition is only part of the story: inflows of people coming from different geographical areas may impact on the degree of ethnic and cultural diversity within the host economy (*Ozgen et al., 2011*) and this changing demography might significantly improve the generation of ideas taking advantage of a larger set of perspectives (*Nathan, 2011b*).
This latter dimension is however more controversial because the positive effect of diversity on innovation is theoretically less straightforward. Excessive diversity is often associated to an increase in transaction costs and social tensions and a potentially positive but concave relation may emerge (*Ozgen et al, 2011*). Finally disentangling between the skills' effect and the diversity effect may be empirically difficult due to both data availability and identification issues.

In order to control for the potential confounding factors associated to diversity and to provide reliable evidence on the direct effect of mobility in terms of changing in the skills composition it is necessary to specify the typology of flows that we are looking for.
The majority of the existent literature on the link between innovation and mobility looks at international migration. The role of internal mobility remained fairly unexplored due to, among other reasons, the difficulties in recovering a reliable indicator for internal flows.
Starting from the seminal work of Zucker, Darby and colleagues (1998a, 1998b, 2002, 2006, 2007) the investigation was focused on the geographic movements of star

scientists (often foreigners) in US and other countries and on their effect on the innovative activities of the host regions. The existence of a positive relation was further supported by studies on Canada (*Partridge and Furtan, 2008*), New Zeland (*Mare' et al, 2011*) and Europe (*Miguelez and Moreno, 2010*). However more recently some authors suggested that the positive evidence associated to international mobility is instead crucially mediated by the role of cultural diversity over and above the effect of migration on the local skills' composition (*Niebuhr, 2010, Lee and Nathan, 2011*).
The focus on international migration intrinsically implies the potential coexistence of both the skills' and the diversity effect. To overcome this limitation and to develop a more dedicated investigation on the role of mobility as mechanism of knowledge diffusion affecting the skills' structure of the host region, we decided to concentrate the analysis on internal mobility.

Alongside with the distinction between internal and international migration another relevant device within the existent literature lies in the characterization of movers. Looking in particular at the case of Britain some studies focused on the mobility of recent graduates (*Faggian and McCann, 2006, 2009*) while others qualified individuals in terms educational qualification looking at the category of highly skilled people (*Gagliardi, 2011*). Both approaches build on the idea that migration inflows stimulate innovation by enriching the knowledge base through new injection of human capital.
Allowing for a slightly different perspective of analysis some researchers have started to model mobility looking at the broader category of knowledgeable individuals interpreted as holders of economically exploitable tacit knowledge. Patent statistics were then used to trace the mobility of inventors (*Almeida and Kogut, 1999, Agrawal et al, 2006*, *Crespi et al, 2007, Kim et al, 2006, Breschi and Lissoni, 2009*).
More recently the attempt to link this mobility measure with local innovative performance has been developed (*Miguelez et al, 2010, Miguelez and Moreno, 2010*). However patent statistics were often used to construct both the variable of interest (e.g. mobility) and the dependent variable (e.g. innovative outcome) introducing a certain degree of circularity and mechanical correlation.

In order to exploit the broader definition of knowledgeable individuals and to focus on those skills that are likely to have a return in term of innovative performance of the local production system, in this paper we have chosen to maintain the emphasis on inventors' mobility. On the other hand to rule out the risk of redundancy we adopted a different measure of innovative output using firm data on innovation and innovation related activities as main dependent variable. The adoption of firms' based data allows among other things to provide a more reliable picture of the geography of innovation at a detailed geographical scale of analysis overcoming the traditional biases of patents data associated to sector and firm' size peculiarities. This is to the best of our knowledge the first attempt to relate patent data and data on firms' innovative performance to address the link between mobility and innovation at a meaningful geographical level of analysis.

**Tracing inventors' mobility using patens data**

The idea of using patents data to analyse the innovative process was extensively exploited within the economic literature (*Trajtenberg et al, 2006*). In particular several studies looked at patents data in order to shed some more light on the effect associated to the mobility of star scientists (*Stolpe, 2001, Rosenkopft and Almeida, 2003, Singh, 2003, Song et al, 2003, Hoisl, 2006, Breschi and Lissoni, 2009, Miguelez and Moreno, 2010 Miguelez et al, 2010*).

Focusing on mobility and related issues the potential advantages coming from patents data are primarily associated with the possibility to exploit individual based information and to trace mobility at a very detailed geographical scale. This is a relevant feature because data on internal mobility and in particular on the mobility of knowledgeable individuals are often difficult to recover especially for specific spatial contexts.
Despite that the adoption of patents data as main data source to trace the mobility of inventors presents a number of shortfalls that need to be addressed.

*Who's who problem*
One of the key feature regarding patents data relates to the exact identification of the inventors. The name of the inventors could be sometimes misspelled or misreported leading to serious problems in the association of different patents to the same individual in the case of multi-patenting inventors (*Trajtenberg et al, 2006*).
This is a key concern when patents data are used in order to trace the mobility of knowledgeable individuals because, due to the characteristics on the data, mobility can be recovered only for those inventors patenting different times in different locations.
In order to deal with this problem we referred to the KEINS database (*Lissoni et al, 2006*) containing all EPO applications. The database represents a "cleaned version" of the raw EPO data treated in order to solve the problems associated to the misreporting/ misspelling of inventors' names[1].

*Identification of movers*
Patents data report detailed geographical information on patenting inventors referring either to the time when the inventor filled the application (priority date) or that related to the registration of the patent.
Geographical information on inventors' residence are reported at postcode level and then available to be assembled at any other spatial scale.

[1] see Lissoni et al, 2006 for further information on the cleaning procedure
[2] The average number of patents is 7.87 for movers and 6.05 for non-movers (note both movers and non-movers are referred to the subsample of multi-patenting inventors).
[3] At least the 75% of people leaving in the area work in the same geo- unit
[4] Almost the 70% of our total sample of firms is classified as small or medium enterprise

As discussed, due to the characteristics of these records it is possible to trace the mobility only in respect to multi-patenting inventors, namely those that patented different times in different locations.

This further implies that we can focus only on a specific typology of inventors and that we are unable to recover information on the potential mobility of single-patenting inventors.

The obvious consequence of this evidence relates to the fact that we implicitly refer to a measure of mobility that could be considered a lower bound for the total population of inventors and a precise measure only for a specific segment (multi-patenting inventors) of the total sample.

*Inventors' characteristics*

A further issue relates to the need of controlling for inventors' characteristics in particular in respect to differentials in inventors' productivity (*Hoisl, 2006*). Despite being beyond the scope of this paper we will deal with that to rule out any doubt regarding the possibility that a sorting mechanism is driving the effect of mobility on innovation. We will address this issue providing some robustness checks of our main results based on the inventors' past history. This implies that we will explicitly take into account individual peculiarities potentially affecting the relation between inventors' mobility and the innovative performance of those economic actors (local firms) operating in the geographical context where these inventors are relocating.

In doing that we will control for the potential truncation bias (*Latham et al, 2011*) associated to the omission of years of activity in the calculation of our measure of duration of patenting careers by restricting the analysis to those inventors that moved within the time span 2000-2007 and constructing the measure of inventors' productivity considering the whole patent history of each individual inventor starting from 1977.

Within our sample of multi-patenting inventors about the 2.6% were identified as effective movers (people that changed their residential address). An in depth analysis of our subsample of movers showed that they are on average as productive as the non-movers[2] suggesting that any potential effect of mobility is likely to be not systematically dependent on selection issues. This is a particularly relevant characteristic of our data because it contributes to support the reliability of our analysis ruling out the potential concerns associated to the existence of differences in productivity as key omitted variable in our estimation.

Finally in the evaluation of our analysis it is important to bear in mind that both the *Who's who problem* and the limitations associated to the *Identification of movers* might generate an underestimation of the magnitude of the flows. From one side the KITES database is fairly conservative implying that similar names are generally associated to the same inventors even if the matching score is not perfect. From the other the

[2] The average number of patents is 7.87 for movers and 6.05 for non-movers (note both movers and non-movers are referred to the subsample of multi-patenting inventors).

characteristics of patents data do not allow to recover information on the potential mobility of single patenting inventors. The estimation of the overall effect of inventors' mobility is then likely to be affected by an attenuation bias contributing to underestimate the effective magnitude.

**Linking inventors mobility and firms' innovative performance: spatial issues**

The analysis of the effect of mobility on firms' innovation is based on the classical Knowledge Production Function (KPF) approach popularized by Griliches (1979, 1986) and Jaffe (1986). The key feature of this model is the assumption that the innovative performance of each firm can be explained by the amount of internal inputs (mainly capital and labour) devoted to the innovative process.
This theoretical framework looks at innovation as an a-spatial process generally unaffected by issues such as location and geography (*Audresch, Feldman, 2004*).
However the rediscovery of the role of locational factors (*Audretsch, 2003; Audretsch and Feldman 1996; Crescenzi et al., 2007; Feldman, 1994; Fritsch, 2002)* and the need of accounting for the externalities associated to these context specific peculiarities (*Moretti, 2004, Duranton, 2007, Gagliardi, 2011*) opened up new perspectives on the analysis of innovation.

Following this background this paper will treat the mobility of knowledgeable individuals and in particular the inflows of inventors within the geographical context where firms are located as a key potential determinant of their innovative performance. From the methodological point of view this implies adopting a "spatial correlation approach" (*Borjas, 1999*) assuming that the effect of mobility on a certain dependent variable can be identified from the spatial correlation between inflows and changes in the outcome variables within each geographical unit of analysis.
The rationale of this choice lies on the idea that areas characterized by relevant inflows of knowledgeable individuals will benefit from their relocation.
The underlying mechanism driving this effect relies to the potential raise in the creativity and productivity of local interactions (*Mare' et al, 2011*). However the channels through which it may operate are multiple. Inflows of inventors and star scientists may increase the availability of research workers for each firm meaning that the positive externality associated to the inflows of knowledgeable individuals is internalized by the labour market. Alternatively the positive effect of mobility on innovation may be associated to less formal interactions based on face to face contacts between individuals within the same geographical context (*Storper and Venables, 2004*) meaning that a pure externality dynamic is the one at play.

The definition of the geographical unit of analysis where these localized formal and informal interactions take place is a key methodological choice.
This paper analyses the link between mobility of inventors and the innovative performance of local firms using English data. As previously discussed the main focus of

our investigation is on the role of internal or within country mobility rather than immigration. The reasons why we restricted the analysis to England instead of considering the whole Britain lies on the characteristics of our mobility data. Focusing explicitly on mobility of multi-patenting inventors the English sample represents a more reliable proxy. About the 80% of the total number of inventors operating in Britain is English accounting for more than the 80% of the total number of patents developed between 2000 and 2007 in the whole country. Most of all about the 95% of detected movers are changing their residential location within England. This preliminary evidence suggests that England can be considered a good representative sample to investigate the mobility of inventors.

Within England we selected the full sample of Travel to Work Areas (TTWAs) as geographical scale of analysis. TTWAs are functional units including both urban and non-urban areas and constructed in order to be self-containing labour markets[3]. Statistics at TTWAs level are referred to people living and working in each specific area implying that any potential relocation of knowledgeable individuals account for people that changed permanently their residence. Most of all the adoption of TTWAs as unit of analysis allows accounting for both formal (market mediated) and informal (non-market mediated) interactions.

In order provide some additional information on the spatial patterns of our mobility measure we developed an in depth analysis of the geographical extend of mobility. By construction the 100% of our movers changed TTWA of residence, the 54.2% moved in a different NUTS3 region, the 47.9% in a different NUTS2 region and the 31.3% changed NUTS1 region of residence. This additional check supports the reliability of our mobility measure confirming that we are not systematically focusing on individuals changing only marginally their residential location but on effective movers.

A similar methodological choice was adopted in other empirical analysis on the impact of migration in Britain. In particular Nathan (2011a) analysing the long term impact of international migration on wages, unemployment rate and houses prices in British cities used urban TTWAs as geographical scale of reference.

The analysis is then performed adopting a firm based KPF approach augmented by our regressor of interest (inflows of inventors). This implies that each firm is located in the relevant TTWA and that we will look at the effect of inventors' inflows within each TTWA on the innovative performance of local firms.

**Data**

The analysis is based on a novel dataset constructed using the CIS (Community Innovation Survey) and the KITES database on patents as key data sources.

[3] At least the 75% of people leaving in the area work in the same geo- unit

The CIS is a firm level survey on innovation and innovation related activities. It allows recovering data on firms' innovative performance in respect to different types of innovation (product, process and organizational). The main advantage associated to the CIS in respect to other measures of innovative performance (such as for example patents data) is the availability of detailed information on the amount of inputs devoted to the innovative process (Capital and Labour) and a large range of firms' characteristics (such as size, sector of activity etc.).
The survey is constructed in order to build a balanced sample among all the sectors of activity reducing the traditional bias of patents data toward some specific highly innovative sectors. Moreover the sample of firms tend to be based on small and medium enterprises[4] implying that the analysis is likely to be focused on a typology of innovation that is substantially different from that examined by using patents data. These peculiarities suggest the possibility of unexpected results in respect to the traditional empirical literature using patents data as main data source.

In order to exploit the longest available time series, avoiding the elimination of too many observations, two waves of CIS have been merged: CIS4[5] and CIS2007[6]. This procedure allows for the creation of a sample of 2,212 firms that are present in both datasets[7]. Previous research using CIS data focused on a single wave. The rationale of this choice reflects the possibility to control for time invariant fixed effects otherwise affecting the robustness of the results.
The obvious drawback is related to the elimination from the final sample of a large number of observations. However further analysis on the sample of excluded firms confirmed that the selection criterion was not systematically affected by firms or area specific characteristics such as the sector of activity, the size of the firm, the region where the firm is located[8] and its product or services specialisation[9]. This additional test supports the robustness of the sample used for the analysis.
In order to recover detailed info on the geographical location of each firm, the final sample of firms coming from the CIS4 – CIS2007 databases was merged with the BSD2004 database[10]. For each firm present in the former sample it was possible to obtain the 7-digit postcode determining its exact location in space. This allows for the identification of the TTWA in which each firm is located.
Data coming from the CIS were used in order to construct the dependent variable (dummy variable taking values 1 if the firm is performing any product or process innovation and 0 otherwise) and the firms' based controls.

[4] Almost the 70% of our total sample of firms is classified as small or medium enterprise
[5] Based on the time interval 2002-2004
[6] Based on the time interval 2005- 2007
[7] The inclusion of other waves of CIS was avoided because of the limited number of common observations.
[8] NUTS 1 level
[9] Descriptive statistics about the sample of excluded firms are not reported in the paper but are available on request
[10] The Business Structure Database (BSD), derived from the Inter-Governmental Department Business Register (IDBR), covers the 99% of economic activity in UK and provides geo- referenced firm- based data with 7 digits postcode

The KITES dataset was exploited in order to build our key regressor, namely inventors' mobility. We computed a number of key methodological choices in order to construct a measure of mobility coherent with our theoretical framework.

We restricted the analysis to the time span 2000-2007 considering all the inventors that moved within this temporal window. This methodological choice is likely to exacerbate the problem associated to the underestimation of flows increasing the potential attenuation bias. However due to the characteristics of patents records, the restriction of the time window to a specific period is the only way in order to have a precise idea of the timing associated to each mobility "event", namely the identification of the exact point in time when each inventor changed its residential location.

This is a particular relevant point considering that we are interested in limiting the influence of any alternative confounding factor that can affect the relation between mobility and innovation over a much longer time span.

The identification of the inventors associated to the selected time span is based on priority date that is considered by OECD the closest to the actual time of invention (*OECD, 2009*).

Within this time window we further adopted a specific temporal criterion in order to merge the data on mobility with our measure of firms' innovative performance coming from the CIS. In particular we associated to each wave of CIS a lagged measure of inventors 'inflows. This implies that those inventors who moved within the time span 2000-2002 were associated to the first wave of CIS[11] while inventors who moved between 2003 and 2005 were associated to the second wave[12]. This choice is driven by our interest in accounting for recent mobility and on the assumption that the comprehensive effect of mobility on local innovative performance has to be evaluated in the short/medium term.

We created different measures of mobility starting from the basic criterion of inflows' count.

The main variable used for our analysis is a dummy taking value 1 if the firm is located in a TTWA experiencing inflows of inventors and 0 otherwise.

In order to deal with potential differences in the productivity level of movers we constructed an additional mobility measure. The share of inventors weighted for the productivity index[13] (calculated based on the number of patents developed by each inventor during the whole career) in respect of the number of "innovation active" resident inventors[14] in each TTWA is taken as proxy for the productivity of movers.

[11] 2002-2004

[12] 2005-2007.

[13] The productivity index will take values between 0 and 1 and is calculated considering for each inventor the actual number of patents minus the number of patents developed by the highest productive inventor within the sample of movers over the number of patents developed by the highest productive inventor minus the number of patents developed by the lowest productive inventors within the same sample of movers.

[14] The number of resident inventors is calculated looking at those inventors that patented in each TTWA between 2000 and 2002 and 2003 and 2005 respectively and that can be considered "innovation active" within our relevant time windows. The rationale of this choice lies in the coherence between our measure of mobility, restricted to recent

The adoption of this variable as additional robustness check allows providing evidence on the reliability of our results in respect to any concern associated to the existence of a systematic sorting mechanism based on the "quality" of movers.

The preference toward the binary variable as key regressor in respect to a measure of actual flows relies to a number of considerations. The main aim of this paper lies in the investigation of the role of mobility as exogenous event rather than on the peculiarities and magnitude of flows. The binary structure of the variable is aimed at being a representative proxy for the phenomenon of interest (i.e. the mobility of knowledgeable individuals) without claiming a specific focus on the quantitative and qualitative dimension of the actual flows[15]. This is partially justified in the light of the peculiar characteristics of patents data and the restrictive approach adopted for the creation of our mobility variable. Despite being a reliable proxy for the phenomenon under consideration our data are likely to underestimate significantly the real magnitude of our flows exacerbating the attenuation bias associated to the adoption of a continuous measure.

The full list of variables is reported in table 1.

**Methodology**

The analysis on the link between inventors' mobility and the innovative performance of firms located in the area of destination of such flows is performed building on the firm based KFP approach (*Griliches, 1979, 1986, Jaffe, 1986*) augmented by our regressor of interest.
Due to the binary nature of our dependent variable we will refer to the standard *Linear Probability Model* (LPM) in estimating the relationship between the inflows of inventors and the probability of firm innovation.
This methodological choice relates to the identification of the potential endogeneity bias coming from omitted variables and reverse causality as first order concern and to the possibility to deal with them more reliably in a linear context.
In particular the issue associated to the reverse causality between innovation and mobility is crucial within the literature on the return of migration. Our main theoretical assumption builds on the idea that the inflows of knowledgeable individuals in a specific geographical context may affect the innovative performance of local firms through their effect on the degree of creativity and productivity of local interactions (*Mare' et al, 2011*). The mobility of inventors becomes the channel through which knowledge tends

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movers, and the measure of stock in each TTWA that need to be restricted only to those resident inventors being "active" in the same time period.

[15] The systematic investigation of the magnitude and qualitative composition of the mobility flows is beyond the scope of the paper. These aspects will be only marginally investigated to support the reliability of our findings in respect to any potential bias coming from systematic differences in these two dimensions.

to travel across different regions and local areas broadening the geographical scope of those knowledge externalities that are on the root of the emergence of novel ideas (*Duranton, 2007*).
However this could be only part of the story. It is in fact reasonable to assume that causality may run in the opposite way. Highly innovative firms and the spatial contexts where they are located may be able to attract a larger number of knowledgeable individuals that are more likely to engage with better job opportunities and greater occasions of exchanging valuable knowledge.

The first best solution to deal with both the omitted variables and reverse causality bias refer to the possibility to adopt a panel structure controlling for firm and TTWA fixed effect and to estimate the relation through 2SLS estimation.
Unfortunately due to the availability of a short time dimension a panel model with firm fixed effect could be problematic. The fixed effect estimation allows only for the identification of the marginal effect and only for time varying regressors (*Baltagi, 2005*). In our case dealing with just two consecutive waves of CIS the within variation could be insufficient in order to estimate our relation of interest.
To overcome this limitation, that is not uncommon among studies based on survey data, we will estimate our regression of interest using repeated cross section of independent waves (*Cameron and Trivedi, 2005*) further controlling for TTWAs, time and sectoral dummies plus a number of relevant firm level controls to minimize the risk of omitted variables at firm level. Furthermore we will account for the structure of the data clustering the standard errors at firm level.

The risk associated to the reverse causality bias is minimized through the construction of a measure of mobility that looks at the inflows of individuals in the beginning of each period, meaning that we are using a lagged measure of mobility in respect to the timing of our dependent variable.
Finally to further rule out any concern on this latter issue we will adopt an instrumental variable approach (2SLS) which implies finding other measured variables that are likely to be correlated with inflows, but not otherwise associated with the dependent variable through unobserved local characteristics.

The main estimation equation will take the following form:

$$P\left(Innovative\ performance^{i}_{c,t-T}\right) = \qquad (1)$$
$$\beta_0 + \beta_1 K^{i}_{c,t-T} + \beta_2 L^{i}_{c,t-T} + \beta_3 Inventors' Inflows^{i}_{c,t-T} + \beta X_{c,t-T} + \delta_c + \delta_{t-T} + \varepsilon^{i}_{c,t-T}$$

Where:

- $P(Innovative\_performance^{i}_{c,t-T})$ is the probability of performing any innovation[16] for firm *i* located in TTWA *c* within the period *t-T*[17];

[16] Firms performing any product or process innovation.
[17] Time spans correspondent to each CIS wave: 2002-2004 and 2005_2007.

- $K^{i}_{c,t-T}$ is the amount of intramural expenditures that each firm *i* located in TTWA *c* within the period *t-T* devoted to the innovative process;
- $L^{i}_{c,t-T}$ is the is the number of high skilled workers[18] that each firm *i* located in TTWA *c* within the period *t-T* performing innovation related activities
- $Inventors\_flows^{i}_{c,t-T}$ , the regressor of interest, is the inflows of inventors (calculated as discussed in paragraph 4) within each TTWA at the beginning (*t*) of each time interval *t-T*;
- $X^{i}_{c,t-T}$ is a vectors of additional controls for firm *i* located in TTWA *c* within the period *t-T*;
- $\delta_{c}$ and $\delta_{t-T}$ are TTWA and time dummies respectively;
- $\varepsilon^{i}_{c,t-T}$ is a well behaving idiosyncratic error term.

In respect to the choice of the instrument a number of alternative possibilities were considered within the (still limited) literature on the causal link between inventors' mobility and innovation.
Hoisl (2006) looked at whether the invention was made in a large city or rather in a rural area assuming that inventions made in large cities should have a greater signalling effect leading to a higher probability of getting an alternative job offer by a competitor.
Miguelez and Moreno (2010) adopted spatial econometrics techniques using the spatial lag of the additional regressors to instrument mobility.

We decided to adopt a different perspective identifying a novel instrumental variable. The main rationale behind our identification strategy builds on the idea that inflows in each TTWA *i* may be instrumented by the push factors operating in others TTWAs *j*. To construct our instrument we refer to the characteristics of the inventions developed in other TTWAs exploiting the nexus between the quality of these inventions and the increasing visibility for the inventor coming from the development of a successful invention.
For each TTWA *j* we calculated the index $Cit^{j}_{t,t+1}$ as the number of citations in the 12 months after the publication for those patents published the year before our mobility event[19] over the total number of patents published in the same period:

$$Cit^{j}_{t,t+1} = \frac{Number\ of\ Citations^{j}_{t,t+1}}{Number\ of\ Patents^{j}_{t,t+1}}$$

The instrument is then constructed comparing for each TTWA *c* the magnitude of our $Cit^{c}_{t,t+1}$ index with the average number of citations per patent in the 12 months after the publication at the national level during the time span 1995-2007.

[18] Personnel with a degree in science or technology
[19] 1999 and 2002 respectively

Computationally it will take the following form:

$$Citations_t^i = \frac{(Cit_{t,t+1}^j - \frac{Number\ of\ Citations_{1995,2007}}{Number\ of\ Patents_{1995,2007}})}{\frac{Number\ of\ Citations_{1995,2007}}{Number\ of\ Patents_{1995,2007}}} * W_{ij}$$

Where $W_{i,j}$ is an inverse distance matrix between each TTWA *i* and all the other TTWAs *j*.

The reasoning behind the adoption of this instrument lies on the idea that a disproportionate increase in the number of recent citations in respect to the medium term average national trend might be interpreted as a signal for the recent development of highly successful inventions. The immediate payoff of that highly successful invention may be associated with greater visibility and greater opportunities of mobility and job offers. In this sense a highly successful invention may be interpreted as an individual push factor increasing the probability of mobility independently of the degree of attractiveness and the innovative performance of specific firms in specific spatial contexts. This economic rationale is indirectly supported by previous related research showing that inventors characterized by more valuable patents (i.e most cited patents) are those with the highest probability of inter-firm mobility (*Trajtenberg et al., 2006*), suggesting that the development of highly successful invention tends to have a strong signalling effect and to open up new job opportunities.

From the methodological point of view the focus on the forward citations received in the 12 months after the publication of the patent is consistent with our interest on the potential signalling effect coming from the recent development of a valuable invention. The choice of the national level as reference term, apart from being justified by its exogenous nature in respect to any local path dependent pattern, allows focusing on those inventions receiving relevant attention outside each local area. Finally the selection of a time interval spanning from 1995 to 2007 ensures that the peak in the number of citations experienced by a certain area represents a unique phenomenon in time (reasonably connected to the development of highly successful inventions) rather than a consolidated trend prior or post our “temporal window”. This latter consideration is particularly relevant to justify the goodness of our identification strategy. It allows qualifying the instrument as exogenous shock with a specific temporal dimension ruling out any potential concern on the possibility that the instrument itself could work as proxy for neighbouring effects and spatial spillovers resulting in a potential break of the exclusion restrictions.

The estimation performed controlling for time, TTWA and sectoral dummies and adopting the instrumental variable approach to deal with the reverse causality between mobility and innovation is likely to solve some key methodological problems.

Despite that we are aware of the fact that the estimation of our relation using a linear model is subject to a number of critics and it may misrepresent the true structure of the relationship between our variables of interest. In order to overcome this methodological limitation and to provide evidence on the robustness of our results we will alternatively estimate our equation adopting a *Control Function* (CF) approach popularized by River and Vuong (1988) and Blundell and Powell (2003). The CF approach consists in a two stage estimation procedure. In the first stage we estimate through *Ordinary Least Squares* (OLS) the relation between our regressor of interest (e.g. mobility) and the instrumental variable. In the second stage the estimation of our full equation augmented by the residuals from the first stage regression will be run adopting techniques for non-linear models[20].

Note that the standard 2SLS estimation using the LPM is robust to misspecification in the first stage whereas the two stage approach is not. This further implies that despite being more efficient than the LPM estimator[21], the CF approach may be subject to potential inconsistencies. This explains why we will use it as an additional robustness check to verify the reliability of our main estimation results.

## Results and robustness checks

The main results for the estimation of the effect of inventors' mobility on the innovative performance of English firms are reported in Table 2.

In column 1 we estimate the standard firm based KPF (adopted as baseline model) controlling for the amount on intramural investment in R&D, the share of employment with degree and the dimension of the firm. Results confirm the relevance of financial investment in innovation related activities as well as the importance of firm size. Both variables are highly significant showing the expected sign. Interestingly enough we do not find any significant effect associated to the employment variable. This result relates to the peculiar characteristics of the CIS sample of firms strongly skewed towards small and medium enterprises with a reasonably limited hiring capacity.

Column 2 introduces our key variable of interest constructed in order to take value 1 if the firm is located in a TTWA that experienced inflows of inventors during the time span under analysis. Results confirm that the inflows of inventors affect positively and significantly the innovative performance of local firms. Our key regressor shows a positive and significant correlation (at 1% level) with the dependent variable.

[20] The second stage estimation is performed using the firthlogit command to deal with separation problems. Note that the conventional response to separation problems is to drop from the analysis those observations that generate the problem (Long and Freese 2006). This is sensible when the separation reflects a real causal process, but in the analyses. In the analysis performed it is more likely that it reflect the fact that we are trying to look at a fairly rare outcome (mobility) in respect to a peculiar group of firms (e.g. those performing product or process innovation). Dropping cases to avoid separation could reduce the sample size making it difficult to compare models.

[21] The CF estimator is in fact equivalent to the LIML estimator in the case of exact identification and it has to be preferred to the IVProbit estimator in terms of efficiency gains (see Rivers and Vuong, 1988 and Blundell and Powell, 2003 for further discussions).

In order to test for the robustness of our results we insert progressively a number of firm level controls: reference markets as proxy for export orientation (Column 3) and a full set of sectoral dummies (Column 4). As expected those firms characterized by a more significant orientation toward export tend to have a better innovative performance. The magnitude and significance level of our main variable of interest, namely inventors' inflows, remain generally unchanged confirming that it tend to be robust to the inclusion of additional and relevant firm level controls. The last two columns (Columns 5 and 6 respectively) include among the controls time and TTWA dummies. Interestingly enough this inclusion reduces the significance level of our variable of interest from 1% to 10% suggesting that local characteristics may play a relevant role in the analysis of the effect of mobility on the innovative performance of local firms and that potential omitted variables at TTWA level are likely to be a more relevant concern within our empirical framework.

This result deserves a deeper analysis. In first instance we tested if there is any additional effect associated to the qualitative composition of our flows. We restricted the analysis to those firms located in TTWAs that experienced inventors' inflows[22] including among the regressors our mobility measure weighted by productivity. Results reported in table 3 confirm that there is no additional effect associated to the composition of flows in terms of differentials in the productivity level of the movers (Column 2).

Despite that it is still questionable whether the results obtained through OLS can be considered a reliable and unbiased estimation. Although the potential endogeneity bias associated to omitted variables and reverse causality is likely to be minimized by the inclusion of a full set of controls and time and area fixed effect and by our lagged measure of mobility, there is still the concern that the causality between mobility and innovation could work in the opposite direction. To rule out any doubt we performed a 2SLS estimation were our key variable of interest, namely inventors' inflows, is instrumented by our citations' based instrument.
Results reported in table 4 do not confirm the relevance of our key variable suggesting the lack of a statistically significant effect on firm' innovation coming from the mobility of inventors once the potential endogeneity bias is controlled for.
The first stage regression (Table 5) shows the expected sign supporting the validity of our instrument and the first stage statistics (Table 6) confirm that the IV strategy performed is not affected by any potential weak instrument bias. This result is consistent based on both the rule of thumb proposed Staiger and Stock (1997) and the thresholds values developed by Stock and Yogo (2005).
To test the reliability of our instrumental variable we checked whether the instrument is systematically correlated with the other regressors included in our main specification. Results reported in table 7 confirm that our citation index is not significantly correlated with any other regressor in the estimation equation.

[22] those for which our shock variable takes value 1

To further deepen the understanding of our findings we split the dependent variable distinguishing between process and product innovation and performing the IV estimation on the new specification. The intrinsic nature of the knowledge flows associable to our mobility measure, focusing on people performing patentable innovations, is likely to have a more direct link with product rather than process innovation. To test whether this affect the significance of the estimates we run two separate regressions (Table 8) reporting the results for product (Column 1) and process innovation (Column 2). Interestingly enough despite being reasonable, due to the typology of inventive activities of our movers, to find a greater impact on product innovation we didn’t find any statistically significant additional effect in our data.

Finally to check whether the result is dependent on misspecification of our key relations we re-run our IV regression adopting the *Control Function* approach (CF). Results reported in table 8 confirm that our regressor on interest is positively correlated to firm innovative performance but is not statistically significant. The significance level of the other variables remains generally consistent with our 2SLS estimates reported in Table 4 further confirming that our finding are not systematically driven by potential misspecification of our estimation equation.

The lack of effect associated to the mobility of inventors' seems to be a robust feature in our sample. However this result deserves a more in depth analysis.
As previously argued the mobility of knowledgeable individuals is broadly recognized as a relevant channel for knowledge diffusion. In spite of that it is reasonable to assume that the payoff of this increasing availability of new knowledge can be effectively translated in economically viable innovations if and only if local firms develop the capability to exploit these new sources of information.
There is an extensive and relevant literature aimed at investigating how different firms' attitudes toward the exploitation of different sources of knowledge affect their innovative performance. Some scholars suggested that valuable information are still exchanged through internal mechanisms and that firms tend to internalize through labour contracts the benefit coming from mobile workers (*Song et al., 2011*). There is however a growing literature building on the role of knowledge externalities suggesting both that the potential benefit of knowledge flows coming from mobility cannot be fully internalized through the "learning by hiring" mechanism and that firms tend to increasingly relying on external sources of knowledge to develop their innovation activities. In this context mobility is often viewed "as a proxy to mediate useful domain knowledge across different companies" (*Breschi and Lissoni, 2005, Song et al, 2011*) and to create new valuable networks.
This latter feature could be a potentially relevant issue within the CIS sample that is generally characterize by a great proportion of small and medium businesses reasonably characterized by a limited hiring capacity and increasingly reliant on alternative market sources of novel information (*UK Data Archive Studies, 2008*).
To test whether differences in the firms' attitude to take advantages from external sources of knowledge may affect the capability to exploit novel information coming

from the mobility of inventors and whether these differences could determine the emergence of potential heterogeneous effects, we restricted the analysis to those firms declaring that they are significantly exploiting "external market sources"[23] of information.

Interestingly enough when we focus on those firms that are more likely to consider external knowledge as additional valuable source of information the effect of mobility on innovation becomes positive and significant at 5% level (Table 10). In particular for those firms exploiting external sources of knowledge the benefit coming from being located in an area experiencing inventors' inflows is likely to increase by 11% the probability of innovation. The reasons behind this greater effect could be dependent on both the quantity and quality of information acquired. It is reasonable to assume that the benefit coming from inflows of knowledgeable individuals, such as inventors, cannot be fully internalized by firms (especially small and medium businesses) and that those referring mainly or exclusively to internal sources of information are more likely to miss relevant opportunities. At the same time external sources of information tends to be characterized by a greater degree of novelty reducing the cognitive lock in that may derive from a too strong focus on internal skills.

Note that our IV strategy results tend to be highly robust even considering the restrictive sample. First stage results reported in table 11 and 12 confirm that the instrument remain significantly correlated with our regressor of interest.

## Conclusions

The paper examines the effect of inventors' mobility on the innovative performance of English firms. The main underlying hypothesis builds on the idea that inflows of knowledgeable individuals might favour the circulation of valuable, individual embodied tacit knowledge operating as channel for knowledge diffusion.

The estimation of this effect is however challenging. Our measure of inventors' mobility coming from patents data is focusing by construction on a specific segment of inventors implying a potential underestimation of the actual flows. We minimized this concern adopting as key measure a binary variable rather than a continuous measure of flows but the magnitude of our estimates have still to be interpreted with caution. Furthermore the characteristics of our dependent variable and the limitations associated to the adoption of survey data affected significantly the choice of our estimation strategy.

The paper does not find a significant effect of inventors' mobility on the full sample of English firms. Despite being positively correlated to innovation our variable of interest,

[23] with reference to the question regarding the importance of different sources of information in the development of innovation we selected those firms rating 2 or 3 is a scale from 0 to 3 the category "market sources of information" that includes suppliers, clients, customers, competitors, other businesses in the industry, consultants, commercial labs and private R&D institutes..

namely inventors' inflows, becomes statistically insignificant once we control for time and area fixed effects and we take into account the potential endogeneity coming from additional omitted variable at firm and area level and reverse causality.
However the analysis demonstrates that once the sample is restricted to those firms showing a specific attitude toward the exploitation of alternative external sources of knowledge the effect of inventors’ inflows becomes statistically significant. As previously emphasized in the evaluation of the magnitude and the significance level of the effect it is still necessary to bear in mind that the key features of patents data when used to trace mobility and the restrictive temporal criterion adopted to construct our mobility measure are likely to underestimate the true value producing a certain degree of attenuation bias in our estimates. This further implies that our results should be considered a sort of lower bound estimate of the real effect.

We interpreted this empirical evidence as suggestive indication for the emergence of heterogeneous effects associated to peculiar firm' characteristics. The availability of novel information due to the relocation of knowledgeable individuals seems to be not relevant per se; it just becomes a significant input once we account for the effective capability of local firms to take advantage from this new available knowledge exploiting addition external sources of information to complement internal skills.
Finally these findings could be interpreted as an indirect, preliminary evidence for the mechanisms through which the externalities coming from the relocation of knowledgeable individuals affect the local environment. We argue that the additional effect on those firms exploiting more extensively external sources of information rather than just internal knowledge might suggest that the dynamic at play is more reasonably based on a pure externality mechanism rather than on internal employment channels. This finding is coherent with the characteristics of our firm level data mainly based on small and medium enterprises that are probably facing greater financial constraints in their hiring capacity.

More research is needed to overcome the relevant challenges associated to the endogeneity of mobility measures as well as to disentangle more precisely the dynamics at play at the local level. The reliability and quality of future research will improve alongside with the quality of data.

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**Tables**

**Table 1: List of key variables**

| *Variable* | *Description* | *Year* | *Source* |
|---|---|---|---|
| *Product or Process Innovation* | Dummy variable taking value 1 if the firm developed any product or process innovation | 2002-2004<br>2005-2007 | CIS4 - CIS2007<br>ONS |
| *Product Innovation* | Dummy variable taking value 1 if the firm developed any product innovation | 2002-2004<br>2005-2007 | CIS4 - CIS2007<br>ONS |
| *Process Innovation* | Dummy variable taking value 1 if the firm developed any process innovation | 2002-2004<br>2005-2007 | CIS4 - CIS2007<br>ONS |
| *R&D* | Dummy variable taking value 1 if the firm is performing any intramural investment in R&D | 2002-2004<br>2005-2007 | CIS4 - CIS2007<br>ONS |
| *Employment with degree* | Share of employees with a degree | 2002-2004<br>2005-2007 | CIS4 - CIS2007<br>ONS |
| *Sme* | Dummy variable taking value 1 if the firm is define as small or medium enterprise | 2002-2004<br>2005-2007 | CIS4 - CIS2007<br>ONS |
| *National mkt*<br>*European mkt*<br>*International mkt* | Dummy variables taking value 1 if the firm has the national, European or international arena as main market of reference (local market as baseline) | 2002-2004<br>2005-2007 | CIS4 - CIS2007<br>ONS |
| *Inventors' inflows* | Dummy variable taking value 1 if the firm is located in a TTWA that experienced inflows of inventors. | 2000-2002<br>2003-2005 | KITES Database<br>CESPRI |
| *Inventors' inflows (weighted productivity)* | Share of inventors' inflows in each TTWA weighted by inventors' productivity over the number of "innovation active" resident inventors in each TTWA. | 2000-2002<br>2003-2005 | KITES Database<br>CESPRI |

**Table 2: OLS Results**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dep. Var.: **Process or Product Innovation** | **OLS** | **OLS** | **OLS** | **OLS** | **OLS** | **OLS** |
| **R&D** | 0.469*** | 0.469*** | 0.416*** | 0.391*** | 0.398*** | 0.392*** |
| | (0.0145) | (0.0145) | (0.0161) | (0.0166) | (0.0165) | (0.0167) |
| **Employment with degree** | 0.0084 | 0.0077 | 0.0047 | 0.0015 | 0.0018 | 0.0015 |
| | -0.0059 | -0.0056 | -0.0049 | -0.0041 | -0.0044 | -0.0043 |
| **Sme** | -0.0392** | -0.0372** | -0.0282* | -0.0414** | -0.0409** | -0.0382** |
| | (0.0166) | (0.0166) | (0.0165) | (0.0171) | (0.0171) | (0.0174) |
| **Inventors' inflows** | | 0.0452*** | 0.0432*** | 0.0456*** | 0.0297* | 0.0415* |
| | | (0.0165) | (0.0162) | (0.0163) | (0.0163) | (0.0215) |
| **National mkt** | | | 0.0548*** | 0.0317* | 0.0340* | 0.0373** |
| | | | (0.0177) | (0.0184) | (0.0184) | (0.0185) |
| **European mkt** | | | 0.0607*** | 0.0463** | 0.0510** | 0.0482** |
| | | | (0.0216) | (0.0220) | (0.0220) | (0.0221) |
| **International mkt** | | | 0.0698*** | 0.0496** | 0.0468** | 0.0392* |
| | | | (0.0215) | (0.0222) | (0.0222) | (0.0223) |
| **Constant** | 0.250*** | 0.240*** | 0.173*** | 0.0809 | 0.127 | -0.0401 |
| | (0.0155) | (0.0158) | (0.0189) | (0.160) | (0.160) | (0.150) |
| **Sectoral Dummy** | | | | YES | YES | YES |
| **Time Dummy** | | | | NO | YES | YES |
| **TTWA Dummy** | | | | NO | NO | YES |
| **Observations** | 4,424 | 4,424 | 4,424 | 4,424 | 4,424 | 4,424 |
| **R-squared** | 0.226 | 0.228 | 0.245 | 0.260 | 0.268 | 0.299 |

Clustered robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

**Table 3: OLS Results with alternative measures of Inventors' inflows**

| | (1) |
|---|---|
| Dep. Var.: **Process or Product Innovation** | **OLS** |
| **R&D** | 0.343*** |
| | (0.0360) |
| **Employment with degree** | 0.0109 |
| | (0.0119) |
| **Sme** | -0.0664* |
| | (0.0353) |
| **Inventors' inflows (weighted productivity)** | -0.0239 |
| | (0.0679) |
| **National mkt** | 0.0150 |
| | (0.0401) |
| **European mkt** | 0.0772 |
| | (0.0492) |
| **International mkt** | 0.0734 |
| | (0.0462) |
| **Constant** | -0.591* |
| | (0.319) |
| **Sectoral Dummy** | YES |
| **Time Dummy** | YES |
| **TTWA Dummy** | YES |
| **Observations** | 888 |
| **R-squared** | 0.329 |

Clustered robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 4: Instrumental variables estimation

| | (1) |
|---|---|
| Dep. Var.: **Process or Product Innovation** | **2SLS** |
| **Inventors' inflows** | 0.0795 |
| | (0.0541) |
| **R&D** | 0.392*** |
| | (0.0164) |
| **Employment with degree** | 0.0015 |
| | -0.0042 |
| **Sme** | -0.0384** |
| | (0.0171) |
| **National mkt** | 0.0370** |
| | (0.0181) |
| **European mkt** | 0.0482** |
| | (0.0217) |
| **International mkt** | 0.0388* |
| | (0.0219) |
| **Constant** | -0.0612 |
| | (0.149) |
| **Sectoral Dummy** | YES |
| **Time Dummy** | YES |
| **TTWA Dummy** | YES |
| **Observations** | 4,424 |
| **R-squared** | 0.299 |

Clustered robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

**Table 5: First Stage regression**

| | (1) |
|---|---|
| Dep.Var.: | **Inventors' inflows** |
| **R&D** | -0.0048 |
| | (0.0072) |
| **Employment** | -0.0020 |
| | (0.0019) |
| **Sme** | 0.0050* |
| | (0.0026) |
| **National mkt** | 0.0052 |
| | (0.0077) |
| **European mkt** | 0.0013 |
| | (0.0087) |
| **International mkt** | 0.0121 |
| | (0.0084) |
| **Citations** | 0.4742*** |
| | (0.0084) |
| **Constant** | 0.4816*** |
| | (0.0179) |
| **Sectoral dummies** | YES |
| **Time dummies** | YES |
| **TTWA dummies** | YES |
| **Observations** | 4,424 |
| **R-squared** | 0.638 |

**Table 6: First Stage Statistics**

| Variable | **F(1, 2222)** | **P value** |
|---|---|---|
| **Inventors' inflows** | 31.81 | 0.0000 |

**Table 7: Robustness check**

| | (1) |
|---|---|
| Dep.Var.: | **Inventors' inflows** |
| **R&D** | -0.0018 |
| | (0.0074) |
| **Employment with degree** | 0.0011 |
| | (0.0017) |
| **Sme** | 0.0004 |
| | (0.0026) |
| **National mkt** | 0.0029 |
| | (0.0090) |
| **European mkt** | 0.0024 |
| | (0.0074) |
| **International mkt** | -0.00345 |
| | (0.0070) |
| **Constant** | 0.160*** |
| | (0.0193) |
| **Sectoral Dummy** | YES |
| **Time Dummy** | YES |
| **TTWA Dummy** | YES |
| **Observations** | 4,424 |
| **R-squared** | 0.900 |

Clustered robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

**Table 8: Product vs Process Innovation**

| Dep.Var.: | (1) Product Innovation | (2) Process Innovation |
|---|---|---|
| **Inventors' inflows** | 0.0421 | -0.00941 |
| | (0.0537) | (0.0412) |
| **R&D** | 0.384*** | 0.236*** |
| | (0.0167) | (0.0146) |
| **Employment with degree** | 0.0025 | -0.0032 |
| | (0.0046) | (0.0036) |
| **Sme** | -0.0305* | -0.0651*** |
| | (0.0170) | (0.0161) |
| **National mkt** | 0.00989 | 0.0305* |
| | (0.0174) | (0.0157) |
| **European mkt** | 0.0391* | 0.0458** |
| | (0.0220) | (0.0203) |
| **International mkt** | 0.0677*** | -0.0081 |
| | (0.0221) | (0.0210) |
| **Constant** | 0.0191 | -0.0672 |
| | (0.155) | (0.158) |
| **Sectoral Dummy** | YES | YES |
| **Time Dummy** | YES | YES |
| **TTWA Dummy** | YES | YES |
| **Observations** | 4,424 | 4,424 |
| **R-squared** | 0.293 | 0.179 |

Clustered robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

**Table 9: Control Function Approach**

| | (1) |
|---|---|
| Dep.Var. | **Product or Process Innovation** |
| **Inventors' inflows** | 0.3823 |
| | (0.2957) |
| **R&D** | 1.787*** |
| | (0.0781) |
| **Employment with degree** | 0.0096 |
| | (0.0234) |
| **Sme** | -0.209** |
| | (0.0848) |
| **National mkt** | 0.243** |
| | (0.1000) |
| **European mkt** | 0.229** |
| | (0.1047) |
| **International mkt** | 0.196* |
| | (0.1073) |
| **Residuals** | -0.210 |
| | (0.3230) |
| **Constant** | -2.849** |
| | (1.188) |
| **Sectoral dummy** | YES |
| **Time dummy** | YES |
| **TTWA dummy** | YES |
| **Observations** | 4,424 |

Bootstrapped standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

**Table 10: Heterogenous effects: Firms extensively exploiting external sources of information to develop their innovation**

| | (1) |
|---|---|
| Dep.Var.: **Product or Process Innovation** | 2SLS |
| Inventors' Inflows | 0.117** |
| | (0.0578) |
| R&D | 0.304*** |
| | (0.0195) |
| Employment with degree | 0.0004 |
| | (0.0058) |
| Sme | -0.0334* |
| | (0.0202) |
| National mkt | 0.0484** |
| | (0.0246) |
| European mkt | 0.0319 |
| | (0.0243) |
| International mkt | 0.0409* |
| | (0.0239) |
| Constant | 0.0157 |
| | (0.233) |
| Sectoral Dummy | YES |
| Time Dummy | YES |
| TTWA Dummy | YES |
| Observations | 3,293 |
| R-squared | 0.226 |

Clustered robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

**Table 11: First Stage regression (reduced sample)**

| | (1) |
|---|---|
| Dep.Var.: | **Inventors' inflows** |
| **R&D** | -0.0048 |
| | (0.0088) |
| **Employment** | -0.0092 |
| | (0.0020) |
| **Sme** | 0.0052* |
| | (0.0049) |
| **National mkt** | 0.0016 |
| | (0.0106) |
| **European mkt** | 0.0048 |
| | (0.0105) |
| **International mkt** | 0.0117 |
| | (0.0097) |
| **Citations** | 0.5391*** |
| | (0.0994) |
| **Constant** | 0.3474*** |
| | (0.1135) |
| **Sectoral dummies** | YES |
| **Time dummies** | YES |
| **TTWA dummies** | YES |
| **Observations** | 3,293 |
| **R-squared** | 0.648 |

**Table 12: First Stage Statistics (Reduced sample)**

| Variable | **F(1, 1927)** | **P value** |
|---|---|---|
| **Inventors' inflows** | 29.37 | 0.0000 |