SERC DISCUSSION PAPER 97

Does Skilled Migration Foster Innovative Performance? Evidence from British Local Areas

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November 2011

This work is part of the research programme of the independent UK Spatial Economics Research Centre funded by the Economic and Social Research Council (ESRC), Department for Business, Innovation and Skills (BIS), the Department for Communities and Local Government (CLG), and the Welsh Assembly Government. The support of the funders is acknowledged. The views expressed are those of the authors and do not represent the views of the funders.

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Acknowledgements

This paper was developed during my Phd visiting period at LSE, Department of Geography and Environment, and it is the development of my RGS Prize winning LED Master Dissertation. Thanks to Steve Gibbons, Riccardo Crescenzi, Ian Gordon, Olmo Silva, Max Nathan and Tamara de la Mata for advices and support and to the personnel of the ONS Microdata Lab for data. All errors remain my own.

Abstract
What is the effect of an increase in the stock of human capital on the innovative performance of a local economy? This paper tests the hypothesis of a causal link between an increase in the average stock of human capital, due to skilled migration inflows, and the innovative performance of local areas using British data. The paper examines the role of human capital externalities as crucial determinant of local productivity and innovative performance, suggesting that the geographically bound nature of these valuable knowledge externalities can be challenged by the mobility of skilled individuals. Skilled migration becomes a crucial channel of knowledge diffusion broadening the geographical scope of human capital externalities and fostering local innovative performance.

JEL Classifications: O15, O31, I2, H22
Keywords: Innovation, migration, education, externalities

1) Introduction

The role of human capital as key determinant of the innovative performance of regions and countries has been deeply analyzed within the economic literature.
Since Lucas (1988) economists have supported the idea that human capital accumulation in specific geographical contexts generates two different effects: a private return in term of earnings and a social return in terms of overall productivity. The latter effect represents the so called "human capital externalities" (*Moretti, 2004a*).

These externalities were often considered a fundamental engine of endogenous growth (*Grossman, Helpman, 1991*) due to their capability to foster technological innovation and productivity (*Jaffe et al, 1993, Saxenian, 1994*). Moreover because of their geographical boundness[2], they were often supposed to be responsible for differences in long run economic performance among geographical areas (*Lucas, 1988*).

However, despite the theoretical relevance of the issue, the empirical literature on the relevance of human capital externalities is still controversial (*Moretti, 2004a*) and there is even less consensus regarding the mechanism at play (*Duranton, 2007*).
A deeper understanding of the mechanisms behind the geographically localized nature of human capital externalities is then crucial in order to shed some more light on real world's economic dynamics.

The limitation in the geographical ray of action of human capital externalities is generally associated with the distinction between codified and tacit knowledge (*Polanyi, 1978*). Tacit knowledge, often assumed to be the real engine of innovation, is both embodied in people (*Feldman, 2000*) and generally bound within specific epistemic communities[3] (*Steinmueller, 2000*). The coexistence of different sources of tacit, individual embodied, knowledge within the same geographical context increases the likelihood of

[2] Limited geographical extension in their ray of action
[3] Groups of individuals pursuing several goals with shared values

innovation, multiplying the opportunities of exchange and the probability to exploit the benefits related to valuable re-combinations of such knowledge. This implies that the degree of geographical fixedness of these human capital externalities depends on the extent to which human capital is not mobile in space and interactions among individuals remain geographically localized in specific spatial contexts.

Building on these considerations the aim of this paper is to contribute to the debate on the relevance of human capital externalities focusing in particular on their transmission channels. I suggest that the migration behaviour of high skilled individual is a crucial mechanism of (tacit) knowledge diffusion, contributing to broaden the geographical scope of human capital externalities and fostering the innovative performance of local areas. The paper tests this hypothesis looking at an increase in the average level of human capital, due to skilled migration, on the innovative performance of local areas in the case of Great Britain.

The possibility to recover reliable predictions is challenged by several empirical shortfalls. In the first instance the endogeneity regarding changes in aggregate human capital, secondly the definition of the most appropriate geographical scope of analysis and the difficulties in measuring both innovative performance and migration flows.
I will try to address these issues through a careful definition of the relevant variables, the identification of the most appropriate geographical unit of analysis and the implementation of a reliable estimation strategy.

The main findings of the paper confirm that human capital externalities related to migration of skilled individuals can be considered a significant determinant of the innovative performance of local areas in Britain. However in respect to part of the existing literature (*Marshall, 1890, Gleaser, 1999, Gleaser, Mare', 2001, Moretti, 2004a, 2004b, Ciccone and Peri, 2005, Duranton, 2007*) no evidence of an additional effect of human capital externalities in urban areas has been found. I will suggest that this empirical evidence is explained by the characteristics of the sample and the sectoral composition of British cities.

The remainder of the paper is organized as follows: the next section introduces an overview of the existing literature. In section three I will discuss the issue related to the choice of the geographical unit of analysis while in section four I will provide a detailed description of the estimation strategy adopted. Section five describes the data. Section six presents the main results and robustness checks, section seven introduces a thematic focus on the urban subsample and the last section concludes.

2) Background

Externalities associated to the process of human capital accumulation were traditionally considered key factors in determining successful economic outcomes (*Romer, 1986, Lucas, 1988, Grossman, Helpman, 2001*) through their effect on technological and innovative capabilities. Moreover, since Marshall (1890) human capital externalities are also accepted as one of the main reasons to justify the existence of cities.
The main argument supporting this positive effect builds on the idea that an increase in the average local stock of human capital affects positively the local economic performance through two channels: the effect on individual productivity and the effect on aggregate productivity (*Moretti, 2004a*), implying that measures of aggregate human capital should matter in the determination of outcomes over and above individual characteristics (*Duranton, 2007*).

Moretti (2004a) distinguished between two fundamental kinds of human capital externalities: the technological externalities, generating technological increasing returns through the positive effect of human capital on all the other production factors due to the sharing of knowledge and skills among knowledgeable individuals (*Lucas, 1988*), and the pecuniary externalities associated with the marshallian labour market pooling effect (*Marshall, 1980*).

Conceptualizing the existence of these valuable knowledge externalities related to human capital and operating among individuals located in the same geographical context implies valuing more the role of location and geography.
Both kinds of externalities, either those mediated by the labour market and those operating through informal social interactions, tend to be geographically bound because of their embeddedness in local formal and informal institutional and relational contexts. The rationale of this statement is intuitive. As Gleaser et al (1992) pointed out "intellectual breakthroughs must cross hallways and streets more easily than oceans and continent". "Co-presence in the same physical space not only improves the visual contact, but goes beyond it into what can be called emotional closeness" (*Leamer, Storper, 2001*) contributing to create those untraded interdependencies that affect the likelihood to exchange valuable, individual embedded, tacit knowledge (*Storper, 1997*).

The geographically bound nature of such externalities could explain the persistence of economic differentials among different areas increasing the importance of a deeper understanding of the mechanisms behind their localized nature.
Addressing the latter issue implies discovering the key microeconomic linkages to endogenous macroeconomic growth (*Audresch, Feldman, 2004*), allowing for a comprehensive evaluation of the innovation process.

An increasing research effort was devoted to disentangle the channels through which knowledge externalities related to human capital operate.
Starting from the evidence of human capital as individually embodied characteristic it was suggested that valuable knowledge tends to be geographically bound to the extent to which highly skilled individuals are not mobile in space. Because of the fact that "knowledge tends to travel along people who master it" (*Breschi and Lissoni, 2001*), the migration behaviour of highly skilled individuals could challenge the geographically bound nature of knowledge externalities associated with human capital, contributing to extend their ray of action. Inflows of highly skilled individuals determine an increase in the local stock of human capital

contributing to the emergence of knowledge externalities coming from the re-combination of new and pre-existent local knowledge (*Audresch, Feldman, 2004*).

In the analysis of the effectiveness of skilled migration in generating valuable knowledge externalities, the empirical economic literature adopted different perspectives.
Looking at the typology of externalities some authors focused on those that Moretti (2004a) defined as pecuniary externalities, meaning human capital externalities mediated by labour market. Among the most influential papers Gleaser et al. (1992) showed that in-flows of highly skilled workers, acting as additional sources of localized human capital, become a crucial determinant of higher rates of economic growth. Zucher, Darby and Brewer (1998) emphasized the role of star scientists as engine of innovation. This finding was further confirmed by Zucher, Darby and Armstrong (1998) applying the same hypothesis to the analysis of the biotechnology sector in California. More recently Faggian and McCann (2006, 2009), looking at the migration behaviour of graduates in Britain, suggested that graduates contribute to determine the knowledge base of the local economy fostering innovative activities and that regional specific learning process in Britain are developed primarily via labour mobility.
Other authors looked at the pure technological externalities coming from social interactions among individuals exchanging knowledge and skills. Breschi et al (2010) suggested that the mobility of inventors is a powerful channel of knowledge diffusion, but that knowledge effectively spills when the transfer of knowledgeable individuals generate new social networks in the area of destination.

Some general predictions can be drawn from the existent literature. Externalities related to human capital seems to be a key determinant of the economic and innovative performance of local economies. Highly skilled migrants facilitating the transfer of valuable, individually embodied, tacit knowledge are one of the main mechanisms of knowledge diffusion. Their geographical relocation and the localized interactions among them (both market mediated or based on informal social interactions) contribute to extend the geographical scope of the knowledge externalities associated to human capital accumulation.

3) Spatial issues of skilled migration

The introduction of the concept of human capital externalities within the economic literature implies abandoning the traditional approach to innovation as an a-spatial process, insensitive to issues like location and geography (*Audresch, Feldman, 2004*).
This evidence further suggested that the existent literature on innovation based on the Knowledge Production Function (KFP) approach (*Griliches, 1979, 1986, Jaffe, 1986*), adopted in a firm based perspective and built around the definition of the innovative output as function of predetermined innovative inputs, has to be considered myopic and misleading. A theoretical approach looking at firms as an enclave, completely unaffected by neighbouring characteristics, is inadequate to analyze real world phenomena.
The attempt to account for these externalities within the innovation process stimulated a relevant theoretical and empirical effort devoted to the redefinition of the Knowledge Production Function approach in a place rather than a firm based perspective (*Audretsch, 2003; Audretsch and Feldman 1996; Crescenzi et al., 2007; Feldman, 1994; Fritsch, 2002; Varga, 1998*) in order to account for the territorial dynamics of innovation.

The change in terms of methodological perspective was a crucial step. However fully accounting for the geographical dimension of knowledge externalities related to human capital is far from being obvious. It is still questionable which is the geographical dimension related to these knowledge flows and how to translate it in geographical units of analysis.
Moreover the specific analytical focus on the impact of skilled individuals relocating in specific geographical context requires both the recovering reliable data on economically meaningful geographical units of analysis and the definition of spatial entities that are likely to rule out any potential bias coming from neighbouring effects associated to commuting patterns.

Many of the existent contributions concentrate specifically on the effect of human capital externalities in cities. The choice of the urban dimension relies on both theoretical and empirical reasons. First, human capital externalities may be at the root of the existence of cities and they are expected to manifest themselves strongly at this level of analysis (*Marshall, 1890*). Second, urban areas, when properly defined, provide economically meaningful units of analysis in respect to arbitrarily defined administrative regions or states (*Duranton, 2007*).

The obvious drawbacks of this choice reflect the fact that the urban dimension could not always be the most appropriate unit of analysis in different national context and that it implies giving up any attempt to define a more general picture of the role of human capital externalities.

Some of the most relevant empirical papers on the role of human capital externalities in cities (*Moretti, 2004b, Ciccone and Peri, 2005*) tend to analyse US cities that are in terms of number, size and heterogeneity a fairly relevant sample. Moreover historical and cultural characteristics of the US support the idea of a strong centripetal effect of cities within the economic landscape.

It is questionable if the application of the same approach to any European country could be considered as appropriate as in the case of United States. European countries are much smaller and the number of observations is generally less relevant. Moreover the sample is more likely to be strongly unbalanced with capital cities, such as London in the case of Britain, resulting as outliers in terms of size, sectoral composition, attractiveness and economic performance.

Finally the literature focusing on cities is generally aimed at addressing the role of human capital externalities on variables that are likely to be locally determined and for which cities result to be an interesting sample such as wages or crime.

However, to the best of my knowledge, very few studies have analysed the impact of human capital externalities on innovation. Focusing on innovation could be interesting to extend the geographical scope of the analysis beyond the urban dimension.

There is some related evidence for Britain, although drawing on a different theoretical background. Some of this evidence tends to focus on the urban dimension investigating the impact of cultural diversity more than human capital interpreted as education and skills. Nathan (2011b, 2011c) analyzed the role of cultural diversity, fostered by migration patterns, in British cities suggesting the existence of positive links between diversity and both wages and employment at the urban level. The attempt to look at the impact on innovation was conducted by Nathan (2011a) finding that cultural diversity due to migration patterns can be considered a relevant determinant of the firms' innovative performance in the case of London.

To extend the analysis beyond the impact on cities the focus of this paper is on the full sample of British Travel to Work Areas (TTWAs) (Fig. 1). TTWAs have the relevant advantage of including both urban and non urban areas (Tab.1). These functional units are constructed in order to be self containing labour markets[4]. This implies that statistics at TTWAs level are referred to people living and working in each specific area and that any potential increase in the local stock of human capital due to inflows of skilled migrants take into account individuals that changed permanently their residence. Moreover, the adoption of TTWAs as unit of analysis allows accounting for both technological externalities, coming from the exchange of skills and knowledge through informal contacts, and pecuniary externality explicitly mediated by the labour market.
A similar methodological choice was adopted in other empirical analysis on the impact of migration in Britain. In particular Nathan (2011c) analyzed a long term impact of migration on wages, unemployment rate and houses prices with a specific focus on cultural diversity using urban TTWAs as main geographical unit of analysis.

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

4) Data

The empirical analysis is based on a novel dataset constructed using as main data sources the Community Innovation Survey (CIS) and the Labour Force Survey (LFS).

The Community Innovation Survey (CIS) provides firm level microdata on innovation activities and related investments. It is particularly suitable within the framework of the Knowledge Production Function (KPF) because it allows the recovery of data on the amount of capital and labour devoted to the innovation process. 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 high innovative sectors. This implies the possibility of unexpected results in respect to the traditional empirical literature using patents data due to both the fact that the spatial distribution of sectors is not random and that their innovative profile is highly specific.

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 7072 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 effect that are otherwise likely to affect 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

[5] Based on data for 16445 firm for the time interval 2002-2004

[6] Based on data for 14872 firms for the time interval 2005- 2007

[7] This implies the elimination of 7800 firms that are present only in the CIS2007 survey and 9373 that are available only for the CIS4 survey. The inclusion of other waves of CIS was avoided because of the limited number of common observations. The choice of considering the same sample of firms over time lies in the possibility to reduce any potential bias coming from changes in firm level characteristics other than size, K and L.

[8] NUTS 1 level

specialisation[9]. This additional test supports the robustness of the sample used for the analysis.
In order to provide more detailed info regarding the 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 is possible to obtain the 7-digit postcode determining its exact location in space. This implies the possibility to locate each firm within the relevant TTWA and to construct the relevant variables for the TTWA level regression.

The dependent variable, defined using CIS microdata aggregated at TTWA level, is defined as the share of innovation active firms located in each TTWA. Innovation active firms are those performing product, process or "wider" innovation (organizational, marketing, acquisition of new equipment and machinery)[11]. This broad measure of innovation is used in order to account for innovation both in manufacturing and services.
CIS data are further used to construct some of the firm based controls exploiting the availability of information regarding the size of the firm, the financial investments in innovation and the internal availability of high qualified personnel.

Data regarding other location specific characteristics, in particular the skilled structure of the population, comes from the Labour Force Survey (LFS).
The LFS is a large dataset containing detailed data on individuals. The main advantage of using this source is the availability of a long

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[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

[11] Specifically innovation active firms in the CIS definition are those introducing a new or significantly improved good or service (product innovation), new or significantly improved processes for producing or supplying goods or services (process innovation), major changes in business structure and practices, including corporate strategy, advanced management techniques, organisational structure and marketing (wider innovation) as well as those engaging innovation projects which have been abandoned or ongoing, or one or more innovative activities in the "Innovative activities and expenditures" part of the survey .

time series and the opportunity to exploit the raw microdata constructing the TTWAs level controls that are more suitable for the theoretical interest of the paper.
These peculiarities are particularly relevant for the aim of the analysis. The paper focuses on the human capital externalities related to the migration behaviour of highly skilled individuals. Data regarding migration and skills characteristics are often difficult to recover and the LFS, despite providing an indirect measure of migration[12], has the advantage of allowing for a focus on specific segments of the population. However it must be highlighted that the LFS is characterized by small within year sample sizes that are likely to generate more pronounced measurement errors (*Dustmann et al, 2003*) in particular when information is aggregated at a very detailed geographical unit of analysis such as TTWAs. This shortfall is likely to affect the precision of the estimates resulting in a higher standard errors[13].

The alternative source would have been characterized either by the mid estimates provided by the ONS (UK National Statistical Office) or by Census data. Both provide very accurate information on immigrants at a detailed spatial level (Local Autorities), but the former does not allow for a specific focus on the segment of skilled migration while for the latter the frequency of data collection is low.
Examining the pros and cons of both data sources, I considered the LFS the more coherent with the aims of the paper.
The LFS data are available at the Local Authorities (LA) level. The data have been re-aggregated at TTWA level using a postcode based weighting scheme[14].

[12] Variation in the share of skilled population within each TTWA
[13] Note that measurement errors due to sampling imprecisions are supposed to be 0 in average. This implies that they are conceptually different from systematic measurement errors coming from misreporting, poor data definition etc.
[14] Additional information are available on request

The final TTWA based database includes 225 observations[15] for two periods[16] coming from:

- CIS data aggregated at TTWA level;
- LFS data aggregated at TTWA level averaged for the two periods taken into account.

All TTWA level regressors are constructed taking the difference between the two time intervals. Table 2 reports the list of variables coming from the CIS data while Table 3 reports the list of variables coming from the LFS.

5) Estimation strategy

The main aim of this paper is to analyse the role of skilled migration on the innovative performance of British local areas assuming that the mobility of skilled individuals can be considered a key channel of knowledge diffusion, contributing to the extension of the geographical scope of human capital externalities.
The definition of the most suitable estimation procedure has to take into account the methodological indications coming from both the literature on innovation and that on migration.

The mainstream approach in the literature on innovation builds on the Knowledge Production Function (KPF) approach originally defined in a firm based perspective (*Griliches, 1979, 1986, Jaffe, 1986*) and subsequently adapted to take into account the spatial dimension of innovation (*Audretsch, 2003; Audretsch and Feldman 1996; Crescenzi et al., 2007; Feldman, 1994; Fritsch, 2002; Varga, 1998*).

Regarding the literature on migration the dominant methodology refers to the work of Borjas (1999) as the "spatial correlation" approach. The main idea is that the effect of migration on a certain

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[15] Some TTWAs are missing because of unavailability of data or changes in the administrative boundaries (and subsequent un-matching postcodes) during the time period took into account.
[16] 2002-2004 and 2005-2007

dependent variable (generally identified with labour market outcomes such as wages or unemployment) can be identified from the spatial correlation between migrants' inflows and changes in the outcome variables within each geographical unit of analysis. As discussed in the previous paragraphs in the US context such spatial units are generally identified with standard metropolitan statistical areas. In the case of Britain Travel to Work Areas (TTWAs) have been identified as the most appropriate spatial scale.

Building on both strands of literature the estimation procedure adopted is constructed around a place based Knowledge Production Function (KPF) defined at TTWAs level where, in line the conclusions arising from the traditional "spatial correlation" approach (*Borjas, 1999*), the local variation in the share of skilled population (used as proxy for migration) is included as key variable of interest. Within this methodological framework the traditional KPF, based on the assumption of the innovation outcome as determined by the amount of internal inputs devoted to the process, can be considered the baseline model extended to account for additional external inputs.

The main challenge in performing this estimation strategy is related to the endogeneity of the regressor of interest. Firstly migrant inflows and innovative performances may be correlated because of common fixed influences. This implies that the immigrant population may be concentrated in certain areas as a consequence of historic settlement patterns, leading to a positive or negative correlation between skilled migration and innovative performance even in absence of a genuine causality.

Second the estimation is potentially affected by a reverse causality bias. It was argued that skilled migration inflows can be considered a fundamental determinant of innovation acting as channels of knowledge transfer and reducing the geographically localized nature of human capital externalities. The empirical proof of the correlation is however controversial. It is in fact reasonable to assume both that migration of highly skilled individuals stimulates further innovation augmenting and enriching the local stock of human capital and that the knowledge capabilities of a region, determining the local innovative performance, can affect the migration behaviour of skilled individuals (*Faggian, McCann, 2006*). Highly innovative TTWAs could be generally able to attract more skilled migrants because the return of their higher education is greater in areas where this stock of human capital is more intensively exploited. This is likely to generate an upward bias in the estimates because any depressing impact of immigration on innovation (such as for example a displacement effect on skilled natives) could be masked by the fact that inflows of skilled migrants occur in areas where this potential negative effect if offset by positive economic shocks (*Dustmann et al, 2003*).

The statistical solution to the endogeneity problem relies to the possibility of controlling for both area fixed effect and reverse causality. The former issue is addressed by estimating the relationship using differences, which implies relating the changes in immigrant concentration between two points in time to changes in the innovative performance of the areas of destination.
The latter shortfall is controlled for adopting 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.
Combining the estimation in differences and the instrumental variables approach it is possible to recover robust and reliable estimates as long as the chosen instrumental variable is appropriate.

The estimation will then be performed using Ordinary Least Squares (OLS) in Differences[17] (see Dustmann et al., 2003) and the estimated equation will takes the following form:

$$\begin{aligned} D(Inn^{c}_{t-(t-1)}) = \beta_0 + \beta_1 D(K^{c}_{t-(t-1)}) + \beta_2 D(L^{c}_{t-(t-1)}) + \\ + \beta_3 D(highskills_{t-(t-1)}) + \beta D(X_{t-(t-1)}) + D(\varepsilon_{t-(t-1)}) \end{aligned} \quad (1)$$

[17] Each variable is inserted in terms of variation at TTWA level between two time intervals corresponding to the waves of the CIS: 2002-2004 and 2005-2007.

Where:

- $D(Inn^{c}_{t-(t-1)})$ is the variation between period t[18] and period t-1[19] in the share of innovation active firms in TTWA c;
- $D(K^{c}_{t-(t-1)})$ is the variation between period t and period t-1 in the share of firms in TTWA c investing financial resources in innovation enhancing activities;
- $D(L^{c}_{t-(t-1)})$ is the variation between period t and period t-1 in the average ratio of skilled/unskilled employees within firms located in TTWA c;
- $D(highskills^{c}_{t-(t-1)})$, the regressor of interest used as proxy for migration, is the variation (in mean) [20] between period t and period t-1 in the share of skilled population in TTWA c[21];
- $D(X^{c}_{t-(t-1)})$ is the average variation (in mean) between period t and period t-1 in other TTWA relevant controls;
- $D(\varepsilon^{c}_{t-(t-1)})$ is the difference in the error term between the two periods, eliminating unobserved time invariant fixed effects.

Regarding the instrumental variable strategy to control for the potential bias due to reverse causality a number of different instruments were traditionally adopted within the literature. Time lag is the simplest approach (*Dustmann et al, 2005*). Accessibility measures[22] were often used building on the idea that immigrants tend to cluster close to main access points (*Ottaviano and Peri, 2006*). Both approaches are not adoptable in this case. Lagged

[18] 2005-2007
[19] 2002-2004
[20] All the variables constructed using LFS data are averaged within the two time intervals (2002-2004 and 2005-2007) in order to merge them with data coming from the CIS.
[21] This implies that the variable "Highskills" refers specifically the migration inflows of high skilled individuals rather than potential changes in the skills composition due to entry of new workers from school
[22] Proxies for changes in the accessibility of different TTWAs due to major infrastructure improvements in terms of both stock or efficiency level or specific geographical characteristics (ex. proximity to coasts etc)

values are likely to be weakly correlated with actual changes in the highly skilled population because during the period taken into account Britain has experienced a relevant shock due to the A8 accession in 2004 (*Dustmann et al, 2010*). On May 1st 2004, Cyprus, the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Slovakia, Slovenia and Poland, became members of the European Union. In the following year, even due to the fact that UK was one of the few EU members that allowed A8 citizens unrestricted access to its labour markets, the share of immigrants from A8 countries as a proportion of the UK population increased over one third of the total increase in the foreign population determining major changes in the magnitude and composition of migration inflows.
From the other side accessibility measures such as ports (*Ottaviano and Peri, 2006*) or land borders (*Bellini et al, 2008*), traditionally adopted in the case of US, are probably less consistent with the geography of Britain (Nathan, 2011c). Moreover they strongly rely on the assumption that immigrants tend to remain clustered in the neighbouring areas of the main access points, but this expectation is likely to be less pertinent in the case of high skilled migrants.

The choice of the instrument was therefore oriented to adopt a shift share instrumental variable approach as that popularised by Card (2005, 2007). The main intuition behind this strategy is that the initial share of immigrants is a relevant predictor of subsequent inflows because migrants tend to be attracted by pre-existing communities.
I calculated the share of population in each TTWA by country of birth in 2001 using this initial share to attribute to each group the growth rate in the skilled population of that group within the whole of Britain between 2002 and 2007.
To construct the specific instrument I built on Ottaviano and Peri (2006). Let $(CoB_i^c)_{2001}$ denote the share of population born in country *i*, living in TTWA c in 2001 defined as base year, then $(CoB_i)_{2001}$ is the share of population born in country *i* among all the British resident at time *t*. Assume that $(g_i)_{2007-2002}$ is the British national growth rate of high skilled population for each country of birth *i* between 2002 and 2007.

The predicted population per country of birth *i*, in each TTWA c at time t will be:

$$(CoB_i^c) = (CoB_i^c)_{2001}[1 + (g_i)_{2007-2002}] \qquad (2)$$

Building on the idea that the national variation of immigrants by country of birth is exogenous in respect to local characteristics and that the geographical distribution of migration inflows is systematically affected by patters of historical settlements, (CoB_i^c) was used as instrument for the variation in the share of high skilled individuals.

6) Results and Robustness Checks

Results on the full sample of TTWAs are reported in Table 4. The number of observations drops to 213 because there are 10 TTWAs for which the dependent variable is not available, one for which the measure of internal labour force is missing and another one for which both variables[23] are not recoverable.

Column 1 report the standard Knowledge Production Function structure interpreted as baseline model where the innovation output is related to internal inputs, capital and labour, controlling for the size of the firms. Results show that the role of financial investments in innovation activities is largely preponderant.

In column 2 the fundamental regressor of interest (variation in the share of high skilled individuals in respect to the total resident population in each TTWA) is included without any statistically significant evidence of a positive effect on the innovative performance of local areas.

The results still confirm the relevance of financial investments and a relative positive correlation between the local propensity to innovate

[23] Due to that the following TTWAs are eliminated from the sample: Badenoch, Barrow in Furness, Dolgellan & Barmouth, Dornoch & lairg, Eilan Siar, Frasembourgh, Pwllheli, Shetland Islands, Stranraer, Thurso and Ullapool & Gairloch. They are all remote rural areas and their elimination is not likely to bias the sample.

and the proportion of small and medium enterprises in each TTWA. Despite being generally at odds with the empirical literature on innovation using patents data as dependent variable and suggesting a positive correlation between size and firms innovative capabilities, the latter result correlates with the main features of the sample characterized by an higher proportion of small and medium enterprises.
Column 3, 4, 5 control for additional time variant TTWA characteristics such as the variation in population density in each TTWA (Col.4), the variation in the proportion of young population and in the share of employment in manufacturing (Col.5) and the variation in the level of long term unemployment (Col.6). Once these further controls (none of them statistically significant) are included, the regressor of interest, the variation in the share of skilled population, becomes significant at 10% level and its significance level remains stable in all the specifications.
This preliminary evidence suggests that there is a positive effect associated with the variation in the share of skilled individuals, but this effect is likely to be mediated by other TTWA peculiarities.

As discussed the estimation provided using Ordinary Least Squares (OLS) in differences allows to control for a potential bias due to unobserved time invariant fixed effect, but do not control the potential endogeneity coming from the reverse causality between the variation in the share of skilled population and the innovative performance of local areas.
In order to rule out this additional source of biasedness an Instrumental Variables approach (2SLS) is adopted.
The variation in the share of skilled migrants is instrumented by the shift-share instrument constructed using LFS data on country of birth (CoB). Results are reported in column 6. The coefficient associated with the variation in the proportion of highly skilled individuals remains significant at 10% level supporting my research hypothesis. The magnitude of the coefficient is large suggesting that one point increment in the share of highly skilled population generates a three points increment in the share of local innovative. The IV point estimate is high relative to the OLS result, however the Hausman test confirms that they are not statistically different. As expected the standard errors are slightly higher then before

confirming that the precision of the estimates is affected by the drawbacks related to the LFS data. The estimates further confirm the relevance of capital investments and the positive role of small and medium businesses, while, in respect to the standard OLS estimation, I find a significant positive effect aligned with the average proportion of highly skilled employees working in the firms located in each TTWA (internal labour force)[24].

The estimation provided using the combination of OLS in differences and Instrumental Variable approach allows to recover robust predictions as long as the instrumental variable strategy can be considered appropriate. Some robustness checks on the reliability of the Instrumental Variable approach adopted are performed in order to confirm the consistency of the estimates.
As initial standard test I report the first stage of the IV regression (Tab.5). A good instrument is expected to be significantly correlated with the instrumented regressor. Results reported in Table 5 confirm the reliability of the instrument that appears to be significantly correlated with the regressor of interest. However the econometric literature on the dangers related to weak instruments (*Staiger and Stock, 1997, Stock and Yogo, 2005*) suggests that a good first stage could be not enough to support the robustness of the instrument. To rule out the risk of a weak instrument bias I refer to both the rule of thumb proposed by Staiger and Stock (1997) and the Stock and Yogo (2005) thresholds values. As reported in table 6 the F statistic for the first stage is well above the value of 10 and it passes the Stock and Yogo test at 15% maximal IV size.

In second instance it is worth testing if the statistical significance of the regressor of interest is dependent (as suggested by the OLS estimates) on the inclusion of additional controls at TTWA level. In order to ensure that the positive effect associated with skilled migrants is robust and that it is not systematically affected by area

[24] It is worth noting that despite the same significance level the magnitude of the coefficient differs significantly between the internal skilled labour force (employees in each firm) and the proportion of external skilled population in each TTWAs. This evidence has to be interpreted in the light of the sample composition composed mainly by SME that are more likely to refer to external sources of knowledge rather than to internal structures.

characteristics, the IV estimation has been replicated progressively eliminating all the additional TTWA controls. Results reported in table 7 confirm that the positive and significant effect of high skilled immigrants is unaffected by the specification of the model given that both the magnitude and the statistical significance level associated with the regressor of interest are unchanged.
Finally, to provide further evidence on the appropriateness of my instrument, a standard OLS regression using the instrument (CoB) as the dependent variable and including all the observed TTWA characteristics as regressors has been run. The results shown in table 8 confirm that the instrument is not correlated with any other variable used as control in the main specification. This evidence strongly confirms that my instrumental variable is isolating exactly the effect that I'm interested in, namely the role of high skilled migration on the innovative performance of British TTWAs.

Robust evidences in support of the fact that the instrumental variable approach adopted is not suffering from weak instrument bias and it is not dependent on the specification of the model has been provided by the empirical investigation. However it is still possible that the instrument is correlated with other variables not inserted in the regression, but potentially affecting the interpretation of the estimates.
In particular there is a relevant literature accounting for the counter effect of native outflows correlated to an increase in the immigrant population in a given area. Such effect is a strongly debated issue within the existing literature, but there is still no consensus on its sign and magnitude (*Borjas, 1994, Card, 2005, 2007*).
The potential correlation between international and internal migration could be either negative, in case of a displacement effect, or positive, in presence of an "agglomeration effect" generating alternatively an upward or downward bias. The empirical evidences on that are still controversial with some studies finding the expected negative effect (displacement) and others finding a zero or even positive effect (see Friedberg and Hunt, 1995 and Borjas, 1997 for a comprehensive review). Looking more specifically at the British case Dustmann et al. (2008) suggested that there is evidence of a displacement effect, but that its magnitude is relatively small in respect to the US due to less intense internal migration flows.

Moreover it is reasonable to assume that this effect, generally analysed in respect to the lower skilled segment of the population and justified by an increasing competition in labour market associated to the lower tiers of the skills distribution, is likely to be less relevant for highly skilled individuals for whom competition in the labour market is more related to specific skills.
Despite this theoretical reasoning, in order to rule out any doubt regarding the correlation of the instrument with native outflows, I regress the instrument itself on the variation in the British population in each TTWA. As shown in table 9, controlling for other TTWA characteristics, the relation is insignificant.
Finally, to ensure that the instrument is isolating exactly the variation within the segment of the highly skilled migrants and that it is not correlated with inflows of low skilled individuals the instrument has been regressed on the variation in the share of the lower skilled population. The results reported in table 10 confirm that even in this case the relation is insignificant.
I can strongly support the assertion that the estimation procedure adopted to recover the causal effect of skilled migrants on the innovative performance of local areas in Britain provides robust and reliable estimates. The estimation using OLS in differences allows for the elimination of a potential bias due to unobserved TTWA fixed effect while the Instrumental Variables approach rules out the risk of endogeneity bias due to reverse causality. The instruments passed a number of robustness checks, further confirming the consistency of the results.

7) Evidence from British Cities

In compliance with the existing literature on the role of human capital externalities it is interesting to provide a specific test on the existence of an additional effect associated with the urban dimension. Since Marshall (1890) human capital externalities were traditionally supposed to have a greater influence in cities. However, as already explained, due to the characteristics of the data used in the analysis and the peculiarity of the British economy, the reliability of this statement remains unsure.

The main aim of this section is to provide a deeper understanding of the dynamics behind the effect and significance of human capital externalities associated to skilled migration in urban areas. The number of urban TTWAs in Britain is too small to provide consistent estimates on the restricted sample. In order to recover the effect of the urban dimension an alternative strategy has been adopted.
In particular, instead of restricting the sample to the urban TTWAs, I constructed a new independent variable that is methodologically equal to the previous one[25], but is restricted to those firms operating in urban areas.
This new measure allows for the preservation of the same number of observations and it is also able to provide some suggestive indications regarding the innovative dynamic of British urban areas.

The econometric analysis is provided using the new dependent variable focusing on urban firms[26]. Results reported in table 11 show that the effect of the variation in the share of highly skilled individuals is positive but not statistically significant either in the OLS specification and after controlling for the endogeneity due to reverse causality through IV[27]. This result is robust to changes in the sample composition[28]. The significance levels of the other variables, in particular the financial investments in innovation, remains consistent with the results obtained from the full sample.

The absence of an "urban effect" within the sample deserves some additional considerations. LFS data generally suggests that urban areas experienced a higher positive variation in the highly skilled population in respect to non urban areas. It remains to question what

[25] Number of the innovation active firms over the total number of firms in each TTWA

[26] This implies that the dependent variable (share of innovation active firms) is different from 0 only in those TTWAs that are classified as urban.

[27] This result is confirmed by the basic test based on the inclusion of the urban dummy within the main regression

[28] Columns 1 and 2 report results for the full sample of TTWA, columns 3 and 4 eliminate London from the sample. Fist stage estimates are reported only for the specification without London (Tab. 12 and 13) because for the one on the full sample it is equivalent to the results reported in table 5 and 6.

breaks the correlation between such skilled inflows and the innovative performance in the case of British cities.
The reason lies with both the characteristics of the data used and the sectoral composition of British cities.

As a preliminary consideration it is worth underlining that CIS data tends to reproduce a balanced sample in terms of sectoral composition and to focus on small and medium businesses[29]. This implies that the analysis is focused on a typology of innovation that is extremely different from the one analysed using patents data as dependent variable. This clarification helps to justify why some of the results are fairly unusual in respect to the standard innovation empirical literature.

The sectoral composition of British urban areas plays an important role in explaining the lack of empirical support to the existence of valuable knowledge externalities in cities. I suggest that, more than particular local characteristics reducing the effectiveness of human capital externalities associated with skilled migration, the absence of the "urban effect" is due to the systematic lower innovative propensity of the sectors traditionally concentrated in urban areas.
The sectoral composition of British cities tends to be strongly skewed toward services specialisation: within the total sample of firms coming from the CIS[30] about 61% of the firms located in urban areas are operating in sectors classified as services (Tab.14).
Despite the broad measure of innovation, constructed in order to take into account forms of innovation activities other than process and product innovation, services are systematically less innovative than manufacturing sectors (Tab.15). This result is much clearer disentangling the percentage of innovative firms by sic frame. Looking in depth at the innovative performance of urban areas the sectors classified as services are steadily characterised, on average, by a lower innovative performance (Tab. 16, Col.1). Moreover, as showed in Table 16 (Col.2), among the manufacturing sectors those contributing more to the composition of urban areas (Construction, Manufacturing in fuels, chemical and plastic and Manufacturing of

[29] About 79% of the total number of firms is defined as sme
[30] 7072 for two years

food, clothing and wood) are even those characterized by the lowest innovative performance. Interestingly more than the 90% of the total number of firms located in urban areas belong to sectors characterized by lower innovative potential while those with the highest innovative performance seems to contribute only marginally to the sectoral composition of British cities. (Tab.16, Col.3).

These descriptive statistics reinforce the reasoning behind the insignificant effect of skilled migration in urban areas in respect to the effect found looking at the total sample of British TTWAs. Furthermore it is important to emphasise that the classification of urban TTWAs is likely to be restrictive due to two key considerations. Firstly, in respect to the existent literature on the effect of human capital externalities in cities, Metropolitan Areas, usually used to account for the role of human capital externalities in US cities, are generally larger than British urban TTWAs. It is possible that the lack of evidence in the British sample is partially due to the smaller size of the geographical unit; TTWAs may be unable to account for the broad concept of metropolitan areas, underestimating the potential effect of these externalities. Secondly, and relating to the previous consideration, it is likely that those sectors showing a best innovative performance (for a large part manufacturing) are concentrated in the surrounding areas of urban centres rather than within the cities.

8) Conclusions

Human externalities, as source of endogenous growth, gained popularity in the last few decades (*Lucas, 1988, Grossman and Helpman, 2001*). Within the literature on innovation they were supposed to be responsible for higher innovative performance and productivity (*Jaffe et al, 1993, Saxenian, 1994*). Despite this powerful theoretical background, the empirical literature is still controversial (*Moretti, 2004a*) and there is no consensus regarding the mechanisms at play behind the effect of human capital externalities on economic and innovative outcomes (*Duranton, 2007*).

The lack of clear evidence is partially due to the endogenous characteristics of such externalities that, "by their very nature, leave no obvious paper trail by which they can be tracked or measured" (*Duranton, 2007*) as well as to the existence of serious challenges in addressing an unbiased estimate of their effect. However a comprehensive understanding of these mechanisms is essential to provide a deeper knowledge of the micro-foundation of macroeconomic growth (*Audretsch and Feldman, 2004*).

This paper is aimed at contributing to the debate on the role of human capital suggesting that the transfer of knowledge associated with the mobility of highly skilled individuals can be considered a crucial mechanism underlying their positive effect on the innovative performance of local areas. I found that human capital externalities coming from the migration behaviour of skilled individuals are a significant determinant of innovation in British local areas. The estimation procedure addresses the main shortfalls potentially biasing the result: the correlation between migration and area fixed characteristics and the reverse causality between migration and innovation. The instrumental variable approach adopted to address causality is consistent to both model specification and other robustness checks.

However, due to the particular characteristics of the sample of analysis, I do not find evidence in support for the existence of an additional effect of human capital externalities in cities.
This empirical evidence is explained by several considerations.
In the first instance, using CIS data, I'm implicitly accounting for a typology of innovation behaviour that differs from to the one addressed in the literature on innovation using patents data. My sample is mainly characterized by small and medium businesses, not necessarily concentrated in highly innovative sectors with a relevant percentage of firms operating in manufacturing.
Second and correlated to the previous consideration, the lack of effect in urban areas can be explained by the sectoral characteristics of British cities, clearly skewed toward services sectors systematically characterized by a lower innovative performance.
Third, it is possible that the dimension of my geographical unit contributes, in the analysis of both the restricted and the full sample,

to the underestimation of the role of these externalities. I have argued that, in particular in respect to the traditional literature on human capital externalities using Metropolitan areas as main unit of analysis, British TTWAs may be potentially unable to fully account for the dimension of the metropolitan areas. This shortfall is expected to be exacerbated by particular characteristics of the CIS data, where innovation tends to be concentrated in manufacturing sectors that are more likely to be localized in the extreme periphery of core urban centres.

The paper offers some reliable statistical evidences in support for the role of human capital externalities, coming from skilled migration, on the innovative performance of local areas. Despite that, in concordance with the existing literature, it is still hard to provide definitive conclusions regarding the size of these externalities. This is partly due to the shortfalls related to the common measures of migration that are affected by different measurement problems. Regarding the LFS, that in the case of Britain is still the most suitable data source in particular to address the role of migration by different skills segments, sampling imprecision due to small sample size may be an issue. In spite of being zero on average and conceptually different from measurement errors due to misreporting and poor data definition (*Dustmann et al, 2003*), this characteristic of the data is likely to generate a certain degree of attenuation bias leading to the estimation of a smaller effect in respect to its real magnitude. This implies that, despite being strongly reliable, the results, confirming the effect of human capital externalities coming from local inflows of skilled individuals, are likely to partially under-represent the magnitude of the real effect.
More research is needed on the topic in order to overcome the empirical challenges related to the estimation and to solve the drawbacks concerning data issues. The precision of the estimates and the provision of clearer results regarding the magnitude of the effect are likely to improve alongside the quality of data.

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Tables and Figures

Figure 1: British Travel to Work Areas (TTWAs)

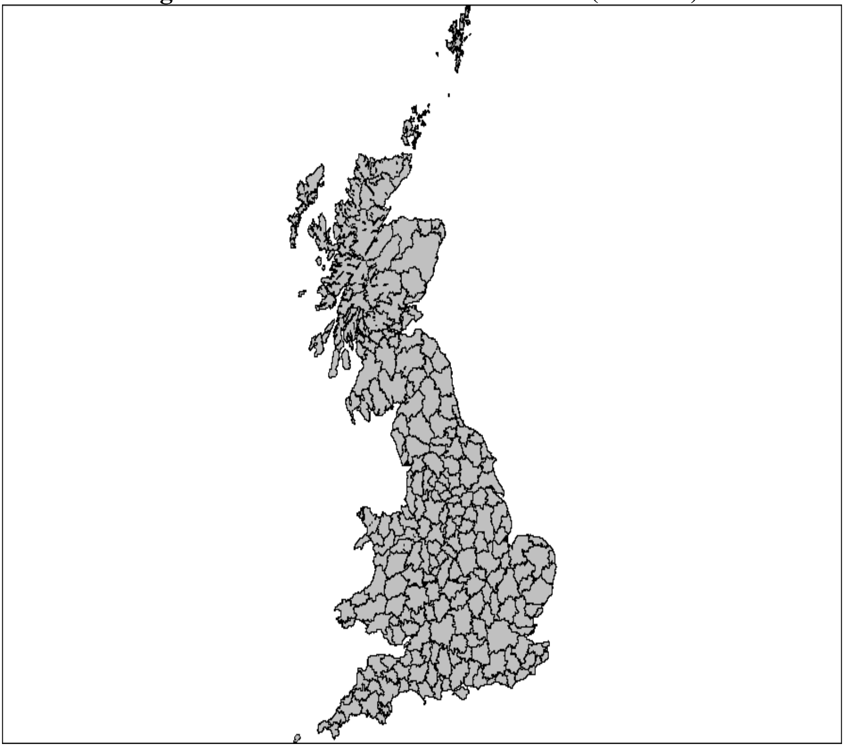

Table 1: Urban/ Non Urban Travel to Work Areas (TTWAs)

Type	N	Freq.	Cumulative
Urban	79	35.11	35.11
Non Urban Welsh	22	9.78	44.89
Non Urban Northern Scotland	24	10.67	55.56
Non Urban Southern Scotland	10	4.44	60.00
Non Urban Northern England	20	8.89	68.89
Non Urban Southern-West England	29	12.89	81.78
Non Urban Rest of England	41	18.22	100.00
Total	225	100.00	

Source: ONS/ CIS

Table 2: CIS Variables

Variable	Description
Innovation active	Variation in the share of innovation active firms (process or product innovation and other innovation activities[31])
Innovation active urban	Variation in the share of innovation active firms operating in urban sectors[32]
Capital	Variation in the share of firms investing in innovation related activities[33]
Labour	Variation in the average percentage of graduate employees within the firms
Sme	Variation in the share of small and medium enterprises

Note: All the variations are calculated as variation between the two periods corresponding to the CIS waves (2002-2004 and 2005-2007)
All variables are calculated at TTWA level

Table 3: LFS Variables

Variable	Description
High skills	Variation in the share of high skilled individuals (degree or equivalent)
Population density	Variation in the population/surface ratio
Young	Variation in the share of individuals with less than 24 year old
Manufacturing	Variation in the share of employment in manufacturing
Long term unemployment	Variation in the share of long term unemployment
Low skills	Variation in the share of low skilled individuals (no qualification)
British high skills	Variation in the share of high skilled British population

Note: All the variations are calculated as variation in mean between the two periods corresponding to the CIS waves (2002-2004 and 2005-2007)
All variables are calculated at TTWA level

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[31] Other innovation activities account for organizational innovation, marketing innovation, acquisition of new equipments or machineries

[32] Mining and Quarrying, Manufacturing of food, clothing and wood, Manufacturing of fuels, chemical and plastic, Manufacturing of electrical and optical, Manufacturing of transport equipments, other Manufacturing, Electricity, gas and water supply, Constructions, Wholesale Trade, Retail Trade, Hotels and Restaurants, Transport and Storage, Financial Intermediation and Real Estate

[33] Intramural, extramural equipment, external knowledge, training, design, marketing

Table 4: Estimation Results: Skilled Migration and local innovative performance

Dep.Var.: Innovation active	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) 2SLS
High skills		0.734	0.779*	0.752*	0.747*	3.304*
		(0.456)	(0.470)	(0.449)	(0.448)	(1.895)
Capital	0.858***	0.858***	0.857***	0.858***	0.859***	0.856***
	(0.0499)	(0.0488)	(0.0492)	(0.0488)	(0.0467)	(0.0440)
Labour	0.0008	0.0017	0.0018	0.0019	0.0019	0.0049*
	(0.0013)	(0.0015)	(0.0016)	(0.0018)	(0.0017)	(0.0028)
Sme	0.171	0.179*	0.183*	0.193*	0.193*	0.213**
	(0.108)	(0.106)	(0.104)	(0.0992)	(0.101)	(0.0983)
Population density			0.0005	0.0006	0.0006	0.0011
			(0.0004)	(0.0004)	(0.0004)	(0.001)
Young				-0.152	-0.147	0.0661
				(0.223)	(0.226)	(0.257)
Manufacturing				0.0680	0.0652	0.103
				(0.0921)	(0.0905)	(0.0966)
Long term unemployment					0.0117	0.0062
					(0.0415)	(0.0414)
Constant	0.0047	-0.0016	-0.0039	-0.0043	-0.0046	-0.0260
	(0.0058)	(0.0054)	(0.0061)	(0.0070)	(0.0066)	(0.0180)
Observations	213	213	213	213	213	213
R-squared	0.887	0.888	0.888	0.889	0.889	0.871

Source: ONS/ CIS-LFS

Notes: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 5: First Stage Results (1)

Dep.Var.: High skills	First Stage
Capital	0.0008 (0.003)
Labour	-0.0008** (0.0003)
Sme	-0.0069 (0.010)
Population density	-0.0002 (0.0001)
Young	-0.0872** (0.0393)
Manufacturing	-0.0175 (0.0141)
Long term unemployment	0.0035 (0.005)
CoB	0.0271*** (0.008)
Constant	-0.018** (0.008)
Observations	213
R-squared	0.115

Notes: Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: First Stage Statistics (1)

Variable	Partial Rsq	F(1,204)	P-value
High skills	0.0659	11.08	0.000

Table 7: Robustness Check (1)

Dep.Var.: Innovation active	(1) 2SLS	(2) 2SLS	(3) 2SLS	(4) 2SLS	(5) 2SLS
High skills	3.304*	3.279*	3.346*	3.357*	3.508*
	(1.895)	(1.908)	(1.903)	(1.918)	(2.048)
Capital	0.856***	0.855***	0.857***	0.857***	0.860***
	(0.0440)	(0.0459)	(0.0457)	(0.0458)	(0.0455)
Labour	0.0049*	0.0049*	0.0048*	0.0048*	0.0051*
	(0.0028)	(0.0028)	(0.0028)	(0.0029)	(0.0028)
Sme	0.213**	0.213**	0.212**	0.215**	0.210**
	(0.0983)	(0.0974)	(0.0982)	(0.0974)	(0.100)
Population density	0.0011	0.0010	0.0010	0.0010	
	(0.0008)	(0.0007)	(0.0007)	(0.0007)	
Young	0.0661	0.0608	0.0491		
	(0.257)	(0.255)	(0.254)		
Manufacturing	0.103	0.104			
	(0.0966)	(0.0978)			
Long term unemployment	0.0062				
	(0.0414)				
Constant	-0.0260	-0.0256	-0.0275	-0.0280	-0.0254
	(0.0180)	(0.0187)	(0.0186)	(0.0192)	(0.0183)
Observations	213	213	213	213	213
R-squared	0.871	0.872	0.870	0.870	0.866

Source: ONS/ CIS-LFS

Notes: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 8: Robustness Check (2)

Dep.Var.: CoB	(1) OLS
Population density	0.0009 (0.0007)
Young	0.1530 (0.3961)
Manufacturing	0.0684 (0.1810)
Long term employment	-0.0391 (0.0267)
Constant	0.9797*** (0.0103)
Observations	213
R-squared	0.011

Notes: Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Robustness Check (3)

Dep.Var.: CoB	(1) OLS
British high skills	-1.8665 (1.2889)
Constant	.9541*** (.0124)
TTWA Controls[34]	YES
Observations	213
R-squared	0.094

Notes: Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10: Robustness Check (4)

Dep.Var.: CoB	(1) OLS
Low skills	-.1652 (.1457)
Constant	.9760 (.0067)
Observations	213
R-squared	0.004

Notes: Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[34] Variables inserted in the main specification of the model as TTWAs controls

Table 11: Estimation Results: Skilled migration and local innovative performance in cities

Dep.Var.: Innovation active	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS
High skills	0.806	2.330	0.816	2.376
	(0.579)	(1.889)	(0.583)	(1.918)
Capital	0.144***	0.142***	0.144***	0.142***
	(0.0370)	(0.0357)	(0.0370)	(0.0356)
Labour	0.0011	0.0029	0.0011	0.0029
	(0.0016)	(0.0028)	(0.00163)	(0.00288)
Sme	0.0688	0.0807	0.0686	0.0806
	(0.0830)	(0.0880)	(0.0831)	(0.0881)
Population density	0.0028*	0.0031*	0.0028*	0.0031*
	(0.0013)	(0.0015)	(0.0013)	(0.0015)
Young	0.263	0.390	0.265	0.396
	(0.269)	(0.302)	(0.270)	(0.304)
Manufacturing	0.0325	0.0552	0.0328	0.0561
	(0.115)	(0.119)	(0.115)	(0.119)
Long term unemployment	-0.0358	-0.0390	-0.0356	-0.0388
	(0.0340)	(0.0349)	(0.0340)	(0.0350)
Constant	-0.0009	-0.0136	-0.0008	-0.0138
	(0.0076)	(0.0180)	(0.0076)	(0.0181)
Observations	213	213	212	212
R-squared	0.177	0.151	0.177	0.150

Source: ONS/ CIS-LFS

Notes: Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 12 First Stage Results (2)

Dep.Var.: High skills	First Stage (excluding London)
Capital	0.0008
	(0.0034)
Labour	-0.0008**
	(0.0003)
Sme	-0.0068
	(0.0104)
Population density	-0.0002
	(0.0001)
Young	-0.0876**
	(0.0393)
Manifacturing	-0.0176
	(0.0141)
Long term unemployment	0.0034
	(0.0051)
CoB	0.0268***
	(0.0078)
Constant	-0.0179**
	(0.0076)
Observations	212
R-squared	0.114

Notes: Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14: First Stage Statistics (2)

Variable	Partial Rsq	F(1,204)	P-value
	Excluding London		
High skills	0.0647	11.63	0.000

Table 15: Sectoral composition of Urban Areas

	% of firms in Urban TTWAs
Manufacturing	39.0
Services	61.0

Source: ONS/ CIS

Table 16: Innovation active firms in Urban Areas by broad sector

	% of Innovation Active firms in Urban TTWAs
Manufacturing	75.2
Services	64.0

Source: ONS/ CIS

Table 17: Innovation active firms in Urban Areas by sic frame

	(1) % of innovative firms in Urban TTWAs	(2) Contribution of each sector to total number of firms in urban TTWA	(3) Cum.
SERVICES			
Wholesale trade	0.66	0.100	0.10
Retail trade	0.54	0.070	0.16
Hotels & restaurants	0.52	0.053	0.22
Transport, storage	0.64	0.092	0.31
Financial intermediation	0.72	0.042	0.35
Real estate, renting & business	0.68	0.253	0.61
MANUFACTURING			
Construction	0.59	0.074	0.68
Mfr of fuels, chemicals, plastic	0.77	0.132	0.81
Mfr of food, clothing, wood	0.76	0.093	0.91
Mining and quarrying	0.70	0.003	0.91
Mfr of electrical and optical	0.85	0.043	0.95
Mfr of transport equipments	0.80	0.019	0.97
Mfr not elsewhere classified	0.82	0.024	0.99
Electricity, gas & water supply	0.82	0.001	1.00

Source: ONS/ CIS

Notes: CIS microdata are treated as confidential. The raw number of firms per sector is not reported to avoid disclosure.