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Skilled mobility, networks and the geography of innovation

Clément Gorin

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Clément GORIN

Skilled mobility, networks and the geography of innovation

Devant le jury composé de :

Corinne AUTANT-BERNARD, Professeur, Université Jean Monnet

Présidente

Maryann FELDMAN, Professeur, University of North Carolina

Rapporteuse

Francesco LISSONI, Professeur, Université de Bordeaux

Rapporteur

Rosina MORENO SERRANO, Professeur, Universitat de Barcelona

Examinatrice

Nadine MASSARD, Professeur, Université Grenoble Alpes

Directrice de thèse

Ernest MIGUELEZ, Chargé de recherche, CNRS

Invité

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1 Introduction

1.1 Background

Since the development of the endogenous growth theory, innovation and knowledge are largely accepted as the main driving forces behind long-term economic growth. From a regional perspective, scholars have established that innovative activity is remarkably concentrated in space, and especially in large urban areas. For instance, Audretsch and Feldman (1999) reported that in 1982 in the US, less than 4% of product innovations took place outside metropolitan areas, while 70% of the population resided in those cities. More recently, Moretti (2012) observed that about twenty US cities with a solid base of human capital kept attracting good employees and offering high wages. As a result, they accounted for the bulk of US innovative activity. Understanding the concentration of innovation should help explaining the persistence of long-run growth differentials among urban areas, and in a more dynamic setting, whether these gaps tend to widen or fall over time.

Jacobs (1969) long ago pointed to the importance of cities as a source of innovative change. She argued that the diversity of people, firms and cultures in urban areas constitutes a fertile ground for innovation. The relation between knowledge and innovation lies on the belief that new discoveries stem from the combination of previously uncon-

ned ideas. Therefore, there would be a positive association between the stock of diverse knowledge available and innovative performance¹. The connection with economic theory was provided by Lucas (1988), who introduced human capital in a neoclassical growth model. In his setting, productivity gains are associated with the clustering of skilled people in urban areas. Although Lucas did not give any indication about the mechanisms by which externalities occurred in the real world, he argued that “the scope of such effects must have to do with the ways various groups of people interact” (p.37). This is due to the tacit nature of knowledge conducive to innovation, which is embodied in individuals’ minds and habits, and is better transmitted through direct and frequent interactions (Howells, 2002). Building on this intuition, Glaeser (1999) designed a model in which dense urban agglomerations provide a faster rate of contact between individuals. Each contact provides an opportunity for learning and lowers the costs of communication, so that workers learn more quickly in metropolitan areas. In a more dynamic setting, Black and Henderson (1999) developed a model in which urban systems grow endogenously through human capital externalities. The model features a simultaneous relationship whereby workers in the city become more productive by accumulating human capital. This makes the city more attractive and increase population growth, which increases in turn the amount of human capital externalities and makes skilled cities grow faster.

The empirical evidence is fairly conclusive. Using US patent citations, Jaffe et al. (1993) found that industry patenting at the metropolitan level was influenced by university research spending in related technological fields, which points to the existence of local knowledge externalities. Glaeser and Mare (2001) documented that workers residing in US cities are more productive, and earn more than their non-urban counterpart. The

¹Fujita and Thisse (2002b, p.170) define knowledge as “(...) the kind of information related to products, technologies and markets, which is difficult to codify because it is tacit, and thus it can typically be collected only through face-to-face communications”.

analysis reveals that workers in cities accumulate human capital faster, which increases the average labour productivity and cause cities with more educated residents to grow faster. The explicit connection to innovation is provided by Carlino et al. (2007), who noticed that US cities with higher employment density also generate more patents per capita, highlighting the role that density plays in the diffusion of idea. Similar evidence is reported by Bettencourt et al. (2007), who found that large metropolitan areas in the US have disproportionately more inventors than smaller ones, and consequently generate more patents. In this regard, Glaeser and Resseger (2010) highlighted strong complementarities between knowledge and agglomeration; knowledge externalities amplify the benefits of agglomeration, while agglomeration facilitates the accumulation of knowledge.

Such circular-causation mechanisms are the foundations of new economic geography and growth models, which explain the uneven distribution of economic activity through the interplay of diverse agglomeration and dispersion forces. In particular, Baldwin and Forslid (2000) designed a model encompassing both labour mobility and knowledge externalities as agglomeration forces. Their main contribution is to show that agglomeration and economic growth are mutually self-reinforcing processes. Depending on labour mobility and the range of knowledge externalities, a core-periphery pattern may emerge as firms and skilled workers cluster within the same location. As this location becomes more attractive, further concentration of factors occurs, pushing its capacity to grow at the expense of peripheral areas. By contrast, when knowledge externalities have a wide spatial range, location decisions have no effect on innovation, which weakens the cumulative mechanism described above and favours the symmetric equilibrium (Fujita and Thisse, 2003). A major limitation of these models is that they do not control for the actual mechanisms through which knowledge diffuses in space (Fujita and Krugman, 2004). A related issue is that the law of motion governing migration

dynamics is very simplistic, as workers respond only to real wage differentials. These two issues are further investigated in the empirical geography of innovation literature.

Going beyond the pure externality perspective, two streams of literature investigated how knowledge diffuses in space and across organisations. First, the empirical geography of innovation literature has established that the transmission of knowledge proceeds mostly through personal ties. Consequently, firms may gain access to knowledge through the recruitment of key workers. When these individuals move away from the place where they originally worked, they bring their embodied knowledge to their new workplace and promote innovation. From an empirical perspective, Almeida and Kogut (1999) tracked knowledge diffusion patterns using patent citations in the semiconductor industry. He found evidence of knowledge flows in the US states where the mobility of inventors across companies is high. Going beyond the direct impact of mobility, Agrawal et al. (2006) showed that mobile inventors are more likely to be cited by their former colleagues. This suggests that social ties facilitate the transfer of knowledge even when inventors are no longer co-located. More generally, a related mechanism for the transmission of knowledge is the presence of scientific networks, because workers and firms that are embedded in those networks are more likely to be exposed to original ideas. This is confirmed by Singh (2005), who argued that co-invention networks explained the subsequent patterns of patent citations, both at the regional and at the firm level. To the extent that mobility patterns remain predominantly local, this could explain the observed concentration of innovation (Breschi and Lissoni, 2009). However, having access to external knowledge is not sufficient to use it for innovation. A second stream of research focused on firms' ability to absorb external knowledge. In an influential contribution, Cohen and Levinthal (1989) argued that firms actively engaging in research are not only more likely to innovate, they are also able to build an absorptive capacity in order to assimilate and use productively the discoveries of others. Griffith

et al. (2003) explicitly modelled absorptive capacity in a model of endogenous growth; they argued that the social returns to R&D and human capital are greater than previously thought. From an empirical perspective, Caragliu and Nijkamp (2012) showed that a lower regional absorptive capacity increases knowledge flows towards neighbouring areas, hampering the regions' capability exploit newly created knowledge, both produced locally and originating from outside.

While the importance of skilled workers for the diffusion of knowledge is well established, far less attention has been devoted to the determinants of their location decisions. This is important because heterogeneity in workers' characteristics and location preferences alters the circular-causation mechanism of agglomeration (Tabuchi and Thisse, 2002). Economists consider mobility as a rational decision in which individuals compare expected utilities at origin and destination as well as the cost of moving. The literature has developed around two views of what influences the level of utility. The traditional approach considers that mobility is driven primarily by the labour market. Empirically, this means that workers are drawn toward locations offering attractive employment opportunities. In an urban context, Scott (2010) investigated what drives inflows of migrant US engineers into different MSA. Their estimation results suggest that local employment opportunities have a major impact on the destination choices of engineers. An alternative approach views mobility as a consumption choice. In this perspective, mobility is a response to spatial heterogeneity in the provision of amenities. Early works focused on natural advantages (Graves, 1980), but more recent contributions have considered the importance of human-produced amenities including social, cultural and skill-dependent amenities, which are particularly important in an urban context (Shapiro, 2006). Finally, Faggian and McCann (2006) studied the mobility of UK graduates entering into first employment. Their analysis suggests that mobility flows are mainly directed by differences in nominal wages, so that regions offering a

higher nominal wage are net absorber of human capital flows and regions with lower nominal wages net losers of human capital.

These findings have implications for the geography of innovation. Models that study growth and geography in an integrated framework recognize the importance of both workers' mobility and knowledge externalities in determining the location of innovation. On the one hand, if a region becomes relatively more attractive, mobile workers will move to this region, causing it to grow at the expense of peripheral areas in a circular-causation mechanism. On the other hand, the strength of agglomeration depends negatively on the range of knowledge externalities. In this setting, the aggregate impact of skilled mobility is ambiguous because it favours the core-periphery equilibrium, while its role in the diffusion of knowledge may lead to dispersion. The relative importance of these two effects critically depends on workers' mobility patterns. For instance, in the presence of long-term mobility, the agglomeration force should be stronger than what theory predicts. By contrast, the increasing development of short-term, circular patterns of mobility should give rise to dispersion. The literature is unclear about which effect prevails, partly because it does not account for the actual mechanisms through which knowledge diffuses in space. This work represents a step in this direction.

1.2 Research questions

Building on these considerations, an important research question is to understand the role of skilled mobility in the geography of innovation. This should help explaining the persistence of long-run growth differentials among urban areas, and in a more dynamic setting, whether these gaps tend to widen or fall over time. Specifically, this thesis

seeks to address the following question.

How does the mobility of skilled workers shapes the diffusion of knowledge, and the resulting spatial distribution of innovative activity?

To answer this question, the thesis proceeds in three steps. Chapter 2 sets the conceptual framework and surveys the related literature. One of the main conclusion of this review is that some new economic geography and growth models provide a useful theoretical framework, because they recognize the importance of skilled mobility and knowledge externalities for the distribution of innovation. However, they fail to provide a reasonable answer to our research question for at least two reasons.

First, the migration dynamics are very simplistic, and introducing heterogeneity in workers' characteristics and location preferences alters the cumulative mechanism of agglomeration. Chapter 3 provides a descriptive analysis on the patterns of inventors' mobility across urban areas, and their spatial dimension. Building on these results, a gravity model is used to analyse formally how employment opportunities, professional networks and urban amenities, influence inventors' mobility flows.

Second, these models do not consider workers' role in the diffusion of knowledge. The literature has established that skilled individuals influence the diffusion of knowledge by moving across organisation, creating network relationships and building absorptive capacities. Chapter 4 implements a spatial model to study these three mechanisms in an integrated framework. It is assumed that that mobility and networks provide access to knowledge, but the proportion of accessible knowledge used for innovation depends on absorptive capacity.

1.3 Methodological choices

Before going into more details, this section highlights three methodological choices common to the empirical chapters. First, this thesis makes extensive use of patent data, and therefore focuses on inventors' mobility and networks. Second, the empirical analysis is performed at the level of urban areas in Europe, an economically meaningful unit of analysis. Third, spatial econometric tools are used to model explicitly the interdependencies between neighbouring cities' innovation processes, and recover unbiased estimates.

Patent data contains considerable information about the patents themselves, the inventors and the assignees. This data is used extensively to compute a range of variables including mobility, networks, innovation and technological indexes, among others. Consequently, inventors are used as a proxy for the broader category of skilled individuals. Arguably, they constitute a representative sample, because they are directly involved in the production of new knowledge and therefore, have a large impact on the innovation. Despite several limitations discussed in detail in the chapters, patent data has the major advantage of being available on a large scale² and consistent across space and time. Finally, this data contains detailed inventors' addresses, and therefore can be geocoded at the level of urban areas, or any other spatial scale of analysis.

There is substantial theory and evidence that innovation is primarily an urban phenomenon. By contrast, most empirical studies on the geography of innovation have used administrative boundaries such as regions or states, especially in Europe. This thesis performs the analysis at the level of urban areas. The definitions developed by Eurostat and the OECD provide harmonized measures of cities throughout European

²This is partly due to the joint efforts of several research teams to provide access to disambiguated patent datasets (Coffano and Tarasconi, 2014; Lai et al., 2013; Pezzoni et al., 2014).

countries. These areas are defined using population density and commuting patterns, so that each represents a self-contained labour market, an economically meaningful unit of analysis. Besides, these definitions do not focus exclusively on large metropolitan areas, but also feature a wide array of small and medium-sized cities, with varying characteristics. However, using a non-standard scale of analysis is challenging in terms of data availability. In this regard, geocoding and data mining techniques were used extensively to build datasets at the city level. This spatial scale of analysis should reflect more closely the dynamics of mobility and innovation, and complements the existing empirical evidence at the level of regions.

From a methodological perspective, spatial econometrics offer a strong potential to investigate interdependencies in neighbouring cities' innovation because it models parsimoniously complex relationships between observational units across space and time. In her review of the literature, Autant-Bernard (2012) argued that spatial models are relevant to study of regional innovation because they account for two sources of dependence that characterize the geography of innovation. First, spatial autocorrelation arise when innovation in a city is affected by the research effort of its neighbours. Second, spatial heterogeneity stems for the spatial concentration of innovative activity. These two phenomena are well established in the empirical literature. Spatial dependence generates endogeneity and cause conventional models to produce biased estimates. This thesis takes advantage of recent developments in spatial econometrics to model explicitly the interdependencies between neighbouring cities' innovation, and recover reliable estimates.

1.4 Overview of the chapters

Chapter 1

This chapter sets the conceptual framework by drawing on three distinct streams of literatures including the new economic geography (NEG), endogenous growth, and the empirical geography of innovation literature. Specifically, the new economic geography (Krugman, 1991) provides an insightful theoretical framework to explain the uneven distribution of economic activity through the interplay of diverse agglomeration and dispersion forces. While research in this field has shed a new light on how labour mobility influences the spatial distribution of economic activity, it has been criticized for the static nature of some of its assumptions (Walz, 1996), and the lack of consideration of knowledge externalities as an agglomeration force (Fujita and Mori, 2005). As a consequence, it fails to provide a reasonable explanation for the spatial concentration of innovative firms, which rely on external knowledge as an input for their activity.

By contrast, endogenous growth theorists have established that sustained innovation depends on knowledge externalities arising from other firms (Romer, 1990). To the extent that these externalities have a limited spatial range (Jaffe et al., 1993), there is a positive relationship between agglomeration and R&D-driven economic growth. More recent theoretical work has explored this association by introducing endogenous growth in a NEG framework, while allowing for labour mobility (Baldwin and Forslid, 2000). This body of literature, known as the new economic geography and growth, has established that knowledge externalities and their geographical range impact the location of innovation. Yet, the microeconomic foundations of these models remain weak (Fujita and Krugman, 2004). In particular, while recognizing the importance of

both mobility and knowledge externalities for the location of innovation, they do not consider these workers' role in the diffusion of knowledge. Besides, the law of motion governing migration dynamics seem over-simplistic in light of the migration literature.

These two limitations are addressed by the empirical literature on the geography of innovation. First, studies have established that the transmission of knowledge proceeds mostly through personal ties. Consequently, firms can gain access to knowledge through the recruitment of key workers (Almeida and Kogut, 1999) or by actively engaging in collaboration networks (Singh, 2005). These two mechanisms are closely related because mobile workers influence the structure of networks (Agrawal et al., 2006) and conversely, social relationships influence mobility decisions. Besides, firms hiring skilled workers are able to build an absorptive capacity in order to capture and use productively external knowledge (Massard and Mehier, 2009). Second, introducing heterogeneity in workers' preferences and location decision weakens the circular-causation mechanism of agglomeration. Empirical evidence suggests workers' do not respond exclusively to market signals, but also to the provision of amenities (Miguelez and Moreno, 2014). More generally, mobility is diverse and each category of workers has different propensities and motivations to move, so that mobility patterns differ considerably.

Chapter 2

While there is large consensus on the importance of skilled workers on the diffusion of knowledge, far less attention has been devoted to the factors driving their location decisions. This chapter investigates the patterns and determinants of skilled workers' mobility across urban areas. First, a descriptive analysis documents the dynamics of inventors' mobility and their spatial dimension. Second, a gravity model is used to analyse how employment opportunities, collaboration networks as well as urban

and natural amenities, influence the flows of inventors between European urban areas. From a methodological perspective, this chapter uses a spatial filtering variant of the Poisson gravity model, which accommodate the nature of the data, while controlling for multilateral resistance and spatial autocorrelation in mobility flows (Krisztin and Fischer, 2015).

Despite the commonly held belief that skilled workers are highly mobile in space, the analysis suggests that mobility remains a rare event. Among multi-patenting inventors, only 9.67% moved from one city to another between 1975 and 2008. Mobility is also limited in space because inventors travel relatively short distances, generally within the same country. These results can be partly explained by the high level of circular and intra-firm mobility. Finally, the analysis highlight significant heterogeneity among countries. Turning to the determinants of inventors' mobility, four results are worth noting. First, inventors are drawn toward cities offering numerous employment opportunities. This finding is in line with the scarce existing evidence, provided by Miguelez and Moreno (2014) at the level of European regions, yet the explicit modelling of spatial autocorrelation and the analysis at the urban scale provide additional robustness to this finding. Second, the decision to move is mediated by network ties, which reduce information asymmetries between inventors and their potential employers, and therefore improve matching (Jackson, 2011). Besides, the definition of networks should not be restricted to direct collaborations. In particular, the centrality of cities, which represent a less restricted view of social networks, also plays a role. Third, contrary to expectations, geographical distance has a limited role in deterring mobility. This may be because it acts as a proxy for other, more meaningful forms of distance. In particular, mobility occurs primarily between cities sharing the same technological specialisation, partly because of the availability of specialised jobs, partly because collaboration networks tend to develop within the same scientific community. More

importantly, cultural and institutional distance translate into greater adaptation costs. Fourth, from a methodological perspective, spatial autocorrelation in mobility flows should be explicitly controlled for when estimating the gravity model in order to obtain unbiased parameter estimates.

These results have implications for the geography of innovation. While both mobility and networks have been shown to influence the diffusion of knowledge, they have often been investigated separately, and it would be interesting to study the interrelation between these two channels, as they appear to be closely related. The results suggest that the diffusion of knowledge may be limited for several reasons. Movers represent only a fraction of the inventors; and those who move travel relatively short distances, generally within the same country. This result is magnified by the fact that a large portion of mobility occurs within firms, and is not necessarily associated with a transfer of knowledge. Besides, the fact that mobility takes place primarily between technologically related cities may cause the transferred knowledge to be redundant, and have a limited economic impact. A more promising finding is that mobility may be encouraged, in particular through the development of research collaborations involving distant research communities.

Chapter 3

Empirical studies on the geography of innovation have established that skilled workers' mobility (Almeida and Kogut, 1999) and collaboration networks (Singh, 2005) shape the diffusion of knowledge across firms and regions. At the same time, the literature on absorptive capacity insisted on the importance of local research capabilities to take advantage of knowledge developed elsewhere (Cohen and Levinthal, 1989). This chapter investigates both phenomena in an integrated framework by assuming that mobility

and networks provide access to knowledge, but the proportion of accessible knowledge effectively used for innovation depends on absorptive capacity (Miguelez and Moreno, 2013a). Such complementarities in regional research efforts are effectively captured using a spatial Durbin model (Autant-Bernard and LeSage, 2011) in which the connectivity structure stems from mobility and collaboration patterns (Hazir et al., 2014).

This chapter contributes to the empirical literature in four ways. First, the analysis is carried out at the level of urban areas, a meaningful unit of analysis with regards to arbitrarily defined regions commonly used in the literature. Second, it proposes a refinement of the typical weight matrices based on purely geographical criteria by using information on the mobility of inventors and their collaborative ties. The model is estimated iteratively using different forms of connectivity to select the matrix associated with the model that fits the data most closely. Results confirm that skilled mobility, and to a lesser extent networks, significantly affect neighbouring cities' innovation processes. Besides, contiguity alone does not reflect the nature of dependence, but serves as a proxy for more meaningful forms of proximity based on social ties. Third, this chapter estimates a spatial knowledge production function on a panel of 488 European urban areas over 1998-2009. Maximum likelihood estimates suggest that innovation at the urban level is strongly affected by the research effort of their neighbours. Specifically, spending in R&D contributes to local innovation, but also significantly increase patenting in neighbouring cities. By contrast, the aggregate impact of human capital is not significant, because the positive effect on local innovation is offset by a negative spillover effect on neighbours. This is interpreted as a competition effect whereby an increase in human capital in a city would draw skilled workers from neighbouring cities, causing it to grow at the expense of peripheral areas. Fourth, this chapter attempts to provide an estimate of absorptive capacity, measured as the complementarity between internal and external resources. There is rather weak evidence of this phenomenon but

results suggests nonetheless that a certain level of human capital allow cities to take advantage of others' discoveries.

These findings have implications for the convergence debate. While greater accessibility encourages convergence, the notion of absorptive capacity implies a self-reinforcing effect leading to divergence (Aghion and Jaravel, 2015). On the one hand, if a region becomes relatively more attractive, mobile workers will move to this region, causing it to grow at the expense of peripheral areas. On the other hand, the strength of agglomeration depends negatively on the range of knowledge externalities. In this setting, the aggregate impact of skilled mobility is ambiguous because it favours the core-periphery equilibrium, while its role in the diffusion of knowledge gives rise to dispersion. The theoretical literature is unclear about which effect prevail, and this chapter provides evidence of both complementarity and competition effects among neighbouring cities innovation processes.

1.5 Main results

One of the main conclusion of Chapter 2 is that some new economic geography and growth models provide a useful theoretical framework to explain the spatial distribution of innovative activity through the interplay of agglomeration and dispersion forces. While recognizing the importance of skilled mobility and knowledge externalities for the distribution of innovation, they neglect these workers' role in the diffusion of knowledge. This should lead to an increased relevance of mobility choices for innovation. In addition, the migration dynamics are very simplistic, and heterogeneity in workers' location preferences weakens the circular mechanism of agglomeration. Some evidence is available in the geography of innovation literature. Empirical studies have established

that skilled workers influence the diffusion of knowledge by moving across organisation, creating network relationships and building absorptive capacities. Besides, labour mobility is diverse and skilled workers do not move exclusively in response to labour market signals.

Building on these considerations, Chapter 3 investigates the patterns and determinants of inventors' mobility across European urban areas. The descriptive analysis suggests that mobility is relatively rare and has a limited spatial dimension. Interestingly, the results points to the importance of circular patterns of mobility, which generally occur within the same firm. The econometric analysis reveals that inventors' do not respond exclusively to labour market signals, but are also attracted to cities providing natural and cultural amenities. In addition, the decision to move is mediated by network ties, which reduce information asymmetries and improve matching. Finally, the fragmentation of cultural and institutional frameworks in Europe significantly reduces mobility. These results suggest that the diffusion of knowledge may be limited. Mobility is rare and generally occurs within the same firms, located in technologically related cities. This may cause may cause the transferred knowledge to be redundant. A more promising finding is that mobility may be encouraged, in particular through the development of research collaborations.

Chapter 4 explicitly models interdependencies between neighbouring cities' innovation by assuming that by assuming that mobility and networks provide access to knowledge, but the proportion of accessible knowledge effectively used for innovation depends on absorptive capacity. The analysis confirms that mobility, and to a lesser extent networks, significantly affect neighbouring cities' innovation. Specifically, spending in R&D contributes to local innovation, but also significantly increases patenting in neighbouring cities. By contrast, the aggregate impact of human capital is not significant, because

the positive effect on local innovation is offset by a negative spillover effect on neighbours. This is interpreted as a competition effect whereby an increase in human capital in a city would draw skilled workers from neighbouring cities, causing it to grow at the expense of peripheral areas. Finally, the results suggest that a certain level of human capital allow cities to take advantage of others' discoveries.

2 Skilled mobility and the geography of innovation

Abstract

This chapter investigates the importance of skilled mobility for the geography of innovation. To answer this question, it draws on three distinct streams of literatures. The new economic geography provides a theoretical framework to explain the distribution of economic activity, but does not consider innovation. By contrast, endogenous growth models recognize the importance of skills and knowledge for innovation, but do not consider geography. Several models overcome these limitations by studying growth and geography in an integrated framework. While recognizing the importance of labour mobility and knowledge for location of innovation, they do not consider workers' role diffusion of knowledge. To investigate these issues, we turn to the empirical geography of innovation literature. Such an approach provides a deeper understanding of the importance of labour mobility, as well as the implications for the geography of innovation.

2.1 Introduction

In proposing a new theory of economic geography Krugman (1991, p.55) asked “What is the most striking feature of the geography of economic activity? The short answer is surely concentration”. There is substantial empirical evidence that what Krugman observed for production was even more pronounced for innovative activity. For instance, Audretsch and Feldman (1999) reported that in 1982 in the US, less than 4% of product innovations took place outside metropolitan areas, while 70% of the population resided in those cities. Building on these considerations, a stream of empirical literature has sought to provide economic foundations to the observed concentration of innovation. One of the main explanation that has been developed is the presence of local knowledge externalities. Endogenous growth theorists have established that innovation depends on firms’ own research capabilities, as well as their ability to use knowledge developed by other firms (Romer, 1990). Due to its non-rival characteristic, knowledge is only partly appropriated by its producer. To the extent that knowledge externalities are predominantly local (Jaffe et al., 1993), this could explain the observed concentration of innovation. This local aspect derives from the tacit nature of knowledge (Howells, 2002), which is embodied in individuals’ minds and habits and therefore, is better transmitted through frequent and direct interactions than long distance communications. In their critical review of this literature, Breschi and Lissoni (2001) argued that knowledge may flow locally, but not necessarily as an externality. Whether or not an externality occurs depend on the type of mechanisms through which knowledge is transferred. Building on these considerations, a series of empirical contributions have investigated the mechanisms of knowledge transfer and their determinants. In particular, this literature insisted on the role of skilled workers’ mobility and the networked nature of knowledge production on innovation. For instance, Almeida and Kogut (1999) found

evidence that skilled workers who change position take their embodied knowledge with them and promote new combination of knowledge. In addition, Agrawal et al. (2006) showed that mobile inventors are more likely to be cited by their former colleagues, reflecting the importance of social ties in the diffusion of knowledge. In this perspective, the limited geographical range of knowledge flows is the result of workers' lack of mobility, or because social relationships are equally bound in space (Breschi and Lissoni, 2009).

This chapter seeks to address the question of how skilled mobility shapes the spatial distribution of innovative activity. To answer this question, it draws on three distinct streams of literatures including the new economic geography (NEG), endogenous growth, and the empirical geography of innovation literature. Each of these provides complementary piece of evidence, but as is often the case, none gives a comprehensive explanation of this phenomenon. While one cannot attempt to survey such large bodies of literature, this chapter connects several key contributions in order to shed light on the relationship between skilled mobility and the geography of innovation. What is lacking is an integrated conceptual framework bringing together skilled mobility, economic geography, and innovation studies. Such an approach would undoubtedly provide a more thorough understanding of the labour mobility as well as the implications for the spatial distribution of innovative activity.

Specifically, the new economic geography (Krugman, 1991) provides an insightful theoretical framework to explain the uneven distribution of economic activity through the interplay of diverse agglomeration and dispersion forces. While research in this field has shed a new light on how labour mobility influences the spatial distribution of economic activity, it has been criticized for the static nature of some of its assumptions (Walz, 1996), and the lack of consideration of knowledge externalities as an agglomeration force

(Fujita and Mori, 2005). As a consequence, it fails to provide a reasonable explanation for the spatial clustering of innovative firms, which rely on external knowledge as a primary input of their activity.

By contrast, endogenous growth theorists have established that sustained innovation depends on knowledge externalities arising from other firms (Romer, 1990). To the extent that these externalities have a limited spatial range (Jaffe et al., 1993), there is a positive relationship between agglomeration and R&D-driven economic growth. Recent theoretical work has explored this association by introducing endogenous growth in a NEG framework, while allowing for labour mobility (Baldwin and Forslid, 2000). This body of literature, known as the new economic geography and growth (NEGG), has established that knowledge externalities and their geographical range impact the location of innovation. Yet, the microeconomic foundations of these models remain weak (Fujita and Krugman, 2004). In particular, while recognizing the importance of both skilled mobility and knowledge externalities for the location of innovation, they do not consider these workers' role in the diffusion of knowledge. This should in principle lead to an increased relevance of mobility choices for the spatial distribution of innovation. Besides, the laws governing migration dynamics seem very simplistic in light of the migration literature, which emphasize the heterogeneity in workers' characteristics and migration behaviour.

To investigate these issues, we turn to the empirical geography of innovation literature. These studies have established that the mobility of skilled individuals both in space and across organizations constitutes an important mechanism of knowledge transfer. Almeida and Kogut (1999) found evidence that skilled workers who change position take their embodied knowledge with them and promote new combination of knowledge. Singh (2005) argued in turn that this effect is depends on mobile worker's capability

to create networks relations. Building on these considerations, a range of authors have investigated the determinants of skilled mobility. In particular, Scott (2010) showed that talented workers move primarily in response to differences in labour market opportunities, although the provision of amenities also play a role. In addition, Miguelez and Moreno (2014) reported that the cost of moving varies with the geographical separation as well as cultural and technological forms of distance. Finally, mobility is diverse and workers have different propensities and motivation to move, so that mobility patterns differ considerably.

The remainder of this chapter is structured as follows. Section 2.2 introduces the basic NEG setting with a focus on the role of skilled mobility. Several models linking economic geography and endogenous growth are reviewed in section 2.3. Section 2.4 surveys empirical contributions on the impact of skilled workers' mobility on the diffusion of knowledge. Empirical evidence on the determinants of skilled mobility is reviewed in section 2.5 and section 2.6 concludes.

2.2 Labour mobility and economic geography

Initiated by Krugman's (1991) pioneering paper, the NEG has developed a solid theoretical framework to explain why economic activity concentrates in certain region leaving others relatively undeveloped. Much of that work focuses on the propensity of firms and workers to cluster together as regions become more integrated. The main novelty of this literature is to show that spatial imbalances can arise within a general equilibrium framework through the interplay of several agglomeration and dispersion forces, which are built upon micro-decisions of representative agents. After considering how labour mobility influences the spatial structure of the economy in the core-periphery model,

we review extensions that introduce workers' heterogeneity in a NEG framework.

2.2.1 Labour mobility in the core-periphery model

Krugman's (1991) core-periphery (CP) model illustrates how the spatial structure of the economy can change endogenously through the interplay of several agglomeration and dispersion forces. In particular, it shows how the mobility of labour across regions determines the agglomeration of economic activity. The model assumes an economy composed of two regions, with two sectors and two production factors.

1. The perfectly competitive agricultural sector produces a homogeneous good under constant return to scale using immobile farmers. This good can be traded freely across regions.
2. The industrial sector operates under increasing returns to scale. The introduction of increasing returns implies that we cannot assume perfect competition. Therefore, the manufacturing sector is modelled using Dixit and Stiglitz's (1977) model of monopolistic competition where each firm produces a horizontally differentiated variety. This sector uses workers who migrate to whichever region offers a higher real wage. Besides, shipping the industrial good involves iceberg transport costs (Samuelson, 1954).

Table 2.1: Basic setting of the CP model

	AGRICULTURE	MANUFACTURE
SECTORS	Agricultural firms (A)	Manufacturing firms (M)
	Perfectly competitive	Monopolistically competitive
	Constant returns to scale	Increasing returns to scale
	Produce an homogeneous good	Produce differentiated varieties
	Costless transportation	Iceberg transportation costs
FACTORS	Peasants (P)	Workers (L)
	Immobile	Mobile in response to real wage differentials
	CES preference for variety	CES preference for variety

In the initial setting, the two regions are identical in every respect, including their endowment of immobile factors. On one hand, the agglomeration forces arise from pecuniary externalities, which result from the location decisions of manufacturing firms and workers. These decisions are governed in turn by a combination of love of variety preferences, increasing returns to scale and transport costs. Pecuniary externalities reinforce one another in a circular causation mechanism that may push manufacturing and workers to agglomerate in the same region. On the other hand, the dispersion forces arise from product market competition and immobile factors of production. Depending on the relative strength of these two set of forces, regions can endogenously develop different production structures and become either an industrialized core or an agricultural periphery.

Going into more details, let us first consider firms' location behaviour. The introduction of increasing returns provides an incentive for manufacturing firms to concentrate production near large markets to benefit from economies of scale. This acts as an agglomeration force since manufacturing firms can find it profitable to produce in a single

location and ship to the other, provided that transport costs are low enough. At the same time, firms located in the core face a larger number of low-priced competitors. Besides, immobile agricultural workers imply that part of the demand remains located in the periphery, so that firms may be encouraged to locate in that region to serve the local market.

Turning to the workers' location behaviour, preference for variety implies that workers prefer to live near large markets offering a greater variety of consumption goods. A larger share of income spent on industrial goods allows firms in that region to pay higher nominal wages, making this location increasingly attractive for workers. Besides, these workers face a lower price for industrial goods since more varieties are produced and they do not incur trade cost, which cause the real wage to rise as well. At the same time, workers in that region face higher competition in the labour market, which causes firms to pay lower wages. This is a dispersion force since some workers have an incentive to move to the periphery where the relative wage may be higher.

one region. Whether or not agglomeration occurs depends on the underlying characteristics of the economy. Small changes in key parameters can have large effects on the production structure of the two regions due to circular causation.

The CP model has shed a new light on how labour mobility influences the agglomeration of economic activity. Yet, the assumptions governing the migration dynamics seem somewhat over-simplistic. First, it assumed that all workers have identical preferences for commodities and are symmetric in their migration behaviour. Second, all workers are homogeneous in their characteristics, in particular regarding their skill level. Third, while migration across regions is allowed, workers remain bound to their sectors of origin. In other words, the model rules out the impact of heterogeneous preferences and workers' characteristics on the geographic distribution of economic activity. In the next subsection, we consider several contributions seeking to address these shortcomings.

2.2.2 Introducing heterogeneity in workers' characteristics

Several studies have introduced heterogeneity in workers' characteristics and migration behaviour in a NEG framework. Murata (2003) and Tabuchi and Thisse (2002) relax the assumption of homogeneous preferences among workers. Mori and Turrini (2005) introduce heterogeneity in workers' skill level, and Tabuchi et al. (2015) explicitly considers differences in the migration costs they face. Finally, Puga (1999) proposes a model in which workers are mobile not only across regions but also across sectors.

Heterogeneity in workers' location preferences

The migration literature has shown that workers not only respond to wage differentials but many other non-market local characteristics. Besides, it is very likely that they

value differently local amenities depending on their motivation, culture or attachment to a particular region, among other factors. Introducing heterogeneity weakens the forward linkage depicted in figure 2.1, and consequently the circular causation mechanism of agglomeration in the CP model. In fact, heterogeneous preferences imply that prices, variety and wages matter less to workers, so that some of them may chose to remain located in the periphery.

Murata (2003) introduced heterogeneity in workers' migration behaviour by combining a simplified NEG model with a discrete choice model of migration. Contrary to the traditional NEG setting depicted in table 2.1, this model considers only one sector where each firms produces a horizontally differentiated variety under increasing returns to scale using mobile workers as the only production factor. Heterogeneous preferences are modelled by introducing a random variable representing idiosyncratic taste differences in residential location in the utility function. Therefore, the overall utility for an individual k is given by

$$V_r^k(\lambda) = \tilde{U}_r(\lambda) + \xi_r^k$$

Where $\tilde{U}_r(\lambda)$ is the indirect utility associated with differentiated goods common to the residents in region r and ξ_r^k is the random variable described above, which is assumed to be *i.i.d.* across individuals and regions. Together, product diversity, taste heterogeneity, and transport costs determine the spatial distribution of economic activity. Workers migrate whenever the interregional difference in indirect utility exceeds the individual migration cost. In this setting, heterogeneity in preferences serves as a probabilistic immobile factor and a dispersion force that weakens the circular causation of agglomeration. Specifically, Murata considers the case of low heterogeneity in preferences where workers tend to migrate to the region with a higher indirect utility from differentiated

goods. By contrast, in the presence of very heterogeneous preferences, workers tend to choose their location with equal probability regardless of transport costs.

In a slightly different setting, Tabuchi and Thisse (2002) yield similar conclusions. Contrary to Murata (2003), their model does not eliminate the traditional immobile factor. They show that taste heterogeneity acts as a strong dispersion force which gives rise to an equilibrium in which the manufacturing sector is only partially agglomerated. Besides, they explicitly consider the case where regions exogenously differ in the level of amenities they offer. This is consistent with the empirical evidence that natural amenities, such as a coastal location and good climate, affect the spatial distribution of industrial activities (Black and Henderson, 1999). Not surprisingly, workers tend to migrate toward the region with the larger endowment in amenities.

Heterogeneity in workers' characteristics

Workers are heterogeneous in the skills they own. By ruling out such characteristics, the CP model fails to explain the observed tendency of spatial segmentation according to skill levels. There is significant evidence that the existing distribution of skill affects the migration decision of workers, as they self-select across locations according to their skill level (Rauch, 1993). Mori and Turrini (2005) explicitly modelled heterogeneous skill level and the resulting distribution of economic activity. Focusing exclusively on pecuniary externalities¹, they showed that skilled workers tend to cluster in the region where aggregate skill and income is higher while unskilled ones remain in the other region. From a methodological perspective, the model departs from the traditional CP setting in two ways. First, manufactured products are both horizontally and vertically differentiated, and producing higher quality products requires skilled workers. Homo-

¹Alternative theoretical explanations for this phenomenon can be found in Black and Henderson (1999) who focus on agglomeration forces generated by human capital externalities.

geneous unskilled workers produce an intermediate input for a variety of final good, while mobile skilled workers are used to improve the quality of the final varieties. Turning to the consumer, the CES utility function incorporates both love for variety and preference for quality. Second, transportation is modelled somewhat differently since a communication fixed cost is added to the iceberg cost so that the perceived quality of products is lower if the goods are shipped to the other region. As in the CP model, circular causation through forward and backward linkages pushes manufacturing firms and workers to agglomerate within a single region. Yet, agglomeration also implies tougher competition among co-located producers. Agents with low skills are not able to endure competition at large agglomerations while those with higher skills locate where they can fully exploit agglomeration economies, since competition matters less to them.

Recently, Tabuchi et al. (2015) proposed an alternative view on the causes of agglomeration. In their model, the emergence of a core-periphery structure results from the interplay between labour productivity and migration cost. Specifically, the simple model features a single sector, manufacturing, using a single factor, labour. The manufacturing sector produces horizontally differentiated varieties under increasing returns to scale, which can be shipped to the other region under iceberg transport costs. Workers are heterogeneous in their skill level and are imperfectly mobile, because they face a cost when moving from one region to the other. Central to this model is the migration cost function. Each migrant bears a specific cost, which is incurred as long as he stays away from his region of origin. The rationale for this is that migration is not a one-time expense. Rather, migrants incur a permanent cost to adapt to their new environment, either because the culture and the language are different, or because of the distance separating them from their relatives. In this setting, agglomeration is driven by technological innovations, which translate into greater labour productivity.

Conversely, the dispersion force arises from imperfect mobility of workers. Together, the interplay between labour productivity and migration costs determine the location of firms and workers. When productivity increases sufficiently, workers migrate toward the more productive region by decreasing order of efficiency, until the economic gains stemming from migration are not sufficiently large to offset their own migration cost. The model has several attractive features. First, it provides an alternative explanation to the observed agglomeration of manufacturing as well as the spatial segmentation of workers according to their skill level. Second, the modelling of migration cost prevent complete agglomeration and both regions comprise skilled and unskilled workers. However, the source of increased labour productivity is unknown, as technological progress is exogenous.

Inter-sectoral mobility of workers

The assumption that workers are bound to their sector of origin seems unrealistic. Puga (1999) proposes a model in which workers are mobile not only across regions but also across sectors. Specifically, he shows that when the supply of labour is sufficiently elastic, the relocation of workers from agriculture to industry affects only slightly the wage ratio between sectors. In this case, agglomeration occurs as more workers move from agriculture to industry where wages are relatively higher. On the contrary, when the supply of labour is inelastic, the relocation of workers reduces the wages paid in industry relative to agriculture, which deter further agglomeration and promotes dispersion.

2.2.3 The need for an alternative approach

Although this first generation of NEG models constitutes an impressive theoretical advance in the study of agglomeration, it faces two major criticisms. First, these models are static in nature. While they can be interpreted as describing the long run spatial distribution of economic activity (Baldwin, 1999), it lacks the adjustment process toward this equilibrium (Walz, 1996). Second, as Fujita and Mori (2005, p.21) put it, “In most models of the NEG so far, agglomeration forces arise solely from pecuniary externalities through linkage effects among consumers and industries, neglecting all other possible sources of agglomeration economies such as knowledge externalities and information spillovers”. Marshall (1920), writing about industrial clusters, argued that firms could take advantage of (1) input-output relationships within industries, (2) the availability of a pool of specialized skills, and (3) knowledge externalities arising from other firms. This early NEG models focused only on agglomeration forces arising from pecuniary externalities through linkage effects among consumers and firms ; that is entries (1) and (2). While relevant, these explanations fall short of providing a reasonable explanation for many other observed clustering of economic activity, where non-market mechanisms play a central role (Audretsch and Feldman, 1996).

Endogenous growth models have established that sustained growth depends on constant technological progress, which depends in turn on knowledge externalities arising from other firms (Romer, 1990; Grossman and Helpman, 1991). To the extent that these externalities have a limited spatial range, as suggested by the empirical literature on knowledge externalities (Jaffe et al., 1993), there should be a positive relationship between the agglomeration of economic activity, innovation and growth. In this setting, innovative firms have an incentive to locate close to one another to benefit from knowledge externalities arising from nearby firms, and reduce the cost of innovation.

Conversely, higher economic growth promotes agglomeration for standard Marshallian reasons (Baldwin and Forslid, 2000).

To sum up, NEG models explain why economic activity concentrates in certain region but do not consider explicitly innovation. By contrast, endogenous growth models emphasized the importance of knowledge externalities in the generation of innovation, but omit the role played by geography in the process. These considerations point to the importance of studying growth and the spatial distribution of economic activity in an integrated framework. Appreciating these dimensions requires a model which relies on knowledge externalities to make both location and growth endogenous. Building on these considerations, more recent contributions have explored the relationship between agglomeration of economic activity and R&D-driven economic growth. This strand of literature, known as the new economic geography and growth (NEGG) is reviewed in the next section.

2.3 Economic geography, innovation and growth

In order to formally investigate the spatial dimension of innovative activity, we turn to the NEGG literature. Initiated by Martin and Ottaviano (1999), this generation of models rely on two main building blocks: Krugman's CP model introduced above and endogenous growth models along the lines of Romer (1990) and Grossman and Helpman (1991). After briefly introducing Romer's modelling framework, we review several NEGG contributions allowing for labour migration.

2.3.1 Innovation and endogenous growth

Generally speaking, endogenous growth theorists model technological change as a result of profit-motivated investments by private economic agents. They assume that a firm investing in capital unintentionally contributes to the productivity of capital held by other firms. This can be either physical capital (Arrow, 1962) or human capital (Lucas, 1988). Romer (1986) instead, assumed that knowledge externalities arising from private research efforts increase the stock of publicly available knowledge. Provided that these externalities are strong enough, they increase the returns to private human capital accumulation which remains permanently above the discount rate, thereby ensuring sustained growth.

The breakthrough to studying technological change was achieved by Romer (1990) and subsequently, Grossman and Helpman (1991). Central to these models is novel formulation of knowledge as a non-rival, partially excludable good :

1. Thanks to its non-rival characteristic, newly developed knowledge increases the stock of publicly available knowledge, which is accessible for anyone engaged in research by means of studying its patent documentation. These externalities increase the productivity of the R&D sector as a whole and the rate at which new varieties are developed, ensuring sustained economic growth.
2. At the same time, the introduction of partial excludability provides firms with an incentive to engage in R&D and earn monopoly profits, since an intellectual property system precludes other firms from using newly developed knowledge. The introduction of incentives to invest in R&D requires modelling the economy within the framework of imperfect competition (Dixit and Stiglitz, 1977).

In sum, knowledge enters the production function in two ways. First, newly developed

technological knowledge is used in production by the firm which developed it. Second, this knowledge increases the total stock of publicly available knowledge and benefits other firms.

From a methodological perspective, Romer's model consist of an economy with three sectors: A perfectly competitive sector producing homogeneous final consumption goods using differentiated inputs; an intermediate sector where each firm produces a differentiated input for the final sector under monopolistic competition. In order to produce a new variety, firms operating in this sector buy blueprints from the innovation sector. The perfectly competitive R&D sector produces patents for new varieties using skilled workers who benefit from technological spillovers. At the equilibrium, economic growth as measured by the rate at which new varieties are created is positive and constant.

2.3.2 Economic geography, innovation and growth in the NEGG

More recent theoretical contributions have explored the relationship between agglomeration of economic activity and R&D-driven economic growth. These models combine Krugman (1991) core-periphery model introduced above and endogenous growth models along the lines of Romer (1990) and Grossman and Helpman (1991).

In line with traditional NEG models, they use circular causation mechanisms to explain the spatial concentration of economic activities, so that growth and agglomeration of economic activity are mutually self-reinforcing processes. Specifically, growth spurs spatial agglomeration of economic activities as firms are drawn toward where innovation take place. This in turn reduces cost of innovation, boosts growth and encourages further agglomeration. From a methodological perspective, both fields share the same basic framework of monopolistic competition, which reflects the importance of economies of scale. Yet, these models depart from earlier NEG models in several ways.

Besides having a different model structure, transport costs and labour mobility are no longer the only factor that leads to centripetal or centrifugal outcomes. A significant achievement is to work both pecuniary and knowledge externalities at the same time, which modifies the traditional forward and backward linkages of the CP model. The introduction of endogenous growth introduces a growth-linked cycle of circular causality. Given the focus on labour mobility, this section describes several models in which workers are mobile across regions. Significant contributions in this field include Walz (1996); Black and Henderson (1999); Baldwin and Forslid (2000) as well as Fujita and Thisse (2002a, 2003).

Walz (1996) represents an early attempt to link growth and geography. He designed a model of R&D-driven economic growth and location based on increasing returns to scale at the local level and migration. He shows that fall in transport cost leads to agglomeration and faster growth. However, the assumption of costless migration and the focus on aggregate rather than firm-level increasing returns seems too restrictive (Baldwin and Martin, 2004). In an urban context, Black and Henderson (1999) model the relationship between urbanization and growth through local knowledge externalities. Urbanization affects the growth of the economy, while growth affects the size of cities. However, the assumption of a migration process that is determined by a city developer seems unrealistic.

Baldwin and Forslid (2000) proposed an ambitious framework encompassing labour mobility and knowledge externalities. In their model, growth and agglomeration are mutually self-reinforcing processes, and the strength of agglomeration depends on the amount of externalities across regions. In line with the traditional CP model, the economy is composed of two symmetric regions and includes an agricultural and an industrial sector, and two production factors, agriculturists and workers.

1. The perfectly competitive agricultural sector produces a homogeneous good under constant return to scale using immobile farmers. This good can be traded freely across regions.
2. The monopolistically competitive industrial sector where each firm produces a horizontally differentiated variety under increasing returns to scale using mobile workers. The introduction of a new industrial variety requires one unit of capital available from the innovation sector at a fixed cost. Shipping the industrial good involves iceberg transport costs.
3. Growth is introduced through a perfectly competitive innovation sector that produces knowledge capital using mobile workers. Following the endogenous growth literature, the cost of producing capital falls as the amount of existing knowledge increases in the economy.

Table 2.2: Basic setting of Baldwin and Forslid (2000)

	AGRICULTURE	MANUFACTURE	INNOVATION
SECTORS	Agricultural firms (A)	Manufacturing firms (M)	Innovative firms (I)
	Perfect competition	Monopolistic competition	Perfect competition
	Constant returns to scale	Increasing returns to scale	Increasing returns to scale
	Homogeneous good	Differentiated varieties	Knowledge capital (K)
	Variable cost (L)	Var. cost (L), fix. cost (K)	Decreasing var. cost (L)
	Costless transportation	Iceberg transport costs	
FACTORS	Peasants (P)	Workers(L)	
	Immobile	Mobile in response to real wage differentials	
	CES preference for variety	CES preference for variety	

Turning to consumers, both agriculturists and workers have the same inter-temporal utility function, which depends on the consumption of the agricultural good and manufacturing varieties that enter the function symmetrically. Forward-looking workers migrate in response to market signals. That is, the difference in the present value of

utility across regions, which depends on discounted real wage difference².

Formally, the I-sector production function can be written as follows.

$$Q_k = \frac{L_I}{a_I}$$

Where L_I is the I-sector employment and a_I the capital unit factor requirement. Introducing technological externalities yields the following function for a_I .

$$a_I = \frac{1}{K_{-1} + \lambda K_{-1}^*}$$

Where K_{-1} represents the stock of capital lagged one period, and the superscript * denotes the other region. Due to sector-specific learning effect, the cost of producing a new variety falls with every new variety produced in both regions. The extent to which externalities are local is captured by parameter λ .

Together, the interplay between labour mobility, knowledge externalities and trade costs determine the distribution of economic activity. In addition to the usual backward and forward linkages of the NEG, the introduction of endogenous growth gives rise to a growth-linked mechanism of circular causality whose strength depends on the level knowledge externalities across regions. From there, the authors examine the stability of different configurations in the cases where externalities are either local or global.

- When externalities are purely local ($\lambda = 0$), the cost of innovation in a region depends exclusively on the number of firms located in that region. The region with a slight head start accumulates I-sector experience faster than the other, this causes the relative capital stocks to diverge indefinitely. This difference in the rate of capital accumulation implies a continual increase in the real wage

²The log-difference in the present values of real wages across regions.

gaps due to preferences for variety, causing more workers to migrate toward that region. Therefore, a core-periphery configuration emerges as all the innovation takes place in the region with a higher number of firms.

- Conversely, if externalities are global ($\lambda = 1$), the location of firms has no impact on the cost of innovation, which weakens the circular causation mechanism described above and favours the symmetric equilibrium. In this sense, knowledge spillovers are a stabilizing factor.

Growth, as measured by the rate at which new varieties are created, is highest when the innovation sector is agglomerated and fully benefit from knowledge externalities. When the innovation sector is fully dispersed, growth is at the lowest. Interestingly, there is a tension between the destabilizing tendency of falling trade costs highlighted in the core-periphery model, and the stabilizing tendency that arises when ideas become easier to trade.

In a similar setting, Fujita and Thisse (2002a, 2003) designed a model where the innovation sector produces patents using skilled workers benefiting from knowledge externalities, which are stronger within a region than across region. Consequently, the agglomeration of skilled workers in a region leads to a higher productivity of skilled workers in the R&D sector of that region.

Overall, to the extent that knowledge externalities are local, the existence of an R&D sector appears to be a strong agglomeration force, which amplifies the circular causation mechanisms of agglomeration. Interestingly, the introduction of the R&D sector in a dynamic setting yields another interesting feature. Agglomeration increases the rate of innovation, which in turns constantly increases the number of firms operating in the manufacturing sector, some of which relocate in the periphery. The more aggregated the economy, the faster the growth in aggregate terms. However, agglomeration gener-

ates spatial divergence in income levels, reflected by the spatial distribution of skilled workers.

2.3.3 The need for deeper microeconomic foundations

The theoretical NEG literature has improved our understanding of how knowledge externalities determine both the productivity and location of innovative activity. Yet, to a large extent, the strength of agglomeration and the resulting distribution of innovative activity critically hinges on the geographical range of knowledge externalities, which in turn depends on some exogenous parameter value. Fujita and Krugman (2004, p.162) argue that “Although the concept of knowledge externalities plays a crucial role in such models, its micro-foundations are rather weak, leaving plenty of room for further development.”

This problem arises because the NEG modelling framework do not account for the actual mechanisms through which knowledge diffuses in space and across firms. By contrast, the empirical geography of innovation literature has established that the mobility of skilled individuals play an important role in the diffusion of knowledge. While NEG models recognize the importance of both skilled workers’ mobility and knowledge externalities in determining the location of innovation, they neglect these workers’ role in the diffusion of knowledge. To the extent that knowledge diffuses according to the mobility patterns of skilled individuals, this should lead to an increased relevance of mobility choices on the spatial distribution of innovative activity.

A related issue, which also applies to earlier NEG models, is that the laws of motion governing the dynamics of workers’ mobility appear very simplistic in light of the migration literature. Specifically, most models assume that workers move exclusively in response to real wage differentials across regions. This contrasts sharply with the mi-

gration literature, which emphasize the heterogeneity in both workers' preference and characteristics. Skilled mobility is a highly diverse phenomenon. Each category of workers has different propensities and motivation to move, so that mobility patterns differ considerably. Consequently, their impact on the diffusion of knowledge, and the resulting distribution of innovative activity is likely to be different. As already shown in section 2.2.2, introducing heterogeneity in workers' migration behaviour alters the cumulative mechanism of agglomeration.

2.4 Skilled mobility and the diffusion of knowledge

Building on these considerations we need to go beyond the pure externality perspective to look at the mechanisms underlying the diffusion of knowledge and their determinants. In order to address these points, we turn to empirical contributions within the geography of innovation and the migration literatures. After highlighting the conceptual framework behind skilled mobility in the diffusion of knowledge, selected empirical contributions are reviewed.

2.4.1 Going beyond the externality perspective

In explaining the limited geographical range of knowledge spillovers, modern approaches to the geography of innovation emphasize the role played by interactions between firms and workers in the innovation process. Central to this argument is the notion that a substantial amount of knowledge conducive to innovation turns out to be tacit (Howells, 2002) and embodied in individuals (Lucas, 1988). While codified knowledge can be transmitted across distance by means of communication technologies, the transfer of tacit knowledge relies on effective interpersonal interactions (Storper and Venables,

2004). In essence, the transmission of complex knowledge is not a routine activity that can be performed through standardized procedures. R&D activity involves long periods of exchange and discussion, during which actors develop a mutual way of communicating through some common codes. This in turn should improve co-ordination, productivity and mitigate the incentives problem in the collaboration between agents. Moreover, direct interactions are often at the origin of new ideas, combining insights from each party that are crucial for innovations. Such exchanges of knowledge is truly effective in the form of frequent and direct interactions (Glaeser et al., 1992).

The empirical evidence is fairly conclusive³. Using US patent (Jaffe, 1989) or innovation counts (Acs et al., 1992), studies found that industry patenting at the state or metropolitan levels (Anselin et al., 1997) was influenced by university research spending in related technological fields. Audretsch and Feldman (1996) focused on the propensity of innovative activity to cluster spatially as a way to assess the spatial dimension of knowledge externalities. Their results suggest that in the US, R&D intensive industries are found to be relatively more concentrated. In an influential contribution, Jaffe et al. (1993) reconstructed the actual paths of knowledge diffusion using patent citations. They showed that innovative firms are more likely to quote research from a university that conducts relevant research located in the same US state and metropolitan area, than from similar universities located elsewhere. Overall the evidence have been widely interpreted as a proof of the existence of local knowledge externalities. At the same time, there is evidence that these externalities are not systematic, and their geographical is found to differ across countries and industries.

An important point is made by Breschi and Lissoni (2001). In their critical review of this literature, they argued that knowledge may flow locally, but not necessarily as an externality. Whether or not an externality occurs depend on the type of mechanisms

³See Audretsch and Feldman (2004) for a more comprehensive review of this literature.

through which knowledge is transferred. In fact, agents may get in touch through a variety of mechanisms, some of which favour the gratuitous exchange of knowledge, while others take the form of market-mediated transactions. These developments point to the importance of going beyond the pure externality perspective to explore the mechanisms through which transferred among agents located in the same geographic area.

2.4.2 Skilled mobility and networks in the diffusion of knowledge

The recent literature has highlighted a variety of mechanisms through which knowledge is transmitted between individuals and firms. Among the many mechanisms that exist, the mobility of skilled workers is regarded as particularly important. While there is significant body of evidence highlighting a positive correlation between the mobility of skilled individuals and innovative performance, there is no clear consensus concerning the specific mechanism at play. Specifically, the literature has documented two main mechanisms.

1. A first strand of literature argue that knowledge is transferred by the labour market (Almeida and Kogut, 1999). The rationale is that when skilled workers move away from the place where they originally worked, they take their embodied knowledge with them and promote new combination of knowledge. Consequently, firms can gain access to knowledge through the direct recruitment of key workers. Besides, firms are capable of building an absorptive capacity, to identify and use productively external sources of knowledge (Massard and Mehier, 2009). In this perspective, the limited geographical range of knowledge flows is the result of workers' lack of mobility (Breschi and Lissoni, 2009).

2. A second strand of literature argue that this effect depends on mobile worker's capability to create networks relations (Singh, 2005). The tacit nature of knowledge relevant to innovative activities makes its transfer and diffusion strongly relying upon socio-professional relationships, or networks. In this case, knowledge flows locally because proximity facilitates the development of social relationships, by exposing agents to relevant social events and reducing the costs of forming and sustaining such ties (Breschi and Lissoni, 2005).

These two mechanisms are closely related. Skilled workers on the move may influence the structure of networks by bridging or closing existing networks. Besides, mobility also gives mobile researchers a strategic position within the network. Agrawal et al. (2006) provides empirical evidence that even though co-location facilitates the development of social relationships, and that network ties tend to persist after formerly collocated individuals are separated. Conversely, social networks are likely to drive mobility decisions for at least two reasons. First, information about the destination may not be easily available, and networks spanned by friends and colleagues are important informal channels through which information is transmitted. A worker embedded in a dense network of relationships is more likely to be informed of vacancies and to know more about the job and the receiving organisation (Jackson, 2011). Second, Millard (2005) examined the location decisions of Italian researchers in the UK and point to the importance of prestige and networks in determining location decisions. This is in line with Laudel (2005), who highlighted the role of the scientific elite in recruiting the next generation of scientists.

A large body of empirical evidence has investigated skilled workers' mobility patterns and collaboration choices and their impact on the diffusion of knowledge. Given the diversity of the modelling strategies and the data used, contributions are classified by

type of worker.

Table 2.3: Empirical contributions classified by categories of workers

Categories	Contributions
Inventors	Agrawal et al. (2006) Almeida and Kogut (1999) Breschi and Catalini (2010) Breschi and Lissoni (2005, 2009) Lobo and Strumsky (2008) Miguelez and Moreno (2013a,b) Singh (2005)
Migrants inventors	Hunt (2011) Hunt and Gauthier-Loiselle (2010) Kerr (2008) Kerr and Lincoln (2010) Niebuhr (2010)
Outstanding researchers	Herrera et al. (2010) Schiller and Revilla Diez (2012) Trippel (2013) Zucker and Darby (2014)
Graduates, Students	Chellaraj et al. (2008) Faggian and McCann (2006, 2009) Stuen et al. (2012)
Skilled workers	Bosetti et al. (2015) Gagliardi (2015)

The first strand of literature tracks the mobility patterns individual inventors across firms and space using patent data. In their pioneering study, Almeida and Kogut (1999) replicated Jaffe et al.'s (1993) exercise for every US state. Using a sample highly cited patents in the semi-conductor industry, they found evidence of local knowledge flows

only in the regions where the intra-regional mobility of inventors across companies is high. In a similar setting, Singh (2005) investigates whether co-invention networks explain the subsequent patterns of patent citations, both at the regional and at the firm level. They apply a using choice-based sampling methods to USPTO patent citations and find that the probability to observe a citation link between two patents is positively related on the existence of a network tie between inventors, either direct or indirect. Agrawal et al. (2006) looked at the mobility patterns of US inventors across different Metropolitan Statistical Areas (MSA). Their results suggest that inventors who move in space are more likely to be cited by their former colleagues. This suggests that social ties facilitate knowledge diffusion, even after formerly co-located inventors are separated.

Looking at migrant inventors in particular, Kerr and Lincoln (2010) used an exogenous surge in the immigration of scientists and engineers in the US caused by the 1990 Immigration Act. They found a strong correlation between skilled workers' inflow and patenting activity at the level of MSA, especially in the case of Chinese and Indian immigrants. These results are consistent with Hunt and Gauthier-Loiselle (2010), who showed that immigrant college graduates files a least twice more patents than their US counterpart. However, this difference may be explained by the disproportionate share of skilled immigrants engaged in science and engineering (Hunt, 2011). Related to this, Niebuhr (2010) used a knowledge production function approach to investigate the importance of cultural diversity for innovative outcomes in German regions. Their results suggest that workers from diverse cultural backgrounds enhance performance of regional R&D sectors. Diversity could provide a wider set of perspective at the origin of novel ideas. Kerr (2008) investigated the importance of ethnic networks in the transmission of knowledge by estimating elasticities for technology transfer across multiple ethnicities and manufacturing industries. He found evidence of knowledge

transfer following ethnic networks between US migrant and their home countries.

In a series of articles, Zucker and her colleagues emphasized the role of outstanding academic scientists in innovation. This category of workers is considered as particularly relevant because mobility is regarded as a normal phenomenon in the academic world. Zucker et al. (1998) introduced the concept of stars in biotechnology based upon productivity measures. They showed that the direct involvement of these scientists significantly determined which firms were ultimately major winners in biotechnology. In their 2006 paper, Zucker and Darby tracked the career paths of highly-publishing academic scientists in the field of science and technology across 25 countries. Their results suggest that their presence played a key role in the location of firms in this sector. Schiller and Revilla Diez (2012) investigated knowledge transfer activities performed by highly cited scientists in Germany and provided evidence for rather strong intraregional knowledge links between these star scientists and local actors. In a similar vein, Tripl (2013) found evidence of substantial knowledge transfer following the movements of star scientists. This is due to their higher propensity to move, and their ability to create knowledge networks between distant areas.

Looking at the migration behaviour of UK graduates, Faggian and McCann (2009) found that graduate migration patterns across regions significantly affect regional innovative performance⁴, as measured by patent applications. Interestingly, their results point to the existence of a cumulative process operating at the regional level. Inflows of recent graduates boosts regional innovative performance, which in turn determines graduates' location decisions. This process feeds on itself so that more innovative regions develop at the expense of others, which gives rise to a core-periphery pattern.

⁴The results are significant for both England and Wales, but found insignificant for Scotland. The authors attribute this difference to the fact that Scottish graduates tend to be less mobile than their British and Welsh counterparts.

Gagliardi (2015) looks at the broader category of skilled individuals, as measured by educational attainment. She found that the share of skilled workers within British Travel To Work Areas (TTWA) significantly affects their innovative performance. Interestingly, she does not find any significant additional effect associated with the urban dimension⁵.

Overall, the evidence points to the relevance of skilled workers' mobility patterns and collaboration networks in the diffusion of knowledge. However, mobility is a diverse phenomenon, and appreciating the effect of workers' mobility requires an understanding of who is moving, the quality of their skills, as well as the nature of their mobility. In particular, the latter may include the direction of the flows, their frequency, their duration, and the propensity to return (Ackers, 2005). Therefore, to assess the impact of skilled mobility on innovation, we must investigate what drives their location decisions.

2.5 The determinants of skilled mobility

While there is large consensus on the importance of skilled workers on the diffusion of knowledge, far less attention has been devoted to the factors driving their location decisions. This is an important issue because heterogeneity in workers' characteristics (Mori and Turrini, 2005; Tabuchi et al., 2015) and location preferences (Tabuchi and Thisse, 2002; Murata, 2003) alters the circular causation mechanism of agglomeration. This section reviews recent empirical evidence on the determinants of labour mobility, with a particular focus on skilled workers. Due to the diversity in the modelling strategy and the data used, the table below classifies the existing empirical evidence by type of worker.

⁵She explain these results by the fact that British cities traditionally concentrate service industries as well as other less innovative manufacturing firms; and that TTWAs may be too narrow to reflect actual metropolitan areas.

Table 2.4: Empirical contributions classified by categories of workers

Category	Contributions
Inventors	Crespi et al. (2007) Hoisl (2007) Lenzi (2009) Nakajima et al. (2010) Miguelez and Moreno (2014)
Scientists & Engineers	Dahl and Sorenson (2010) Scott (2010)
High technology workers	Chen and Rosenthal (2008) Dorfman et al. (2011) Hansen and Niedomysl (2009)
Students & Graduates	Brown and Scott (2012) Faggian and McCann (2006, 2009) Gottlieb and Joseph (2006) Nifo and Vecchione (2014)
Skilled migrants	Facchini and Lodigiani (2014)

Economists traditionally consider mobility as a rational decision in which an individual compares the expected utility of staying with the expected utility obtained at an alternative location. The individual will decide to move whenever the expected utility differential exceeds the cost of moving. The literature has developed around two alternative views of what influence the level of utility.

The human capital approach views the decision to move as an investment to maximize lifetime earnings, net of migration costs. This approach was adopted for instance in Krugman (1991), in which mobility is a response to spatial heterogeneity in the net returns to labour. Empirically, this means that workers are attracted toward locations offering better employment opportunities, more attractive salaries and other pecuniary

incentives. In an urban context, Scott (2010) investigated what drives inflows of migrant US engineers into different MSA for 13 different technological categories between 1994 to 1999. Using a fractional Logit model, he found that local employment opportunities have a major impact on the destination choices of engineers, far above amenities or even wages. These results are in line with Brown and Scott (2012), who analysed the location choices of university degree holders by applying a multinomial Logit model to Canadian 2001 census data. They showed that skilled individuals are drawn to thick labour markets to match their specialized skills with employers' needs. Therefore, degree holders are more likely to move to locations that are specialized in their industry. From macroeconomic perspective, Miguelez and Moreno (2014) focused on the geographical mobility of inventors across European regions. By applying a gravity model to EPO data from 1975 to 2005, they found that job opportunities and to a lesser extent, amenities are important determinants of inventors' mobility. Besides, their results show that mobility occurs primarily between technologically related regions. Finally, Faggian and McCann (2006, 2009) studied the mobility of UK graduates entering into first employment using a three-stage least squares model on 2000 survey data. The analysis suggests that mobility flows are mainly directed by differences in nominal wages, so that regions offering a higher nominal wage are net absorber of human capital flows and regions with lower nominal wages net losers of human capital. More interestingly, a centre-periphery pattern seems to emerge which reflects the rank order of the region within the national urban hierarchy.

While relevant, the assumption that workers respond exclusively to market mechanisms is restrictive, and falls short of providing a reasonable explanation for mobility between locations with similar levels of economic development. An alternative approach views mobility as a consumption choice. Individuals may choose to live where the provision of locally-produced goods and services, or amenities, satisfy their preferences. In

this perspective, mobility would be a response to spatial heterogeneity in the provision of amenities. These two views are not incompatible in the sense that potential movers compare utility differentials across alternative locations, and these utilities are a function of both economic and non-economic factors. This approach was adopted by Tabuchi and Thisse (2002) and Murata (2003) among others. Early works focused on natural advantages such as pleasant landscapes, proximity to the coast or a temperate climate. Building on this initial intuition, other economists have considered the importance of human-produced amenities including social, cultural (Glaeser et al., 2001) and skill-dependent amenities which are particularly important in an urban context. For instance, Miguelez and Moreno (2014) showed that mild winter temperatures and proximity to the coast significantly affect inventors' location decisions. Shapiro (2006) argued that the presence of educated population in the city increases the quality of life so that the effect of human capital goes beyond the productivity. However, recent studies have established that the relative importance of amenities have been exaggerated (Storper and Scott, 2009; Hansen and Niedomysl, 2009), and that labour mobility is driven primarily by differences in labour market opportunities. For instance, Dorfman et al. (2011) find that natural amenities are not a major factor of high-tech workers' location decisions and metropolitan areas of the US.

Another variable entering workers' location decision is the cost of moving. In most of the NEG literature surveyed above, a considerable attention have been paid to the cost of moving goods. However, the cost of moving people is not explicitly taken into account, with the exception of Tabuchi et al. (2015). Empirically, economists have often relied on geographical distance to act as a proxy for pecuniary and non-pecuniary cost of moving. More recent studies refined the analysis by documenting other, more meaningful forms of distance. For instance, Miguelez and Moreno (2014) suggested that differences in cultures, languages and institutions translate into greater adapta-

tion costs, and inventors are more likely to move to regions sharing the same cultural background and language. Nifo and Vecchione (2014) studied the importance of institutions on the mobility decisions. Using a Probit model on a sample of 47300 Italian graduates, they found that institutional quality is a major determinant of mobility.

The above reasoning overlooks the fact that information about destination may not be easily available. Knowing about labour market conditions, or looking for a job in potential destinations may involve significant search and information costs. Social networks, spanned by friends and colleagues are important informal channels through which information are transmitted. Dahl and Sorenson (2010) investigated the professional mobility of Danish scientists and engineers between 2004 and 2006 using a Mixed Logit model. Their results suggest that differences in wages, but more importantly, distance to family and friends, explain mobility patterns.

Overall, the evidence suggests that workers move in response to labour market signals, as well as spatial disparities in the provision of amenities. Besides, geographical distance and other forms of separation, such as cultural or institutional distance, increase the cost of moving. Going into more details, several studies have considered the importance of personal characteristics such as life-cycle (Crespi et al., 2007) and productivity (Hoisl, 2007) on skilled workers' mobility decisions. This suggests that mobility is diverse and each category of workers has different propensities and motivations to move, so that mobility patterns differ considerably. This is an important issue because heterogeneity in workers' characteristics and location preferences alters the cumulative mechanism of agglomeration.

2.6 Conclusion

This chapter seeks to address the question of how skilled mobility shapes the spatial distribution of innovative activity. To answer this question, it draws on three distinct streams of literatures including the new economic geography, endogenous growth, and the empirical geography of innovation literature.

The new economic geography (Krugman, 1991) provides an insightful theoretical framework to explain the uneven distribution of economic activity. Interesting extensions to the basic model have shown that heterogeneity in workers' characteristics (Mori and Turrini, 2005; Tabuchi et al., 2015) and location preferences (Tabuchi and Thisse, 2002; Murata, 2003) alter the circular causation mechanism of agglomeration. However, these models fail to provide a reasonable explanation for the spatial clustering of innovative firms, because they do not consider knowledge externalities as an agglomeration force (Fujita and Mori, 2005). To the extent that that sustained innovation depends on knowledge externalities arising from other firms (Romer, 1990), and that knowledge flows have a limited spatial dimension (Jaffe et al., 1993), there is a positive association between knowledge, agglomeration and growth. Recent theoretical work has explored this association by introducing endogenous growth in a NEG framework, while allowing for labour mobility (Baldwin and Forslid, 2000). These studies established that knowledge externalities and their geographical range impact the location of innovation. However, while recognizing the importance of both skilled mobility and knowledge externalities for the location of innovation, the microeconomic foundation of these models remain weak (Fujita and Krugman, 2004), partly because they do not consider these workers' role in the diffusion of knowledge. The empirical geography of innovation literature has established that the mobility of skilled individuals both in

space and across organizations constitutes an important mechanism of embodied knowledge transfer. Skilled workers on the move can transfer embodied knowledge from their initial workplace to the new one (Almeida and Kogut, 1999), and conversely channel back the knowledge they acquired thanks to the link they have kept with their previous environment (Agrawal et al., 2006). Besides, firms hiring skilled workers are not only more likely to innovate, they are also able to build an absorptive capacity in order to capture and use productively external knowledge (Massard and Mehier, 2009). In this perspective, knowledge flows locally either because mobility takes place across short distances, or because the social context in which workers are embedded is equally bound in space (Breschi and Lissoni, 2009). While there is large consensus on the importance of skilled workers on the diffusion of knowledge, far less attention has been devoted to the factors driving their location decisions. There is evidence that mobile workers do not exclusively respond to labour market signals, but are also sensitive to the provision of amenities (Miguelez and Moreno, 2014). Besides, the cost of moving is affected by various forms of distance including geographical, cultural and institutional forms of separation. This is an important issue because heterogeneity in workers' characteristics (Mori and Turrini, 2005) and location preferences (Tabuchi and Thisse, 2002) weakens the circular causation mechanism of agglomeration.

These findings have implications for the convergence debate. Depending on labour mobility and the range of knowledge externalities, a core-periphery pattern can emerge as firms and skilled workers cluster within the same location. As this location becomes more attractive, further concentration of firms and factors occurs, pushing its capacity to innovate and grow at the expense of peripheral areas. By contrast, when knowledge externalities have a wide spatial range, location decisions have no effect on innovation, which weakens the circular causation mechanism described above and favours the symmetric equilibrium. In this setting, the aggregate impact of skilled mobility is am-

ambiguous because it favours the core-periphery equilibrium, while its role in the diffusion of knowledge acts as a dispersion force. The theoretical literature is unclear about which effect prevails, because it does not account for the mechanisms through which knowledge diffuses in space. In light of the geography of innovation literature, the impact of skilled workers on innovation critically depends on their mobility patterns. For instance, in the presence of long term mobility, the agglomeration force should be stronger than what theory predicts. By contrast, the increasing development of short-term, circular patterns of mobility should give rise to dispersion. The migration literature makes it clear that mobility is diverse. Each category of workers has different propensities and motivation to move, so that mobility patterns differ considerably. Consequently, their impact on the diffusion of knowledge, and the resulting distribution of innovative activity is likely to be different. Building on these considerations, further work should investigate the patterns and determinants of skilled workers' mobility.

3 Patterns and determinants of skilled mobility across urban areas

Abstract

Skilled workers drive economic development of cities through their effect on productivity and innovation. However, they are mobile and tend to cluster within a few urban areas. Therefore, an important question is what factors shape these mobility flows, and influence the geography of innovative activity. This chapter investigates the patterns and determinants of inventors' mobility across European urban areas. First, a descriptive analysis documents the patterns of inventors' mobility. Second, a gravity model is used to analyse how labour markets, networks and amenities influence the flows of inventors. From a methodological perspective, the spatial filtering variant of the Poisson gravity model accommodates the nature of the data, while controlling for multilateral resistance and spatial dependence in mobility flows. The descriptive analysis suggests that inventors' mobility occurs primarily between relatively large and collocated urban areas, partly because of the high level of circular mobility. The econometric analysis reveals that social networks and to a lesser extent employment opportunities and urban amenities, significantly influence mobility flows.

3.1 Introduction

Models that study growth and geography in an integrated framework recognize the importance of workers' mobility and knowledge externalities in determining the productivity and the location of innovation (Baldwin and Forslid, 2000). At the same time, the empirical geography of innovation literature insists on the importance of skilled mobility for the diffusion of knowledge (Almeida and Kogut, 1999). This leads to an increased relevance of mobility choices for the distribution of innovation. However, extensions to the basic core-periphery model show that heterogeneity in workers' characteristics (Mori and Turrini, 2005) and location preferences (Murata, 2003) alter the cumulative mechanism of agglomeration. Therefore, an important question is what factors shape these mobility flows, and influence the geography of innovative activity. This study focuses on inventors, which represent a specific category of skilled workers. Arguably, inventors constitute a representative sample, because they are directly involved in the production of new knowledge and therefore, have a large impact on the innovation.

Economists traditionally consider mobility as a rational process in which workers compare expected utilities at origin and destination. In this setting, a worker will decide to move whenever the expected utility differential exceeds the cost of moving. The literature has developed around two alternative views of what influences the level of utility. The traditional approach considers that mobility is driven primarily by the labour market. This may include employment opportunities, financial incentives along with attractive working conditions. In addition, information about destination may not be easily available, and professional networks help matching workers to positions by reducing information asymmetries (Jackson, 2011). However, purely economic factors

cannot explain mobility between locations with similar levels of economic development. An alternative approach views mobility as a consumption choice in which workers move in response to spatial disparities in the provision of amenities. Early works focused on natural advantages such as climate (Graves, 1980), but more recent contributions considered other human-produced amenities including social, cultural (Glaeser and Mare, 2001) and skill-dependent amenities which are particularly important in an urban context (Shapiro, 2006). Existing evidence on the determinants of inventors' mobility in Europe adopt a fairly microeconomic perspective. Lenzi (2009) explores the mobility patterns for a group of Italian inventors in the pharmaceutical sector using survey and patent data. Crespi et al. (2007) analyses the mobility of inventors from academia to private firms for six European countries. Closer to this work, Miguelez and Moreno (2014) adopted a macroeconomic approach to investigate the determinants of inventors' mobility across European regions.

This chapter contributes to the empirical literature in four ways. First, the analysis is carried out at the level of urban areas, a meaningful unit of analysis with regard to regions commonly used in the literature. Second, it takes advantage of a large-scale dataset to shed light on the patterns of inventors' mobility across European urban areas, and their spatial dimension. To my knowledge, such a descriptive analysis does not exist for Europe, especially at the level of urban areas. Building on these results, a gravity model is used to analyse formally how job opportunities, professional networks and amenities influence the flows of inventors between urban areas. Interestingly, while both skilled mobility and networks influence the diffusion of knowledge, they have been investigated separately. Studying the interactions between the two is interesting because mobility influences the structure of networks by creating new or bridging existing networks (Miguelez, 2013). Conversely, social relationships help matching workers to positions by reducing information asymmetries, so that networks influence mobility de-

cisions. Fourth, spatial dependence in mobility flows is explicitly taken into account using spatial econometrics techniques. Accounting for the dependence structure in mobility flows is an important issue (Bertoli and Moraga, 2013) and spatial filtering provides a natural tool to deal with such interdependencies (Patuelli et al., 2015).

Despite the commonly held belief that skilled workers are highly mobile in space, the analysis suggests that mobility remains a rare event. Among multi-patenting inventors, only 9.67% moved from one city to another between 1975 and 2008. Mobility is also limited in space; inventors who move travel between relatively large and co-located urban areas, and 90% of these moves occur within the same country. These results can be partly explained by the high level of circular and intra-firm mobility. Finally, the analysis highlights significant heterogeneity among countries, with about 80% of all moves taking place either in Germany, France or the UK. Likewise, the propensity to move varies importantly across technological sectors. Turning to the determinants of inventors' mobility, five results are worth noting. First, inventors are drawn toward cities offering numerous employment opportunities along with attractive working conditions. This finding is in line with the scarce existing evidence, provided by Miguelez and Moreno (2014) at the level of European regions, yet the explicit modelling of spatial autocorrelation and the analysis at the urban scale provide additional robustness to this finding. Second, the decision to move is mediated by network ties, which reduce information asymmetries and improve matching (Jackson, 2011). Besides, the definition of networks should not be restricted to direct collaborations. The centrality of cities in the network of inventors significantly affects mobility flows. Third, workers are attracted to cities with a pleasant environment, providing green spaces and cultural amenities. More generally, while urban amenities have received significant attention in the literature, empirical progress has been hampered by the lack of data. In addressing this issue, this chapter uses data mining techniques to collect specific data on the provision of urban amenities

for all urban areas in Europe. Fourth, contrary to expectations, geographical distance has a limited role in deterring mobility. This is because geographical distance acts as a proxy for other, more meaningful forms of distance. In particular, mobility occurs primarily between cities sharing the same technological specialisation, cultural and institutional backgrounds. Fifth, from a methodological perspective, spatial autocorrelation in mobility flows should be explicitly controlled for when estimating the gravity model in order to obtain unbiased parameter estimates.

These results have implications for the geography of innovation. While both mobility and networks have been shown to influence the diffusion of knowledge, they have often been investigated separately. Besides, the results suggest that the diffusion of knowledge may be limited for several reasons. Movers represent only a fraction of inventors, and those who move travel relatively short distances, generally within the same country. This result is magnified by the fact that a large portion of mobility occurs within firms, and does not necessarily imply a transfer of knowledge. Besides, mobility occurs primarily between technologically related cities, so that the transferred knowledge may be redundant, and have a limited economic impact. A more promising finding is that mobility may be encouraged, in particular through the development of research collaborations involving distant research communities.

The remainder of this chapter is structured as follows. Section 3.2 briefly reviews the related literature. Section 3.3 describes the data, with a focus on the definition of urban areas and the measurement of mobility. Section 3.4 documents the patterns of inventors' mobility across European urban areas and their spatial dimension. Turning to the determinants of inventors' mobility, section 3.5 describes the model and discusses the estimation results. Section 3.6 concludes.

3.2 Background

Economists traditionally consider mobility as a rational process in which workers compare expected utilities at origin and destination. In this setting, a worker will decide to move whenever the expected utility differential exceeds the cost of moving. The literature has established that utility in a given location depends on employment opportunities as well as the provision of amenities, and the cost of moving is expected to rise with distance, which acts as a proxy for pecuniary and non-pecuniary mobility costs. Specifically, the traditional approach views mobility as a response to spatial disparities in employment opportunities. In this setting, workers would depart from cities in which employment and wages are low toward cities where labour market conditions are more attractive. This is particularly important for talented workers because they are relatively more mobile and willing to find a position that maximise the return to their skills. In addition, Krugman (1991) showed that the concentration of skilled workers in a region creates a market pooling effect, which draws additional firms and workers toward this location and expands employment opportunities in a circular-causation mechanism. In the same spirit, Berry and Glaeser (2005) argued that skilled cities host more entrepreneurs, which may employ additional skilled workers. However, purely economic factors cannot explain entirely mobility decisions. An alternative approach views mobility as a response to disparities in the provision of amenities. Early works focused on natural advantages such as pleasant landscapes, proximity to the coast or a temperate climate (Graves, 1980). Building on this intuition, other economists have considered other human-produced amenities including social, cultural (Glaeser and Mare, 2001) and skill-dependent amenities which appear to be particularly important in an urban context (Shapiro, 2006). For instance, in his work on the creative class, Florida (2002) claimed that talented individuals value open-minded environments offering a high de-

gree of tolerance and diversity. These two views are not incompatible in the sense that potential movers compare utility differentials across different alternative locations, and these utilities are a function of both economic and non-economic factors.

From an empirical perspective, Miguelez and Moreno (2014) studied the mobility of inventors across European regions. Using EPO data from 1975 to 2005, they found that job opportunities and to a lesser extent, amenities are important determinants of inventors' mobility. Besides, they showed that geographical distance is a significant predictor of inventors' mobility patterns. Finally, other meaningful forms of distances such as social ties, institutional frameworks and cultural similarities are shown to play a role. Looking at geographical distance in particular, Breschi and Lenzi (2010) documented the mobility patterns of inventors across US cities between 1978 and 2004. Their result highlight the existence of two distinctive spatial patterns, whereby inventors move both at short and long distances, suggesting that the cost of mobility decreases as inventors move further away. In an urban context, Scott (2010) investigated what drives inflows of migrant engineers into different MSA for 13 different technological categories. He found that local employment opportunities have a major impact on the destination choices of these skilled individuals, far above amenities or even wages. This is consistent with Dorfman et al. (2011) found that natural amenities are not a major factor of high-tech workers' location decisions in US metropolitan areas. Considering other determinants of mobility, Nifo and Vecchione (2014) looked at the importance of institutions in driving location decisions. Using a sample of 47300 Italian graduates, they found that institutional quality significantly affects mobility. Faggian and McCann (2006, 2009) studied the migration of UK graduates entering into first employment. Their analysis suggests that more educated individuals are more likely to move. Besides, migration flows are mainly directed by differences in nominal wages. They showed that regions offering higher wages are net absorber of human capital, and develop at the expense of

regions in which salaries are lower. Interestingly, a centre-periphery pattern seems to emerge, which reflects the rank order of regions within the national urban hierarchy.

The above reasoning overlooks the fact that information about destination may not be easily available. Knowing about labour market conditions, or looking for a job in potential destinations may involve significant search and information costs. Social networks, spanned by friends and colleagues are important informal channels through which information are transmitted. The theoretical literature on social networks surveyed in Jackson (2011) has identified two main channels through which networks relationships can affect labour market outcomes. If a worker is embedded in a dense network, he is more likely to be informed of vacancies and to know more about the job and the receiving organisation. Such networks are particularly important for cross-country mobility, since workers may lack specific skills such as language fluency or knowledge of the institutions. From the firms' perspective, professional networks may be used to improve screening and signalling of unobserved workers' ability, allowing them to select the most able workers. In sum, recruiting through professional networks may reduce information asymmetries and improve matching. Nakajima et al. (2010) provided empirical evidence on the importance of networks for matching inventors to firms. Using US patent data from 1975 to 1997, they showed that networked inventors are more productive and have longer tenure than non-networked inventors. While we cannot observe whether inventors do use their networks when looking for a job, we can expect higher levels of mobility between cities whose inventors have collaborated frequently in the past. Krabel and Flother (2014) studied the mobility of skilled German graduates entering the labour market. They found that professional network ties directly impact job search success and labour mobility. Interestingly, they argued that graduates are less likely to move when living in a metropolitan area where the share of highly qualified employees is relatively high.

Additional evidence on the determinants of inventors' mobility adopt a more microeconomic approach. Crespi et al. (2007) studied the mobility of inventors from academia to the private sector. Using a sample of academic inventors who were granted a EPO patent between 1993 and 1997, they reported that individual life cycle significantly affects mobility. Besides, mobility patterns are found to differ greatly across technological sectors and countries, which points to the importance of academic labour market regulations and institutions. Hoisl (2007) studied the interrelation between inventors' productivity and inventors' mobility using a random sample of 2697 inventors residing in Germany between 1993 and 1997. Their results highlight the existence of a simultaneous relationship. Movers are on average more productive than non-moving inventors, but more productive inventors are also less likely to move. In a similar setting, Lenzi (2009) investigated mobility decisions of 106 Italian inventors in the pharmaceutical sector using survey data. The analysis suggests that inventors' personal characteristics, inventive productivity, and geographical location matter for mobility choices. The descriptive part of this study is closest to Breschi and Lenzi (2010), who documented the mobility patterns of inventors across US Core Based Statistical Areas (CBSA) between 1978 to 2004. To my knowledge, no comparable evidence is available for Europe, especially at the level of cities. This would be interesting because mobility patterns in Europe are expected to be quite different from the United States for several reasons. First, it is well-known the Europe exhibit lower levels of mobility than the United States, both regarding the degree and the spatial extent of mobility. However, differences do not only include mobility patterns. The empirical evidence from Europe suggests that mobility is driven mainly by labour market variables rather than amenities (Migueluez and Moreno, 2014). Yet, these studies have not considered the importance of urban amenities in particular. Finally, there is limited evidence on the importance of network ties in driving the mobility decisions of European inventors, though some evidence is

available for the United States (Nakajima et al., 2010).

3.3 Data

The analysis is carried out at the level of urban areas. The gravity variables include size and distance, measured by the number of inventors and the driving distance between urban areas, respectively. Mobility is computed by recording changes in inventors' addresses in patent documentation. Turning to the variables of interest, research investment and human capital are used to proxy the labour market for inventors. In addition, two measures of networks are used, a bilateral collaboration count as well as a more multilateral network centrality index. Besides, various amenities including social, cultural and natural amenities are considered. Finally, control variables include a technological proximity index as well as a same country indicator variable.

Table 3.1: List of variables

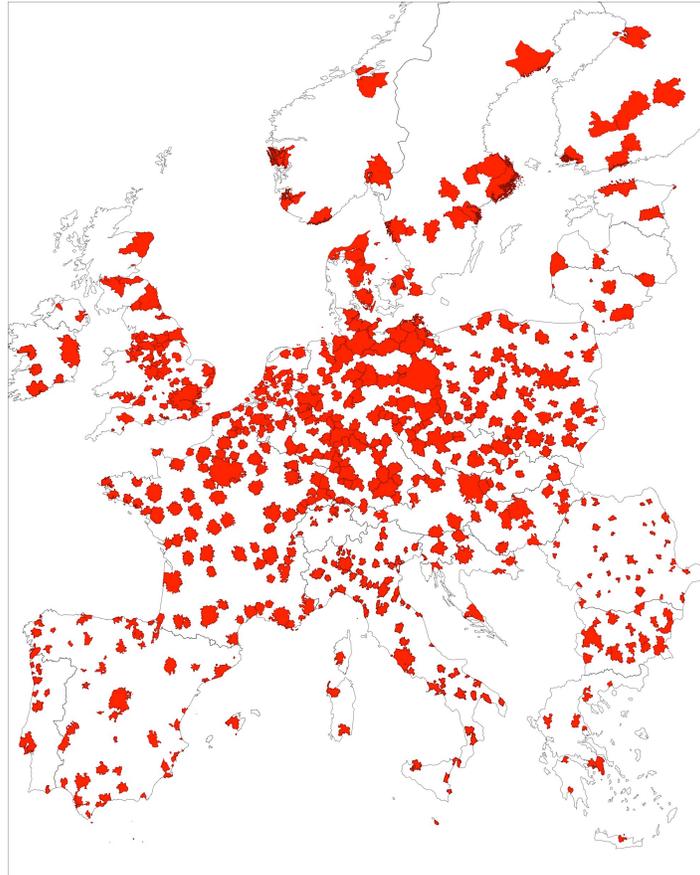
Variable	Proxy	Source
Mobility	Changes in inventors' addresses	Invpat
<i>Gravity</i>		
Size	Number of inventors	Invpat
Distance	Driving distance	OpenStreetMap
<i>Labour markets</i>		
Research investment	Spending in research and development	Eurostat
Human capital	Human resources in science and tech.	Eurostat
<i>Networks</i>		
Direct collaborations	Collaboration count	Invpat
Centrality	Betweenness centrality index	Invpat
<i>Urban amenities</i>		
Social life	Bars, cafes, pubs, restaurants	OpenStreetMap
Culture	Cinemas, galleries, museums, theatres	OpenStreetMap
Green spaces	Surface of public parks and gardens	OpenStreetMap
<i>Natural amenities</i>		
Seaside	Distance to the coast	OpenStreetMap
Climate	Average summer temperature	WolrdClim
Rain	Average winter precipitations	WolrdClim
<i>Controls</i>		
Technology	Technological proximity index	Invpat
Culture, institutions	Same country dummy	–

Urban areas

Larger Urban Zones (LUZ) were created by Eurostat to provide a harmonized definition of metropolitan areas throughout the European Union as well as several other countries. In the 2012 version, which uses 2006 as a reference year, LUZ are defined on the basis of population size, population density and commuting patterns, so that each represents

a self-contained labour market (Dijkstra and Poelman, 2012). This edition covers 695 cities in 31 countries¹.

Figure 3.1: Larger Urban Zones



Specifically, each LUZ is composed of a densely populated city core and a commuting zone around it. The urban core is composed of high-density contiguous population grid cells ($> 1500 \text{ inh/km}^2$) whose total population is greater than 50 000. The core is then adjusted to LAU2 delineations² and include those LAU2 with at least 50% of their population residing inside the urban core. The commuting zone includes LAU2 where more than 15% of their employed resident population work within the urban

¹The 28 European Union current member States, Norway, Switzerland and Iceland.

²LAU2 consists of municipalities or equivalent units in the 28 EU member states.

core. To ensure homogeneity, LAU2 surrounded by a single LUZ are included and non-contiguous LAU2 are dropped.

Mobility

Mobility is computed from the Invpat database (Lai et al., 2013). The database contains patent applications at the USPTO from 1975 to 2010, and includes information about inventors, patents and assignees³. Mobility is computed by recording changes in inventors' personal addresses. Consider an inventor who fills a patent at time t while residing in city i ; in $t + 1$, this same individual fills another patent while residing in city j . Therefore, one can observe that between t and $t + 1$, this individual has moved from i to city j . This measure of mobility is fairly straightforward but presents three obvious drawbacks. First, the use of patent data restricts the analysis to those inventors with at least two patents, when single-patenting inventors represent about 56% of the sample. Second, a move is recorded only if those inventors applied for a patent before and after the move, so it represents a lower-bound measure of mobility. Third, patents record inventors' location at a point in time, therefore it is not possible to determine precisely when the move took place. I consider that mobility occurs exactly between the application dates of the patents at origin and destination, if there is no more than a four-year lag between the two. Addresses are then geocoded at the level of LUZ. Mobility computed this way identifies inventors who filled at least two patents while residing in different LUZ.

Another issue is that in practice, it is difficult to determine whether two inventors are the same person, since the USPTO does not require unique identifiers for inventors. Therefore, disambiguation is necessary to determine whether two patents belong to the same inventor career by comparing all pairs of inventor-patent instances. In particular,

³The database contains inventors' names and addresses, assignees' names, patent numbers, dates of application and granting and detailed technological classes.

two issues arise from this exercise. The first is misspelling of the same inventor's name on different occasions while the second occur when two inventors with the same name are not actually the same person. To overcome this difficulty, Lai et al.'s (2013) disambiguation algorithm uses information in patent documentation to identify likely matches⁴. The routine computes a cumulative similarity score for each pair of inventor-patent instances, the greater the similarity score, the greater the probability that the two patents belong to the same inventor career. The threshold value of the score has been set to a relatively high value to ensure a rather conservative approach.

Gravity

The gravity variables include economic size and distance. In migrations studies, a common practice is to use population rather than economic variables such as GDP. This chapter uses the number of inventors at origin and destination to measure the number of potential movers. Intuitively, a higher level of mobility is expected between cities with a large stock of inventors. Distance is measured in several ways including geodesic and driving distance (Luxen and Vetter, 2011) between cities' geographical centres. Distance between origin and destination is expected to reduce inventor flows for at least three reasons. First, the direct cost of moving is higher, this may include transportation and other pecuniary costs of relocation. Second, distance increases search costs and reduces the quality of information about the destination, such as employment opportunities or income differentials. Finally, movers may also face significant non-pecuniary costs. If he has spent a substantial amount of time in the city of origin, moving to a distant city means being separated from family, friends and colleagues (Dahl and Sorenson, 2010).

Labour market

Employment opportunities are measured using human resources in science and tech-

⁴Variables used for the disambiguation include first names, middle initial, last names, location, assignees, number of shared technology classes, and number of shared co-inventors.

nology. It is a general proxy for human capital, the presence of universities, research centres and technology-oriented firms. In addition, total R&D spending is used to measure the research effort in the public and the private sectors. The expected impact of these variables is unclear at least for the city of origin. On the one hand, cities with a large labour market for inventors host more potential movers, which increases the probability of a move. On the other hand, working in a city where many firms, universities, research centres are located makes it easier to find a position within the area, and to the extent that intra-city mobility is a substitute to inter-city mobility, this decreases the probability of a move.

Networks

A network of inventors can be viewed as a social network whose nodes are individual inventors and links are co-inventorship relations. Co-inventorship refers to the situation where the patent lists more than one inventor. If two inventors have collaborated in the past, then a social tie exist. The network variable full counts for each year the number of collaborations between inventors residing in city i and those residing in j . I acknowledge a certain degree of endogeneity between the network variable and the dependent variable since mobility influences the structure of networks by creating new, bridging or closing existing networks. To attenuate this issue, the network variable is lagged one year.

In addition, a measure of centrality is used to abstract from the duality of the network variable, which represents a rather restrictive view of social networks. Centrality measures the relative position of a city within the network. It characterizes whether a particular city has a favourable position in the network and how a city's network positioning changes over time. Following Berge et al. (2017) the betweenness centrality index (BC $_i$) of a city can be broken down into three components. (1) A city's par-

ticipation intensity, which measures of how well a city is embedded in the network of collaboration. (2) A city's relative outward orientation, which assesses the openness of a city with respect to established network linkages. A high number of internal collaborations would have a negative influence as it potentially reduces the number of actors connecting different cities. (3) A city's diversification of network links, which indicates how collaborations are distributed along other cities in the network. The more concentrated the collaborations, the less the region is central in the sense that it links only a few other cities. The BC of a city, which is defined as the number of bridging paths stemming from a city between all dyads of the network, can be defined as follows.

$$BC_i = \sum_{i \neq j} \sum_{k \neq i, j} \frac{g_{ij}g_{ik}}{n_i} \quad (3.1)$$

n_i is the number of inventors active in region i . g_{ij} and g_{ik} are network links between city i and city j or k , respectively. In an aggregate context, equation (3.1) collapses to the following equation.⁵

$$BC_i = \bar{g}_i s_i (1 - h_i) \quad (3.2)$$

$\bar{g}_i = g_i - g_{ii}$ is the number of outer collaborations, and reflects the participation intensity of the city. $s_i = \bar{g}_i / g_i$ is the share of outer collaborations, which measures the relative outward orientation of the city. $h_i = \sum_{k \neq i, j} (g_{ij} / \bar{g}_i)^2$ is the Herfindahl-Hirschman index of the distribution of i 's outer collaborations. It varies between zero and one depending on the degree of diversification of network links to other cities. The resulting centrality index is normalized to one, so that the most central city has an index value equal to unity. As for the previous network measure, mobility flows are expected to be greater

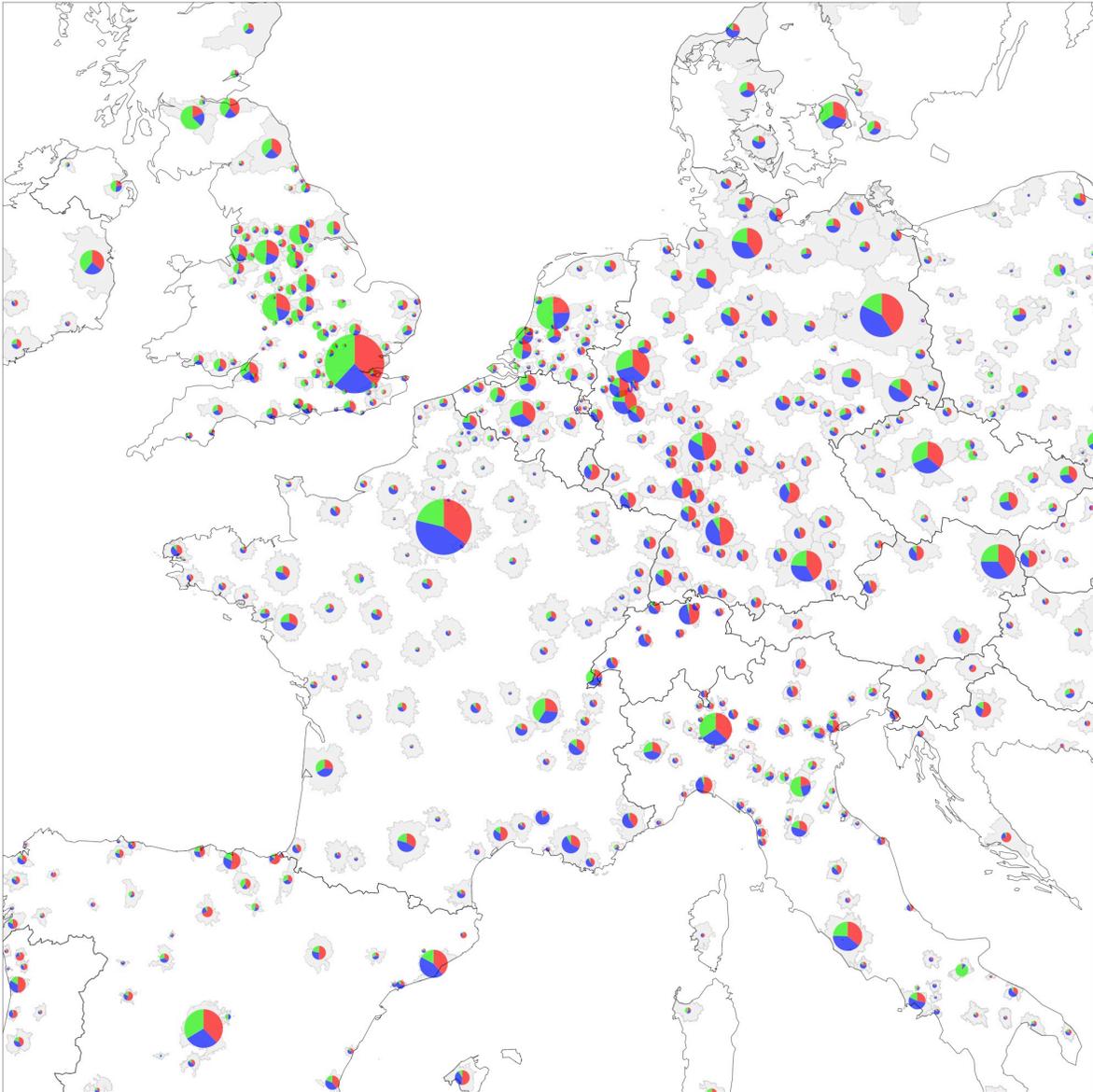
⁵See Berge et al. (2017, p. 20-21) for a formal proof.

between cities with a high degree of centrality.

Amenities

While the role of urban amenities in the location decisions has received significant attention in the literature, empirical progress have been hampered by the lack of data. In addressing this issue, this chapter uses the OpenStreetMap database to collect specific data on the provision of amenities for all urban areas in Europe. Specifically, amenities are grouped into three broad categories. First, to measure whether a city has a vibrant social life, an index including the number bars, cafes, pubs and restaurant is computed for each city. In addition, the cultural amenities index includes the number of cinemas, galleries, museums and restaurants. Finally, amenities in the form of urban green spaces are measured by an index including the surface in square-kilometres of public parks and gardens. Figure 3.2 represents the distribution of the three types of amenities in European urban areas.

Figure 3.2: Urban amenities in Europe



Social amenities are represented in red, cultural amenities are in blue and green spaces are in green. All variables are normalized to a range between zero and one, so the size of the slices represents the relative position of cities in the provision of each type of amenities.

The analysis on the role of urban amenities is exploratory because there is a significant lag with the dependent variable. Data on mobility is exploited up to the year 2007, while data on amenities reflect the current situation. Even though there is no explicit

role for time in a cross-sectional setting, the amenities variables are normalized to a range between zero and one, so that the index value reflects the relative position of urban areas in the provision of amenities. Therefore, it is assumed that this position remains stable over time.

Controls

Inventors may be specialized in a very specific field, and have only a few alternative destinations to choose from. In an aggregate context, a technological proximity index is computed by grouping the patents into technological sectors and comparing their relative distribution across cities. Using the classification provided by the NBER patent data project, patents are grouped into 6 broad technology classes and 40 subclasses. An issue is that patent with multiple classes often belong to more than one sector, which makes the aggregation difficult. Sectors are weighted according to their relative frequency of apparition in the patents. Following Jaffe (1986), technological proximity is computed as the uncentered correlation between i and j 's vectors of technological class.

$$t_{ij} = \frac{\sum f_{ih}f_{jh}}{\sqrt{\sum f_{ih}^2 \sum f_{jh}^2}}$$

f_{ih} and f_{jh} denote the share of city i and j 's patents of technological class h , respectively. The resulting index t_{ij} varies between zero and one depending on the level of technological proximity. The technological proximity index is computed using 34 technological subclasses⁶. An index value close to unity indicates that two cities are technologically similar, while a value close to zero indicate that they are technologically distant. Inventors flows are expected to be larger between cities that have a similar

⁶Each of the 6 class has a subclass named "Miscellaneous", which is considered too heterogeneous to reflect a city's technological specialisation.

technological specialisation.

Even though workers are in principle free to move, they are in practice confronted with a series of obstacles hampering their movement. Differences in cultures, languages and institutions may translate into greater adaptation costs. Inventors' mobility may be hampered by institutional and legal barriers, which may vary significantly across countries. In the same manner, inventors are more likely to relocate in a city sharing the same cultural background and language, in order to minimize mobility costs. Institutional and cultural proximity are captured using a dummy variable that takes the value one if the two cities are located in the same country and zero otherwise. Intuitively, inventors flows are expected to be smaller between cities belonging to different countries.

3.4 Patterns of inventors' mobility

This section documents the patterns of inventors' mobility across LUZ between 1975 and 2008. During this period, 72.62% of all patents were filled by inventors residing in urban areas. This share, although substantial, is somewhat lower than that reported by Jaffe et al. (1993) for the United States. Among multi-patenting inventors, only 9.67% were mobile, which suggests that mobility is a rare event, and contradicts the commonly held belief that skilled workers are highly mobile in space. The final sample includes 15361 inventors who moved across at least two of the 695 LUZ between 1975 and 2008, for a total of 30628 moves. Table 3.2 shows that about 80% of inventors moved only once or twice during their career. Likewise, the number of cities visited, defined as the number of different cities where an address has been recorded, exhibit a large positive skew, which suggests that circular mobility is important.

Table 3.2: Distribution of inventors per number of moves and cities visited

N. moves	N. inventors (%)	N. cities	N. inventors (%)
1	9045 (58.88)		
2	3361 (21.88)	2	13881 (90.37)
3	1230 (8.01)	3	1246 (8.11)
4	666 (4.34)	4	173 (1.13)
5+	1059 (6.89)	5+	61 (0.40)
15361 (100)		15361 (100)	

Circular mobility is identified when the city of origin for the move m is the same as the city of destination for the move $m + 1$. Each pair of moves is compared in sequence for the 6316 inventors who moved at least twice during their career, for a total of 15267 moves. This is a rather restrictive measure of circular mobility since each move is compared only with the next, so this figure is probably lower-bound. Nonetheless, this form of mobility represents about three-quarters (74.08%) of these inventors' mobility.

Building on these considerations, one may wonder whether circular mobility occurs because inventors move primarily between different establishments of the same firm (Breschi and Lenzi, 2010). For instance, if the inventor works for a multinational firm, changing location does not imply working for another firm, but simply moving from one establishment to another. In this sense, intra-firm mobility is defined as a move between two establishments of the same firm located in two distinct cities. Determining whether two assignees belong to the same firm is difficult, since the assignees' names alone cannot be used to identify the firm that holds the patent. Problems arise from misspellings, from different forms of the same company's name and from subsidiaries having completely different names from the parent. Lai et al. (2013) performed a disambiguation of firms' names using the NBER file of patent assignee to identify the

same firms listed as assignee on distinct patents. The following figures should be interpreted with caution as information about the assignee at both origin and destination is available in only 66.85% of the cases. In this sub-sample, intra-firm mobility represents 69.64% (14259) of the moves so that inter-firm mobility is limited. Linking this to circular mobility, among inventors the 4449 inventors who moved at least twice, and for which assignee information is available, about half (49.23%) of circular mobility occurs within the same firm, suggesting that the two phenomena are closely related.

Table 3.3: Distribution of moves per country

Country	National moves		International moves			
			as orig.	(%)	as dest.	(%)
Germany	14227	(51.74)	813	(25.96)	745	(23.79)
United Kingdom	5997	(21.81)	448	(14.30)	399	(12.74)
France	2693	(9.79)	349	(11.14)	384	(12.26)
Netherlands	1201	(4.37)	300	(9.58)	286	(9.13)
Italy	1081	(3.93)	122	(3.90)	144	(4.60)
⋮						
Belgium	288	(1.05)	217	(6.93)	242	(7.73)
Switzerland	172	(0.63)	304	(9.71)	319	(10.19)
Austria	82	(0.30)	177	(5.65)	195	(6.23)
Others	1755	(6.37)	402	(12.82)	451	(14.4)
	27496	(100)	3132	(100)	3132	(100)

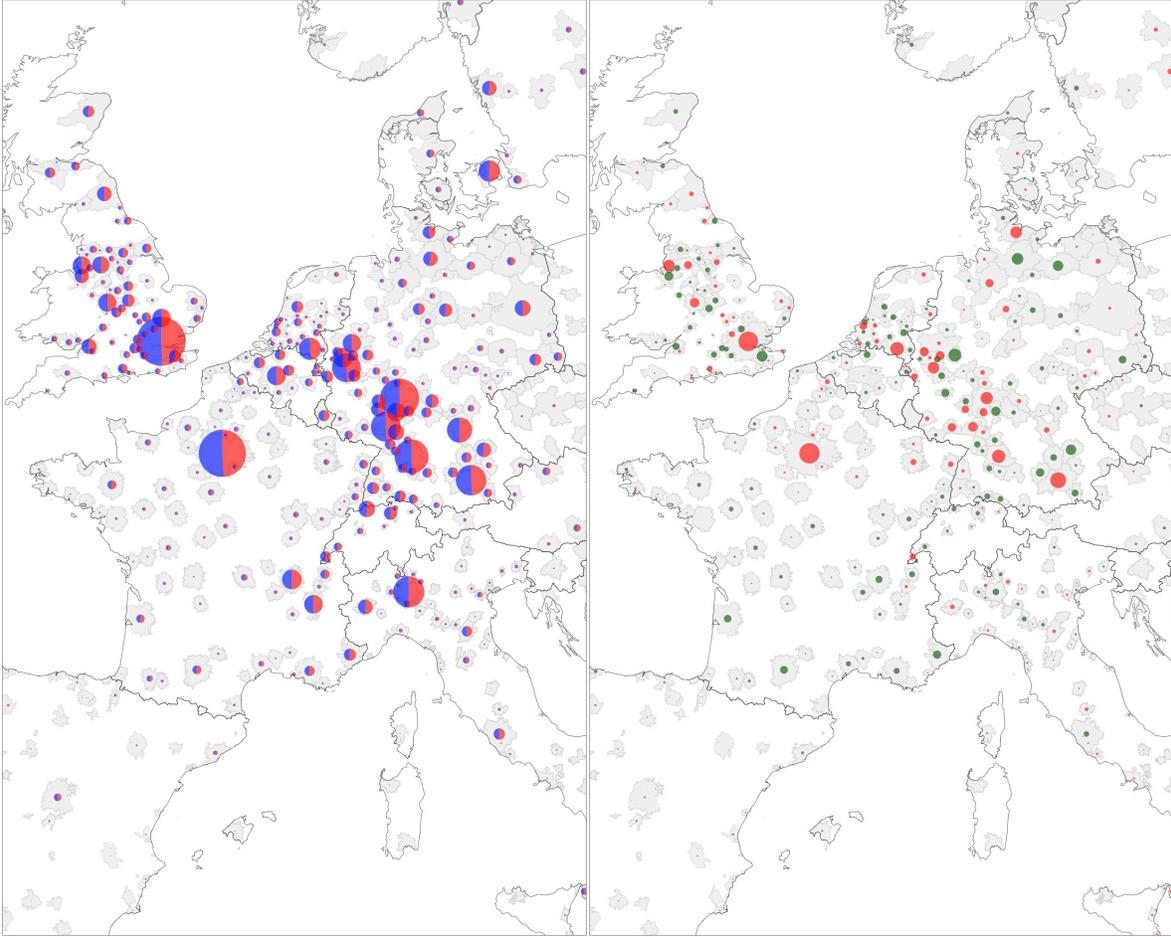
The upper panel lists the top 5 countries according to the total number of moves. Belgium, Switzerland and Austria are listed due to their high level of international mobility. There are 28 countries in total.

Turning to the spatial dimension of mobility, table 3.3 describes the distribution of national and international moves per country. Here, three figures are worth noting. First, Germany represents about half of all national moves and a quarter of international moves. This can be explained by the importance of intra-firm and circular mobility

and by the higher level of patenting activity in Germany, which represents 39.69% of all patents. Second, 89.77% of the mobility occurs within the same country, whereas international mobility only represents a fraction of the moves. Interestingly, in Belgium, Switzerland and Austria, the magnitude of international mobility both as origin and destination is much higher than in the other countries. Speculatively, these countries may act as international hubs for inventors, partly due to their central location in Europe and their reliance on foreign workers, due to the small size of their domestic labour market. Finally, both national and international mobility take place across relatively short distances, while inventors who move nationally travel on average 180 km, the mean driving distance for those who move across borders is 532 km. Both these figures are much lower than those reported by Breschi and Lenzi (2010) who show that mobile US inventors travel on average 867 km⁷. The distribution of moves by distance has a large positive skew, which means that the vast majority of moves take place across short distances.

⁷Moves to Alaska, Hawaii and Puerto Rico are excluded.

Figure 3.3: Inward, outward (left) and net (right) mobility of inventors

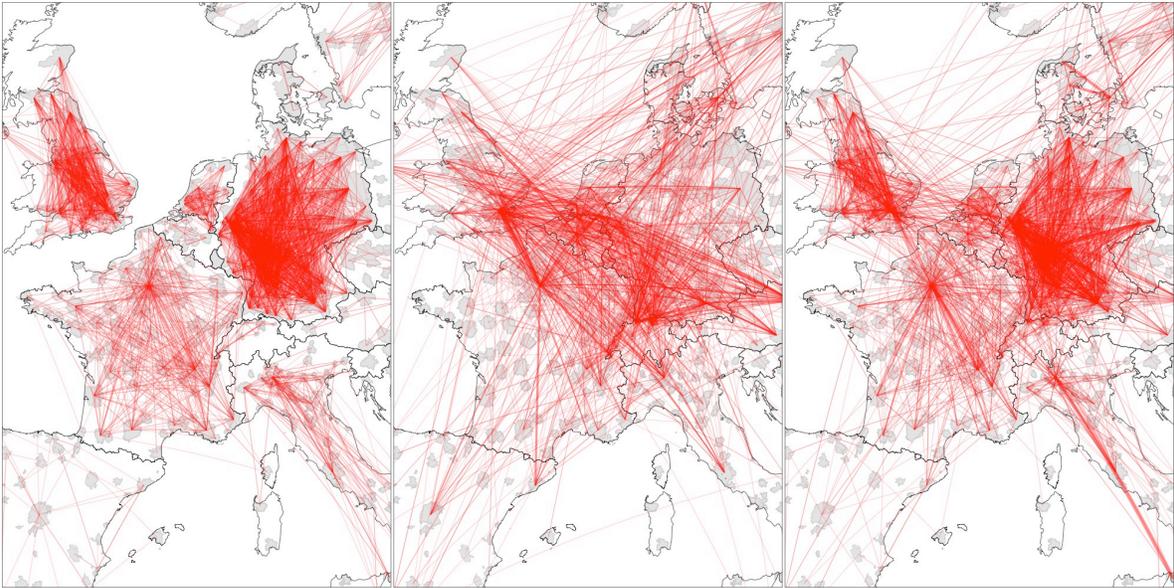


Left panel: Inward mobility is in blue while outward mobility is in red. The size of the largest bubble corresponds to 2495 moves (inward + outward). Right panel: Positive net mobility is in green while negative net mobility is in red. The size of the largest bubble corresponds to a 126 moves difference between inward and outward mobility.

Looking at a finer spatial scale, figure 3.3 depicts the distribution of inventors' mobility across LUZ. The left panel confirms earlier findings that mobility occurs primarily between a selected number of large urban areas, such as those located in the Rhur, southern UK, or Paris and Milan. Interestingly, the distribution of inward and outward mobility is remarkably similar, as confirmed by the right panel. This result may be explained by the large amount of short-range circular mobility. This suggest that we

should not think of mobility between cities in terms of attraction and repulsion, at least in our case. Dynamic urban areas are associated with a larger turnover, with higher levels of inward and outward mobility than other cities. Interestingly, in France and the UK, several large urban areas are losing inventors to the benefit of the periphery. In a more dynamic setting, figure 3.4 depicts national, international and circular movements of inventors. Mobility patterns vary considerably across countries, and reflect to a certain extent their respective urban configurations. For instance, in France and the UK, the capital cities occupy a central position, while in Germany mobility is more evenly distributed across the urban continuum.

Figure 3.4: National (left), international (middle) and circular (right) mobility



Finally, mobility patterns vary according to the technological specialisation of inventors. Each patent has a list of technology classes, which provides information about the inventors' area of expertise. However, assigning a particular technological sector to inventors is difficult for at least two reasons. First, some inventors are specialised in activities classified in two distinct technological fields. In this case, the inventor's

patents would list technological classes belonging to different sectors. Second, a patent often has more than one designated inventor, and the relative contribution of each inventor to the patent is unknown. This may be problematic when a patent is filled by an interdisciplinary team in which inventors are specialised in distinct sectors. The first specialisation is defined as the sector which appear most often in an inventor career and represent at least 40% of the listed patent classes. Following the same selection rule, a second specialisation is defined for inventors who engage in cross-sector activities. Using this criterion, less than a third (27.81%) of mobile inventors are specialised in two sectors, the majority of them being specialized in the chemical sector, and having the drugs & medical sector as a second specialisation. Table 3.4 reports the number of inventors and the distribution of moves for each technological sector, using the first specialisation.

Table 3.4: Distribution of moves per technological specialisation of inventors

Technological sector	N. inv.	National	Intern.	All
Chemical	5583	11615	1174	12789
Computers & communications	1852	2864	394	3258
Drugs & medical	1326	2220	409	2629
Electrical & electronic	2486	3984	512	4496
Mechanical	2472	2280	250	4454
Others	1411	2118	241	2530
Σ	15130			30156

472 moves were made by the 231 inventors with no specialisation according to this definition.

Note that the propensity to patent may be greater in some sectors. The greater the number of patents, the greater the probability to observe a move. Therefore, mobility in those sectors may be inflated in comparison to others sectors with a lower propensity to patent.

3.5 Determinants of inventors' mobility

3.5.1 Model

The model is based on the utility maximizing framework. Assuming that inventors are rational and freely mobile, their decision to move from one city to another is based on a comparison between the expected utilities at origin and destination. In this setting, the individual utility is a function of location-specific variables, and the cost of moving depends on a measure of distance between origin and destination. Formally, the utility of individual k associated with city i can be written as follows.

$$U_i^k = u(X_i) + \epsilon_i^k \quad (3.3)$$

The model states that the individual utility from living in i , depends on a component common to all individuals $u(X_i)$, and a stochastic term ϵ_i^k , which represent factors specific to inventor k . These factors include anything that leads k to value X_i differently than a randomly selected individual. By definition, $E(\epsilon_i) = 0$ because any systematic component is included in u . It follows that an individual decides to move if the expected utility differential is greater than the cost of moving.

$$E(U_i^k) < E(U_j^k) - C(d_{ij}) \quad (3.4)$$

When this condition is satisfied, the mobility variable takes the value one and zero otherwise. Aggregating individual movements at the city level, we can write the empirical gravity model.

$$Y_{ij} = \beta_0 X_i^{\beta_1} X_j^{\beta_2} X_{ij}^{\beta_3} \epsilon_{ij} \quad (3.5)$$

Y_{ij} is a vector of mobility flows between i and j . X_i and X_j are matrices representing the characteristics at origin and destination, respectively. Similarly, X_{ij} is a matrix recording various measures of distance between origin and destination. β_0 is a vector of ones and $\beta_1, \beta_2, \beta_3$ are scalar parameters to be estimated. Finally, ϵ_{ij} is a vector of disturbances with $E[\epsilon_{ij}|X_i, X_j, X_{ij}] = 1$ assumed to be statistically independent from the explanatory variables. This leads to the following equation.

$$E[Y_{ij}|X_i, X_j, X_{ij}] = \beta_0 X_i^{\beta_1} X_j^{\beta_2} X_{ij}^{\beta_3} \quad (3.6)$$

The dependent variable takes non-negative integer values, many of which are zero, which invalidates the normality assumption, especially when the range of values taken by the dependent variable is limited. Santos Silva and Tenreyro (2006) propose to overcome this issue using a Poisson specification of the gravity model along with the Poisson Pseudo Maximum Likelihood (PPML) estimator proposed by Gourieroux et al. (1984). The PPML estimator is like the Poisson maximum likelihood estimator except that the data generating process does not need to be the Poisson. This estimator has been shown to be robust to different patterns of heteroskedasticity and conveniently deals with the zero values, as the model can be estimated in its multiplicative form. The PPML estimator has the appealing feature coefficients estimates can be interpreted in terms of elasticities if the dependent variable is in level and the covariates are in logarithms. A profitable approach is to model the expected value as an exponential function. Because the exponential is always positive, it ensures that predicted values for Y will also be positive. Assuming that observed mobility flows follow a Poisson distribution with μ_{ij}

as the expected flows, and are independent of other mobility flows, the observed flows have the following probability distribution.

$$Prob(y_{ij}) = \frac{\exp(-\mu_{ij})\mu_{ij}^{y_{ij}}}{y_{ij}!}$$

Following Krisztin and Fischer (2015), equation (3.6) can be rewritten as follows.

$$\mu_{ij} = E[Y_{ij}|X_i X_j X_{ij}] = \exp[\ln \beta_0 + \beta_1 \ln X_i + \beta_2 \ln X_j + \beta_3 \ln X_{ij}] \quad (3.7)$$

Maximum likelihood estimation of the Poisson regression model assumes that all observations are mutually independent. In a gravity setting, this implies that mobility flows between any pair of cities is independent from flows between any other pair of cities. Such an assumption is not likely to hold for several reasons. First, movers face a discrete choice in choosing between alternative destinations (Beenstock and Felsenstein, 2016). If a mover living in city i can choose either cities j or k as alternative destinations, it follows that flows from i to j are not independent from flows from i to k . Second, mobility flows between a pair of cities do not only depend on their respective attractiveness, rather, it is influenced by pull and push factors across all possible origins and destinations, the multilateral resistance to migration (Bertoli and Moraga, 2013; Behrens et al., 2012). As a result, the model residuals may exhibit spatial autocorrelation, which directly violates the independence assumption, and produce consistent but biased parameter estimates (Krisztin and Fischer, 2015). The problem of alternative destinations is analogous to one that arises in the gravity model of international trade. In their influential contribution, Anderson and van Wincoop (2003) argued that accounting for the interaction structure is important when estimating the gravity equation. A variety of approaches have been taken to control for multilateral

resistance, from the inclusion of ad-hoc remoteness index to the introduction of origin and destination-specific indicator variables. This latter solution is not satisfactory for at least two reasons. First, Behrens et al. (2012) and Koch and LeSage (2015) argued that the inclusion of origin and destination fixed effects captures heterogeneity rather than spatial dependence. Second, the city-specific determinants of mobility cannot be introduced into the model. Recently, Patuelli et al. (2015) show that the inclusion of origin-specific and destination-specific spatial filters effectively control for omitted multilateral resistance terms, while filtering out autocorrelation in mobility flows. The rationale is that many mobility cost variables such as distance, culture or institution are spatially correlated, so that spatially proximate cities tend to have similar resistance terms.

In this framework, we distinguish two forms of spatial dependence in a gravity framework⁸. Origin-based dependence assumes that flows from an origin to a destination are correlated with other flows from neighbours to origin to the same destination. Conversely, destination-based dependence assumes that flows from an origin to a destination are correlated with other flows from the same origin to neighbours to destination. Connectivity is introduced in the model using a W matrix. One issue is that W cannot be estimated and needs to be specified in advance, using some relevant criterion. The specification of W is always subject to arbitrariness and it has become common practice to investigate whether results are robust to the specification of W . However, LeSage and Pace (2014) argued that estimates should not be overly sensitive to changes in the weight matrix in a well-specified spatial model. The preferred specification of W is based on cut-off driving distance. Specifically, two cities are considered as neighbours when their respective geographical centres are less than 150 km apart⁹. Formally,

⁸The structure of dependence in a gravity framework is more complex in the sense that each city is associated with several observations as an origin and as a destination.

⁹A shortcoming to this approach is that interdependencies are not merely spatial (Behrens et al.,

$$W_{ij} = \begin{cases} 1 & \text{if } d_{ij} \leq 100 \\ 0 & \text{otherwise} \end{cases}$$

The resulting matrix is sparse and symmetric, with zeros on the diagonal and ones on the off-diagonals when observation i depends on observation j . W is used for spatial autocorrelation diagnostics, and for the computation of spatial filters. Traditional diagnostics may not be appropriate for Poisson residuals (Chun, 2008). Instead, I follow Lin and Zhang (2007) and use a Moran's I log-linear residual test to detect spatial autocorrelation in the residuals.

Eigenvector spatial filtering was introduced by Griffith (2003) for areal data and recently extended to flow data. Applications to mobility flows¹⁰ include United States interstate migration (Chun, 2008; Chun and Griffith, 2011), and German journey-to-work flows (Griffith, 2009). This approach is based on the assumption that spatial autocorrelation in the disturbances arises from missing origin and destination variables, which are spatially autocorrelated (Tiefelsdorf and Griffiths, 2007), very much like the missing origin and destination multilateral resistance terms. A spatial filter made of synthetic variables can be used to control for spatial autocorrelation¹¹. This approach has the advantage that the model can then be estimated as if observations were independent, using conventional regression techniques. This is particularly attractive because the dependent variable represents Poisson distributed counts, and spatial models are less developed for this type of data.

2012; Beenstock and Felsenstein, 2016)

¹⁰Other applications to flow data include trade (Krisztin and Fischer, 2015; Patuelli et al., 2015), patent citations (Fischer and Griffith, 2008) and research collaborations (Scherngell and Lata, 2013).

¹¹In the presence of spatial autocorrelation, the residuals can be divided into a spatial component and the white noise. Spatial filtering enforces independence by isolating the stochastic spatial component from the white noise using a set of proxy variables called a spatial filter.

Specifically, spatial filtering relies on the spectral decomposition of a transformed W into eigenvalues and eigenvectors, and then uses a subset of eigenvectors as origin and destination explanatory variables into the model. Eigenvectors can be interpreted as independent map patterns describing the latent spatial autocorrelation of a variable. The W matrix is transformed as follows.

$$\left(I - \frac{ll'}{n}\right) W \left(I - \frac{ll'}{n}\right)$$

I is the $n \times n$ identity matrix, l is an $n \times 1$ vector of ones and l' its transpose. The n eigenvector of the above matrix describe the full range of possible and mutually orthogonal uncorrelated map patterns, and their corresponding eigenvalues index the nature and degree of spatial autocorrelation portrayed by each eigenvector. Eigenvectors are extracted in sequence to maximise the Moran Coefficient (MC) while being uncorrelated with the preceding eigenvectors. For parsimony, it is not sensible to include all eigenvectors in the spatial filter, a two-step procedure is used to identify a relevant subset of eigenvectors. First, eigenvectors are selected on the basis of their MC values exceeding some predefined threshold. Here, the common rule $e_i/e_1 \geq 0.25$ is used, where e denotes the associated eigenvalues, to keep eigenvectors associated with strong and positive spatial autocorrelation. This subset is further reduced through a stepwise Poisson selection technique¹² (Tiefelsdorf and Griffiths, 2007). Filters at origin and destination are obtained using $E_i = l \otimes E$ and $E_j = E \otimes l$ respectively, where E is the $n \times Q$ matrix of eigenvectors and the resulting E_i and E_j are $n^2 \times Q$ matrices, Q being the number of selected eigenvectors. The spatial filter includes the subset of Q eigenvectors that are common to all cross-sections. Adding the spatial filter to equation

¹²As noted by Patuelli et al. (2015), selection based on AIC or BIC is not possible in the case of Quasi-Poisson models since they have no likelihood, so it is manually performed by iterative backward elimination of the eigenvector with the highest p-value.

(3.6) gives the following equation.

$$\mu_{ij} = \exp \left[\ln \beta_0 + \beta_1 \ln X_i + \beta_2 \ln X_j + \beta_3 \ln X_{ij} + \sum_{q=1}^Q E_q \Phi_q \right] \quad (3.8)$$

$\exp \left[\sum_{q=1}^Q E_q \Phi_q \right]$ is the spatial filter that accounts for origin and destination spatial autocorrelation. E_q denotes the q^{th} eigenvector and Φ_q its associated coefficient.

3.5.2 Results

This section summarizes the main estimation results obtained. The sample used is restricted to inventors who moved across 497 LUZ between 2000 and 2007. To avoid extreme heterogeneity, I follow Miguelez and Moreno (2014) and pool mobility flows into two distinct four-years periods¹³, corresponding to 2000–2003 and 2004–2007.

¹³In this chapter, the panel specification is not implemented. In fact, the main advantage of using the longitudinal structure of the data would be to include origin-destination-pairs fixed effects, to account for time-invariant pair-specific unobserved heterogeneity that is not captured by the covariates. Using random effects would be inappropriate here because we cannot assume that unobserved heterogeneity is related with unobserved effects that are time-invariant and not specific to origin-destination pairs (Scherngell and Lata, 2013). A disadvantage of fixed effects is that time-invariant variables cannot be included in the model. However, variables such as geographical distance, cultural and institutional proximity are of special interest for this study. With regards to spatial dependence, fixed effects do not effectively control for spatial autocorrelation and precludes the use of a spatial filter. A time-varying spatial filter would rely on a connectivity matrix specific to each period, and there is no theoretical motivation to do so in this study. Besides, the eigenvector selection procedure in a panel framework is unclear from a mathematical point of view (Patuelli et al., 2011).

Table 3.5: Descriptive statistics

Variable	Mean	St. dev.	Min.	Max
<i>Gravity</i>				
Number of inventors	106.07	312.91	0.00	4287.25
Driving distance	967.34	519.11	0.00	3291.00
<i>Labour markets</i>				
Spending in R&D ($\times 10^6$)	734.10	1377.46	0.00	15210.75
Human resources in S&T	11450.71	14875.90	49.75	173200.20
<i>Networks</i>				
Direct collaborations	0.29	14.75	0.00	4880.00
Betweenness centrality index	0.03	0.09	0.00	1.00
<i>Urban amenities</i>				
Social life index	0.03	0.07	0.00	1.00
Cultural index	0.03	0.07	0.00	1.00
Green spaces index	0.03	0.06	0.00	1.00
<i>Natural amenities</i>				
Distance to the coast	145.43	150.51	0.22	628.49
Summer temp. index	0.46	0.18	0.00	1.00
Winter prec. index	0.21	0.13	0.00	1.00
<i>Controls</i>				
Technological proximity index	0.16	0.20	0.00	1.00
Same country dummy	-	-	0.00	1.00

Values are averaged over 2000-2007, except for amenities.

Table 3.6 reports the estimation output for the unfiltered PPML gravity model in the first two columns and its spatially filtered counterpart in columns (3) and (4). Broadly speaking, all coefficients estimates have the expected sign and significance. The adjusted Moran's I suggests that inventors' mobility between two cities are positively associated with flows from and to neighbouring cities. This motivates the use of a spatial

specification in order to obtain unbiased parameter estimates. The selected eigenvectors effectively fill this purpose, as shown by the Moran's I statistic, which is divided by about 4.5 when adding the spatial filter. As a result, the spatial model consistently exhibit lower standard errors than its unfiltered counterpart, and the goodness-of-fit measure¹⁴ points to this model as the preferred specification.

¹⁴For the goodness-of-fit measure, the model is fitted twice, once with a regular likelihood Poisson model and once with the quasi variant model. The log-likelihood is extracted from the former and the dispersion parameter from the latter.

Table 3.6: Estimation results for labour market and networks

	Quasi-Poisson		Spatially filtered QP	
	00–03 (1)	04–07 (2)	00–03 (3)	04–07 (4)
<i>Gravity</i>				
Stock of inventors (o)	0.590*** (0.013)	0.599*** (0.017)	0.596*** (0.010)	0.611*** (0.013)
Stock of inventors (d)	0.551*** (0.017)	0.631*** (0.021)	0.596*** (0.015)	0.631*** (0.018)
Driving distance (od)	−0.307*** (0.017)	−0.346*** (0.022)	−0.297*** (0.015)	−0.304*** (0.019)
<i>Labour market</i>				
Spending in R&D (d)	0.193*** (0.038)	0.213*** (0.072)	0.419*** (0.021)	0.330*** (0.045)
Human res. in S&T (d)	0.172*** (0.039)	0.134** (0.074)	0.396*** (0.020)	0.262*** (0.044)
<i>Networks</i>				
Collaborations (od)	0.705*** (0.010)	0.737*** (0.013)	0.631*** (0.009)	0.677*** (0.012)
Centrality (o)	0.188*** (0.019)	0.248*** (0.027)	0.153*** (0.014)	0.216*** (0.018)
Centrality (d)	0.219*** (0.019)	0.255*** (0.027)	0.154*** (0.014)	0.256*** (0.018)
<i>Controls</i>				
Tech. proximity (od)	0.763*** (0.085)	1.374*** (0.122)	0.855*** (0.088)	1.437*** (0.115)
Same country (od)	2.292*** (0.035)	1.937*** (0.043)	2.390*** (0.037)	2.098*** (0.042)
Constant	−10.345*** (0.173)	−10.303*** (0.280)	−11.327*** (0.120)	−11.487*** (0.166)
Adjusted log likelihood	−21972.08	−35409.02	−10298.94	−16466.88
Adjusted Moran's I	0.343***	0.352***	0.076***	0.082***
Number of spatial filters			61	61

*90%, **95% and ***99% confidence levels. Standard errors are robust.

Gravity

In line with gravity theory, the results confirms that size and distance are important determinant of inventors' mobility. Specifically, the coefficient associated with the stock of inventors remain strongly positive and significant over the two periods, with estimated elasticities around 0.6. Looking at driving distance in particular, estimates are negative and significant, which suggest that the pecuniary and non-pecuniary costs associated with moving significantly impede inventors' mobility. However, the importance of distance is greatly reduced when we introduce other variables that have a spatial dimension. This is because geographical distance serves as a proxy for other, more meaningful forms of distance. In this regard, appendix A1.1 compares various forms of distance using the preferred specification for the period 2004-2007. Consistently with Breschi and Lenzi (2010), distance does not affect mobility in a linear manner, the inclusion of a squared distance variable reveals that the cost of moving is high but strongly decreases as we move further away.

Labour market

Turning to the labour market variables, R&D spending, and to a lesser extent human capital, significantly influence inventors' mobility. The estimates tend to be lower in the second period. This difference may be attributed to the measure of mobility, which is likely to be truncated toward the end of the dataset¹⁵, which cause the mobility variable to be imperfectly observed. Overall, the evidence shows that employment opportunities strongly influence the mobility decisions of inventors. This is consistent with the evidence reported by Miguelez and Moreno (2014) at the level of European regions, and provide additional robustness due to the explicit modelling of spatial dependence, and

¹⁵4608 moves took place during the first period while only 1422 occurred during the second. This is because the database contains just a few observations for toward the end of the dataset. This problem is magnified by the way mobility is computed, because a move is assumed to take place between the application dates of the two patents.

the analysis at the city level.

Networks

Looking at the network variables, both direct social ties and the centrality index are strongly positive and significant. This confirms that collaboration networks play an important role in matching workers to positions (Nakajima et al., 2010), because it reduces information asymmetries and improve matching (Jackson, 2011). The elasticities associated with direct collaborations are large with regards to the labour market variables, which suggests that inventors' mobility is driven primarily by social ties. Comparing the two network variables, direct social ties matter more than the centrality index. This is not surprising given that the former measures direct social connections between inventors, which is more likely to influence the decision to move. Nonetheless, the fact that the two variables remain significant when introduced jointly in the regression suggests that the importance of inventors' networks goes beyond the effect of direct collaborations. The relative position of the city within the network, which represent a less restrictive definition of networks, is also important. Finally, spatial filtering tends to reduce the importance of network variables, since the social context in which inventors are embedded has a strong spatial dimension.

Amenities

Looking at the importance of urban and natural amenities, table 3.7 reports estimates including amenities for the period 2004-2007. The estimates are reported for the Quasi-Poisson model and its spatially-filtered counterpart.

Table 3.7: Estimation results with amenities

	Quasi Poisson (1)	Spatially filtered QP (2)
<i>Gravity</i>		
Stock of inventors (o)	0.609*** (0.017)	0.609*** (0.013)
Stock of inventors (d)	0.653*** (0.023)	0.675*** (0.019)
Driving distance (od)	-0.357*** (0.023)	-0.359*** (0.020)
<i>Labour market</i>		
Spending in R&D (d)	0.167** (0.072)	0.311*** (0.052)
Human res. in S&T (d)	0.226*** (0.075)	0.306*** (0.056)
<i>Networks</i>		
Direct collaborations (od)	0.717*** (0.014)	0.668*** (0.013)
Centrality (o)	0.244*** (0.027)	0.219*** (0.019)
Centrality(d)	0.169*** (0.033)	0.226*** (0.023)
<i>Urban amenities</i>		
Eat & drink (d)	-2.469*** (0.727)	-1.451** (0.625)
Culture (d)	1.248* (0.621)	1.189* (0.591)
Greenspaces (d)	1.135*** (0.320)	0.695*** (0.195)
<i>Natural amenities</i>		
Distance to coast (d)	-0.383*** (0.027)	-0.217*** (0.023)
Summer temperatures (d)	1.197*** (0.158)	1.033** (0.445)
Winter precipitations (d)	-0.349*** (0.069)	-0.206 (0.106)
<i>Constant</i>		
Technological proximity (od)	1.334*** (0.125)	1.380*** (0.119)
Same country (od)	1.997*** (0.045)	2.105*** (0.044)
Constant	-12.509*** (0.877)	-12.742*** (0.544)
Adjusted log likelihood	-35307.08	-16546.87
Adjusted Moran's I	0.354***	0.078***
Number of spatial filters		67

*90%, **95% and ***99% confidence levels. Standard errors are robust.

The coefficients on natural amenities reveal that inventors tend to move toward cities near the coast, with a pleasant weather and low precipitations. However, the significance of the temperature and precipitation variables is reduced when adding the spatial filters. This is hardly surprising because spatial filters based on geographical distance capture the impact of variables that change slowly as we move across space. Turning to urban amenities, the estimation results suggest that the presence of cultural amenities, and to a lesser extent green spaces, significantly influence inventors' mobility. Contrary to expectations, the coefficient on social amenities is negative and significant in the two specifications. A possible explanation is that a simple count of bars and restaurant is a poor proxy for the quality of social life. Perhaps, controlling for the quality of these establishments would provide different results.

Controls

The coefficients associated with the technological proximity index and the same country indicator variable are strongly positive and significant. The latter result is in line with the descriptive analysis, and confirms that inventors' mobility in Europe is largely a national phenomenon. This may be explained by the diversity of cultures and the fragmentation of institutional frameworks in the European Union, which translate into greater migration costs. This may be one reason why skilled mobility in Europe is lower than in the United States. Bear in mind that the indicator variable is arguably a rather simple proxy to capture elements as diverse as culture, institutions or language. However, spatial filters also capture the effect of variables that change slowly as we move across space. Finally, technological proximity is an important determinant of inventors' mobility. This may be because specialized workers do not have many alternative destinations to choose from, in the sense that they can benefit from employment opportunities in cities with a similar technological specialisation. Similarly, co-invention networks are primarily developed between inventors belonging to same technological

field. To the extent that these networks influence mobility decisions, this should increase again the probability to observe a move between technologically proximate cities.

3.6 Conclusion

Highly skilled professionals are regarded as one of the main driver for the economic development of cities through their effect on innovative capabilities. Skilled individuals are mobile in space and tend to cluster within a limited number of urban areas, therefore a crucial question is what factors shape this flows and influence the levels of economic development across urban areas. Building on these considerations, it takes advantage of a large-scale dataset to shed light on the patterns and determinants of inventors' mobility across European urban areas. First, a descriptive analysis is carried out to document the patterns of inventors' mobility and their spatial dimension. Second, a gravity model is used to analyse how the labour market, professional networks as well as natural and urban amenities, influence the flows of inventors between urban areas. From a methodological perspective, this chapter uses a spatial filtering variant of the Poisson gravity model, which accommodate the nature of the data, while controlling for multilateral resistance and spatial autocorrelation in mobility flows.

Despite the commonly held belief that skilled workers are highly mobile in space, the analysis suggests that mobility remains a rare event. Among multi-patenting inventors, only 9.67% moved from one city to another between 1975 and 2008. Mobility is also limited in space. Inventors who move travel between relatively large and co-located urban areas, and 90% of these moves occur within the same country. These results can be partly explained by the high level of circular and intra-firm mobility. Finally, the analysis highlight significant heterogeneity among countries, with about 80% of all

moves taking place either in Germany, France or the UK. Likewise, the propensity to move vary importantly across technological sectors. Turning to the determinants of inventors' mobility, four results are worth noting. First, inventors are drawn toward cities offering numerous employment opportunities along with attractive working conditions. This finding is in line with the scarce existing evidence, provided by Miguelez and Moreno (2014) at the level of European regions, yet the explicit modelling of spatial autocorrelation and the analysis at the urban scale provide additional robustness to this finding. Second, the decision to move is mediated by network ties, which reduce information asymmetries between inventors and their potential employers, and therefore improve matching (Jackson, 2011). Besides, the definition of networks should not be restricted to direct collaborations. In particular, the centrality of cities, which represent a less restricted view of social networks, also plays a role. Third, workers are attracted to cities with a pleasant climate, numerous green spaces and cultural amenities. While the role of urban amenities has received significant attention in the literature, empirical progress have been hampered by the lack of data. In addressing this issue, this chapter uses data mining techniques to collect specific data on the provision of urban amenities for all urban areas in Europe. Fourth, contrary to expectations, geographical distance has a limited role in deterring mobility. This may be due to the availability of fast transportation across cities and because it acts as a proxy for other, more meaningful forms of distance. In particular, mobility occurs primarily between cities sharing the same technological specialisation, partly because of the availability of specialised jobs, partly because collaboration networks tend to develop within the same epistemic community. More importantly, cultural and institutional distance translate into greater adaptation costs. Fourth, from a methodological perspective, spatial autocorrelation in mobility flows is a serious issue and should be explicitly controlled for when estimating the gravity model in order to obtain unbiased parameter estimates.

These results have implications for the geography of innovation. While both mobility and networks have been shown to influence the diffusion of knowledge, they have often been investigated separately, and it would be interesting to study the interrelation between these two channels, as they appear to be closely related. Another implication concerns the ongoing construction of the European Research Area, which aims to facilitate the diffusion of local and external knowledge, in particular through the mobility of skilled individuals. The results suggest that the diffusion of knowledge may be limited for several reasons. Movers, represent only a fraction of the inventors, and those who move travel relatively short distances, generally within the same country. This result is magnified by the fact that a large portion of mobility occur within firms, and do not necessarily imply a transfer of knowledge. Besides, the fact that mobility occurs primarily between technologically related cities may cause the transferred knowledge to be redundant, and have a limited economic impact. Finally, the results highlight significant heterogeneity across cities, and countries. A more promising finding is that mobility may be encouraged, in particular through the development of research collaborations involving distant research communities.

Further research on other categories of skilled workers would be welcome, as inventors represent only a fraction of the skilled workforce. Skilled mobility is a diverse phenomenon and what may be true for inventors does not necessarily hold for other categories of skilled workers. However, the study of mobility is often made impossible by the lack of harmonized and reliable data. Finally, the empirical analysis is fairly macroeconomic and do not consider the influence of personal characteristics such as age, gender, tenure or productivity on the mobility patterns of inventors as in Crespi et al. (2007); Lenzi (2009).

4 Accessiblity, absorptive capacity and innovation in urban areas

Abstract

Empirical studies on the geography of innovation have established that skilled workers' mobility and collaboration networks shape the diffusion of knowledge across firms and regions. At the same time, the literature on absorptive capacity insisted on the importance of local research capabilities to take advantage of knowledge developed elsewhere. This chapter investigates both phenomena in an integrated framework by assuming that mobility and networks provide access to knowledge, but the proportion of accessible knowledge effectively used for innovation depends on absorptive capacity. Such complementarities in regional research efforts are effectively captured using a spatial Durbin model in which the connectivity structure stems from mobility and collaboration patterns. Results confirm the relative importance of these two channels in the diffusion of knowledge, and suggests that human capital increases absorptive capacity. These findings have implications for the geography of innovation. While greater accessibility encourages convergence, the notion of absorptive capacity implies a self-reinforcing effect leading to divergence.

4.1 Introduction

Since the development of endogenous growth theories, knowledge and innovation are largely accepted as key driving forces behind long-term economic growth (Romer, 1986). In this regard, economists have established that innovation depends on firms' own research capabilities, as well as their ability to use knowledge developed by other firms. At the regional level, the production function approach suggests that innovation depends on the level of human capital as well as the resources devoted to research. In addition, regions may benefit from additional inputs emanating from the research effort of neighbouring regions (Moreno et al., 2005). Building on these considerations, two streams of literature have analysed how knowledge is transmitted across firms and regions. The empirical geography of innovation literature has established that the transmission of knowledge proceeds mostly through personal ties. This is due to the tacit nature of knowledge, which is embodied in individuals, and is better transmitted through direct and frequent interactions (Howells, 2002). This effect is found to be particularly important in urban areas where the concentration of individuals provides numerous opportunities for interaction and reduces the cost of communication (Glaeser, 1999). Consequently, firms can gain access to external knowledge through the recruitment of key workers (Almeida and Kogut, 1999) or by actively engaging in collaborations networks (Singh, 2005). A second stream of research focused on firms' ability to absorb external knowledge (Cohen and Levinthal, 1989). Specifically, having access to knowledge, in particular through mobility and networks, is not sufficient so that only firms endowed with the capacity to decode and understand others' discoveries can use it productively (Caragliu and Nijkamp, 2012). Therefore, there exist a complementarity between internal and external inputs to innovation in the sense that firms actively engaging in research increase their likelihood to innovate, but also develop their

ability to understand and assimilate the discoveries of others (Cassiman and Veugelers, 2006). These two phenomena are interrelated and should be jointly analysed because they are key factors in explaining regional innovation.

This chapter investigates the interactions among cities' research activity by studying accessibility, absorptive capacity and innovation in an integrated framework. The main hypothesis is that mobility and networks provide access to knowledge, while the proportion of accessible knowledge effectively used for innovation depends on absorptive capacity (Miguelez and Moreno, 2013b). Specifically, this chapter contributes to the empirical literature in four ways. First, the analysis is carried out at the level of urban areas, a meaningful unit of analysis with regards to arbitrarily defined regions commonly used in the literature. Second, it proposes a refinement of the typical weight matrices based on purely geographical criteria by using information on the mobility of inventors and their collaborative ties (Miguelez and Moreno, 2013a). In this chapter, the notion of neighbourhood does not necessarily refer to spatially proximate cities, although it is often the case, but rather cities that are linked by mobility flows and networks ties. The iterative estimation method developed by Hazir et al. (2014) is used to draw inferences on the relative importance of these different forms of connectivity. Third, this chapter estimates a production function for innovation using a spatial Durbin model (Autant-Bernard and LeSage, 2011) on a panel of 488 European urban areas over 1998–2009. The results provide an assessment of the relative importance of mobility and networks in accessing external knowledge. Fourth, there is evidence of absorptive capacity, as only a fraction of the accessible knowledge is used for innovation, depending on the level of human capital.

The main result is that innovation in cities is significantly influenced by the research activity of their neighbours. In other words, there is evidence of strong spatial depen-

dence among cities' innovation processes. Specifically, three results are worth noting. First, the analysis confirms the importance of skilled mobility, and to a lesser extent networks, in accessing external knowledge. A related conclusion is that contiguity alone poorly reflects the nature of dependence, but serves as a proxy for more meaningful forms of proximity based on social ties. Second, maximum likelihood estimates confirm that R&D spending contributes to local innovation, but also significantly increases patenting in neighbouring cities. By contrast, the aggregate impact of human capital is not significant, because the positive effect on local innovation is offset by a negative spillover effect on neighbours, reflecting the existence of a competition effect between cities to attract skilled individuals. On theoretical grounds, these opposing effects are well documented. While endogenous growth models established that human capital increases the rate of innovation, the new economic geography highlights a strong competition effect associated with the mobility of workers. Third, this chapter provides an estimate of absorptive capacity, measured as the complementarity between local and external inputs, and shows that a certain level of human capital helps to take advantage of neighbours' discoveries.

These results have implications for the convergence debate. While greater accessibility encourages convergence, the notion of absorptive capacity implies a self-reinforcing effect leading to divergence (Aghion and Jaravel, 2015). Models that study growth and geography in an integrated framework recognize the importance of both workers' mobility and knowledge externalities in determining the location of innovation (Baldwin and Forslid, 2000). On the one hand, if a region becomes relatively more attractive, mobile workers will move to this region, causing it to grow at the expense of peripheral areas in a circular-causation mechanism. On the other hand, the strength of agglomeration depends negatively on the range of knowledge externalities. In this setting, the aggregate impact of skilled mobility is ambiguous because it favours the core-periphery

equilibrium, while its role in the diffusion of knowledge give rise to dispersion. The theoretical literature is unclear about which effect prevails, partly because it does not account for the actual mechanisms through which knowledge diffuses in space. This work represents a step in this direction, as there is evidence of both complementarity and competition effects among neighbouring cities' innovation processes.

The remainder of this chapter is structured as follows. Section 4.2 reviews the related literature. Section 4.3 describes the data and section 4.4 introduces the empirical model. Section 4.5 discusses the estimation results and section 4.6 concludes.

4.2 Background

A number of empirical studies have established the existence of knowledge flows across firms and regions (Jaffe et al., 1993) so that the production of innovation depends on the amount of R&D activity carried out locally, as well as the possibility to take advantage of neighbours' research effort (Moreno et al., 2005). Building on these considerations, two streams of literature have investigated the mechanisms through which knowledge is transmitted in space.

The empirical literature on the geography of innovation has established that the transmission of knowledge proceeds mostly through personal ties. This is due to the tacit nature of knowledge, which is embodied in individuals' minds and habits, and is better transmitted through direct and frequent interactions (Howells, 2002). Consequently, firms can gain access to knowledge through the recruitment of key workers. The rationale is that when these individuals move away from the place where they originally worked, they bring their embodied knowledge to their new workplace and promote innovation. From an empirical perspective, Almeida and Kogut (1999) tracked knowledge

diffusion patterns using patent citations in the semi-conductor industry. They found evidence of knowledge flows only in the US states where the intra-regional mobility of inventors across companies is high. Miguelez and Moreno (2013a) reported similar evidence at the regional level. Using a spatial knowledge production function on a panel of European regions, they showed that regions linked by labour mobility and collaboration networks influence their respective innovation outcomes. In fact, a related mechanism for the transmission of knowledge is the presence of scientific networks, because they reduce uncertainty and coordination problems. As a result, firms that are embedded in collaboration networks are more likely to be exposed to original ideas. Singh (2005) estimated the probability of knowledge flow between pairs of inventors. By applying a choice-based sampling method to USPTO patent citations, he found that co-invention networks explain the subsequent patterns of patent citations, both at the regional and at the firm level. Finally, mobility and networks are two related phenomenon. Skilled workers on the move influence the structure of networks by creating new, bridging or closing existing networks. Conversely, a worker embedded in a professional network is better informed about vacancies and the receiving organisation, so that social relationships influence mobility decisions. For instance, Agrawal et al. (2006) looked at the mobility patterns of US inventors across MSA and showed that mobile inventors are more likely to be cited by their former colleagues, suggesting that social ties persist even after formerly co-located inventors are separated.

The second stream of research focuses on firms' ability to absorb external knowledge. In a series of articles, Cohen and Levinthal (1989, 1990) argued that R&D does not only generate knowledge, but also facilitates the imitation of knowledge developed elsewhere. The intuition is that firms actively engaged in research in a particular technological field can assimilate more readily the discoveries of others. In this sense, there is a complementarity between internal and external inputs to innovation (Cassiman and Veugelers,

2006). The concept of absorptive capacity, originally developed in the context of firm theory, has been recently extended to larger spatial units such as regions. Absorptive capacity at the regional level can be defined as the ability of firms and individuals within the region to assimilate and use productively accessible knowledge developed elsewhere. Regions with a greater absorptive capacity are open to new ideas, and better able to use them for innovation. The connection with economic theory is provided by Griffith et al. (2003, 2004) who accounted explicitly for absorptive capacity in a structural model of endogenous growth. The empirical results suggest that the social returns to R&D and human capital are greater than previously thought at the industry level. This is consistent with Mukherji and Silberman (2013), who provided an estimate of absorptive capacity at the level of urban areas. Specifically, they interpret origin and destination fixed effects of a gravity model of patent citations as a measure of absorptive capacity, and use these estimates in a panel production function for innovation. Their results suggest that innovation in cities depends on their ability to use external knowledge produced in neighbouring areas. At the regional level, Caragliu and Nijkamp (2012) showed that a weak absorptive capacity increases knowledge flows towards neighbouring areas, hampering the regions' capability to decode and efficiently exploit new knowledge, both produced locally and originating from outside.

Such interdependencies among neighbouring regions' innovation processes can be explicitly modelled using a spatial specification. In her review of the literature, Autant-Bernard (2012) argued that spatial models are relevant to study of regional innovation because they account for two sources of dependence that characterize the geography of innovation. First, spatial autocorrelation arises when innovation in a region is affected by the research effort of its neighbours. Second, spatial heterogeneity stems from the spatial concentration of innovative activity. These sources of dependence generate endogeneity and cause conventional models to produce biased and inconsistent estimates. From an

empirical perspective, Miguelez and Moreno (2013a) looked at the role of mobility and networks on diffusion of knowledge for a panel of regions. Specifically, they estimated a series of gravity models of knowledge diffusion and used fitted values on mobility and networks to estimate a production function with neighbouring effects. Their main contribution is to model explicitly the sources of interaction in regional innovation, rather than using a connectivity structure based exclusively on geography. Recently, Hazir et al. (2014) proposed an interesting methodology to build weight matrices using multiple criteria. They computed a series of matrices based on collaborations and distance by means of gridding, and estimated the model iteratively to select the matrix associated with the best model fit. The resulting matrix is used to draw inference on the relative importance of different forms of connectivity. From a theoretical perspective, Autant-Bernard and LeSage (2011) showed that spatial dependence in innovation could be modelled parsimoniously using a spatial Durbin model. They demonstrated that to the extent that innovation inputs are not perfectly observed, and that both observable and unobservable inputs exhibit spatial dependence, the model should include spatial lags for the dependent as well as the independent variables.

4.3 Data

The analysis is carried out at the level of urban areas. Innovation is measured by the number of patents in a city, weighted by forward citations in order to control for patent quality. Local inputs to innovation take the form of research investment and human capital. The amount of external inputs that a city can access from its neighbours depends on bilateral mobility flows, network collaborations as well as geographical proximity. Finally, control variables include population and technological diversity.

Table 4.1: List of variables

Variable	Proxy	Source
Innovation	Citations weighted patents	Crios-Patstat
<i>Inputs</i>		
Research investment	Spending in research and development	Eurostat
Human capital	Human resources in science and technology	Eurostat
<i>Connectivity</i>		
Mobility	Changes in inventor's addresses	Crios-Patstat
Networks	Bilateral collaboration counts	Crios-Patstat
Geo. proximity	Inverse driving distance	OpenStreetMap
<i>Controls</i>		
Size	Population	Univ. of Geneva
Tech. diversity	Technological diversity index	Crios-Patstat

Patent data contains extensive information about the patents, the inventors and the assignees. Specifically, information relative to the patent include the date of application, detailed technological categories as well as citations made to previous patents. Besides, information about inventors comprise names and personal addresses, among others. This chapter uses the Crios-Patstat database (Coffano and Tarasconi, 2014), which records patent applications at the European Patent Office up to 2013. The data is used extensively to compute innovation, mobility, networks and technological diversity at the level of urban areas. This requires geocoding inventors' addresses to determine whether the patent was filled by an inventor residing in a city, which is done by cleaning and parsing addresses, before matching them against the OpenStreetMap database to retrieve geographical coordinates. Cities are defined using Functional Urban Areas (FUA), which provide a harmonized definition of metropolitan areas throughout the European Union (OECD, 2013). FUA are defined using population density and com-

muting patterns, so that each represents a self-contained labour market, an economically meaningful unit of analysis (appendix A2.1).

The number of patents is used as proxy for innovation. Although patents represent a well understood measure of innovation, available on a large scale and consistent across space and over time, it has several limitations (Griliches, 1990). First, patents represent invention but not necessarily innovation, because some inventions are never exploited commercially. Second, not all inventions are patented, either because they don't meet the patentability criteria or because the firm favours other means of appropriability. Third, patents vary greatly in their economic value, and the distribution of this value is skewed toward the low end. In addressing this last issue, Trajtenberg (1990) argued that the number of citations received may be used as a proxy for patent value. Intuitively, highly cited patents should be more valuable than those that received only a few citations. However, counting citation-weighted patents involves two truncation problems, one regarding patent counts and the other, citation counts (Hall et al., 2005). First, there is a significant time lag between the patent application and the grant. As we approach the last year of the dataset, we observe only a fraction of the patents applied for that will eventually be granted (appendix A2.2). For this reason, a three-year safety lag is taken by exploiting patent data up to 2009. Second, the number of citations received by a patent is truncated because they are observed up to the last year of the dataset. Consequently, the citation intensity of patents applied for in different years is not directly comparable¹. This chapter uses the fixed effects approach developed by Hall et al. (2001). For each patent, the citation intensity is expressed as a ratio to the mean citation intensity of its cohort, which includes patents with the same application

¹For instance, it is not obvious that a five year old patent that received 11 citations is more valuable than a four-year old patent cited 10 times. Hall et al. (2001) discussed other sources of bias that may affect citation. For instance, there has been an increase in the number of patents over time, so that recent patents tend to be more cited than older ones. Besides, the average number of citations per patent has increased over time, and recent citations may be less valuable.

date. Rescaling citations this way removes the effects due to truncation, the effects due to systematic changes over time in the propensity to cite, and the effects due to changes in the number of patents making citations. However, there is no way to do so without removing real differences between cohorts, which do not result from truncation.

Mobility is computed by tracking changes in inventors' personal addresses in patent documentation. For instance, consider an inventor who fills a patent at time t while residing in city i . In $t + 1$, this same individual fills another patent while residing in city j . Therefore, we can say that between t and $t + 1$, this individual has moved from i to j . This measure of mobility is fairly straightforward but presents three drawbacks. First, the use of patent data restricts the analysis to inventors with at least two patents. Second, a move is recorded only if those inventors applied for a patent before and after the move, so this measure is lower bound. Third, patents record inventors' location at a point in time, therefore it is not possible to determine precisely when the move took place. It is assumed that mobility occurred exactly between the application dates of the patents at origin and destination, if there is no more than a four-year lag between the two. Mobility computed this way identifies inventors who filled at least two patents while residing in different urban areas. Another issue is that in practice, it is difficult to determine whether two inventors are the same person, since patent offices do not require unique identifiers for inventors. Therefore, disambiguation is necessary to determine whether two patents belong to the same inventor by comparing all pairs of inventor-patent instances. Inventors cannot be matched on the basis of their names for a least two reasons. The first is misspelling of the same inventor name on different occasions. The second occurs when two inventors with the same name are not actually the same person. The Massacrator routine developed by Pezzoni et al. (2014) is used to identify likely matches² (appendix A2.3).

²I thank Michele Pezzoni for running several custom calibrations of Massacrator.

Turning to the network variable, a patent has often more than one designated inventor, if two inventors collaborate on the same patent, then a social tie exists. A network of inventors can be viewed as a social network whose nodes are individual inventors and links are co-inventorship relations. The network variable counts for each year, the number of collaborations between inventors residing in city i and those residing in j (appendix A2.4). Technological diversity is computed by grouping the patents technological classes into 30 broader sectors defined by Schmoch (2008), and comparing their relative distribution across cities. An issue is that patent with multiple classes often belong to more than one sector, which makes the aggregation difficult. Sectors are weighted according to their relative frequency of apparition in the patents (appendix A2.5). For each city, the technological diversity index is computed as $1 - \sum_{t=1}^n s_t^2$ where s_t is the relative share of the technological sector t in the city. An index a value close to unity indicates that the city is technologically diverse.

Table 4.2: Descriptive statistics

	N. obs	Mean	St. Dev.	Min.	Max.
Number of patents	5856	100.91	264.50	0.00	3477.00
<i>Inputs</i>					
Spending in R&D ($\times 10^6$)	5856	272.91	811.13	0.00	14011.98
Human ressources in S&T	5856	2890.82	8333.77	0.00	142625.00
<i>Connectivity</i>					
Mobility	488 ²	0.01	0.17	0.00	144.00
Networks	488 ²	0.29	7.06	0.00	2499.00
Distance	488 ²	752.89	408.43	10.00	2223.70
<i>Controls</i>					
Population ($\times 10^3$)	5856	551.22	1047.53	19.00	11870.00
Tech. diversity index	5856	0.80	0.20	0.00	1.00

The analysis focuses on 488 cities over 12 years.

Finally, total R&D expenditures are used as a proxy for the research effort. The level of human capital is measured by the total number of R&D personnel and researchers in full time equivalent.

4.4 Model

The model is based on a knowledge production function (Griliches, 1979), which expresses innovation output (inn) in a city i as a function of domestic inputs (int) such as R&D spending and human capital, as well as a set of characteristics (chr) specific to i . Since knowledge developed by neighbouring cities enter the production function, external inputs (ext) are added to the model. This function is assumed to take a Cobb-Douglas form.

$$inn_i = chr_i^{\beta_1} \times int_i^{\beta_2} \times ext_i^{\beta_3} \quad (4.1)$$

Spatial econometrics provide a natural tool to investigate the interdependencies in neighbouring cities' research activity. Autant-Bernard and LeSage (2011) provide a formal motivation to estimate equation (4.1) using a spatial Durbin model (SDM). Specifically, to the extent that innovation inputs are not perfectly observed and that both observable and unobservable inputs exhibit spatial dependence, the model should include spatial lags for the dependent as well as the independent variables. These assumptions seem reasonable in our setting because R&D spending and human capital represent rather aggregate measures of innovation inputs and, as made clear in the previous section, cities' research activities are expected to exhibit spatial dependence. This gives the following empirical model, expressed in logarithms.

$$Y_t = \rho WY_t + \beta X_t + \theta WX_t + c + \varepsilon_t \quad (4.2)$$

Y is a vector of innovation output (*inn*). X is a matrix of local innovation inputs (*int*) and city-specific characteristics (*chr*) with β the associated vector of coefficients. Connectivity is introduced in the model through the weight matrix W . Two spatial lags vectors, WY and WX , account for spatial dependence, and represent external inputs to innovation (*ext*). Each vector is a linear combination of neighbouring observations' dependent and independent variables, respectively. The scalar parameter ρ capture the global dependence among cities' innovation output, while the vector θ may be interpreted as the average impacts of external inputs on local innovation. In addition, c is a vector of individual effects and ε_t is a vector of independent and identically distributed error terms with zero mean and constant variance σ_0^2 .

One of the main weaknesses of the spatial economic literature is the arbitrary choice of the weight matrix. This is because W cannot be estimated and needs to be specified in advance according to some relevant criterion. This chapter proposes a refinement of the typical matrices based purely on geographical distance by using information on the mobility of inventors and their collaborative network patterns. In this setting, physical distance remains important because it increases the cost of mobility as well as the cost of forming and maintaining network ties (Breschi and Lissoni, 2009). At the same time, there is evidence of long-range knowledge flows (Owen-Smith and Powell, 2004), and distant cities may influence each others if they are linked by labour mobility and collaboration networks. Following Hazir et al. (2014), the weight matrix is expressed as a convex combination of three components. The strength of interactions between cities is assumed to be a function of bilateral (1) mobility flows, (2) network collaborations and (3) geographical proximity. Letting W_M , W_N and W_D be the corresponding matrices,

with λ_M , λ_N , and λ_D their associated weights respecting $\lambda_M + \lambda_N + \lambda_D = 1$, W is expressed as follows³.

$$W = \lambda_M W_M + \lambda_N W_N + \lambda_D W_D$$

The resulting matrix has zeroes on the diagonal and non-null elements on the off-diagonals when observation i depends on observation j . In order to make the three matrices comparable in magnitude, $W_{M,N,D}$ are normalized to a range between 0 and 1. Using different values of $\lambda_{M,N,D}$ with increments of 0.1, sixty distinct weight matrices are generated, reflecting different forms of connectivity. Equation (4.2) is then estimated iteratively using each of the weight matrices. By comparing the different specifications, one can observe how the model fit varies in response to changes in the connectivity structure, and select the weight matrix associated with the model with the highest log-likelihood, as shown in table 4.3. The values of $\lambda_{M,N,D}$ associated with this matrix can be used to draw inferences on the relative importance of different forms of connectivity.

³LeSage (2014) argued that a sparse and symmetric weight matrix performs better. The mobility and network matrices are made symmetric so that for instance, the mobility between i and j reflects the total number of moves between the two cities, regardless of the direction. Besides, the inverse distance matrix is made sparse by keeping only the 15 nearest neighbours. The results are robust to changes in the number of distance-based neighbours.

Table 4.3: Structures of dependence

Rank	λ_M	λ_N	λ_D	Log-lik.
1	0.5	0.4	0.1	-1388.6
2	0.4	0.5	0.1	-1392.1
3	0.7	0.2	0.1	-1400.7
\vdots	\vdots	\vdots	\vdots	\vdots
52	0.0	1.0	0.0	-1499.8
53	1.0	0.0	0.0	-1500.6
60	0.0	0.0	1.0	-1516.6

As noted by LeSage and Pace (2009), specifying the weight matrix using non-spatial notions of proximity raises endogeneity concerns. In particular, mobility flows and network ties used in the definition of W should be correlated with the inputs to innovation. This is clearly a limitation of this empirical strategy, and to attenuate this issue, the weight matrix is lagged one period⁴. Nonetheless, this connectivity structure has the advantage of being derived from the economic literature, rather than being a vague spatial pattern based on geography. Going back to the main hypothesis, it is assumed that mobility and networks provide access to knowledge, but the proportion of accessible knowledge effectively used for innovation depends on absorptive capacity. In our setting, absorptive capacity can be measured as the complementarity between internal and external inputs (Cassiman and Veugelers, 2006). Cities that engage actively in research and employ talented individuals should understand more readily the discoveries of others. Therefore, equation (4.2) is estimated with the addition of interaction terms between the domestic inputs and the spatial lag.

⁴The correlation coefficient between the different matrices is 0.214 on average (appendix A2.4).

$$Y_t = \rho WY_t + \beta X_t + \theta W X_t + \phi X_t W X_t + c + \varepsilon_t \quad (4.3)$$

XWX is measure of absorptive capacity capturing the complementarity between internal and external inputs to innovation, and ϕ is the associated vector of coefficients. Estimation results for the two models are presented in the next section. For clarity, the model in equation (4.2) is referred to as the accessibility model, while equation (4.3) is called the absorption model.

4.5 Results

The two models are estimated on a panel of 488 FUA located in 13 European countries (appendix A2.1) over 1998–2009. These cities account for over 92% of all patents applied for in European urban areas over this period. To avoid extreme heterogeneity, the data is pooled into three-years periods corresponding to 1998–2000, 2001–2003, 2004–2006 and 2006–2009. Besides, the weight matrix is not time-varying in our setting, so mobility and network data are pooled over the sample period. To attenuate endogeneity concerns, all independent variables are lagged one year. Table 4.4 reports the estimation output for the accessibility model. The linear model presented in the first two columns serves as a benchmark, while coefficient estimates for the spatial Durbin model are presented in columns (3) and (4). Each model is estimated twice, once as a regular model and once with the addition of individual fixed effects⁵. The spatial Durbin models exhibit a better fit than their non-spatial counterpart and the log-likelihood

⁵For all models, the Hausman test rejects the null hypothesis that individual effects are uncorrelated with the independent variables, so the fixed effects model is preferred over random-effects. In addition, the maximum likelihood estimator is generally inconsistent in the presence of fixed effects (Lee and Yu, 2010), especially when the length of the panel is short. The incidental parameter problem is solved using the Lee Yu transformation.

statistic clearly favours the fixed effects specifications. Consequently, the discussion of the results is based on the estimation output presented in column (4).

Table 4.4: Estimation output for the accessibility model

	Linear model (1)	Linear model (2)	Spatial Durbin (3)	Spatial Durbin (4)
<i>Internal inputs</i>				
R&D spending	0.178*** (0.018)	0.093*** (0.017)	0.078*** (0.021)	0.034** (0.013)
Human capital	0.071*** (0.017)	0.055** (0.021)	0.038** (0.015)	0.027* (0.017)
<i>External inputs</i>				
W × R&D spending	–	–	0.012** (0.004)	0.037** (0.014)
W × Human capital	–	–	–0.034** (0.013)	–0.029* (0.012)
<i>Controls</i>				
Population	0.675*** (0.044)	0.279*** (0.104)	0.638*** (0.043)	0.171* (0.074)
Tech. diversity	1.692*** (0.119)	1.073*** (0.109)	1.256*** (0.124)	1.003*** (0.127)
Rho (ρ)	–	–	0.604*** (0.028)	0.488*** (0.040)
Fixed effects	No	Yes	No	Yes
Log-likelihood	–	–316.3	–1187.8	168.2

*90%, **95% and ***99% confidence levels. Standard errors are robust.

Accessibility

Our first hypothesis is that bilateral mobility and networks significantly affect neighbouring cities' research activity. The Rho estimate is positive and significant at the 1% level, which confirms the existence of strong and positive spatial dependence. Looking at the sources of dependence, table 4.3 shows that the best model fit is obtained when W is computed using weights of 50% on mobility, 40% on networks and 10% on distance. Interestingly, the case when W is expressed only by distance yields the worst fit, which confirm earlier findings that contiguity alone does not reflect the nature of

dependence among innovation processes, but serves as a proxy for more meaningful forms of proximity based on social ties. In addition, it implies that the mobility and networks among distant cities matters for patenting. Distinguishing W_M from W_N , the matrix expressed by mobility alone outperforms the network matrix in terms of model fit, so that mobility has a slightly stronger spillover effect⁶. These findings motivate the use of a spatial specification that model explicitly the sources of interactions among neighbouring cities' research activity. Considering the variables of interest, both the R&D spending and the human capital variables have the expected sign and remain significant at the 5% and 10% level when adding the fixed effects. Because the Rho statistic is significant, their impact on the dependent variable must be interpreted in terms of direct, indirect, and total effects, reported in table 4.5.

Table 4.5: Average marginal effects for the accessibility model

	Direct effect	Indirect effect	Total effect
<i>Inputs</i>			
R&D spending	0.036** (0.014)	0.035** (0.013)	0.071** (0.028)
Human capital	0.027* (0.011)	-0.028** (0.011)	-0.001 (0.006)
<i>Controls</i>			
Population	0.168* (0.073)	1.085** (0.428)	1.254** (0.495)
Tech. diversity	0.988*** (0.130)	2.693*** (0.753)	3.681*** (0.799)

*90%, **95% and ***99% confidence levels. Standard errors are robust.

The direct effect measures the impact of a unit change in one input of the typical city i on the dependent variable of this same city i , averaged across all cities in the sample. In our framework, this means that a 1% change in R&D investment increases

⁶The measure of mobility is sensitive to the disambiguation procedure. A robustness check using a more conservative definition of mobility (appendix A2.3) favours the W computed using weights of 40% on mobility, 50% on networks and 10% on distance, which is very similar. Estimation results are robust to this change in the connectivity structure.

patenting in the city by 0.036%, which is an average elasticity response because of the log-transformation. Similarly, the elasticity of patenting associated with an increase in the level of human capital is 0.027%. The direct effect differs slightly from the estimates reported in table 4.4, because the spatial Durbin model produces a small feedback effect⁷. By contrast, the indirect effect captures the average impact on the dependent variable city i , of a unit change in one input of cities j neighbouring i . The indirect effect typically represent a measure of spillovers, which arise in our setting from bilateral mobility and networks. A 1% change in neighbouring cities spending in R&D produces on average a spillover impact of 0.035% on local innovation. Interestingly, the indirect effect associated with an increase human capital is negative and significant. This is interpreted as a competition effect. Unlike R&D investments, which partly consists of research infrastructures; human capital is a mobile factor that relocates in space, and tend to cluster within a few urban areas. It seems plausible that an increase in human capital in a given city makes it more attractive to other skilled workers, and especially to those located in neighbouring cities who face a lower mobility cost. Consequently, the total impact of human capital is not significant, because it increases local patenting but has a negative spillover effect on neighbours. On theoretical grounds, these opposing effects are well documented. While the endogenous growth literature makes it clear that human capital increases the rate of innovation, new economic geography models highlight a strong competition effect associated with the mobility of workers. Turning to the control variables, the coefficient associated with population and technological diversity have the expected sign and remain significant in all the specifications.

Absorptive capacity

Our second hypothesis is that the amount of accessible knowledge effectively used for

⁷A variation in one input in city i impact city i 's output but also spillovers the output of neighbouring cities, say j . This impact on j 's output produce in turn a spillover impact on output of cities neighbouring j , and i is one such city (LeSage and Pace, 2009).

innovation depends on cities' absorptive capacity. In other words, cities that engage actively in research and employ talented individuals can use a larger share of their neighbours' knowledge, accessible through mobility and networks. The estimation results for the absorption model are detailed in table 4.6. Since R&D spending is associated with a positive spillover effect, the model includes two interaction terms between the spatial lag and the domestic inputs, interpreted as a measure of complementarity between internal and external inputs to innovation. The linear model presented in columns (1) and (2) serves as a benchmark, while coefficient estimates for the spatial Durbin model are presented last two columns. As before, the preferred specification is the spatial Durbin model with fixed effects in column (4), which has the highest log-likelihood.

Table 4.6: Estimation output for the absorption model

	Linear model (1)	Linear model (2)	Spatial Durbin (3)	Spatial Durbin (4)
<i>Internal inputs</i>				
R&D spending	0.215*** (0.022)	0.098*** (0.021)	0.077** (0.030)	0.033* (0.014)
Human capital	0.090** (0.035)	0.029 (0.033)	0.056* (0.024)	0.023 (0.025)
<i>External inputs</i>				
W × R&D spending	–	–	0.014** (0.005)	0.038** (0.015)
W × Human capital	–	–	–0.074** (0.029)	–0.011 (0.014)
<i>Absorptive capacity</i>				
W RD × RD	0.119*** (0.041)	0.036 (0.038)	0.054* (0.023)	0.021 (0.035)
W RD × HC	0.073*** (0.027)	0.028** (0.011)	0.041** (0.016)	0.018* (0.007)
<i>Controls</i>				
Population	0.650*** (0.048)	0.413*** (0.131)	0.634*** (0.043)	0.173 (0.126)
Tech. diversity	2.028*** (0.145)	1.213*** (0.136)	1.242*** (0.124)	0.999*** (0.127)
Rho (ρ)	–	–	0.597*** (0.028)	0.486*** (0.040)
Fixed effects	No	Yes	No	Yes
Log-likelihood	–	–315.5	–1182.8	–266.7

*90%, **95% and ***99% confidence levels. Standard errors are robust.

As in the accessibility model, the Rho estimate confirms the existence of strong and positive spatial dependence. Table 4.7 report the direct, indirect and total effects for the absorption model. An additional 1% expenditures in R&D in a typical city increases patenting in that city by 0.035% produces an average spillover impact of 0.034% on neighbouring cities. Turning to human capital, both direct and indirect impacts become insignificant in the fixed effects specification. Interestingly, when interacted with the spatial lag of R&D spending, the coefficient on human capital remains significant at

the 10% level, with a direct impact of 0.021%.

Table 4.7: Average marginal effects of the absorption model

	Direct effect		Indirect effect		Total effect	
<i>Inputs</i>						
R&D spending	0.035*	(0.015)	0.034**	(0.014)	0.070**	(0.026)
Human capital	0.024	(0.019)	-0.012	(0.014)	-0.012	(0.011)
<i>Absorptive capacity</i>						
W RD \times RD	0.023	(0.021)	0.012	(0.011)	0.035	(0.030)
W RD \times HC	0.021*	(0.009)	0.013	(0.010)	0.034*	(0.014)
<i>Controls</i>						
Population	0.213*	(0.092)	1.046*	(0.456)	1.259**	(0.497)
Tech. diversity	1.084***	(0.133)	2.607***	(0.755)	3.691***	(0.805)

*90%, **95% and ***99% confidence levels. Standard errors are robust.

Overall, there is rather weak evidence of absorptive capacity. Nonetheless, the results confirm the existence of a complementarity between internal and external inputs to innovation, and suggest that certain level of human capital helps to take advantage of neighbours' discoveries. Contrary to expectation, there is no comparable evidence for the R&D spending variable. Finally, the controls have the expected sign and significance.

4.6 Conclusion

Empirical studies on the geography of innovation have established that skilled workers' mobility and collaboration networks shape the diffusion of knowledge across firms and regions. At the same time, the literature on absorptive capacity insisted on the importance of local research capabilities to take advantage of knowledge developed

elsewhere. This chapter investigates both phenomena in an integrated framework by assuming that mobility and networks provide access to knowledge, but the proportion of accessible knowledge effectively used for innovation depends on absorptive capacity. Such complementarities in regional research efforts are effectively captured using a spatial Durbin model in which the connectivity structure stems from mobility and collaboration patterns.

This chapter contributes to the empirical literature in four ways. First, the analysis is carried out at the level of urban areas, a meaningful unit of analysis with regards to arbitrarily defined regions commonly used in the literature. Second, it proposes a refinement of the typical weight matrices based on purely geographical criteria by using information on the mobility of inventors and their collaborative ties. The model is estimated iteratively using different forms of connectivity to select the matrix associated with the model that fits the data most closely. Results confirm that skilled mobility, and to a lesser extent networks, significantly affect neighbouring cities' innovation processes. Besides, contiguity alone does not reflect the nature of dependence, but serves as a proxy for more meaningful forms of proximity based on social ties. Third, this chapter estimates a spatial knowledge production function on a panel of 488 European urban areas over 1998–2009. Maximum likelihood estimates suggest innovation at the urban level is strongly affected by the research effort of their neighbours. Specifically, spending in R&D contributes to local innovation, but also significantly increase patenting in neighbouring cities. By contrast, the aggregate impact of human capital is not significant, because the positive effect on local innovation is offset by a negative spillover effect on neighbours. This is interpreted as a competition effect whereby an increase in human capital in a city draws skilled workers away from neighbouring cities, causing it to grow at the expense of peripheral areas. Fourth, this chapter provides an estimate of absorptive capacity, measured as the complementarity between internal

and external resources. There is rather weak evidence of this phenomenon but results suggests nonetheless that a certain level of human capital helps to take advantage of others' discoveries.

These findings have implications for the convergence debate. While greater accessibility encourages convergence, the notion of absorptive capacity implies a self-reinforcing effect leading to divergence. Models that study growth and geography in an integrated framework recognize the importance of both workers' mobility and knowledge externalities in determining the location of innovation (Baldwin and Forslid, 2000). On the one hand, if a region becomes relatively more attractive, mobile workers will move to this region, causing it to grow at the expense of peripheral areas in a circular-causation mechanism. On the other hand, the strength of agglomeration depends negatively on the range of knowledge externalities. In this setting, the aggregate impact of skilled mobility is ambiguous because it favours the core-periphery equilibrium, while its role in the diffusion of knowledge give rise to dispersion. The theoretical literature is unclear about which effect prevails, partly because it does not account for the actual mechanisms through which knowledge diffuses in space. This work represents a step in this direction, as it provides evidence of both complementarity and competition effects among neighbouring cities innovation processes.

Perhaps, a more fine-grained study taking into account regional specificities in innovation would provide a better understanding on the relative importance of these two opposing effects. More generally, the impact on the distribution of innovation critically depends on the nature of mobility. For instance, in the presence of long term mobility, the agglomeration force should be stronger than what theory predicts. By contrast, the increasing development of short-term, circular patterns of mobility should give rise to dispersion. From a methodological perspective, spatial models offer a strong potential

to investigate complementarities in research because they model parsimoniously complex relationship between observational units across space and time. However, specifying the weight matrix using non-spatial notions of proximity raises endogeneity concerns. Further theoretical work in this direction would offer a great potential for empirical analysis (Qu and Lee, 2015). In the same spirit, it would be interesting to implement a dynamic panel with a time-varying weight matrix that allow the connectivity structure to change over time (Lee and Yu, 2012). This would allow for a more detailed and dynamic analysis of the importance of mobility and networks in the diffusion of knowledge.

5 Conclusion

5.1 Main results

This thesis investigates the question of how skilled mobility shape the diffusion of knowledge and the resulting spatial distribution of innovation. To answer this question, it proceeds in three steps. Chapter 2 sets the conceptual framework and provides a review of the literature. Chapter 3 investigates the patterns and determinants of skilled workers' mobility across urban areas. Chapter 4 focuses on the role of skilled mobility, networks and absorptive capacity in the diffusion of knowledge across urban areas.

One of the main conclusion of Chapter 2 is that some new economic geography and growth models provide a useful theoretical framework to explain the spatial distribution of innovative activity through the interplay of agglomeration and dispersion forces. While recognizing the importance of skilled mobility and knowledge externalities for the distribution of innovation, they neglect these workers' role in the diffusion of knowledge. This should lead to an increased relevance of mobility choices for innovation. In addition, the migration dynamics are very simplistic, and heterogeneity in workers' location preferences weakens the circular mechanism of agglomeration. Some evidence is available in the geography of innovation literature. Empirical studies have established

that skilled workers influence the diffusion of knowledge by moving across organisation, creating network relationships and building absorptive capacities. Besides, labour mobility is diverse and skilled workers do not move exclusively in response to labour market signals.

Building on these considerations, Chapter 3 investigates the patterns and determinants of inventors' mobility across European urban areas. The descriptive analysis suggests that mobility is relatively rare and has a limited spatial dimension. Interestingly, the results points to the importance of circular patterns of mobility, which generally occur within the same firm. The econometric analysis reveals that inventors' do not respond exclusively to labour market signals, but are also attracted to cities providing natural and cultural amenities. In addition, the decision to move is mediated by network ties, which reduce information asymmetries and improve matching. Finally, the fragmentation of cultural and institutional frameworks in Europe significantly reduces mobility. These results suggest that the diffusion of knowledge may be limited. Mobility is rare and generally occurs within the same firms, located in technologically related cities. This may cause may cause the transferred knowledge to be redundant. A more promising finding is that mobility may be encouraged, in particular through the development of research collaborations.

Turning to the impact of skilled mobility, Chapter 4 explicitly models the interdependencies between neighbouring cities' innovation. The main assumption is that mobility and networks provide access to knowledge, but the proportion of accessible knowledge effectively used for innovation depends on absorptive capacity. The analysis confirms that mobility, and to a lesser extent networks, significantly affect neighbouring cities' innovation. Specifically, spending in R&D contributes to local innovation, but also significantly increases patenting in neighbouring cities. By contrast, the aggregate impact

of human capital is not significant, because the positive effect on local innovation is offset by a negative spillover effect on neighbours. This is interpreted as a competition effect whereby an increase in human capital in a city would draw skilled workers from neighbouring cities. Finally, the results suggest that a certain level of human capital helps to take advantage of others' discoveries.

These findings have implications for the convergence debate. Depending on labour mobility and the range of knowledge externalities, a core-periphery pattern may emerge as firms and skilled workers cluster within the same location. As this location becomes more attractive, further concentration of firms and factors occurs, pushing its capacity to innovate and grow at the expense of peripheral areas. By contrast, when knowledge externalities have a wide spatial range, location decisions have no effect on innovation, which weakens the circular-causation mechanism described above and favours the symmetric equilibrium. In this setting, the aggregate impact of skilled mobility is ambiguous because it favours the core-periphery equilibrium, while its role in the diffusion of knowledge gives rise to dispersion. There exist both complementarity and competition effects among neighbouring regions' innovative activity. The theoretical literature is unclear about which effect prevails, partly because it does not account for the actual mechanisms through which knowledge diffuses in space. In this regard, the geography of innovation literature has established the importance of skilled mobility in the diffusion of knowledge. However, the impact on the distribution of innovation critically depends on the nature of mobility. For instance, in the presence of long term mobility, the agglomeration force should be stronger than what theory predicts. By contrast, the increasing development of short-term, circular patterns of mobility should give rise to dispersion. The migration literature makes it clear that mobility is diverse.

5.2 Direction for future research

Further research should focus on other categories of skilled workers, because inventors represent only a fraction of the skilled workforce. Each category of workers has different propensities and motivation to move, so that mobility patterns differ considerably. Consequently, their impact on the diffusion of knowledge, and the resulting distribution of innovative activity is likely to be different. In addition, while both mobility and networks influence the diffusion of knowledge, they have often been investigated separately, and it would be interesting to study the interrelation between these two channels, as they appear to be closely related. From a methodological perspective, spatial models offer a strong potential to investigate complementarities in research because they model parsimoniously complex relationship between observational units across space and time. However, specifying the weight matrix using non-spatial notions of proximity raises endogeneity concerns. Further theoretical work in this direction would offer a great potential for empirical analysis.

More generally, there seems to be a consensus among economic geographers and urban economists on the importance of large cities for innovation. This argument is backed by substantial evidence exploring specific aspects of this relationship. Specifically, empirical studies reported that dense urban areas concentrate more human capital and generate more knowledge externalities. Besides, these cities are centres of production and consumption, which attracts both skilled workers and innovative firms in a cumulative mechanism. As a consequence, large urban areas are found to be more productive, more innovative and tend to grow faster. It is tempting to translate these pieces of evidence into a general hypothesis that large cities have a definite advantage over smaller ones, and that higher concentration necessarily leads to better innovative performance.

However, we should not fall back on narrow categorizations – high-skilled versus low-skilled or core versus periphery – in our description of the economic landscape. These classifications represent useful descriptions of the reality, but they mask a great deal of variation. This is particularly important in a European context, because the vast majority of the reported evidence is based on US data, and the EU has a more polycentric and less concentrated urban structure. In this regard, Dijkstra et al. (2013) argued that the concentration of people and growth in the largest European cities has slowed down or reversed over the last decade. In a French context, Bouba-Olga and Grossetti (2015) questioned the identification of productivity-agglomeration relationship. They argued that specialization rather than size, drives differences in productivity. Finally, urban economists have long established that negative externalities such as congestion costs, labour crowding and high cost of living, may increase the appeal of smaller urban centres. Taken together, these arguments cast a very different light on the role played by urban areas on European economic performance. In a recent contribution, McCann and Acs (2011) argued that productivity is driven primarily by a city’s connectivity, rather than to its scale. This is consistent with the evidence reported by Fitjar and Rodriguez-Pose (2011) for south west Norway. Despite a low population density and a limited investment in research, this region has remained innovative by developing strategic international collaborations with dynamic regions. Building on these considerations, different cities may opt for distinct strategies by using different combinations of internal and external inputs for innovation. While large urban areas can rely on their local pool of skills and knowledge, smaller urban areas may benefit from the research effort in the core, in particular through the development of mobility and networks. Future research should focus on small and medium-sized urban areas to identify different innovation strategies. In this regard, it would be interesting to design a typology to classify urban areas along various criteria including size, internal research

capabilities, levels of mobility, embeddedness in networks and technological diversity among others. In a more dynamic perspective, it would be interesting to monitor how these cities move along the urban hierarchy. For instance, the innovation output to input ratio may be greater in medium-sized cities than in large metropolitan areas. Such an approach would certainly provide a deeper understanding of the importance of smaller urban centres, as well as European specificities in innovation.

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Appendix

A1 Appendix for Chapter 3

A1.1 Distance

Table A1: Estimation results using various forms of distance

	Spatially filtered Quasi Poisson	
	(1)	(2)
Stock of inventors (o)	0.916***	0.580***
Stock of inventors (d)	0.887***	0.541***
Driving distance (od)	-1.529***	-20.341***
Squared driving distance (od)		7.515***
R&D expenditure (d)		0.278**
Human res. in S&T (d)		0.237***
Collaborations (od)		0.185***
Centrality (o)		0.185***
Centrality (d)		0.215***
Tech. proximity (od)		0.778***
Same country (od)		2.198***
Constant	-4.197***	-9.157***

*90%, **95% and ***99% confidence levels.

A1.2 Technology

Table A2: Technological classes and subclasses

- 1 – Chemicals
 - 11 Agriculture, food, textiles
 - 12 Coating
 - 13 Gas
 - 14 Resins
 - 14 Organic compounds
 - 15 Resins
 - 19 Miscellaneous
- 2 – Computers, communications
 - 21 Communications
 - 22 Computer hardware, software
 - 23 Computer peripherals
 - 24 Information storage
 - 25 Electronic business methods and software
 - 29 Miscellaneous
- 3 – Drugs, medical
 - 31 Drugs
 - 32 Surgery, medical instruments
 - 33 Genetics
 - 39 Miscellaneous
- 4 – Electrical, electronic
 - 41 Electrical devices
 - 42 Electrical lighting
 - 43 Measuring, testing
 - 44 Nuclear, x-rays
 - 45 Power systems
 - 46 Semiconductor devices
 - 49 Miscellaneous
- 5 – Mechanical
 - 51 Mat. proc, handling
 - 52 Metal working
 - 53 Motors, engines, parts
 - 54 Optics

55	Transportation
59	Miscellaneous
6	– Others
61	Agriculture, husbandry, food
62	Amusement devices
63	Apparel, textile
64	Earth working, wells
65	Furniture, house fixtures
66	Heating
67	Pipes, joints
68	Receptacles
69	Miscellaneous

Source: NBER Patent Data Project

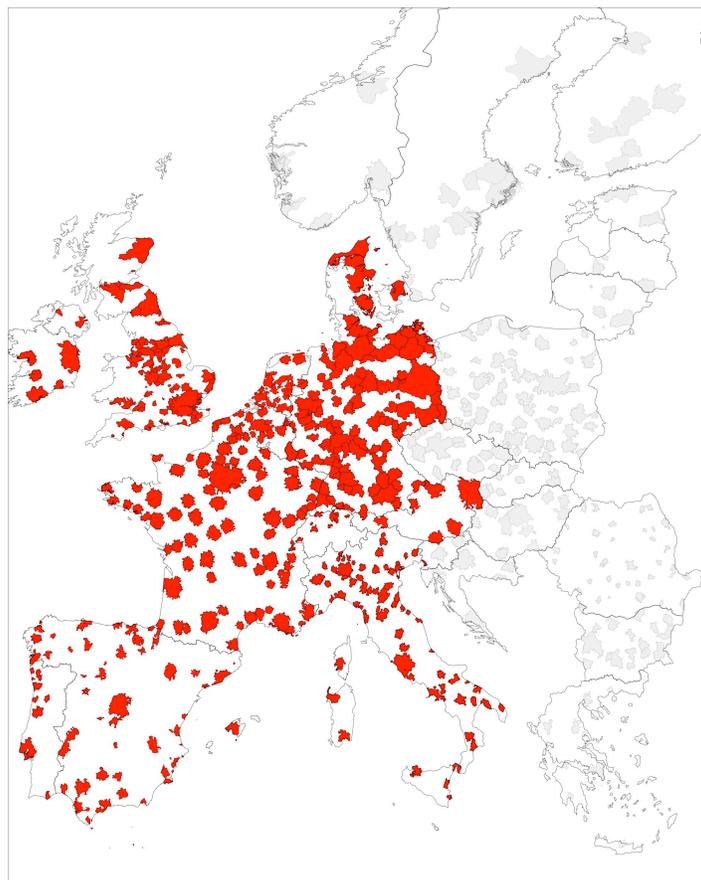
A2 Appendix for Chapter 4

A2.1 Functional Urban Areas

Each FUA is composed of a densely populated city core and a commuting zone

- Core: (1) All grid cells with a density of more than 1 500 inhabitants per sq km are selected. (2) The contiguous high-density cells are then clustered, gaps are filled and only the clusters with a minimum population of 50 000 inhabitants are kept as core. (3) All the municipalities with at least half their population inside the urban centre are selected as candidates to become part of the city. (4) The city is defined ensuring that there is a link to the political level, that at least 50% of city the population lives in an urban centre and that at least 75% of the population of the urban centre lives in a city.
- Commuting zone: (1) All municipalities with at least 15% of their employed

Figure A1: Functional Urban Areas

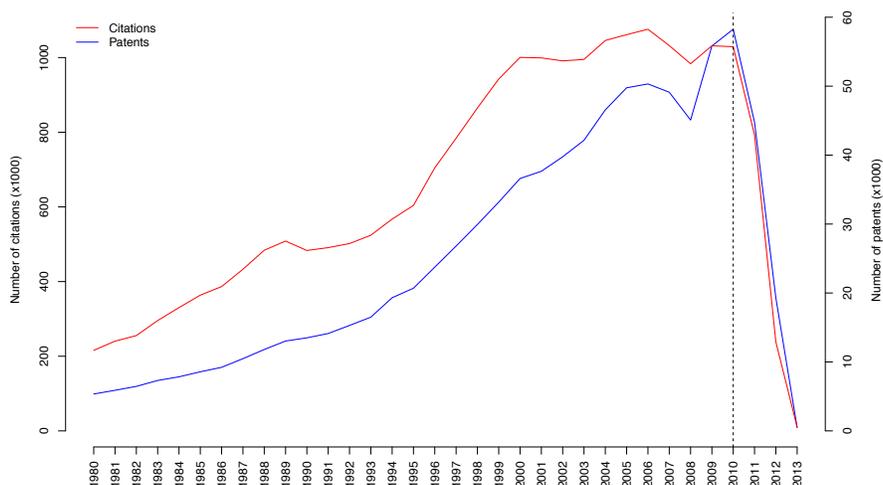


FUA in red are used in the econometric analysis.

residents working in a city are identified. (2) Municipalities surrounded by a single functional area are included and non-contiguous municipalities are dropped. (3) If 15% of employed persons living in one city work in another city, these cities are treated as a single city.

A2.2 Innovation

Figure A2: Patents and citations over time



Source: CRIOS

A2.3 Disambiguation

The Massacrator routine uses a three-step procedure: cleaning and parsing, matching, and filtering. Specifically, (1) cleaning and parsing involve purging names and surnames strings of typographical errors and converting them to a standard character set. Strings may be parsed into several substrings, whenever appropriate. (2) Then inventors whose names match, either exactly or closely are selecting as likely candidates. (3) During the filtering stage, the selected pairs are filtered using additional information present in the patent documents. The disambiguation is a trade-off between precision and recall.

Table A3: Calibrations of Massacrator

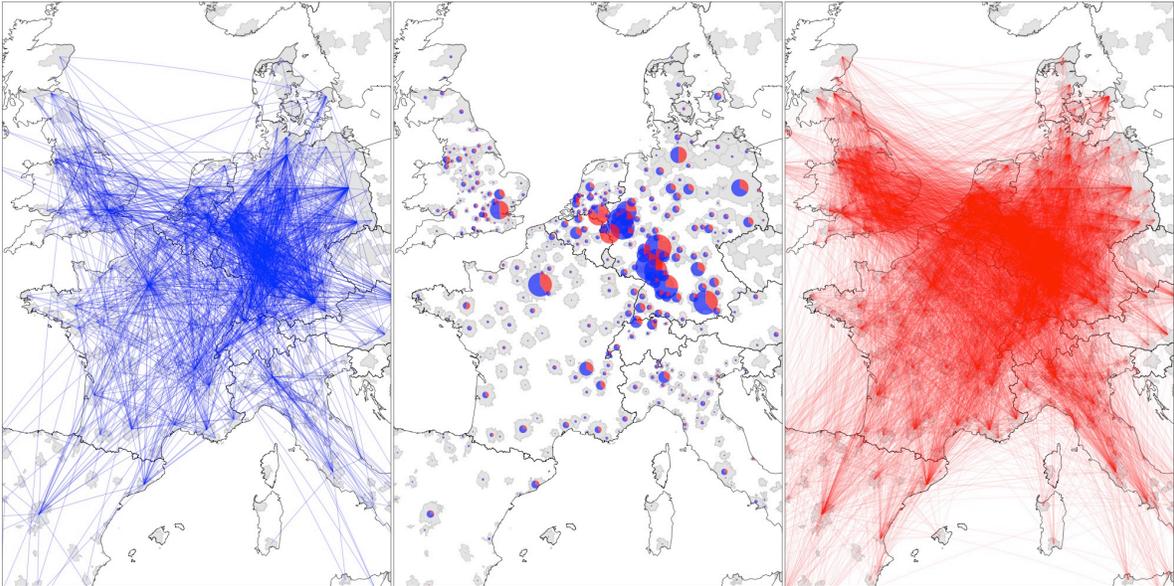
Variables	C1	HR	C3	C4
<i>Network</i>				
Coinventor	1	1	1	1
Three degrees	1	1	1	1
<i>Geographical</i>				
City	0	0	0	0
Province	1	1	0	0
Region	1	1	0	0
State	0	0	0	0
Street	0	0	0	0
<i>Applicant</i>				
Applicant	1	1	1	1
Small applicant	1	1	1	1
Group	0	0	0	0
<i>Technology</i>				
IPC4	1	1	1	1
IPC6	1	1	1	1
IPC12	1	1	1	1
<i>Citations</i>				
Citations	0	0	0	0
ASE	0	0	0	0
<i>Other</i>				
Rare surnames	0	0	0	0
Three years	0	0	0	0
N criteria to be met	2	3	2	3

Calibrating Massacrator requires choosing (1) the number of filtering variables and (2) the number of criteria to be met in order for the pair to be considered as a match. For exploratory purposes, four calibrations based on the high-recall calibration of Massacrator (HR) are tested. C1 tests the sensitivity of disambiguation results to the number of

criteria to be met. C2 and C3 test the sensitivity of the disambiguation to the removal of geographical criteria. C1 and C3 perform best, both by the number of movers and the number of moves. Results suggest that disambiguation is much more sensitive to the number of criteria to be met, rather than the inclusion of geographical criteria. The preferred measure of mobility is C1, and C2 is used for robustness checks.

A2.4 Connectivity

Figure A3: Connectivity structure



Left panel: Mobility flows, 1998-2009. Right panel: Collaboration networks, 1998-2009. Middle panel: Relative connectivity of cities with regards to their level of mobility flows (blue), both inward and outward, and their number of collaborations (red).

Table A4: Correlation between weight matrices

	W_M	W_N	W_D
W_M	1	0.395	0.086
W_N	0.395	1	0.161
W_D	0.086	0.161	1

A2.5 Technology

Table A5: Technological classes and subclasses

- A – Electrical engineering, Electronics
 - 1 Electrical engineering
 - 2 Audiovisual technology
 - 3 Telecommunications
 - 4 Information technology
 - 5 Semiconductors
- B – Instruments
 - 6 Optics
 - 7 Technologies for Control/Measures/Analysis
 - 8 Medical engineering
 - 9 Nuclear technology
- C – Chemicals, Materials
 - 10 Organic chemistry
 - 11 Macromolecular chemistry
 - 12 Basic chemistry
 - 13 Surface technology
 - 14 Materials, Metallurgy
- D – Pharmaceuticals, Biotechnology
 - 15 Biotechnologies
 - 16 Pharmaceuticals; Cosmetics
 - 17 Agricultural and food products
- E – Industrial processes
 - 18 Technical processes (chemical, physical, mechanical)
 - 19 Handling; Printing
 - 20 Materials processing, textile, glass, paper
 - 21 Environmental technologies
 - 22 Agricultural and food apparatuses
- F – Mechanical engineering Machines, Transport

- 23 Machine tools
- 24 Engines, Pumps, Turbines
- 25 Thermal processes
- 26 Mechanical elements
- 27 Transport technology
- 28 Space technology; Weapons
- G – Consumer goods, Civil engineering
- 29 Consumer goods
- 30 Civil engineering

Source: ISI, OST, INPI

A simple count of patent classes is not satisfactory as multidisciplinary patents would be over-represented. Building on these considerations, sectors within patents need to be weighted according to some relevant criterion. Three aggregations are performed. A1 retain only first sector. Conversely, A2 gives equal weight to all sectors. Finally, A3 weights sectors according to their relative frequency. The preferred aggregation is A3 and the other two are used for robustness checks.

Table A6: Aggregation of patent classes

Patent	Sector	Rank	A1	A2	A3
A	1	F	1	1/2	1/3
A	2	-	0	1/4	1/3
A	2	-	0	1/4	1/3
B	1	F	1	1	1

List of acronyms

CBSA	Core Based Statistical Areas
EU	European Union
FUA	Functional Urban Areas
LUZ	Larger Urban Zones
NEG	New Economic Geography
NEGG	New Economic Geography and Growth
MSA	Metropolitan Statistical Areas
TTWA	Travel To Work Areas
UK	United Kingdom
US	United States of America

Abstract

The fact that innovative activity is remarkably concentrated in space, and in particular in cities, has motivated an important research effort to understand the spatial dimension of innovation, and the underlying mechanisms at work. While the literature has established the importance knowledge flows for location of innovation, the mechanisms through which they diffuse in space remain largely understudied. In particular, studies have insisted on the importance of skilled workers' mobility and the networked nature of knowledge production for innovation. Building on these considerations, this thesis investigates the role of skilled mobility in the diffusion of knowledge, and the resulting distribution of innovative activity.

To answer this question, the thesis proceeds in three steps. Chapter 2 sets the conceptual framework and surveys the related literature. One of the main conclusion of this review is that some new economic geography and growth models provide a useful theoretical framework, because they recognize the importance of skilled mobility and knowledge externalities for the distribution of innovation. However, they fail to provide a reasonable answer to our research question for at least two reasons.

First, the migration dynamics are very simplistic, and introducing heterogeneity in workers' characteristics and location preferences alters the cumulative mechanism of agglomeration. Chapter 3 provides a descriptive analysis on the patterns of inventors' mobility across urban areas, and their spatial dimension. Using these results, a spatial filtering gravity model is used to analyse formally how employment opportunities, professional networks and urban amenities, influence inventors' mobility flows.

Second, these models do not consider workers' role in the diffusion of knowledge. The literature has established that skilled individuals influence the diffusion of knowledge

by moving across organisation, creating network relationships and building absorptive capacities. Chapter 4 implements a spatial Durbin model to study these three mechanisms in an integrated framework. It is assumed that that mobility and networks provide access to knowledge, but the proportion of accessible knowledge used for innovation depends on absorptive capacity.

These results have implications for the geography of innovation. While long-term mobility acts as a strong agglomeration force, the development of short-term, circular patterns of mobility should give rise to dispersion. The relative importance of these two effects is uncertain, because workers have different propensities and motivation to move, so that mobility patterns differ considerably. This should help explaining the persistence of long-run growth differentials among urban areas, and in a more dynamic setting, whether these gaps tend to widen or fall over time.