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Do inventors benefit from knowledge spillovers following a move to a cluster?

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Abstract

Due to their dense social network and high levels of local labor mobility, clusters are characterized by a distinctive environment. As these mechanisms are underlying the local dissemination of knowledge, clusters differentiate themselves from other regions by their high levels of knowledge spillovers. To test whether clusters indeed distinguish themselves from other regions in terms of knowledge spillovers, this study tracks a sample of approximately 2,000 moving inventors residing in Europe over time in order to analyze whether the knowledge production of these inventors, measured in patent applications, changes following a move to a cluster. The study distinguishes between cluster and non-cluster regions. It is found that compared to the average patent applications over the four years before the move, inventors moving from a non-cluster to a cluster region experience the biggest increase in their patent applications in the year of the move and the four consecutive years relative to inventors moving between different regions. This points to the presence of knowledge spillovers in clusters.

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1. Introduction

"Untangling the paradox of location in a global economy reveals a number of key insights about how companies continually create competitive advantage. What happens inside companies is important, but clusters reveal that the immediate business environment outside companies plays a vital role as well" (Porter M. E., 1998) In the past decades, clusters and how their distinctive environment affects their superior economic performance has gained increasing attention. For example, clusters experience a relatively high growth in new business formation (Mercedes, Porter, & Stern, 2010). Additionally, firms operating in clusters are more innovative and more productive than they could be in isolation (Ketels, European Clusters, 2004). Given that countries are always seeking ways to support economic development, clusters have gained increasing attention from policymakers over the past few decades as a tool to increase the competitiveness of their country. The fact that almost 25 percent of total European employment is generated by clusters reflects the economic relevance of these geographic concentrations of interrelated firms (European Commission, 2022). However, as clusters are dynamic environments that are constantly subject to changing market conditions due to the high rates of innovation, it is difficult to understand what exactly drives their superior economic performance.

One important mechanism underlying the continuous development of clusters are knowledge externalities, often referred to as knowledge spillovers. Such spillovers occur "when recipient firms exploit knowledge that has been originally developed by another firm" (Yang & Steensma, 2014) and are thus considered externalities as they affect firms outside the market mechanism. These knowledge spillovers continuously spread the newly created knowledge throughout the cluster's entire network (Oettl & Agrawal, 2008). Given that gaining access to new information contributes to innovation, these knowledge externalities facilitate constant innovation (Kahn, 2018). Research on knowledge spillovers and the underlying mechanisms is mainly theoretical. In addition, many studies examine whether clusters as a whole or whether individual firms benefit from improved economic performance through knowledge spillovers. However, in order to determine whether knowledge spillovers are present in clusters, one should analyze the source through which these externalities enter firms, namely inventors. The fact that these spillovers are externalities and thus intangible, however, poses as a challenge for conducting research on whether inventors experience being affected by knowledge externalities. Some inventors may for example not be aware of being affected by knowledge spillovers (Malmberg & Maskell, 2002). Consequently, as most studies analyzing whether knowledge spillovers have an impact on inventors are based on surveys (e.g. Sherwat, Fallah, & Reilly, 2009; Huber, 2012), the findings are ambiguous. Instead of surveying inventors, this study analyzes the knowledge production of inventors by looking at their patent applications in order to determine whether they are being affected by knowledge spillovers present in clusters. In order to determine whether clusters are characterized by substantially higher levels of knowledge spillovers compared to other regions, it is analyzed whether the knowledge production of inventors increases following a move to a cluster. Accordingly, this study aims to provide an answer to the following question:

Do inventors benefit from local knowledge dissemination within clusters through an increased knowledge production following a move to a cluster?

This research is focused on European clusters. Using data from the OECD REGPAT database, a sample of approximately 2,000 inventors residing in Europe is formed. Constructing inventor IDs and combining these with data on their residential address gathered from their patent applications enables the tracking of these inventors over time. A change in the residential address of an inventor is recorded as a move. Using data from the European Cluster Observatory, it is distinguished between cluster regions and non-cluster regions. The results show that in the year of the move and in four years following the move, inventors moving from a non-cluster to a cluster region experience the biggest increase in terms of patent applications compared to their average patent applications over the four years prior to the move. This points to the presence of knowledge spillovers in cluster regions.

This paper is organized as follows, first, the mechanisms underlying knowledge spillovers are explained and it is discussed how these mechanisms are especially present in clusters in the Theoretical Framework. Next, the Data and Methodology are described, which is followed by a discussion of the Results. Finally, the Discussion and Conclusion are presented.

2. Literature review

Innovation is one of the main contributors to firm growth. Not only does innovation strengthen a firm’s financial position through an increase in sales and capital, but it also results in the growth of employees (Kogan, Papanikolaou, Seru, & Stoffman, 2017). Innovation is a process with the introduction of something new as the outcome (Kahn, 2018). By being in possession of unique knowledge that led to the introduction of this novel product, service, or method, firms gain a competitive advantage (Kuczmarski, 1996). Given these positive effects of innovation on firm performance, many firms have tried to cultivate innovation within their organization (Roberts, 2007). Few, however, are able to maintain a culture that truly embraces innovation.

What do firms need to do to foster innovation? The process of innovation starts with the generation of a new idea (Kahn, 2018). This phase is based on the creation of new knowledge, hence firms can support this phase by efficiently allocating resources toward the development of new knowledge. For example, by channeling more capital to research and development (R&D). Besides this internal generation of new knowledge, innovation can also emerge from the recombination of existing knowledge. There are various channels through which a firm can gain access to knowledge from outside the firm's boundaries, such as collaborations, foreign direct investments, and the hiring of skilled labor (Martin, Aslesen, Grillitsch, & Herstad, 2018). Due to the limited appropriability of knowledge, firms may gain access to external knowledge while the sender did not intend to share this knowledge. These knowledge flows are not priced by the market and are hence referred to as knowledge externalities (Oettl & Agrawal, 2008). Such knowledge spillovers are found to increase firm performance in terms of growth in the number of employees, labor productivity, net sales, output, and new venture product innovations (Chyi, Lai, & Liu, 2012; Gilbert, McDougall, & Audretsch, 2008; Ramadani, Abazi-Alili, Dana, Rexhpei, & Ibraimi, 2017; Raspe & van Oort, 2011; Zhu, He, & Luo, 2019). However, as knowledge externalities tend to weaken over distance, not all firms will be able to enjoy these benefits. One of the first empirical studies into where knowledge spills over to is Jaffe, Trajtenberg, and Henderson (1993). Before their research, it was generally assumed that knowledge spilled over to other firms in the same country and did not exceed the country border. There was no clear evidence on whether knowledge spillovers weakened over longer distances and what mechanisms drove these spillovers. By comparing the geographic locations of patent citations to the locations of the originating patents, Jaffe et al. sought to understand the effect of distance on knowledge spillovers. Their results show that patent citations are twice as likely to come from the same state as the cited patent and two to six times as likely to come from the same city or region. This points to the geographic localization of knowledge spillovers.

2.1 Why are knowledge spillovers spatially localized?

There are two mechanisms explaining this localized knowledge diffusion – social networks and labor mobility. Why social networks result in the local dissemination of knowledge has to do with the composition of knowledge (Oettl & Agrawal, 2008). Knowledge consists of explicit and tacit components. Explicit knowledge is formalized and codified and therefore fairly easy to store and access. Tacit knowledge, on the other hand, is non-codified.

Since this type of knowledge is largely experience-based, it is carried by individuals, making it harder to communicate. In order to apply tacit knowledge, interaction with the carrier is required. Because of this tacit component of knowledge, the probability of a knowledge transfer between two individuals increases when both are socially tied (Singh, 2005). That is to say, the exchange of knowledge is mediated by social relationships (Agrawal, Cockburn, & McHale, 2006; Kaiser, Kongsted, & Rønde, 2011; Miguélez & Moreno, 2015; Trippl, 2013). The strength of social relationships is strongly influenced by physical distance, as separation constrains individuals from performing social activities (Mok & Wellman, 2007). Accordingly, living in close proximity to each other increases face-to-face interactions as well as the likelihood of future interactions (Latané, Liu, Nowak, Bonevento, & Zheng, 1995). Sequential interactions are needed to build trust between two individuals, which causes distance to negatively impact the strength of social relationships. As a result, individuals are more likely to form social relationships with someone who lives nearby, causing the local emergence of social networks. Consequently, since the exchange of knowledge is mediated by social relationships, flows of knowledge are also bound to be spatially localized.

How these local knowledge flows ultimately lead to the local diffusion of knowledge can be explained using social network theory. Instead of explaining individual outcomes by focusing on individual characteristics, the social network theory considers a broader perspective by also taking the individual’s environment into account (Borgatti & Ofem, 2010). This means that an individual’s opportunities, decisions, and actions are not only determined by a function of an individual’s human capital, which includes inputs such as education and social class. Instead, the network in which an individual is embedded also greatly influences individual outcomes. Within this network, all actors are connected with a set of ties, each tie representing a social relationship. By connecting ties with other ties, paths are formed. These paths facilitate the flow of knowledge between two actors, even between actors that are not directly tied. Through these indirect linkages, the knowledge exchanged between two individuals may also flow to other actors who are indirectly tied to these two individuals. This mechanism facilitates the diffusion of knowledge flows throughout a whole social network, which, as previously stated, is bound to be spatially localized. Accordingly, knowledge spillovers tend to be geographically localized.

Another cause of the local diffusion of knowledge is labor mobility, which is interrelated with the existence of social networks. When working on innovations, inventors acquire new knowledge. Because this knowledge partly consists of a tacit component, interaction with the inventor is required to apply this knowledge (Oettl & Agrawal, 2008). Inventors will carry this new knowledge gained at their former job with them when moving to a new firm. Through social interactions with their new colleagues, this knowledge is diffused throughout the whole firm. Firms hiring inventors solely to gain access to their knowledge is also referred to as *learning-by-hiring* (Rosenkopf & Almeida, 2003). Because inventors often maintain linkages with their former colleagues, they also facilitate knowledge flows from their new firm (the receiving firm) back to their old firm (the source firm). Inventors, therefore, act as a bridge by facilitating knowledge flows between the receiving and the source firm (Trippl, 2013). As a result, both firms benefit from increased knowledge flows following the move of an inventor (López, Peón, & Ordás, 2006; Oettl & Agrawal, 2008; Rosenkopf & Almeida, 2003; Sonmez Z., 2017).

Not only the receiving firm and the source firm, but also the receiving country enjoys benefits from moving inventors in terms of increased knowledge flows. Oettl and Agrawal (2008) prove that the knowledge flows from the source firm to the receiving firm generated as a result of the move exceed the firm boundaries by showing that a moving inventor causes an increase of four percent in the number of times that inventors in the receiving country cite the mobile inventor’s source firm. Since it is controlled for cites from the inventor’s receiving firm to its source firm, these results show that not only does the receiving firm benefit from the knowledge flows that result from labor mobility, but these knowledge flows also spill over to other firms located in the same country as the receiving firm. As the knowledge flows from the receiving firm to the source firm and from the source firm to the receiving country are not reflected in the inventor’s wage, they are considered externalities (Møen, 2005; Dahl, 2002).

It can thus be stated that labor mobility facilitates the diffusion of knowledge. Central to why this knowledge is disseminated especially locally is the fact that inventors tend to be mobile within spatially defined labor markets. Labor markets tend to be locally active, since hiring employees from outside the region increases the transaction costs for both the employer and employee (Andersson & Thulin, 2011). To start with, employers face increased exploratory costs when hiring outside the region as the pool of potential employees increases (Uhlbach & Anckaert, 2021). In addition, when an employee is hired from far outside the region, employers often have to take responsibility for seeking new housing for the newly hired employee (Kubiciel-Lodzińska & Solga, 2018). Moreover, the adaptation costs, which comprise the number of days a new employee is less productive than the average employee in the firm, are higher for employees from outside the region, as they need time to get familiar with the firm culture and to become acquainted with their new colleagues. In a similar manner, employees face increased transaction costs when looking for jobs outside the region due to higher exploratory costs and considerable financial and social costs associated with moving to a new region (Breschi & Lissoni, 2009). When examining the distance traveled by moving inventors in Europe, Miguélez and Moreno (2015) find that inventors travel on average 395 kilometers. As the average distance between pairs of European NUTS-2 regions is 1,787.5 kilometers, this finding points to localized labor mobility. Similar results are obtained in studies focusing on one particular country (Andersson & Thulin, 2011; Drivas, Economidou, Karkalakos & Tsionas, 2016). Hence, given that transaction costs increase when hiring from (searching for a job) outside the region, employers (employees) are prone to search for new employees (employers) in close geographic distance to their firm (prior job). Consequently, as moving inventors cause their knowledge to spill over to firms surrounding the receiving firm, this local labor mobility causes the local diffusion of knowledge.

2.2 Are clusters characterized by higher knowledge spillovers?

It can thus be concluded that social networks and labor mobility are driving forces behind the local dissemination of knowledge. Accordingly, one could assume that regions with a denser social network and higher labor mobility rates benefit from higher levels of knowledge diffusion. Regions characterized as such are *clusters*, defined as “geographic concentrations of interconnected companies, specialized suppliers, service providers, firms in related industries and associated institutions (e.g., universities, standard agencies, trade associations) in a particular field that compete but also cooperate.” (Porter M. E., 2000).

Clusters are characterized by a distinctive environment that aids the formation of social relationships and thus the emergence of social networks. The first distinguishing feature of clusters is the close geographic proximity of a large number of firms (Porter, 2000). Because distance negatively impacts the likelihood of future interactions (Latané, Liu, Nowak, Bonevento, & Zheng, 1995), the close geographic proximity of the firms in a cluster fosters frequent interactions between employees working within this cluster. This encourages the formation of social relationships between these employees and accordingly the emergence of a local social network. The second feature distinguishing clusters from other regions is the high degree of innovation, which forces firms to constantly adapt to changing market conditions. Such a turbulent environment generates high uncertainty and forces firms to be highly flexible (Saxenian, 1990). Firms operating in such an environment tend to spread risk by entering into collaborations with other firms. Through these collaborations, they gain access to new knowledge, markets, and technologies by pooling skills and resources (Pittaway, Robertson, Denver, & Neely, 2004). The high industry specialization of the activities that occur in a cluster facilitates the emergence of such collaborations, as it is easier to transfer knowledge originating from the same industry (Dingler & Enkel, 2016). These collaborations strengthen the link between all actors in a cluster's network even further (Schrader, 1991). As the continuously changing market conditions force firms to continually innovate, learn, and adapt, these tight linkages are of great importance. The stronger the ties of a cluster's social network, the better the performance of these firms and the overall cluster (Eisingerich, Bell, & Tracey, 2010). Saxenian (1990) observed the effect of such a dense social network in the Silicon Valley cluster – a well-known cluster located in the United States. When analyzing what drove the high performance of the computer and semiconductor cluster, she concluded that especially the cluster's dense social network "fosters the recombination of experience, skill and professional relationships of Silicon Valley, which benefits the whole region." (Saxenian, 1990).

Besides dense social networks, clusters are also characterized by high labor mobility that results from above-average labor turnover rates (Andersson & Thulin, 2011; Dahl, 2002; Klumbies & Bausch, 2015). Because of a cluster's dense social network and the geographic concentration of firms, the process of searching for a new job is more efficient in cluster areas. Firstly since employees are better informed about suitable local job vacancies due to the tight social links (Dahl & Pedersen, 2004). Secondly because a cluster's dense social network facilitates the provision of recommendations to the potential employer (Behrenz, 2001), which is found to increase the likelihood of receiving a job offer (Fernandex, Castilla, & Moore, 2000). Besides the employees, the employers also benefit from the dense social network, as it allows them to easier identify high-performing employees (Breschi & Lissoni, 2009; Huber, 2012). This is especially useful for firms located in a cluster as the turbulent environment in which the firms operate amplifies the need to constantly adapt to changing market conditions (Schrader, 1991). By gaining access to external knowledge sources through, for example, the hiring of high-performing employees, firms foster constant adaptation and innovation (Martin, Aslesen, Grillitsch, & Herstad, 2018). Because of this, headhunting activities are high in clusters, especially since all firms in a cluster operate in the same industry (Saxenian, 1990). This dynamic job market is one of the distinctive features of a cluster contributing to the success of such a region in the long run, as it promotes knowledge flows between firms within a cluster (Almeida & Kogut, 1999; Saxenian, 1994).

The high industry specialization of the geographically concentrated and interconnected firms is accompanied by a high demand for a particular type of labor. This causes labor mobility to be mainly local (Bilbao-Osorio & Rodríguez-Pose, 2004). Because of the high number of job opportunities, specialized workers are inclined to settle in the vicinity of such a demand cluster, causing the emergence of a highly specialized local labor market (Marshall, 1890). Once established near a cluster, employees are discouraged from moving because the advantages of living near a cluster often outweigh the disadvantages of moving in terms of financial and social costs (Breschi & Lissoni, 2009). Because of increased transaction costs when hiring someone from outside the cluster, employers are prone to use this highly specialized local labor pool when looking for new employees (Amend & Herbst, 2008; Huber, 2012; Otto & Fornahl, 2010). Accordingly, given that labor mobility within a cluster is mainly local, the knowledge carried by inventors employed by firms operating within a cluster is disseminated especially locally.

Therefore, a cluster's distinctive climate contributes to a relatively dense social network and high local labor mobility. As both mechanisms drive the diffusion of knowledge, there are relatively high levels of knowledge externalities within clusters. Consequently, firms operating in a cluster reap the benefits of this local knowledge dissemination in terms of improved innovative activity. Paci and Usai (1999) show that patent applications are higher in specialized areas. Additionally, Audretsch and Feldman (2004) find more competitive areas to be characterized by a high number of patent applications. Likewise, Wallsten (2001) finds that begin located close to highly innovative firms increases a firm's product innovations as well. As clusters are characterized by high industry specialization and a highly competitive and innovative environment due to the constant need for adaptation to changing market conditions, these findings suggest that firms located in clusters profit from improved innovative activity, which points to the presence of considerable knowledge spillovers within cluster areas. Comparing the number of product innovations of firms located in clusters with firms located in other areas provides similar results; knowledge spillovers are more common in cluster firms, as clustering positively affects product innovations (Gilbert, McDougall, & Audretsch, 2008). How individual inventors operating in a cluster firm are affected by knowledge spillovers has been studied relatively less. Kaygalak and Reid (2016) show that inventors employed by cluster firms live closer together compared to inventors that are employed by non-cluster firms. Since proximity supports knowledge externalities, this finding suggests that inventors employed by cluster firms benefit from relatively higher levels of knowledge externalities. However, using survey data from R&D workers employed in the Cambridge Information Technology Cluster, Huber (2012) shows that approximately two-thirds of the R&D workers do not reap any benefits from their firm being located in a cluster in terms of knowledge externalities. But, as stated by Krugman (1991, p. 53), "knowledge flows are invisible" and thus spillovers may happen without any tangible interaction (Malmberg & Maskell, 2002). Hence, these workers may not be aware of being affected by knowledge spillovers. Consequently, these results may not reflect reality. By way of contrast, survey data from inventors employed in 15 U.S. telecommunication clusters shows that, in fact, more than two-thirds of the inventors do benefit from being located in a cluster through local knowledge spillovers (Sherwat, Fallah, & Reilly, 2009). Survey-based research, therefore, provides ambiguous results with regards to whether inventors benefit from being located in a cluster. To gain a better insight into whether inventors benefit from local knowledge dissemination within clusters, I will empirically investigate whether their patenting activity changes following a move to a cluster. Accordingly, this study aims to provide an answer to the following question:

Do inventors benefit from local knowledge dissemination within clusters through an increased knowledge production following a move to a cluster?

3. Data

3.1 Data sources

In order to analyze whether moving to a cluster affects an inventor's knowledge production, this research will analyze whether an inventor's total patent applications per year changes after relocating to a cluster region. Patent applications are hence used as a proxy for an inventor's knowledge production. This is a widely used measurement of knowledge output. As patents are exclusive rights granted for inventions, they function as a valuable source of information regarding the development of new knowledge (Zhenzhong & Lee, 2008). Moreover, as patent data is standardized, these data enable the comparison of the production of knowledge across different countries over a long period of time. There is, however, one caveat with using patent applications as a measure for knowledge production, as not all inventions are patented. This means that, in reality, more knowledge is created than is represented by patent application statistics (Basberg, 1987), which will most likely result in an underestimation of the knowledge production by inventors pre and post-move.

Data on patent applications are obtained from the Organization for Economic Co-operation and Development (OECD). This international organization, consisting of 37 member countries, helps countries find innovative policy solutions by conducting evidence-based policy analyses and by providing economic data (OECD, 2022). The OECD publishes several patent-related databases, which are updated annually. One of these databases is the OECD REGPAT database. This database encompasses patent applications filed to the European Patent Office (EPO) and patent applications filed under the Patent Cooperation Treaty (PCT). For this research, the January 2021 Edition of the OECD REGPAT Database is used.

Because differences in patent applications are compared between inventors, it is crucial that the process of application and examination is similar for all these patents (Basberg, 1987). Although both the EPO and PCT provide unified methods for filing patent applications, they differ in examination procedures (Lee & Schwerbrock, 2021). Unlike the EPO, which uses one examination procedure for deciding on whether patents are granted or not, the PCT does not provide a unified examination system. When filing a patent under the PCT, the country designated by the applicant is responsible for the examination of the patent application. The use of different examination procedures may exogenously affect patent-related statistics. Hence, for this study, only the patent applications filed to the EPO are considered for this research.

The OECD REGPAT EPO dataset is composed of 9.8 million observations of individual inventors filing for a patent application between 1978 and 2020. Each observation contains information about the year in which the patent application was filed and about the inventor's name and address. As more than 85 percent of the patent applications concern a collaboration between two or more inventors, the dataset comprises a total of almost 3.7 million unique patent applications by 3.2 million unique inventors. All observations are linked to regions that are categorized according to the 2013 version of the Nomenclature of Territorial Units for Statistics (NUTS) classification system on the NUTS-3 level utilizing the residence addresses of inventors. This allows for the tracking of inventors over time. The dataset contains observations across 5,157 regions all over the world. The biggest share of inventors resides in the United States. Their share equals 29 percent of the sample. This is followed by inventors from Japan and Germany, whose share equals 18 and 17 percent respectively. As this study focuses solely on European clusters, all inventors that are recorded at least once in a non-European country are completely dropped from the sample, meaning that other patent applications from the same inventor are excluded as well. Only dropping a single patent application may result in overlooking a movement, which might bias the results. This restriction results in a sample of 3.8 million observations that comprises 1.7 million unique patent applications by 1.3 million unique inventors. In addition, due to the absence of regional data gathered from external data sources before 2000 for a majority of the regions, the time period analyzed for this research covers the period from 2000 to 2019. A sample of 2.7 million observations remains, which comprises 1.2 million unique patent applications by 903.453 unique inventors.

3.2 Cluster identification

This research is focused on inventors residing in European countries and hence only European clusters are analyzed. Data from the European Cluster Observatory is used to determine what regions are considered cluster regions. This platform gathers cluster-specific data on the NUTS-2 level covering regions across 36 countries: the EU-27 countries, Albania, Iceland, Israel, Lichtenstein, Macedonia, Norway, Serbia, Turkey, and the United Kingdom. In addition, the platform provides an EU-wide comparative cluster mapping and statistical analysis of the geographical concentration of economic activities.

Due to amendments in the NUTS classification, several regional codes do not correspond between the OECD REGPAT EPO and European Cluster Observatory datasets. Because of these amendments and the resulting diverging codes, it is not possible to match these regions with data from the European Cluster Observatory and other external data sources. As a result, for these specific regions, it is unclear whether the region is a cluster or non-cluster region. Because it is crucial for this study to know to what type of region an inventor is moving to, inventors that are recorded at least once in a region of which the code is subject to change are completely dropped from the sample. What remains is a dataset of approximately 1.8 million observations, consisting of 814.236 unique patent applications by 589.831 unique inventors across 916 NUTS-3 regions in 20 European countries. Table A1 in Appendix A provides an overview of the final list of countries and what regions within these countries are excluded from this study either due to missing data on control variables or due to amendments in the NUTS classification.

The European Cluster Observatory determines cluster strength for all NUTS-2 regions using a four-star method based on Michael E. Porter's cluster mapping theory (The European Cluster Observatory, 2022). Seeing that clusters are complex multi-faceted concepts, this methodology builds upon four performance measures that cover overall size, specialization, productivity, and dynamism (Ketels & Protsiv, 2014). A cluster's size is measured in the number of employees or enterprises and the level of specialization is assessed according to the location quotient index. Additionally, productivity is measured by the average wage per employee. Besides these static measures, the strength of a cluster is also reflected in the dynamism of its growth. Consequently, the four-star method also includes a measure that captures the annual growth in employees. For each of the four measures, a star is assigned to the regions that are in the top-20% in Europe. These are summed up in order to form a single-cluster performance indicator.

Knowledge spillovers are expected to be particularly present in the regions that are assigned four stars. These regions are characterized by a dense social network due to a relatively large cluster size and high level of specialization. Because of the large size, the frequency of interactions increases, which facilitates the emergence of a social network within which knowledge is disseminated (Oettl & Agrawal, 2008). Additionally, the number of collaborations increases in the level of specialization (Pittaway et al., 2004). This causes the dissemination of knowledge within networks of inventors. Not only are these regions characterized by a dense social network, but also by a relatively high local labor mobility due to the growing local labor pool, which is reflected in the dynamism measure. Because the presence of knowledge is positively related to productivity, the four-star regions are also characterized by high levels of knowledge (Crespi, Haskel, & Slaughter, 2008). Hence, given that high levels of knowledge are present and seeing that a dense social network and local labor mobility drive knowledge dissemination, it can be assumed that the four-star regions are characterized by high levels of knowledge spillovers. Consequently, for this research, only the regions that are assigned four stars are considered cluster regions.

According to the European Cluster Observatory, 47 regions are assigned four stars and are thus considered cluster regions for this research. Six of these cluster regions are located in countries that are excluded from this study. The 41 remaining cluster regions equal 21 percent of the total NUTS-2 regions analyzed for this research. Table A2 in Appendix A lists the regions identified as cluster regions. Figure 1 visualizes the distribution of these clusters across Europe. The map shows that the majority of the clusters are located in the ‘Blue Banana’ region, a densely populated core area in the European economy (Hospers, 2003). The appointment of 7 out of the 8 Swedish regions as cluster regions may appear as striking. This, however, is due to the Swedish forest industry cluster, which makes considerable contributions to their economy. For 5 out of the 7 Swedish cluster regions, the forestry industry is ranking highest in size, specialization, productivity, and growth. Of the approximately 1.2 million unique patent applications, 45 percent were filed by either one inventor or a group of inventors not residing in a cluster region at the time of filing. This means that more than half of the patent applications were filed by either one inventor residing in a cluster region or by a group of inventors from which at least one inventor was residing in a cluster region at the time of filing.

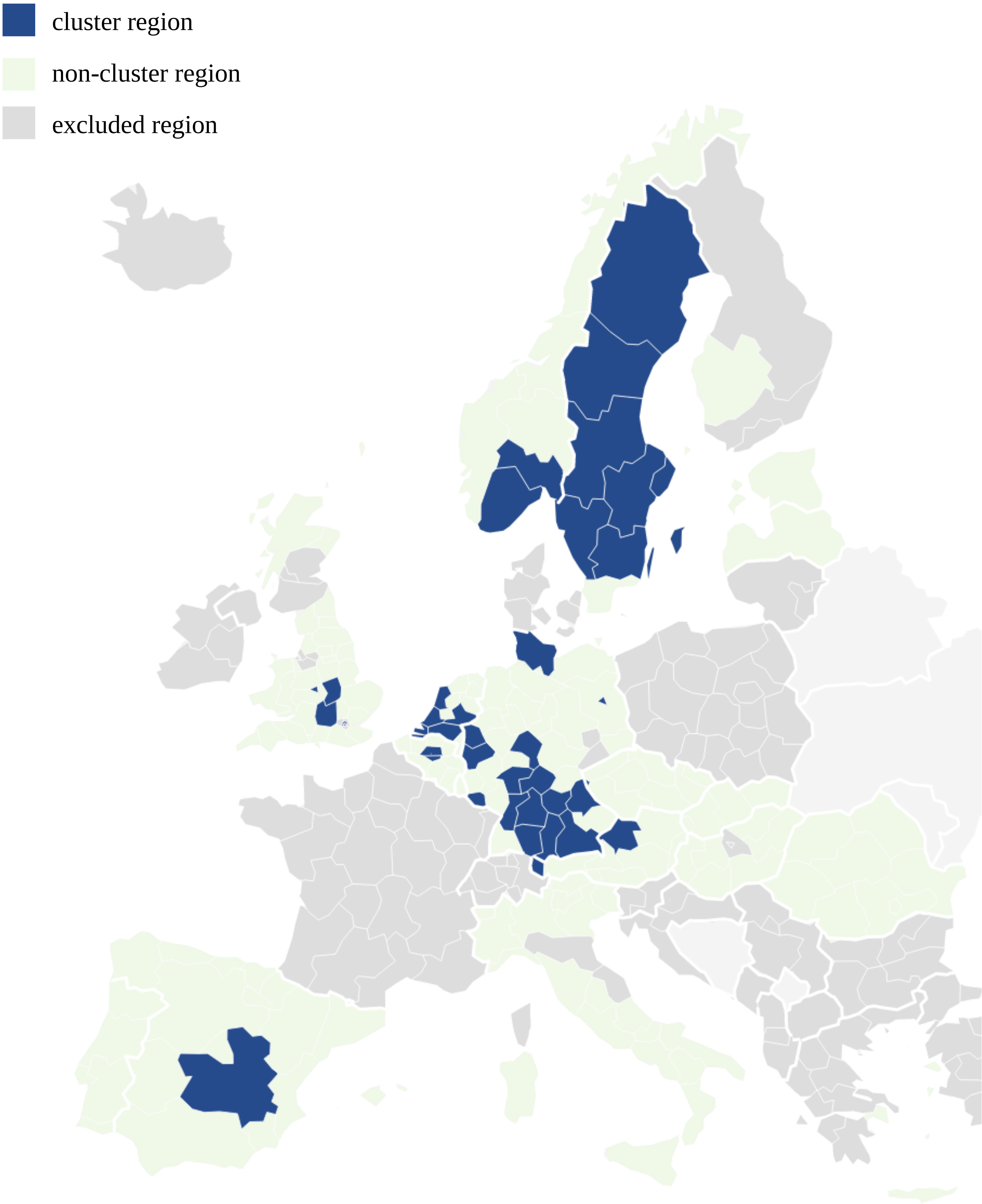

Figure 1. Cluster regions identified using the four-star method.

This four-star method was last conducted in 2013. For this study, it is assumed that the 41 regions identified as cluster regions remain cluster regions throughout the whole period analyzed. Seeing that 2013 is somewhat in the middle of the period analyzed for this research and given that the emergence of a cluster happens gradually over a longer period of time, this assumption is expected to have little impact on the results.

3.3 Inventor relocation

In order to be able to track inventors over time, unique inventor IDs are created based on inventor names. Because the name of the same inventor is sometimes recorded in different ways of spelling, a fuzzy match is performed on the inventor names – inventor names are stripped from punctuation marks, diacritical marks, and digits to optimize the matching of inventor names.

The identification of the movement of an inventor is fundamental to this study. Using the inventor IDs and the NUTS-3 region in which their residential address is located, it is possible to track inventors over time. A change in the NUTS-3 region for an inventor with the same inventor ID is registered as a move. Only 39 inventors applied for at least one patent every year during the period analyzed for this study – which is less than 1 percent of the total sample of inventors. Due to the years in which no patent was applied for, gaps emerge in the timeline of inventors. It can be assumed that inventors did not apply for a patent during these years, however, these gaps become problematic when determining the exact moment of movement. If an inventor applies for a patent in 2010 and 2013, it is unclear where the inventor resides in 2011 and 2012. As the sample of inventors applying for a patent each year during the period analyzed equals only 39 inventors, this sample is too small to prove a causal effect. As a result, I am forced to allow some level of uncertainty with regard to the exact moment of the move. When transforming that data on patent applications filed to the EPO into time series ranging from 2000 to 2019, if a change in the NUTS-3 code of the residential address of the inventor is identified and there is a gap of one or more years between the patent application with the new address and the patent application with the old address, it is assumed that the movement takes place in the year when the patent application is filed in which the new address is recorded. Hence, in case an inventor files for a patent application in 2010, while residing in NL335, and in 2013, while residing in DE300, it is assumed that the inventor moved in 2013. Accordingly, for 2011 and 2012, it is assumed that the inventor resides in the NUTS-3 region that was recorded on the patent application filed in 2010, namely NL335. When assuming that the inventor moved in the year following the year in which the last patent application with the inventor's old address was filed, a risk is taken as one cannot be sure whether the inventor has already relocated or not. This risk is eliminated by assuming that the movement takes place in the same year in which the new address is recorded. In line with this way of thinking, it is assumed for inventors who move within a certain year, i.e. for which a change in the residential address is recorded in the same year, that they move in the year following the year in which the two different addresses are recorded. One caveat of this assumption is that a move may be registered too late. In such a case, an inventor may already enjoy knowledge spillovers before the move is recorded. This may bias the results.

The distribution of the total amount of years in which an inventor applied for a patent is skewed to the left – 62.5 percent of the inventors applied for a patent in only one year, 94.2 percent applied for a patent in five years or less and 98.5 percent applied for a patent in ten years or less. This large share of one-patent inventors most likely comprises occasional inventors, working in small firms or as entrepreneurs (Schettino, Sterlacchini, & Venturini, 2013). To minimize the risk of measurement errors, inventors who applied for a patent in seven years or less are dropped from the sample. A sample of 17,044 unique inventors remains.

For 54 percent of this sample, no move was recorded during the period analyzed. As this study examines the effect of a movement to a cluster, these inventors are dropped from the sample. To isolate the true effect of a movement to a cluster, the inventors who move more than once are also dropped from the sample. A sample of 2,768 inventors remains. The effect of a move is assessed by comparing the knowledge production of an inventor during the four years before the move to the year of the move and the four consecutive years. Accordingly, to be able to do so, at least four years before and after the move must be available. In other words, the move must have taken place after 2003 and in 2015 at the latest. As a result, an additional 842 inventors are dropped completely. What remains is a sample of 1,926 unique inventors that are observed between 2000 and 2019, who patented in at least eight years during this period, and who moved once between 2004 and 2015. This sample comprises the inventors who filed a relatively large number of patent applications. Because of this, the sample represents the mobile top inventors in Europe. Figure 2 visualizes the distribution of these inventors across Europe. The figure shows an absence of inventors in some regions that were initially included. This is a consequence of the strict requirements set with regard to the inventors that are analyzed for this research.

Next, to be able to test for a change in the knowledge production of the inventor following a move, five year dummies are created that indicate the year of the move and the four consecutive years. Using the data on the cluster regions, a variable is created that specifies whether an inventor moves from a non-cluster to a non-cluster region, from a non-cluster to a cluster region, from a cluster to a cluster region, or from a cluster to a non-cluster region. Subsequently, the variables of interest are formed by creating an interaction between these

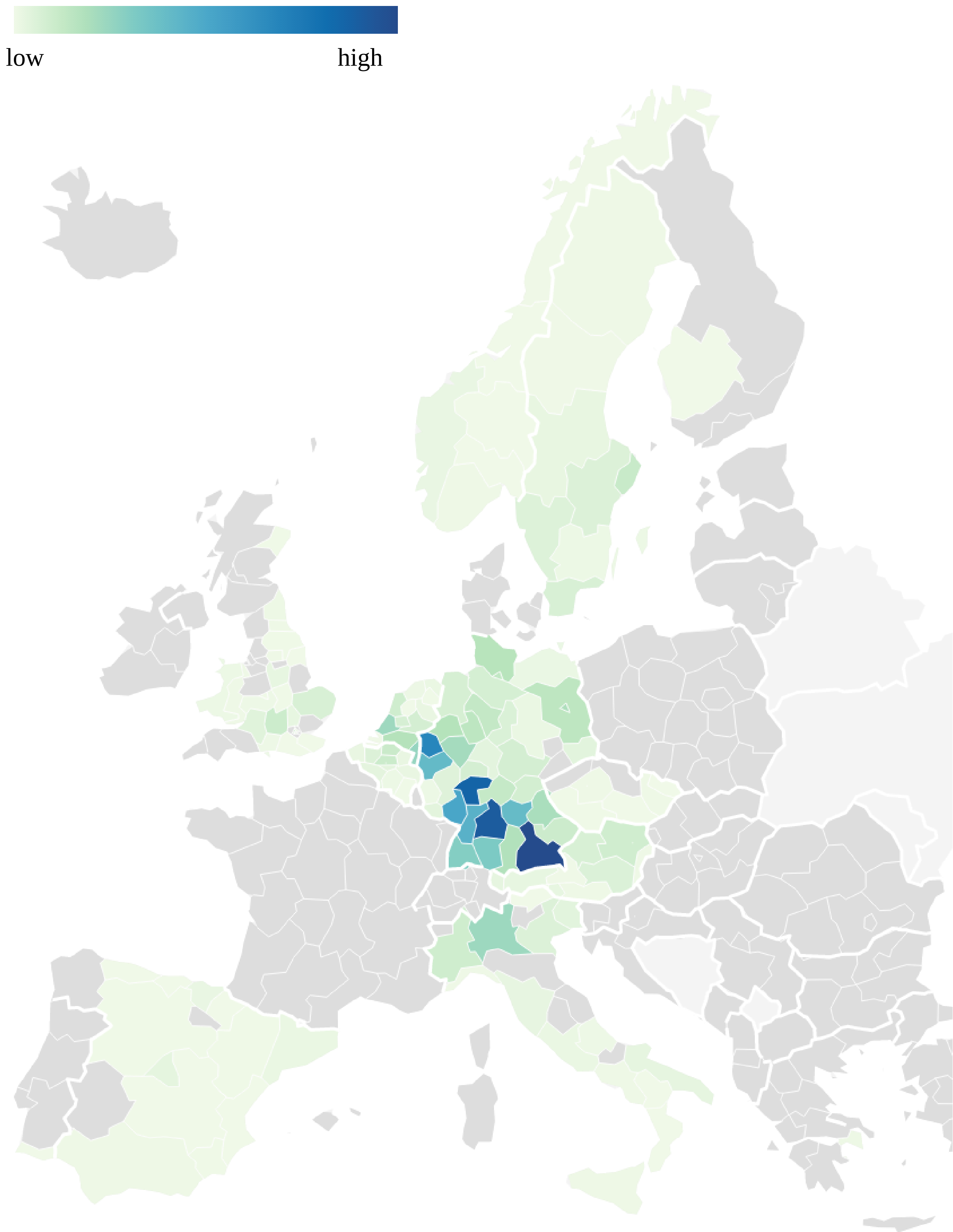

Figure 2. Inventor density across Europe.

variables and the set of year dummies. Five variables are formed that indicate whether an observation is recorded in the year of the move or the first, second, third, or fourth year following a move and whether the inventor moved from a cluster or non-cluster region to a cluster or non-cluster region.

3.4 Control variables

To control for regional influences that may influence the knowledge production of the inventor, a set of control variables is added to the dataset. Not all data is available on the NUTS-3 level, hence some control variables are measured either on the NUTS-2 or NUTS-1 level. Data on all control variables are retrieved from EUROSTAT. Some regions suffer from gaps in data on the control variables. These gaps are mainly due to amendments in the NUTS codes. As explained in section 3.2, these regions are excluded from this study. If there is a gap of one year, this gap is manually replaced by the average of the values of the previous and the following year.

Table 1

Descriptive statistics

Variable			Mean	Std. Dev.	Min	Max
Patents		NC	5.38	9.52	1	174
		C	9.81	14.36	1	138
Employed persons		NC	909,248	700,954	103,000	4,372,300
		C	1,049,942	619,383	137,900	2,606,800
R&D expenditures		NC	2.87	2.99	1.90	2.53
(x mil. euros)		C	5.18	4.84	9.00	2.53
Educational attainment (%	*Level 0-2*	NC	25.37	13.34	2.70	64.80
of population)		C	19.47	5.95	9.40	44.20
	Level 3-4	NC	48.51	13.68	15.10	79.40
		C	48.95	10.82	20.30	65.40
	Level 5-8	NC	26.12	8.62	8.70	51.20
		C	31.58	10.03	13.30	68.30
Population density per km2		NC	546.92	768.80	6.00	7,994.60
		C	912.44	1,352.18	2.50	10,844.60

Note: NC = non-cluster region and C = cluster region.

To control for differences in labor market size and growth, data on the number of employed persons per NUTS-2 region are included. In addition, it is controlled for differences in innovation capacity and propensity to innovate by including data on research and development (R&D) expenditures per NUTS-1 region. As education is an important input for the production of knowledge, the percentage of the population that obtained educational attainment of level 0-2 (less than primary, primary, and lower secondary education), level 3-4 (upper secondary and post-secondary non-tertiary education) or level 5-8 (tertiary education) per NUTS-2 region is included in the dataset. Seeing that knowledge is expected to flow faster and easier in densely populated areas, it is also controlled for population density. Lastly, if an inventor moves to a new country, she may need to get acquainted with the new culture, which may slow down the process of embedding in a new social network. As a result, she may not be able to reap full benefits from the knowledge spillovers following a move. When moving within the same country, the common culture helps smooth the flow of knowledge and aid its interpretation. In order to control for this, a variable is added to the dataset indicating for the year of the movement and the four consecutive years whether a move is within the same country or between different countries. Table 1 shows substantial differences between non-cluster and cluster regions. Cluster regions are characterized by a higher number of employed persons, higher R&D expenditures, a higher-skilled population, and a higher population density.

4. Methodology

To determine whether inventors benefit from knowledge spillovers that are to a significantly higher level present in clusters, I analyze whether the knowledge production of an inventor changes as a result of a relocation in the year of the move and the four consecutive years following the move.

As the dependent variable is measured in nonnegative integers, a count data model would be most suited for this research. Because patent data is often characterized by overdispersion, as a majority of the observations record zero patents, a negative binomial regression would be the most suited estimation technique for analysis. However, one caveat of count data models is that these models do not handle fixed effects very well. Seeing that the propensity to patent is likely to differ among inventors, this deficiency of these count data models is likely to result in distorted results, due to the inability to correctly incorporate inventor fixed effects in the model. An alternative would be including inventor characteristics that explain this variation within inventors, such as intrinsic traits and acquired experiences (e.g. education). These data, however, are not included in the OECD REGPAT database. Following Bhaskarabhatla, Cabral, Hegde, and Peeters (2020), who found that "inventor-specific fixed effects explain 18%-37% of the observed variance in inventors' patenting performance" (Bhaskarabhatla et al., 2020), not allowing for the effect of time-invariant inventor capabilities on the knowledge production of inventors through inventor fixed effects would cause endogeneity. Accordingly, instead of performing a negative binomial regression analysis, this study performs an Ordinary Least Squares (OLS) regression to estimate the effect of relocating on an inventor's knowledge production. To minimize the overdispersion of the dependent variable, which is measured in patent applications per inventor *i* in year *t*, the variable is transformed to $log(patent + 1)$. The following regression model is estimated which models the linear relationship between the knowledge output of an inventor and a set of explanatory variables:

$$log(Y_{it} + 1) = \beta_0 + \beta_x X_{it} + \beta_z Z_{rt} + \beta_v V_{it} + \alpha_i + \phi_r + \gamma_t + \varepsilon_{irt}$$

where the dependent variable Y refers to the total number of patent applications per inventor i in year t. The constant term is denoted by β_0. The vector X_{it} indicates for the year of the move and the four consecutive years whether inventor i relocated from a (non-)cluster region to a (non-)cluster region. The vector Z_{rt} represents the characteristics per region r in year t that are controlled for. These characteristics include employed persons, R&D expenditures, education level, and population density and are measured as explained in Table 2. Employed persons, R&D expenditures, and population density enter the estimation in logarithmic scale to assure a normal distribution of the variables. Lastly, V_{it} indicates whether the move of inventor i was between regions within the same country or between regions across different countries for the year in which the move took place and the four consecutive years. The vectors α_i, ϕ_r and γ_t represent the inventor, region, and year fixed effects. Lastly, the random error term is denoted by ε_{irt}.

Table 2

Variable descriptions

Variable	Description
Knowledge production output measure	
Patent	Number of patents filed by inventor *i* in year *t*.
Movement indicators	
Moment of move	Categorical variable indicating whether inventor *i* is relocating from a NC to a NC region (1), a NC to a C region (2), a C to a C region (3) or a C to a NC region (4) in the year of movement. This variable equals 0 during the four years prior to the move.
One year after move	Categorical variable indicating whether inventor *i* relocated from a NC to a NC region (1), a NC to a C region (2), a C to a C region (3) or a C to a NC region (4) one year following the move. This variable equals 0 during the four years prior to the move.
Two years after move	Categorical variable indicating whether inventor *i* relocated from a NC to a NC region (1), a NC to a C region (2), a C to a C region (3) or a C to a NC region (4) two years following the move. This variable equals 0 during the four years prior to the move.
Three years after move	Categorical variable indicating whether inventor *i* relocated from a NC to a NC region (1), a NC to a C region (2), a C to a C region (3) or a C to a NC region (4) three years following the move. This variable equals 0 during the four years prior to the move.
Four years after move	Categorical variable indicating whether inventor *i* relocated from a NC to a NC region (1), a NC to a C region (2), a C to a C region (3) or a C to a NC region (4) three years following the move. This variable equals 0 during the four years prior to the move.
Regional characteristics	
Employed persons (log)	Number of individuals aged 15 to 64 who perform work, even if just for one hour per week, per region *r* in year *t*.
R&D expenditures (log)	Gross domestic expenditure on R&D for the business enterprise sector per region *r* in year *t*.
% of population with level 0-2 education	Percentage of the population that obtained education attainment between level 0 and 2 per region *r* in year *t*.
% of population with level 3-4 education	Percentage of the population that obtained education attainment between level 3 and 4 per region *r* in year *t*.
% of population with level 5-8 education	Percentage of the population that obtained education attainment between level 5 and 8 per region *r* in year *t*.
Population density (log)	Persons per square kilometer per region *r* in year *t*.
Common culture indicator	

Moment of move within country	Categorical variable indicating whether inventor *i* is relocating within the same country (1) or between different countries (2) in the year of movement. This variable equals 0 during the four years prior to the move.
One year after move within country	Categorical variable indicating whether inventor *i* is relocating within the same country (1) or between different countries (2) in the year following the movement. This variable equals 0 during the four years prior to the move.
Two years after move within country	Categorical variable indicating whether inventor *i* is relocating within the same country (1) or between different countries (2) two years following the move. This variable equals 0 during the four years prior to the move.
Three years after move within country	Categorical variable indicating whether inventor *i* is relocating within the same country (1) or between different countries (2) three years following the move. This variable equals 0 during the four years prior to the move.
Four years after move within country	Categorical variable indicating whether inventor *i* is relocating within the same country (1) or between different countries (2) four years following the move. This variable equals 0 during the four years prior to the move.

Note: NC = non-cluster and C = cluster.

5. Results

Table 3 presents the results of the OLS regression on an inventor's knowledge production. The dependent variable is measured in the log of the number of patents applied for by an inventor in year *t* plus one. In Model 1, year dummies of the moment of the movement and the four consecutive years are regressed on the knowledge production of the inventor. In this model, no distinction is yet made between cluster and non-cluster regions. Hence, this model shows the general effect of moving on the number of patents applied for by an inventor per year. Furthermore, the inventor, region, and year fixed effects are excluded. The model displays a positive effect on the number of patents applied for by an inventor per year in the year in which the inventor relocates to a new region, which is significant at the 1 percent significance level. This effect remains positive over the subsequent four years, but decreases in magnitude while remaining significant at the 1 percent significance level. This indicates that inventors who move apply for relatively more patents in the year of the move and the four consecutive years compared to the average patents applied for over the four years prior to the move. This effect is significant at a 1 percent significance level in all five the years. In Model 2, the inventor, region, and year fixed effects are included. This causes all coefficients to increase in size while remaining significant at the 1 percent significance level. The coefficients show a positive effect of moving on the knowledge production of inventors. As in Model 1, the effect decreases in the first year after the move compared to the year of the move. However, in contrast to Model 1, where the effect decreases in the years after the move, the effect in Model 2 remains relatively stable during the four years following the move. This suggests that the decrease in size over time in inventors' knowledge production is partly explained by the inventor, region, and year fixed effects. Model 2 indicates that compared to their average patent applications over the four years before their move, moving inventors experience the biggest increase in patent applications in the year of the move. While this effect decreases from the year of the move to the first year following the move, it stabilizes during the four years following the move. During this whole period, the effect is significant at the 1 percent significance level.

Model 3 distinguishes between cluster and non-cluster regions. Hence, instead of estimating a general movement effect, Model 3 shows whether there is a difference in the effect of a move between different types of regions. This model also includes the inventor, region, and year fixed effects. All four move categories at the time of relocation show positive effects that are significant at the 1 percent significance level, indicating that moving inventors file for relatively more patent applications in the year of the move compared to their average patent applications over the four years prior to the move. In the year of moving, the coefficient from non-cluster to cluster has the greatest magnitude, followed by non-cluster to non-cluster, whereas cluster to non-cluster has the lowest magnitude. This indicates that an inventor moving from a non-cluster region to a cluster region experiences the biggest increase in patent applications in the year of the move relative to the other move categories compared to the average number of patent applications over the four years prior to the move. This effect is significant at the 1 percent significance level. Non-cluster to cluster remains the category with the highest magnitude in the four years following the move, while the cluster to non-cluster remains the category with the lowest magnitude. While the effect for moving from a non-cluster to a cluster region remains significant at the 1 percent significance level during these four years, the effect for moving from a cluster to a non-cluster region becomes insignificant. In the fourth year following the move, the cluster to non-cluster category is omitted due to collinearity.

The size of the non-cluster to non-cluster coefficient decreases until the second year following the relocation, while increasing in size during the third and fourth years following the move. The size of both the non-cluster to cluster and cluster to cluster categories fluctuates during the four years following the move; both decrease in size from the year of the move to the first year following the move and from the second year to the third year after the relocation, while increasing in size from the first to the second year following the move and from the third to the fourth year after moving. Overall, Model 3 shows the greatest effect for all move categories during the year of the move. This effect decreases in size from the year of the move to the first year after the move, but remains relatively stable during the four years after the move. While greater in magnitude, this effect is similar as is shown in Model 2. The non-cluster to non-cluster, non-cluster to cluster, and cluster to cluster categories remain significant at the

Table 3

Regression Results for Inventor Knowledge Production

	(1)	(2)	(3)	(4)
Moment of move	0.165***	0.178***		
	(0.004)	(0.007)		
Non-cluster to non-cluster			0.540***	0.544***
			(0.039)	(0.039)
Non-cluster to cluster			0.809***	0.812***
			(0.085)	(0.085)
Cluster to cluster			0.529***	0.528***
			(0.025)	(0.026)
Cluster to non-cluster			0.309***	0.305***
			(0.049)	(0.049)
One year after move	0.064***	0.082***		
	(0.006)	(0.009)		
Non-cluster to non-cluster			0.294***	0.298***
			(0.047)	(0.047)
Non-cluster to cluster			0.574***	0.576***
			(0.095)	(0.095)
Cluster to cluster			0.265***	0.264***
			(0.035)	(0.035)
Cluster to non-cluster			-0.022	-0.025
			(0.050)	(0.050)
Two years after move	0.062***	0.089***		
	(0.006)	(0.011)		
Non-cluster to non-cluster			0.214***	0.217***
			(0.050)	(0.050)
Non-cluster to cluster			0.588***	0.591***
			(0.101)	(0.101)
Cluster to cluster			0.293***	0.293***
			(0.039)	(0.039)
Cluster to non-cluster			0.044	0.042
			(0.046)	(0.046)
Three years after move	0.042***	0.081***		
	(0.006)	(0.012)		
Non-cluster to non-cluster			0.248***	0.250***
			(0.056)	(0.056)
Non-cluster to cluster			0.563***	0.566***
			(0.104)	(0.104)
Cluster to cluster			0.273***	0.273***
			(0.045)	(0.045)
Cluster to non-cluster			0.036	0.034
			(0.042)	(0.042)
Four years after move	0.027***	0.085***		
	(0.007)	(0.014)		
Non-cluster to non-cluster			0.295***	0.297***
			(0.061)	(0.062)
Non-cluster to cluster			0.637***	0.640***
			(0.111)	(0.111)
Cluster to cluster			0.302***	0.302***
			(0.053)	(0.053)
Cluster to non-cluster				
Constant	0.561***	1.772***	1.966***	6.853
	(0.010)	(0.189)	(0.178)	(4.448)
Inventor FE	No	Yes	Yes	Yes
Region FE	No	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes
Control variables	No	No	No	Yes
N	17,334	17,334	17,334	17,334
Inventors	1,926	1,926	1,926	1,926

Note. Standard errors are reported in parentheses. All models include standard errors clustered by inventors.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

1 percent significance level during these four years, while the cluster to non-cluster category becomes insignificant. This indicates that inventors who move from a non-cluster to a non-cluster region, a non-cluster to a cluster region, and a cluster to a cluster region experience a significant increase in the number of patent applications during the year of the move and the four consecutive years compared to their average patent applications over the four years before the move. This effect is greatest for the non-cluster to cluster category in all five the years, indicating that inventors moving from a non-cluster to a cluster region experience the biggest increase in knowledge production following their move relative to the other move categories compared to their average knowledge production over the four years prior to their relocation.

In Model 4, the control variables have been added. For the sake of readability, Table 2 does not present the results for the control variables. Table C1 in Appendix C presents the full regression output. Adding the control variables results in a limited change in the coefficients of the move categories and therefore, the findings and the interpretation are the same as for Model 3.

Due to a high correlation between the year dummies of the moment of the move and the four consecutive years and the variables indicating per year whether an inventor is moving between regions within the same country or between regions in different countries, these latter variables are not included in the four models just discussed. To analyze whether inventors moving within the same country experience a different effect compared to inventors moving between different countries, a separate model is estimated which excludes the move categories but includes the variables indicating whether a move was within the same country or between different countries. The results of this regression estimation are presented in Table 4. Both Model 5 and 6 include the inventor, region, and year fixed effects and the control variables.

The move categories in Model 5 both show a positive effect on the patents applied for by an inventor in the year of the move and the four following years. This effect is significant at the 1 percent significance level. In Model 6, the variable indicating whether a move is within the same country or between different countries is broken down by year, from the year of the move until the fourth year after the move. The move between different countries category remains the category of the greatest size in all five the years. Both categories show a significant effect at the 1 percent significance level over the five years. However, for both Model 5 and 6, when taking the standard deviation into account, the difference between both variables tends towards zero, implying an insignificant difference between both types of moves. This indicates that moving inventors in general experience an increase in their patent applications in the year

Table 4

Regression Results for Inventor Knowledge Production

	(5)	(6)
Move within the same country	0.473***	
	(0.021)	
Move between different countries	0.601***	
	(0.077)	
Moment of move		
Move within the same country		0.537***
		(0.022)
Move between different countries		0.664***
		(0.078)
One year after move		
Move within the same country		0.265***
		(0.029)
Move between different countries		0.480***
		(0.091)
Two years after move		
Move within the same country		0.280***
		(0.034)
Move between different countries		0.390***
		(0.094)
Three years after move		
Move within the same country		0.274***
		(0.040)
Move between different countries		0.370***
		(0.097)
Four years after move		
Move within the same country		0.303***
		(0.049)
Move between different countries		0.394***
		(0.101)
Employed persons (ln)	-0.388	-0.385
	(0.358)	(0.357)
R&D expenditures (ln)	-0.032	-0.032
	(0.057)	(0.057)
% of population with level 3-4 education	-0.004	-0.003
	(0.006)	(0.006)
% of population with level 5-8 education	0.007	0.008
	(0.006)	(0.006)
Population density (ln)	0.299	0.290
	(0.311)	(0.306)
Constant	6.080	5.881
	(4.317)	(4.317)
Inventor FE	Yes	Yes
Region FE	Yes	Yes
Year FE	Yes	Yes
N	17,334	17,334
Inventors	1,926	1,926

Note. Standard errors are reported in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Of moving and the four consecutive years, compared to their average patent applications over the four years prior to their move. However, categorizing the move variable into a relocation within the same country and relocation between different countries shows that both inventors moving within the same country and between different countries experience a similar increase in their patent applications during the year of the move and the four consecutive years compared to their average patent applications over the four years prior to their move.

6. Discussion en conclusion

Seeing that innovation is one of the main contributors to firm growth, firms often channel resources to the development of new knowledge in order to initiate innovation. Through investing in R&D or through gaining access to external knowledge sources, firms can grow their knowledge production. However, firms can also gain access to new knowledge through knowledge externalities. These knowledge flows are externalities as they affect firms outside the market mechanism, meaning that firms cannot control gaining access to these knowledge flows. Since these knowledge externalities tend to be localized due to the local emergence of social networks and local labor mobility, only the firms in close distance to an innovative firm benefit from these knowledge flows. Accordingly, cluster regions – geographic concentrations of interconnected businesses that are characterized by a dense social network and high labor mobility – are expected to experience relatively high levels of knowledge spillovers. Consequently, it is expected that firms operating in a cluster benefit from improved innovative activity by gaining access to new knowledge through inventors who are affected by the knowledge externalities present in the cluster. To test whether clusters are actually characterized by higher levels of knowledge spillovers compared to other regions, it was analyzed in this study whether the knowledge production of a sample of approximately 1,926 inventors residing in Europe, who patented in at least eight years between 2000 and 2019, and who moved once between 2004 and 2015, increased after moving to a cluster region. The results show a positive and significant general effect of moving on the knowledge production of inventors in the year of the move and the four years following the move compared to their average patent applications over the four years prior to the move. This effect is greatest in the year of the move, decreases from the year of the move to the first year after the move and then remains stable during the four years following the move.

Splitting the general effect up into different move categories shows a considerable increase in the magnitude of the effect per move category compared to the general effect of moving. In the four years following the move, this substantial difference with the general moving effect is likely explained by the insignificant coefficient for the cluster to non-cluster category, which tends to zero. By distinguishing between the types of moves, it becomes clear that the cluster to non-cluster category is most likely the cause of this large difference and that the values of the other three move categories are in fact higher than is shown by the general effect. All the move categories show a positive and significant effect during all five years, except for the cluster to non-cluster category during the four years after the move. The non-cluster to cluster move is the category with the greatest magnitude during all five years. This shows that inventors moving from a non-cluster to a cluster experience the greatest increase in knowledge production relative to the other move categories compared to their average knowledge production over the four years prior to their move. This is in line with the expectations. Because knowledge spillovers are especially present in clusters, inventors moving to cluster regions are expected to experience the biggest increase in knowledge production. This applies especially to inventors who move from a non-cluster to a cluster region. Compared to inventors moving from a non-cluster region, inventors who move from a cluster region are expected to carry relatively more knowledge. Firstly, because of the high industrial specialization of clusters, which causes inventors employed in cluster regions to be an expert in their field. Additionally, due to the highly competitive and innovative environment resulting from the constant need for adaptation to the changing market conditions, inventors that worked for firms operating in a cluster are likely to be aware of the newest technologies in their industry. This is partly explained by the relatively high levels of knowledge spillovers present in clusters. Hence, because the inventors who move from a cluster region come from an environment in which a lot of new information is continuously generated and circulated, inventors who move from a non-cluster region are expected to experience the greatest increase in access to new knowledge. Consequently, as the inventors moving from a non-cluster region gain access to relatively much new knowledge, this is likely to result in a bigger increase in the production of knowledge, measured in patent applications, compared to inventors moving from a cluster region. This is also reflected in the results – the non-cluster to cluster category is the category of the greatest size during the year of the move and the four consecutive years. This shows that compared to their average patent applications over the four years prior to their move, inventors moving from a non-cluster to a cluster region experience the greatest increase in their patent applications in the year of the relocation and the four years following the move relative to the other move categories. This increase in patent applications is greatest during the year of the move, but decreases in size from the year of the move to the first year following the move. During the four years following the move, the effect remains relatively stable. The relatively bigger increase in patent applications for inventors moving from a non-cluster region to a cluster region suggests that clusters are characterized by a distinctive environment that promotes the production and dissemination of new knowledge. This paper argues that it is most likely that knowledge spillovers underlie this distinctive environment. By moving to such a region, inventors gain access to the continuously newly generated knowledge flows through these knowledge externalities. This ultimately results in a significant increase in their patent applications during the period following the move.

Finally, the results also show a slightly bigger increase in the knowledge production of inventors moving between different countries relative to inventors moving within the same country. However, taking the standard errors into account shows that the difference between both move categories tends to zero, which implies an insignificant difference. This finding is opposite to what was expected. When moving to a new country, an inventor is expected to need some time to get acquainted with the new culture, which slows down the process of embedding in a new social network. Consequently, the inventor is expected to not be able to reap full benefits from knowledge spillovers following a move. On the other hand, moving within the same country is expected to smooth the flow of knowledge and aid its interpretation due to the common culture. As the results show no significant difference, this may be interesting for future research.

7. Limitations

There are several limitations in this study and these should be taken into account when interpreting the results. The main limitation relates to the internal validity. To make causal claims about the effect of moving to a cluster, the treatment – moving to a cluster – must be randomly assigned. As this study uses a sample existing only of moving inventors, treatment is in all likelihood not randomly assigned. Because of this, the found effect may be the result of the treatment group being different rather than the result of treatment. As a result, the found effect may not be causal. The results should therefore be interpreted with caution.

Secondly, while the difference in size of the general effect and the coefficients of the move categories in Table 3 for the four years following the move is likely explained by the insignificant value of the cluster to non-cluster category which tends to zero, this is not the case for the year of the move. In this year, there is still a significant difference between the general effect and the effects of the move categories, however the coefficient for the cluster to non-cluster category significantly different from zero, at the 1 percent significance level, and about double in size compared to the general effect. Why the general effect differs in size from the move categories during the year of the move is likely due to the move categories not being perfectly independent from each other. As independence is needed in order to assume a causal relation, the results should be interpreted with caution.

A third threat to the internal validity of this study is the omission of the cluster to non-cluster category in the fourth year following the move due to collinearity. As non-collinearity is assumed in order to state a causal effect, the results should be interpreted with caution.

In addition, due to gaps in the data resulting from years in which inventors did not apply for a patent, assumptions must be made about where the inventor is residing. These assumptions can result in the detection of a move at a later time period *y* than the actual move took place. This may bias the results, as inventors may benefit from knowledge spillovers prior to when the move is recorded. In addition, the use of patent applications as a proxy for the knowledge production of inventors may result in an underestimation of the knowledge production by inventors pre and post-move, as not all inventions are patented.

Another limitation regards the representativeness of this study. In this research, only the regions that ranked in the top-20% of Europe in terms of size, specialization, productivity, and dynamism were appointed as cluster regions, as knowledge spillovers were expected to be particularly present in these regions. These clusters comprise Europe's top clusters. While this study suggests the presence of knowledge spillovers in these clusters, it is questionable whether these knowledge spillovers are present to the same extent in clusters with a lower ranking in terms of the four performance measures. Additionally, in order to minimize measurement errors due to gaps in the data resulting from years in which inventors did not apply for patents, it was required that inventors patented at least in eight years during the time period analyzed. This resulted in dropping the majority of the observations in the original dataset. Consequently, only the top moving inventors residing in Europe remained. This should be taken into consideration when concluding about the findings. It is not likely that inventors applying for relatively less patens or employees who never applied for a patent experience the same increase in patent applications following a move to a cluster as was found in this study.

In addition, no distinction was made between sectors in this study. This means that the dataset includes clusters specialized in business services, but also clusters specialized in forestry. However, sectors differ in innovativeness, which means that if a distinction is made between sectors, the effect of moving to a cluster can be different than what was found in this study.

Finally, the OECD REGPAT dataset provides information regarding the residential address of inventors. It is assumed that inventors are employed in the same areas as where they are residing. In reality, this may not always be the case. Consequently, inventors that are recorded as working in a cluster region may in fact be working in a non-cluster region and inventors working in cluster regions may be recorded as working in a non-cluster region. This may distort the results.

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Appendix A

Table A1

List of final countries and excluded regions

Country	Country code	Excluded regions		
		NUTS-3	*NUTS-2*	*NUTS-1*
Austria	AT	ATZZZ		
Belgium	BE	BEZZZ		
Czech Republic	CZ	CZZZZ		
Estonia	EE	EEZZZ		
Finland	FI	FIZZZ	FI1B; FI1C; FI1D	
Germany	DE	DE80J; DE80N; DE915; DE919; DE91C; DEA2D; DEB1C; DEB1D; DED2C; DED2D; DED2E; DED2F; DEE01; DEE05; DEE06; DEE07; DEE08; DEE09; DEE0A; DEE0B; DEE0C; DEE0E; DEZZZ	DED4; DED5	
Greece	GR	ELZZZ; GRZZZ		EL5; EL6
Hungary	HU	HUZZZ	HU10; HU11; HU12	
Italy	IT	ITZZZ	ITH5; ITI3	
Latvia	LV	LVZZZ		
Luxembourg	LU			
Malta	MT	MTZZZ		
Netherlands	NL	AN000; NLZZZ		
Norway	NO	NO060; NOZZZ; SJ000		
Portugal	PT	PT119; PT11A; PT11B; PT11C; PT11D; PT11E; PT16D; PT16E; PT16F; PT16G; PT16H; PT16I; PT186; PT187; PTZZZ		
Romania	RO	ROZZZ		
Slovakia	SK	SKZZZ		
Spain	ES	ESZZZ		
Sweden	SE	SEZZZ		
United Kingdom	GB	GBZZZ; GY000; IM000; JE000; UKD31; UKD32; UKD43; UKH13; UKH33; UKJ23; UKJ24; UKJ33; UKJ42; UKN01; UKN02; UKN03; UKN04; UKN05; UKN07; UKN08; UKN09; UKN10; UKN11; UKN12; UKN13; UKN14; UKN15; UKN16	UKD6; UKD7; UKM2; UKM3; UKM7; UKM8; UKM9	

Table A2

List of cluster regions

NUTS-2 code	Region
AT13	Vienna
AT31	Upper Austria
AT34	Vorarlberg
BE10	Brussels Capital Region
BE24	Flemish Brabant
BE31	Walloon Brabant
DE11	Stuttgart
DE12	Karlsruhe
DE14	Tübingen
DE21	Oberbayern
DE23	Oberpfalz
DE25	Mittelfranken
DE26	Unterfranken
DE27	Schwaben
DE30	Berlin
DE71	Darmstadt
DE73	Kassel
DEA1	Düsseldorf
DEA2	Köln
DEC0	Saarland
DEF0	Schleswig-Holstein
ES42	Castile-La Mancha
NL22	Gelderland
NL32	North Holland
NL33	South Holland
NL34	Zeeland
NL41	North Brabant
NO01	Oslo and Akershus
NO04	Agder and Rogaland
SE11	Stockholm
SE12	East Middle Sweden
SE21	Småland with Islands
SE23	West Sweden
SE31	North Middle Sweden
SE32	Central Norrland
SE33	Upper Norrland
UKF2	Leicestershire, Rutland, and Northamptonshire
UKG3	West Midlands
UKI1	Inner London – West
UKI2	Inner London – East
UKJ1	Berkshire, Buckinghamshire, and Oxfordshire

Appendix B

Table B1

Correlation matrix.

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	patent	1.000																			
2	year	0.007	1.000																		
3	inv_id	0.005	0.020	1.000																	
4	nuts3	-0.007	0.079	-0.029	1.000																
5	moment_of_move	0.106	-0.003	0.007	-0.012	1.000															
6	one_yr_after_move	0.040	0.074	0.007	-0.012	-0.107	1.000														
7	two_yr_after_move	0.035	0.152	0.007	-0.012	-0.107	-0.107	1.000													
8	three_yr_after_move	0.007	0.229	0.007	-0.012	-0.107	-0.107	-0.107	1.000												
9	four_yr_after_move	-0.001	0.307	0.007	-0.012	-0.107	-0.107	-0.107	-0.107	1.000											
10	log_employed_persons	0.025	-0.018	0.041	-0.001	-0.008	-0.003	0.003	0.008	0.013	1.000										
11	log_rd_expenditures	0.009	0.120	0.002	-0.430	-0.001	0.015	0.032	0.047	0.063	0.334	1.000									
12	perc_educ_0_2	-0.013	-0.145	-0.059	0.414	-0.053	-0.071	-0.089	-0.107	-0.120	0.018	-0.239	1.000								
13	perc_educ_3_4	0.010	-0.183	0.043	-0.424	0.031	0.029	0.025	0.017	0.006	-0.013	0.178	-0.632	1.000							
14	perc_educ_5_8	0.001	0.382	0.012	0.069	0.020	0.042	0.066	0.096	0.124	-0.004	0.042	-0.316	-0.535	1.000						
15	log_population_density	0.016	-0.017	0.014	-0.036	-0.020	-0.019	-0.018	-0.017	-0.016	0.392	0.076	0.026	-0.172	0.183	1.000					
16	moment_of_move_within_country	0.108	0.001	0.002	0.001	0.899	-0.113	-0.113	-0.113	-0.113	-0.017	-0.020	-0.008	0.005	0.003	-0.023	1.000				
17	one_yr_after_move_within_country	0.043	0.083	0.002	0.001	-0.113	0.899	-0.113	-0.113	-0.113	-0.011	-0.002	-0.028	0.003	0.027	-0.022	-0.119	1.000			
18	two_yr_after_move_within_country	0.028	0.165	0.002	0.001	-0.113	-0.113	0.899	-0.113	-0.113	-0.005	0.015	-0.047	-0.001	0.053	-0.021	-0.119	-0.119	1.000		
19	three_yr_after_move_within_country	0.002	0.247	0.002	0.001	-0.113	-0.113	-0.113	0.899	-0.113	0.000	0.032	-0.069	-0.009	0.086	-0.020	-0.119	-0.119	-0.119	1.000	
20	four_yr_after_move_within_country	-0.003	0.329	0.002	0.001	-0.113	-0.113	-0.113	-0.113	0.899	0.005	0.048	-0.084	-0.021	0.117	-0.019	-0.119	-0.119	-0.119	-0.119	1.000

Appendix C

Table C1

Regression Results for Inventor Knowledge Production

	(1)	(2)	(3)	(4)
Moment of move	0.165*** (0.004)	0.178*** (0.007)		
Non-cluster to non-cluster			0.540*** (0.039)	0.544*** (0.039)
Non-cluster to cluster			0.809*** (0.085)	0.812*** (0.085)
Cluster to cluster			0.529*** (0.025)	0.528*** (0.026)
Cluster to non-cluster			0.309*** (0.049)	0.305*** (0.049)
One year after move	0.064*** (0.006)	0.082*** (0.009)		
Non-cluster to non-cluster			0.294*** (0.047)	0.298*** (0.047)
Non-cluster to cluster			0.574*** (0.095)	0.576*** (0.095)
Cluster to cluster			0.265*** (0.035)	0.264*** (0.035)
Cluster to non-cluster			-0.022 (0.050)	-0.025 (0.050)
Two years after move	0.062*** (0.006)	0.089*** (0.011)		
Non-cluster to non-cluster			0.214*** (0.050)	0.217*** (0.050)
Non-cluster to cluster			0.588*** (0.101)	0.591*** (0.101)
Cluster to cluster			0.293*** (0.039)	0.293*** (0.039)
Cluster to non-cluster			0.044 (0.046)	0.042 (0.046)
Three years after move	0.042*** (0.006)	0.081*** (0.012)		
Non-cluster to non-cluster			0.248*** (0.056)	0.250*** (0.056)
Non-cluster to cluster			0.563*** (0.104)	0.566*** (0.104)
Cluster to cluster			0.273*** (0.045)	0.273*** (0.045)
Cluster to non-cluster			0.036 (0.042)	0.034 (0.042)
Four years after move	0.027*** (0.007)	0.085*** (0.014)		
Non-cluster to non-cluster			0.295*** (0.061)	0.297*** (0.062)
Non-cluster to cluster			0.637*** (0.111)	0.640*** (0.111)
Cluster to cluster			0.302*** (0.053)	0.302*** (0.053)
Cluster to non-cluster				
Employed persons (ln)				-0.459 (0.364)
R&D expenditures (ln)				-0.037 (0.058)
% of population with level 3-4 education				-0.003 (0.006)
% of population with level 5-8 education				0.007 (0.006)
Population density (ln)				0.308

				(0.309)
Constant	0.561***	1.772***	1.966***	9.040*
	(0.010)	(0.189)	(0.178)	(1.510)
Inventor FE	No	Yes	Yes	Yes
Region FE	No	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes
N	17,334	17,334	17,334	17,334
Inventors	1,926	1,926	1,926	1,926

Note. Standard errors are reported in parentheses. All models include standard errors clustered by inventors.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$