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ESSAYS ON
TECHNOLOGY TRANSFER AND DIFFUSION

Ph.D. Thesis

Dimitrios Karamanis

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I would like to dedicate this thesis to my loving parents ...

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Abstract

Economic growth is driven by innovation activity carried out locally as well as by the ability of a region to learn from external technological achievements. Technological inventions have become the most important source of growth. Producing new knowledge, however, is not cheap and highly concentrated in few countries or in some regions within the same country. The present thesis studies the transfer of the patented technological knowledge to the market and across space.

Specifically, it studies the propensity and time length of the transferring rights of university and individual inventors patents to the market. The novelty lies in exploiting a particular feature of the patent system that ables one to infer the time of commercialisation of the patented technology. The aim is to offer to the science and technology policymakers an unbiased evidenced-based analysis of an extensive corpus of more than 20,000 university and 197,000 inventors' patents granted over their entire enforceable life. With this approach, also important issues can be studied such as characteristics of transferred patents, propensity and timing of licensing of federally funded academic patents compared to their counterparts and differences in licensing outcomes for the different funding institutions, which have not been adequately addressed so far in the literature. Furthermore,it is also examined whether federally funded patents differ from the non federally funded in the propensity and time length required for commercialization.

Additionally, the thesis also considers technology transfer via the mobility of high skilled individuals across space, that of patent inventors. The latter, have a significant economic contribution: they are deeply involved in the production of innovation, which in turn is the main driver of economic growth and well-being and are also important vehicle of knowledge transmission - when skilled workers move from place to place, their knowledge and skills move as well. The contribution of knowledge flows on the shape of the geographical distribution of innovative and economic activities and consequently on inequality among regions and countries has motivated scholars to document them and study their boundaries. The inventor moves are tracked by relying on patent data. A gravity model is used to examine whether proximity, namely geographic, technological, economic, and cultural between countries and country level factors shape the flows of these talented individuals.

As a comparison, in the same framework, also the flows of simple, less skilled migrants are analysed. The contribution of this essay lies in using one simple common framework to comprehensively analyse the determinants - and particularly the various types of proximities - for both highly and less skilled individuals and further assess the role of these two groups of migrants on local innovation activity.

Overall, the empirical analysis of technology transfer to the market and around the world undertaken in the present thesis, offers useful and novel insights to important policy issues surrounding technology transfer of university and individual inventors' patents which are also relevant beyond US borders as a number of European countries consider or have already adopted policies to facilitate the efficient transfer of technologies to the marketplace. Further, by studying the mobility of patent inventors, important factors that make a region an attractor of talented individuals can be identified and relevant policies can be suggested into that direction.

ΠΕΡΙΛΗΨΗ

Η οικονομική μεγέθυνση προωθείται από τις καινοτόμες δραστηριότητες που λαμβάνουν χώρα σε τοπικό επίπεδο καθώς και από την ικανότητα μίας περιοχής να υιοθετεί ξένα τεχνολογικά επιτεύγματα. Οι εφευρέσεις έχουν αναδειχθεί ως η πιο ουσιαστική πηγή μεγέθυνσης. Η παραγωγή νέας γνώσης ωστόσο, δεν είναι φθηνή ενώ είναι έντονα συσσωρευμένη σε λίγες χώρες ή σε ορισμένες περιοχές εντός της ίδιας χώρας. Η παρούσα διατριβή μελετά την ροή πατενταρισμένης τεχνολογικής γνώσης στην αγορά σε ευρύ επίπεδο. Πιο συγκεκριμένα, ερευνά την τάση και την χρονική διάρκεια των δικαιωμάτων ευρεσιτεχνίας των πανεπιστημιακών και ιδιωτικών πατεντών στην αγορά. Η πρωτοτυπία έγκειται, στην αξιοποίηση ενός ιδιαίτερου χαρακτηριστικού του συστήματος κατοχύρωσης ευρεσιτεχνιών που συντελεί στην εκτίμηση του χρόνου εμπορευματοποίησης μίας κατοχυρωμένης τεχνολογικής ιδέας. Στόχος είναι να προσφερθεί στην επιστήμη και στους νομοθετούντες αναφορικά με την τεχνολογία, μία αμερόληπτη και βασισμένη σε στοιχεία ανάλυση που έχει προκύψει από ένα ευρύ δείγμα περισσότερων από 20.000 πανεπιστημιακών και 197.000 ιδιωτικών διπλωμάτων ευρεσιτεχνίας, χορηγούμενων για όλη την «βιώσιμη» περίοδό τους. Με τη συγκεκριμένη προσέγγιση είναι επίσης δυνατόν, να μελετηθούν σημαντικά θέματα, όπως τα χαρακτηριστικά που καθιστούν μία πατέντα αξιόλογη να κατοχυρωθεί ή οι διαφορές ως προς τη τάση και τη διάρκεια της κατοχύρωσης μιας ακαδημαϊκής πατέντας μεταξύ των επιδοτούμενων από το κράτος σε σύγκριση με αντίστοιχες μη επιδοτούμενες, θέματα που δεν έχουν μελετηθεί επαρκώς ως τώρα στην βιβλιογραφία. Επιπλέον, εξετάζεται αν οι κρατικά επιδοτούμενες πατέντες διαφέρουν από τις μη κρατικές ως προ της τάση και την χρονική διάρκεια που απαιτείται για την εμπορευματοποίησή τους. Επιπρόσθετα, η διατριβή μελετά τη ροή της τεχνολογίας μέσω της κινητικότητας των ατόμων με υψηλή εξειδίκευση, όσων δηλαδή δημιουργούν πατέντες. Αυτοί έχουν μία σημαντική οικονομική συνεισφορά: εμπλέκονται έντονα στην παραγωγή καινοτομίας, η οποία με τη σειρά της είναι ο βασικός κινητήριος μοχλός της οικονομικής μεγέθυνσης και της ευημερίας, ενώ συνιστούν ταυτόχρονα και μέσο μεταλαμπάδευσης της γνώσης - όταν οι εξειδικευμένοι εργάτες μετακινούνται από μία περιοχή σε μία άλλη, οι γνώσεις και οι δεξιότητες τους επίσης μεταφέρονται. Ο τρόπος με τον οποίο η ροή της γνώσης καθορίζει τη γεωγραφική κατανομή των καινοτόμων οικονομικών δραστηριοτήτων και συνεπώς την ανισότητα μεταξύ των περιοχών και των χωρών, έχει κινητοποιήσει τους ερευνητές να την καταγράψουν και να τη μελετήσουν. Προκειμένου να εντοπιστούν οι μετακινήσεις των εφευρετών,αναλύονται δεδομένα πατεντών. Χρησιμοποιείται ένα μοντέλο βαρύτητας ώστε να εξετασθεί αν η εγγύτητα· γεωγραφική, τεχνολογική, οικονομική και πολιτισμική μεταξύ των χωρών, αλλά και οι ιδιαίτεροι παράγοντες κάθε χώρας, διαμορφώνουν την ροή αυτών των «ταλαντούχων» ατόμων. Σαν

σύγκριση, στο ίδιο πλαίσιο, εξετάζονται επίσης οι ροές απλών, λιγότερο εξειδικευμένων μεταναστών. Η συνεισφορά της εν λόγω μελέτης εντοπίζεται στην χρήση ενός απλού κοινού πλαισίου, ώστε να αναλυθούν συνολικά οι παράγοντες και ιδιαίτερα οι διάφοροι τύποι εγγύτητας, τόσο για τα υψηλά όσο και για τα λιγότερο εξειδικευμένα άτομα και επιπλέον, να εκτιμηθεί ο ρόλος αυτών των δύο κατηγοριών μεταναστών στη διαμόρφωση της τοπικής δραστηριότητας καινοτομίας.

Εν κατακλείδι, η εμπειρική ανάλυση της ροής της τεχνολογίας στην αγορά και σε όλον τον κόσμο, η οποία εξετάζεται στη συγκεκριμένη διατριβή, προσφέρει χρήσιμες και πρωτότυπες πληροφορίες για σημαντικά θέματα πολιτικής σχετικά με τη ροή των ακαδημαϊκών, καθώς και αυτών που ανήκουν σε ιδιώτες, πατεντών, θέματα τα οποία είναι επίσης σχετικά και πέρα από τα όρια των Η.Π.Α., καθώς αρκετές ευρωπαϊκές χώρες θεωρούν απαραίτητες ή έχουν ήδη υιοθετήσει πολιτικές προκειμένου, να διευκολύνουν την αποτελεσματική ροή των πατεντών στην αγορά. Επιπρόσθετα, μελετώντας την κινητικότητα των δημιουργών πατεντών είναι δυνατόν να αναγνωρισθούν σημαντικοί παράγοντες που καθιστούν μία περιοχή ικανή να προσελκύσει άτομα με υψηλή εξειδίκευση και συνεπώς να προταθούν σχετικές πολιτικές προς αυτή την κατεύθυνση.

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Chapter 1

Introduction

1.1 Motivation

Generation of new technological knowledge lies at the heart of economic growth (Romer, 1986; Grossman and Helpman, 1991). Technological inventions have become the most important source of growth, replacing land, energy, and raw materials. During the last two decades, the value of patents and other intellectual property assets has surged to become a large part of the wealth portfolio of firms today. In the US for instance, in the early 1980's intangible assets represented 38% of the portfolios of US firms, while in the mid 1990's and 2000's this share rose to 70% (WIPO, 2003). "The economic product of the United States", as Alan Greenspan stated, has become "predominantly conceptual" (Trei, 2004). Intellectual property forms part of those conceptual assets. Producing new knowledge, however, is not cheap and highly concentrated in few countries or in some regions within the same country (Audretsch and Stephan, 1996).

The discovery of new useful knowledge about products and processes is defined as 'invention' (Schmookler, 1957) and is most frequently protected by the use of patents that grant exclusive rights to the owner of the invention for a limited time in exchange for full disclosure. Users of this type of intellectual property (IP) can be corporations, universities, research institutions, small businesses, non-profit organizations or even independent inventors.

Among these agents, universities have long been recognized as a driving force of innovation activity (Mansfield, 1991; Adams, 1990; Jaffe, 1989). In particular, university inventions are critical elements in Research and Development (R&D) in the industry sector. As universities cannot themselves fully develop and commercialize their, mostly embryonic in nature, inventions, one way to fully realize the potential of their research outcome is by signing licensing agreements with the industry sector (Hall et al., 2003). Understanding the transfer of rights of university patents to the market, as well as, the specific characteristics of the transferred patents is of special interest for a number of agencies, such as national science and technology policymakers, lawmakers, and for those setting research funding priorities. In the US, in particular, innovation and research public policy greatly favors the creation and diffusion of academic inventions via a wide range of activities. For instance, an important way has been the channeling of large federal funds to promote academic research, which, in many cases, accounts up to 70% of universities' R&D activity. Policy issues surrounding technology transfer of university patents, are relevant not only for the US but for many countries consider or have already adopted policies to facilitate the efficient transfer of academic technologies to the marketplace (Mowery and Sampat, 2005).

Up today, quantitative analysis of technology transfer activity of university patents in general and federally funded university patents in particular has been limited by the lack of comprehensive and accessible data. As university technology transfer datasets are proprietary in nature, previous scholarly work in this field has focused on case study analyses of a single or a handful of large universities documenting evidence that may not hold or extend to other academic research institutions (Wright et al., 2014; Ziedonis, 2007; Elfenbein, 2007; Mowery and Ziedonis, 2015). Patents that result from this funding are the return on this taxpayer investment. Science and technology policy makers are increasingly interested in understanding whether this funding and related commercialization activities align with the US economic growth and workforce development objectives.

Innovation activity also takes place by individual inventors. Patented inventions by individual inventors constitute approximately 15% of total patents, according to United States Patent and Trademark Office (USPTO). While this may not seem as a big share, scholars have shown that individual inventors' inventions play a significant role in large firms' R&D strategies. Large corporations will often look for complementary inventions outside their research labs to enhance their innovative performance. One of the main places they will seek for such complementary assets are individual inventors; startups and universities are also important alternatives. Individual inventors, on the other hand, in many occasions would prefer not to fully develop their inventions; instead, they would prefer to license or sell them to corporations that they will be in charge with dealing with all the development and production challenges (Arora and Gambardella, 2010; Gambardella et al., 2007).

Patent inventors that are researchers in a university or in a firm or in any other institution are great contributors of technological knowledge generation and transmission. They consist a specific class of highly skilled workers, which is more homogeneous as a whole, than the tertiary educated workers lies on the following reasons. Although inventors are just a small proportion of skilled labour, they have a significant economic contribution: they are deeply involved in the production of innovation, which in turn is the main driver of economic growth and well-being (Dahl and Sorenson, 2009). They are also important vehicle of knowledge transmission; when skilled workers move from place to place, their knowledge and skills move as well (Breschi and Lissoni, 2009; Glaeser et al., 1995; Lucas, 1988). Knowledge that flows across space can shape the geographical distribution of innovative and economic activities and consequently the (in)equality among regions and countries (Saxenian, 1994; Swann et al., 1998; Verspagen, 1999).

1.2 Structure of the Thesis

The present thesis aims to study transfer of the patented knowledge to the market and across space. To effectively study this issue, the thesis is organised into three essays each one consisting a separate chapter.

The second chapter focuses exclusively on patents created by academic institutions and studies the technology transfer activity of university patents in the US. It studies the propensity and time length of the transferring rights of university patents to the market. By exploiting a particular piece of information of the US patent system, i.e., the patent renewal fee structure, it can be determined whether university patents are licensed over their enforceable lifecycle and at what point in time the licensing takes place. Therefore, an unbiased evidenced-based analysis of an extensive corpus of over 20,000 university patents granted between 1990 and 2000, over their entire enforceable life, is offered to the science and technology policymakers. Prior to this study, there was no independent unbiased analysis of the subject matter. With this approach, important issues can also be studied, such as characteristics of transferred patents, propensity and timing of licensing of federally funded academic patents compared to their counterparts and differences in licensing outcomes for the different funding institutions, which have not been adequately addressed so far in the literature. Furthermore, along with the information derived from the renewal fee scheme, information that comes this time from the patent document wrapper is used, which discloses government interest statements. From this observation, the government (federal) funded patents can be distinguished from the rest of the patents. As federal funds constitute a major financial support of the US academic research it is interesting to examine whether federally funded patents differ in the propensity and time length required for commercialization.

The third chapter studies the commercialization propensities of individual patent inventors. The main interest in this chapter lies in assessing how patents' characteristics, size of the research team, prior patenting experience of the inventor, inventor's previous corporate ties, as well as some state macroeconomic factors are associated with commercialization of inventor owned US patents. Generally, it is difficult to observe commercialization. The novelty of this chapter lies in exploiting a particular piece of information, which has been overlooked thus far, and relates to a particular feature of the US patent system, i.e., the patent renewal fee structure. , namely switches from Small Entity Status (SES) to Large Entity Status (LES) for renewal fee purposes. This switch of patent fee payments is a way of inferring that the patented technology has made it to the market. The chapter concludes that patent characteristics, size of research teams, prior patenting experience and past corporate patenting activity are positively associated with increased likelihood of transferring patent rights to large corporations.

The forth chapter considers technology transfer via the mobility of patent inventors across space. To track inventor moves, the study relies on patent data. A gravity model is used to examine whether proximity, namely geographic, technological, economic, and cultural between countries and country level factors shape the flows of these talented individuals. As a comparison, in the same framework, the flows of simple, less skilled migrants are also analysed. The contribution of this chapter lies in using one simple common framework to comprehensively analyze the determinants - and particularly the various types of proximities - for both highly and less skilled individuals. The evidence shows that proximity matters for migration flows. Gravity emerges everywhere; in the mobility of the highly skilled workers as well as in the average migrant worker. It is found, however, that inventors are less geographically restricted and, therefore, their effective reach is beyond that of the average workers. Similarity in technological structure of production is the main driver of inventor moves - especially for inventors from the most innovative countries, whereas social proximity matters more for the average migrant flows. Attractive country features for inventor inflows are the level of economic and financial development, the number of inventors and the trade linkages between origin and host country. Most of these factors as well as the tertiary education level of the host country appear to be also important for the less skilled migrant flows. Finally, the knowledge that moves with the inventors has a positively contributes to local innovation production.

Overall, the empirical analysis of technology transfer to the market and around the world undertaken in the present thesis, offers useful and novel insights to important policy issues surrounding technology transfer of university patents which are also relevant beyond US borders as a number of European countries consider or have already adopted policies to facilitate the efficient transfer of academic technologies to the marketplace. Further, by studying the mobility of patent inventors, important factors that make a region an attractor of talented individuals can be identified and relevant policies can be suggested into that direction.

Chapter 2

Academic Patents and Technology Transfer

In this chapter a particular facet of the US patent system is exploited, which thus far has been overlooked in the literature: the patent renewal fee scheme relating to switches from small to large entity status. Based on this observation, someone is able to determine whether university patents are licensed over their enforceable lifecycle and at what point in time the licensing occurs. It is found that while the funding source of patented inventions makes no difference to the propensity of an academic patent being licensed, federally sponsored patents are less likely to be licensed early compared to their non-federally funded counterparts.

2.1 Introduction

Universities have long been recognized as a driving force of innovation activity (Mansfield, 1991; Adams, 1990; Jaffe, 1989). In particular, university inventions are critical elements in Research and Development (R&D) in the industry sector. As universities cannot themselves fully develop and commercialize their, mostly embryonic in nature, inventions, one way to fully realize the potential of their research outcome is by signing licensing agreements with the industry sector (Hall et al., 2003).[1]

Understanding the transfer of rights of university patents to the market, as well as, the specific characteristics of the transferred patents is of special interest for a number of agencies, such as national science and technology policymakers, lawmakers, and for those

[1]Indeed, Jensen and Thursby (2001) in a survey of university technology transfer managers, find that 71% of US university inventions are of embryonic nature. Licensing agreements is one mechanism for transferring technologies; other mechanisms may include informal technology transfer, university spinoffs, other Intellectual Property (IP) ownership, and "giving it away"/placing it in the public domain.

setting research funding priorities.[2] In the US, in particular, innovation and research public policy greatly favors the creation and diffusion of academic inventions via a wide range of activities. For instance, an important way has been the channeling of large federal funds to promote academic research, which, in many cases, accounts up to 70% of universities' R&D activity (National Science Board, 2012, Figure 5-2). In addition, to facilitate universities (and small businesses) to file for subsequent patent applications for their inventions and to promote the development and commercialization of the latter, the US congress passed *The University and Small Business Patent Procedures Act of 1980* ('Bayh-Dole' Act) by establishing a unified framework where universities can elect to retain ownership of federally funded inventions.[3] The rationale of the Act was to stimulate commercialization of the federally funded patents. Since its enactment, most of the US universities actively engaged in research, created and funded offices of technology transfer to facilitate the licensing, commercialization and transfer of federally funded and other university inventions.[4] Such policy issues, surrounding technology transfer of university patents, are also relevant beyond US borders as a number of European countries consider or have already adopted policies to facilitate the efficient transfer of academic technologies to the marketplace (Mowery and Sampat, 2005).

To date, quantitative analysis of technology transfer activity of university patents in general and federally funded university patents in particular has been limited by the lack of comprehensive and accessible data. As university technology transfer datasets are proprietary in nature, previous scholarly work in this field has focused on case study analyses of a single or a handful of large universities documenting evidence that may not hold or extend to other academic research institutions (Wright et al., 2014; Ziedonis, 2007; Elfenbein, 2007;

[2]The terms 'academic' and 'university' patent are used interchangeably throughout the chapter.

[3]Prior to 1980, each US federal government agency funding research had its own patent licensing agreements and practices. The lack of uniform government patent policy and the government ownership of inventions conceived during work on a federal contract, acted as a disincentive to obtain patents and commercialize these discoveries (Eisenberg, 1996).

[4]By 2009, the 180 university institutions that participated in the Association of Technology Managers (AUTM) reported that these organizations employed over 2,106 full time equivalent licensing and technology transfer personnel (AUTM, 2010). There has also been a dramatic increase in the number of invention disclosures, patents and license activity. Total invention disclosures to University Offices of Technology Transfer (OTT) by academic faculty grew from 10,987 in 1998 to 20,115 in 2008 (AUTM, 2008). In 2009, AUTM reported 20,309 invention disclosures, filing of 18,214 patent application and 3,414 granted patents awarded to the 180 university institutions that participated in the 2009 Licensing Survey. While US university patents accounted for approximately 0.75% of the US patents granted to the US entities in 1980, in 2005 they accounted for approximately 5% (NBER, Patent Data Project, 2013). In addition, based on the AUTM (2005) report the license income of US universities rose from $ 218 million in the fiscal year of 1991 to $1.54 billion in the fiscal year of 2009 (real values of 1991). The role of technology transfer and licensing of university inventions as well as the quality of academic technology after the Bayh-Dole Act is studied by Macho-Stadler et al. (2007) and Sampat et al. (2003), respectively.

Mowery and Ziedonis, 2015).[5] Further, the contribution of the US taxpayers to the US higher education R&D expenditures is about 62% (National Science Board, 2012). Patents that result from this funding are the return on this taxpayer investment. Science and technology policy makers are increasingly interested in understanding whether this funding and related commercialization activities align with the US economic growth and workforce development objectives.

The present chapter studies the propensity and time length of the transferring rights of university patents to the market. The novelty of this work lies in exploiting a particular piece of information, which has been overlooked thus far, and relates to a particular feature of the US patent system, i.e., the patent renewal fee structure. Based on this observation, someone is able to determine whether university patents are licensed over their enforceable lifecycle and at what point in time the licensing takes place. This study, therefore, aims to offer to the science and technology policymakers an unbiased evidenced-based analysis of an extensive corpus of over 20,000 university patents granted between 1990 and 2000, over their entire enforceable life. Prior to this study, there was no independent unbiased analysis of the subject matter. With this approach, important issues can be studied, such as characteristics of transferred patents, propensity and timing of licensing of federally funded academic patents compared to their counterparts and differences in licensing outcomes for the different funding institutions, which have not been adequately addressed so far in the literature.

The renewal patent fee scheme provides rich information, which can be exploited at least in two ways. First, it can be used to infer academic technology transfer to the marketplace. Changes in the patent fee schedule relate to changes in patent assignee (university, here) status, which in turn could imply engagement of a university patent in commercialization activities. More specifically, patent assignees in the United States Patent and Trademark Office (USPTO) system pay issue fees and subsequently renewal fees to maintain the enforceability of a US patent at the 3.5, 7.5 and 11.5 year after issuance. The US patent system has two different patent fee structures: for small entities (for instance non-profit institutions and small businesses) and for large entities. Universities have the right to pay and elect Small Entity Status (SES) fees for their patents. When a university enters into license agreement with a large corporation for a particular patent loses its small entity status for the particular patent and is obliged to pay all of the particular patent's subsequent fees according to the Large Entity Status (LES) patent fee schedule. This publicly available information is employed, i.e., the switch from SES to LES status, to infer licensing of academic inventions and

[5] Most of the economic analysis of the outcomes of federal funding research have relied on proprietary databases of individual universities, survey data by industry organizations, like the Association of University Technology Managers that relies on input from its members, and lists of patent published by University Offices of Technology Transfer and the commercialization offices of the federal agencies funding the work.

consequently academic transfer to the marketplace. Second, based on renewal patent fee scheme the speed at which university patents are licensed can be assessed. The time length of commercialization of an academic patent can be calculated by the time a patent switches to LES, i.e., by issuance (grant) and at the first, second and third maintenance fee event, corresponding to 3.5, 7.5, and 11.5 year after patent grant, respectively.

Along with the information derived from the renewal fee scheme, information that comes this time from the patent document wrapper is used, which discloses government interest statements.[6] From this observation, someone is able to distinguish the government (federal) funded patents from the rest of the patents. As federal funds constitute a major financial support of the US academic research it is interesting to examine whether federally funded patents differ in the propensity and time length required for commercialization. From the patent document wrapper someone is further able to distinguish among four big funding agencies, which account for the vast majority of the academic federal R&D support (National Science Board, 2012), namely the Department of Defence, the Department of Energy, the National Institutes of Health, and the National Science Foundation. Each of these agencies has different research and development imperatives focused on the agency's mission. Consequently, their research agendas and the associated licensing guidelines could have different effects on the marketing management of their respective funded technologies (Eisenberg, 1996). Further, each funding agency has different criteria based for financing research and these criteria are also very likely to influence the nature of innovative output (Azoulay et al., 2011). Therefore, it is interesting to examine whether different federally funding agencies are associated with different propensities to engage in commercialization activities.

The study mainly relates and contributes to the strand of literature that examines factors related to technology transfer and commercialization of university inventions.[7] A branch of this literature focuses on patent or invention level[8], while another stream of this literature considers university as the observation unit.[9] A related parallel strand of research has examined patent renewal data. Since the groundbreaking work of Pakes (1986) and Schankerman and Pakes (1986) renewal data have been used extensively to infer the private economic value

[6]Any research organization, which receives federal support, is obliged to include a statement at the patent application that the government has certain rights in the invention.

[7]For an in-depth literature review on university entrepreneurship and university technology transfer processes, consult Rothaermel et al. (2007) and Bradley et al. (2013).

[8]For theoretical contributions in the field see Hellmann (2007), and Hellmann and Perotti (2011). The studies of Mowery and Ziedonis (2015), Ziedonis (2007), Elfenbein (2007), Wright et al. (2014) provide empirical evidence.

[9]On theoretical side, see the study of Jensen et al. (2003). Empirical contributions include the studies of Lach and Schankerman (2008) and Belenzon and Schankerman (2009) among others.

of patents. To our knowledge, Bessen (2008) was the first to examine full renewal data of US patents; that is, he examined each patent renewal decision at the 3.5, 7.5 and 11.5 year after issuance. Hegde and Sampat (2009), Serrano (2010) and Rassenfosse and van Pottelsburghe de la Potterie (2012) are some of notable studies that used renewal data for US patents. Particularly, the works of Bessen (2008) and Rassenfosse and van Pottelsburghe de la Potterie (2012) have also explicitly accounted for whether the patent fees paid correspond to large or small entity status. Their sole motivation, however, for doing that was to infer the economic value of patents in money-metric variables and not to infer technology transfer of academic patents. The specific study adds to the aforementioned literature strands by employing a wide spectrum of university patents expanding thus upon previous work, which has either relied on proprietary information of licensing activity of a handful of universities or performed aggregate analysis at university level. Instead, the whole population of academic patents is employed, as provided by the USPTO and a piece of information that has not been yet exploited is considered. Therefore, this study consists the first attempt in the literature that studies the relationship between academic innovation output and propensity of academic technology commercialization at a large scale and comprehensive manner.

The proposed methodology is applied to a large sample of US universities over the period 1990-2000 aiming to answer two main questions: (i) Are federally funded university patents more (less) likely to be transferred to the marketplace than non-federally funded? and (ii) Are federally sponsored university patents faster transferred to the marketplace than non-federally funded?

The results are easy to summarize. Federally funded university patents are no less likely to be commercialized than non-federally funded patents. Accounting for different funding agencies, one can find that patented inventions funded by the Department of Defense are about 6% less likely than non-federally funded patents to be licensed. With respect to other funding agencies the differences are not significant. In terms of timing, federally funded patents are less likely to be licensed at early stage compared to their non- federally sponsored counterparts. Among the government sponsored patented inventions, the Department of Energy funded patents appear to be the least likely to be licensed early, while at the opposite side of the spectrum, the patents funded by the National Institute of Health are the most likely to be licensed early. It should be noted that non-federally patents include corporate funded patents, but also include patents that were either funded by other types of sponsors (such as local government, non-profit institutions and other universities) or not funded by a specific research grant.

Along with government support, the study also controls for a range of patent characteristics that could be associated with the propensity and time of academic technology commercialization. The size of prior and posterior art base and scope of a patent, the number of inventors and assignees involved, as well as, their patenting experience are found to shape both the propensity and speed of university patents' licensing. Results are robust and do not alter even when peculiar cases of patent status fees and outliers are considered.

From the outset of this work, it is important two things be stressed, that are not done in this study. First, a causality explanation between (the type of) government funding and technology transfer is not offered. Rather, insights on the licensing propensity of academic inventions are provided that contain statements of government interest indicating federally funded research and market development, controlling for a series of patent characteristics. Proper discussion of causality requires information at a finer level and different set up of the data.[10] Restrained by data unavailability, someone is only able to talk about association and refrain from drawing nuanced policy statements. Second, efficiency issues of the funding source, federal or not are not discussed. As there is no information on the actual dollar amount of the research projects, one cannot infer on the relative efficiency of federal to non-federal research grants. In this study, all findings are conditioned on the patent level.

The remainder of the chapter proceeds as follows. Section 2.2 introduces the empirical specification under estimation. Section 2.3 presents the sources and construction of the dataset. Section 2.4 discusses the results. Section 2.5 summarizes the findings and concludes.

2.2 Methodology

The first question this chapter aims to answer is whether federally funded university patents are associated with different propensity toward technology transfer compared to all other university patents. The likelihood of a patent being licensed over its lifecycle can be described using a probit model defined as follows:

$$Prob(SwitchtoLES = 1/X_i^{'}\beta) = \Phi(X_i^{'}\beta) \tag{2.1}$$

where the endogenous variable $SwitchtoLES$ takes the value of 1, if a patent, i, has paid LES fees at any point during its patent life, and 0 otherwise; Φ is the cumulative distribution function of the standard normal distribution; β is a set of coefficients of patent's characteristics included in the control set X, defined as:

[10]For example, one needs to match samples, where everything else would be alike (choosing similar research projects, with same probability of being patented and commercialized), but the funding source. In such set up, one is more comfortable in deriving causal implications.

$$X_i^{'}\beta = \beta_0 + \beta_1 Federal_i + \beta_2 Citations_i + \beta_3 Scope_i + \beta_4 Inventors_i + \beta_5$$
$$Assignees_i + \beta_6 InventorActivity_i + \beta_7 AssigneeActivity_i + \beta_8 GrantYear_i$$
$$+ \beta_9 TechnologyDummy_i + \varepsilon_i$$

The inclusion in X of a wide variety of patent metrics, allows someone to explore a number of important characteristics of the transferred patents: First and foremost, X includes a dummy, $Federal$ that takes the value of 1, if a patent i discloses federal support and 0 otherwise; a set variable $Citations$ that consists of the number of (i) backward patent citations (*BacwardCitesPat*), (ii) backward non-patent citations (*BackwardCitesNonPat*), and (iii) patent citations patent i receives (*ForwardCites*) - all measures of patent quality.[11]; a set variable $Scope$ that controls for the scope and usage of a patent and includes the number of claims, $Claims$, the application length, $ApplicationLength$, number of classification codes - the four-digit International Patent Classification, $IPC4Digit$, and three-digit US classification code, $USC3Digit$ - and technology field dummies, *TechnologyDummy*; the number of inventors ($Inventors$) in a patent and assignees (*Assignees*) that a given patent is assigned, capture the level of difficulty and economic importance; the patenting experience of inventors and assignees' of a patent denoted as *InventorActivity* and *AssigneeActivity*, respectively; and finally, a set of dummies for the grant (issue) year of the patent. All these patent metrics have been commonly used in the literature (Bessen, 2008; Hall et al., 2005; Lanjouw and Schankerman, 1999; Harhoff et al., 1999). Table A.1 in the Appendix provides the definition of these variables and references to the literature. All these patent metrics shape the likelihood of a patented technology to be transferred to the market place. For instance, a quality patent, reflected in the number of citations, with large scope and usage, reflected in classification codes and number of claims, respectively, which required high level of knowledge (facilities/labs), reflected in the number and experience of inventors (assignees), would be more likely to the transfer faster at the market place than a patent that satisfies less from the aforementioned characteristics.

Among the set of coefficients of the control variables, the coefficient of $Federal_i$ is the primary coefficient of interest, which shows whether government sponsored patents are more

[11]For example, granted patent with a larger prior art base may disclose a broader and ultimately more valuable invention - 'standing on the shoulders of giants'. It should be noted here that forward citations have been shown to be positively influenced by licensing (Drivas et al., 2014; Chan, 2015; Sampat and Ziedonis, 2005). Therefore, any positive coefficient that may be found between forward citations and likelihood of switching to LES could have an alternative explanation. In other words, licensing may cause an increase in forward citations. To partly alleviate this concern, in alternative specifications, the number of forward citations is included only within the first four years since grant. Results are qualitatively similar to those displayed in the chapter. It is important to thank an anonymous referee for suggesting this robustness check.

or less likely to switch to LES fees than their non-federally counterparts. Arguably, federally supported patents are less likely to be licensed by corporate funded inventions. Further, in a case study of inventions at the University of California, Wright et al. (2014) find that federally funded inventions are less likely to be licensed by corporate funded inventions; however, that difference between federally supported patents and corporate funded counterparts disappears when considering the cases where the corporate sponsor licenses the invention. However, given the limited work at the invention level, the licensing propensity of federally funded patented inventions is eventually an empirical issue.

An allied question worth examining is whether the nature of funding agencies affects the propensity to switch to LES status. In doing so, Federal is replaced with five dummy variables $DODfunding_i$, $DOEfunding_i$, $NIHfunding_i$, $NSFfunding_i$, and $OTHERfunding_i$ denoting the source of federal funding, i.e, the Department of Defense (DOD), the Department of Energy (DOE), the National Institutes of Health (NIH), which is part of the Department of Health and Human Services, the National Science Foundation (NSF), and other unclassified federal source, respectively, and equation (1) is re-estimated. As before, the literature provides little guidance as to what to expect.[12] It should be noted that while causality is not claimed, there is still the possibility of a selection issue with respect to some variables. Specifically, university administrators could be doing a better job in drafting their patent applications for patents of higher quality and therefore possibility of licensing. For instance, they might be more careful in citing all the prior art or disclosing accurately the federal funding source. Indeed, Sampat (2010) shows that applicants are more careful in citing all the relevant prior art for their more important inventions. Even though this may cause a bias in the results, it is still insightful to examine the relation of these patents characteristics with the likelihood of switching to LES.

The second question the chapter attempts to answer is equally unexplored and further contributes to a debate in the literature that is, whether federally funded patents reach the marketplace faster compared to their non-federally supported counterparts. A longstanding premise is that federally funded patents may be more basic and upstream in nature than their non-federally funded counterparts (Cohen et al., 1998; Henderson et al., 1998) leading to longer timeframes for these discoveries to move from basic research to applied research to product/service development in the marketplace. In addition, non-federally funded patents, many of which derived from corporate-funded patents, can be licensed by the research sponsor. Therefore, it can be the case that federally funded patented inventions may take more time for their potential to be observed and therefore more time to be commercialized.

[12]A study by Wu (2010) finds that NSF's Experimental Program to Stimulate Competitive Research has contributed positively to research competitiveness.

To examine the dynamic aspects of technology transfer, only patents that have switched to LES are considered and estimated, with the use of an ordered probit model, the propensity a university patent i to switch to LES by grant year, first, second, and third maintenance fee event.

An index model used for a single latent variable y_i^*, which is unobservable, is described as below:

$$y_i^* = X_i^{'}\beta + u_i \tag{2.2}$$

$y_i = 1 \;\; if \; y_i^* < c_1, \;\; y_i = 2 \;\; if \; c_1 < y_i^* \leq c_2, \;\; y_i = 3 \;\; if \; c_2 < y_i^* \leq c_3, \;\; y_i = 4 \;\; if \; y_i^* > c_3,$ where, c_i are the cutoff values which are unobservable to the researcher and are estimated through the model.

The probability, P that a patent i will take the value of: one is $Pr(y_i = 1) = 1 - \Phi[x_i\beta - c_1]$, two is $Pr(y_i = 2) = \Phi[x_i\beta - c_1] - \Phi[x_i\beta - u_2]$, three is $Pr(y_i = 3) = \Phi[x_i\beta - c_2] - \Phi[x_i\beta - u_3]$, four is $Pr(y_i = 4) = \Phi[x_i\beta - c_3]$, where, Φ is the standard normal cumulative density function (cdf).

Finally, the effect of a change in a regressor X_r on the probability of selecting alternative j is called marginal effect and defined separately for each value of y. For a case of continuous variable x, is defined as: $dPr(y_i = 1)/dx_i = -d\Phi[x_i\beta - c_1]/dx_i = -\beta\phi[x_i\beta - c_1]$, $dPr(y_i = 2)/dx_i = \beta\phi[x_i\beta - u_1] - \beta\phi[x_i\beta - u_2]$, $dPr(y_i = 3)/dx_i = \beta\phi[x_i\beta - u_2] - \beta\phi[x_i\beta - u_3]$, and $dPr(y_i = 4)/dx_i = \beta\phi[x_i\beta - u_3]$, where, ϕ is the probability density function (pdf) and the marginal effects on different alternatives should sum up to zero.

Equations (4.1) and (4.2) are estimated using Maximum Likelihood Estimation (MLE) techniques.[13]

Next section discusses the data.

2.3 Data

Before presenting the data sources and constructions of variables, it is useful to outline a typical process of academic technology transfer. Figure 2.1 displays a flowchart of such a process. After a university researcher discloses an invention to the OTT, the OTT assesses the technology and assigns it to a technology management officer, who in turn tries to find the

[13]The log-likelihood function for the ordered probit is $lnL(\beta) = \sum_{j=1}^{N}\sum_{j=0}^{m} Z_{ij} ln[\Phi_{ij} - \Phi_{i,j-1}]$, where Z_{ij} an indicator variable, which is equal to 1 if $y_i = j$, and $\Phi_{ij} = \Phi[c_j - X_i'\beta]$ and $\Phi_{ij-1} = \Phi[c_{j-1} - X_i'\beta]$.

best way to transfer and therefore utilize the technology. Usually, the officer communicates with firms, which have sponsored the research or the technology falls in their field of research. Even if the officer does not find a licensee, s/he may apply for a patent. Upon finding a licensee, the latter may be asked to pay some or all of the past prosecution costs. A license, therefore, may be struck before patent application, between patent application and patent grant and even after grant. A number of patents, however, are not licensed. While this is a typical technology transfer process, universities have been engaged in a number of different ways to collaborate with corporations and startups to transfer their technologies to the marketplace.[14]

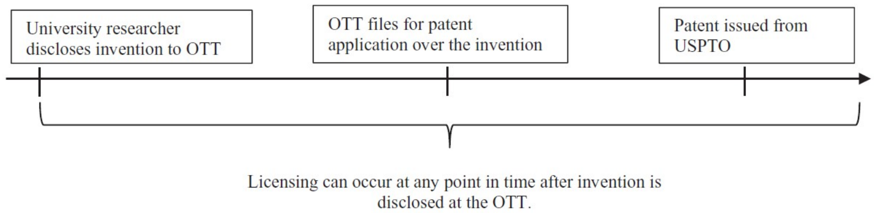

Figure 2.1: Flowchart of a typical academic technology transfer.

To analyze technology transfer activity of university patents to the marketplace, information is derived from various sources. First and foremost, patents where the assignee (owner) of the patent is a US university have to be identified. Second, information is compiled on maintenance renewal fee events for these patents in order to record whether and when they change their statues, over their enforceable lifecycle, in order to proxy technology transfer and the time length of realization. Third, additional information is used to distinguish between federally and non-federal funded university patents. The former, are further classified according to the funding provider. Lastly, information is gathered on patent, inventor, and assignee, among other, characteristics of both federally and non-federally funded patents.

Below, it is described how the dataset was constructed and a brief discussion of its important aspects is provided.

2.3.1 Data Construction

The empirical analysis relies on a sample of 20,877 US university patents issued between 1990 and 2000.

[14] For in-depth reviews of all the different modes of technology transfer consult Siegel and Phan (2006), Rothaermel et al. (2007) and Bradley et al. (2013).

The main source of the data is the *Patent Data Project*, sponsored by the National Bureau of Economics Research (NBER).[15] The NBER identifies and classifies all the patent owners to types of entities. This study collects patents, which identified as assignee a 'US University'. Patents assigned to a single or multiple US universities are included in the sample. Patents that have co-assignees that are not US universities are excluded.

Information on maintenance renewal fee events for the patents of the sample is acquired from the *Patent Maintenance Fee Event Data* from the Google bulk downloads, a dataset created and updated weekly by the USPTO.[16] This dataset includes all renewal events for all utility patents issued by the USPTO. All patents, issued from applications filed on or after December 12, 1980, are subject to maintenance fees, which must be paid to maintain the patent in force. Maintenance renewal event data are coded to a finer level. In addition to cataloging the specific events of renewals at the 3.5 (first renewal), 7.5 (second renewal) and 11.5 (third and final renewal) year after issuance for each patent, the event codes were assembled in the dataset indicating whether the university has paid SES fees or LES fees at that event for a particular patent. To claim SES, universities and academic research organizations must also certify that they have not assigned, granted, conveyed, or licensed, any rights in the invention to any person, concern, or organization, which would not qualify as a person, small business concern, or a nonprofit organization. When a university patent enters into license agreement, it loses its small entity status and is obliged to pay all of the particular patent's subsequent fees according to the Large Entity Status (LES) patent fee schedule (see, Chapter 37 of the Code of Federal Regulations §1.27 (a)). For the rest of the patents in the university's portfolio that are not licensed to a LES corporation, the university still pays SES fees.[17] The latter, are typically 50% lower than LES fees (§35 U.S. Code 41 (a),(b) and (d)(1)); such fees represent a significant cost of patent ownership and maintenance to universities. Therefore, universities have high incentives to claim SES, whenever they are entitled. Falsely claiming SES status for the purpose of filing or maintaining a patent is considered fraud by the USPTO and can render a patent unenforceable and invalid. Consequently, there is a high level of compliance in accurately reporting the entity status among patent owners. For these reasons, the switch from SES to LES provides a reliable indication of academic technology transfer to large entity corporations.

To distinguish between university patents, which received federal support (*Federal*), from those which did not, the study relies on information provided in the patent document wrapper

[15]https://sites.google.com/site/patentdataproject/

[16]http://www.google.com/googlebooks/uspto-patents-maintenance-fees.html

[17]Recently through the passage of the *Leahy-Smith America Invents Act* in 2011, there was an addition of a micro-entity status for issue and renewal fees purposes. However, this status does not enter the sample since it came in effect by the USPTO in March 19, 2013 (Federal Register, 2012).

that discloses government interest statements. This piece of information has only been recently used in the literature.[18] When a research organization retains US domestic patent rights to a patent, which derives from federally funded research, the research organization is under an obligation to include a statement at the patent application that informs the reader the government has certain rights in the invention. The statement usually appears either in the "Government License Rights" section that follows the second paragraph of the specification or as the first paragraph of the specification (Manual of Patent Examination Procedures, Section 310). The patent contains the following generic statement, "The invention was made with Government support (Grant Number)" indicating also the type of the institution which provided the funding.[19] Based on this information, the study further distinguishes among the four biggest funding agencies of university patents, which account approximately 91% of the academic federal R&D support (National Science Board, 2012): the Department of Defense, the Department of Energy, the National Institutes of Health, and, lastly, the National Science Foundation, and accordingly defines $DODfunding$, $DOEfunding$, $NIHfunding$, and $NSFfunding$.[20] The remaining government patents, ($Otherfunding$) belong to funding agencies that appear considerably less frequently in the data (such as National Aeronautics and Space Administration, NASA, and United States Department of Agriculture, USDA) or that, could not be classified.

It should be noted, the switch from SES to LES entity status represents a lower bound of patent licensing and commercialization activity since universities are free to license the patent to other educational institutions or organizations that also quality for small entity status, university spin-outs, start-ups, and other small businesses. Indication of licensing activity in these cases will not be apparent. Nonetheless, successful start-ups are those that generally grow or are bought by large corporations which by default will result in paying LES fees for their licensed patents. Therefore, while all licensing activity by small corporations cannot be captured through this methodology, the licensing activity that became successful down the road can be captured.

[18] Pressman et al. (2006) employed this information to identify which DNA patents had disclosed NIH funding and examined whether the NIH-licensing guidelines were violated. Drivas and Economidou (2013) used this information to examine whether federally funded patents are more basic in nature than their non-federally funded counterparts.

[19] For example, for patent 5,710,287, the statement is "This invention was made with Government support under the NIH Grant#CA 42031 and the NIH Grant#CA 55131 awarded by the National Institutes of Health. The Government has certain rights in the invention." For patent 5,268,573: "This invention was made with support from the National Science Foundation, United States Government, under Grant No. CHE-9158375. The government has rights in this invention."

[20] Specifically, the DOD accounts for 9%, the DOE for 4%, the NIH for 65%, and the NSF for 13% of the academic federal R&D support (National Science Board, 2012, Appendix Table 5-3).

In such cases, however,the second question of the chapter cannot be estimated accurately as the timing of first successful technology transfer is only captured after rights have been transferred to large corporations. To the best of our knowledge there are no data on the percentage of startups and small firms that either license technologies or become large corporations themselves. Therefore,one unfortunately cannot estimate the extent to which this lack of observation distorts the timing of licensing to large corporations. Even still,if switches from startups and small firms to large firms are similar between federally and non-federally funded patents, then it is not expected for this distortion to bias the results between these two sets of sponsors.

The dataset was accessed on February 15, 2013, which enables the study of the entire renewal history of all university patents issued until 2000. The Google bulk download maintenance fee dataset does not provide information on the kind of status entities claimed by the time of grant. This information was graciously provided by the Office of the Chief Economist at the USPTO. This final addition to the data enabled the analysis of SES/LES status information over the entire lifecycle of an issued university patent during the timeframe of the study.

Information on variables included in the control set, X, comes from two sources. The number of claims ($Claims$), of assignees ($Assignees$), of the 4-digit International Patent Code ($IPC4Digit$), and technology field ($TechnologyField$) are extracted from the NBER.[21] A variable within the NBER data (denoted as $pdpass$), disambiguates assignee names and tags each patent applicant with a unique assignee number, supporting the accurate identification of each university. Therefore, the number of patents that each assignee has at each point in time can be constructed ($AssigneeActivity$). The rest of the control variables namely, all types of citations ($BackwardCitesPat$, $BackwardCitesNonPat$, and $ForwardCites$), number of inventors ($Inventors$), the 3-digit US Classification code ($USC3Digit$), application length ($ApplicationLength$), and grant year ($GrantYear$), are obtained from the database of Lai et al. (2011).[22] This database disambiguates inventor names and gives them a unique inventor identification number and enabled the construction of the number of patents that each inventor has at each point in time ($InventorActivity$).

[21]First, each patent was classified according to its primary US Classification, in one of the 37 technology fields, as defined in Hall et al. (2001). The latter study had categorized US classifications in 36 broad technology fields; however, in the 2006 NBER update, there was an addition of a 37th technology field in the area of Computers and Communication Technologies.

[22]Information on the data is provided at https://dataverse.harvard.edu/dataverse/patent.

2.3.2 Data Analysis

Figure 2.2, shows the number of university patents issued per year in the US during the period 1990-2000.

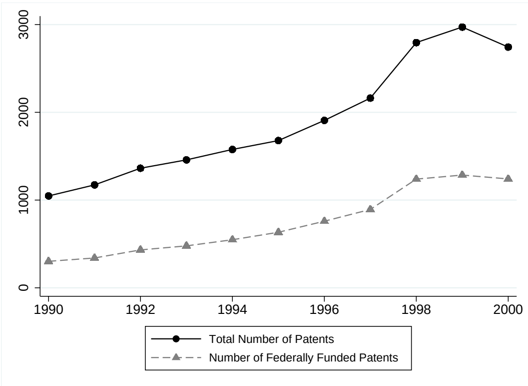

Figure 2.2: University Patents Issued in the US

A notable increase is observable in the number of academic patents issued per year (bold line), as well as, in the number of federally funded patents (dashed line). The latter, comprises a big share of total university patents for all years under consideration. Out of 20,877 patents used in this study, 8,150 patents (39%) disclose federal support, 18,709 patents (89.6%) were renewed at the first renewal, 14,106 (67.6%) in the second renewal, and 9,577 (45.9%) in the third renewal. These statistics are consistent with Bessen (2008), who considers the cohort of US patents issued between 1985 and 1991.

According to the NSF's WebCASPAR database and Science and Engineering Indicators (2012), federal funding accounted for roughly 59% of academic research, local government for 8%, corporations for 7%, other institutions for 20% and other universities for 6%. From this comparison, one can see that federally funded patents are under-represented by funding a disproportionate amount of research that does not result in patents. This finding could be due to reasons. First, federal funding may be more basic in nature and therefore such research may less frequently result in patents than research funding from other sources and consequently result in fewer patents. Second, there might be an under-reporting of federal interest to the patent document. In other words, there could other university patents that are federally funded but the inventor or the assignee did not disclose. Indeed Rai and Sampat (2012) in a study of 30,000 academic biomedical patents issued between 1980-2007 found that in many cases federal funding is not disclosed even though research took place with federal funding.

Table 2.1: Allocation of University Patents by Funding Source

		University Patents		
		All	**Federally Funded**	**Non-Federally Funded**
Switch to LES (%) :		34.0	36.2	32.6
Switch to LES (%)	by grant year:	43.2	36.6	47.8
	at 3.5 year:	32.0	33.5	30.9
	at 7.5 year:	16.7	19.2	14.8
	at 11.5 year:	8.1	10.7	6.4
Observations		20,877	8,150	12,727

		DOD	**DOE**	**NIH**	**NSF**	**OTHER**
Switch to LES (%) :		31.9	33.1	39.0	35.4	36.1
Switch to LES (%)	by grant year:	29.2	22.0	43.3	34.9	37.6
	at 3.5 year:	36.0	24.4	34.4	34.9	36.2
	at 7.5 year:	24.8	23.9	16.1	19.8	19.5
	at 11.5 year:	10.0	29.7	6.2	10.4	6.7
Observations		1,063	1,301	3,377	971	1,438

Abbreviations denote LES: Large Entity Status, DOD: Department of Defense, DOE: Department of Energy, NIH: National Institutes of Health, and NSF: National Science Foundation.

Table 2.1 below provides summary statistics of the switch in status from SES to LES of all patents in the sample (panel A) and of federally funded according to their funding source (panel B).

On average, 7,095 (34%) patents in the sample have switched to LES. This should be considered as a lower bound of successful technology transfer as patents licensed to small business and other non-profit organizations need not change their status to LES.[23] Federally

[23]To provide some external validation of this method, of identifying patents that were licensed, the study examines for the case of Harvard University how many inventions that were patented during 1991-2000 were licensed from evidence reported in Elfenbein (2007). It should be noted that this methodology captures technology transfer to large firms or technology transfer to small firms or start-ups that later on grew in large firms or further licensed to large firms. This methodology cannot capture technology transfer to small firms and start-ups. For this reason, the figures of licensing should be viewed as a lower bound of how many academic patents are actually licensed to the private sector. Indeed, based on AUTM data from the 2006 report, the last year such data were collected, approximately 33% of licenses are struck with large firms, 51% with small firms and the rest with start-ups. These numbers are not directly comparable with the chapter's ones since there is not a one-to-one relationship between patents and licenses Pressman et al. (2006); patents could be licensed as bundles and patents could be licensed more than once. Still, this figure denotes that academic licensing activity is not limited to large corporations but even to smaller firms. While the study does not observe licensing events until 2012 as this study does, it finds 51% of these inventions to be licensed. It is found that 46.9% of Harvard University patents have switched to LES. It should also be noted that there is not one-to-one relation between invention disclosures and patents Wright et al. (2014). With this in mind, the two figures are reasonably close.

funded patents are approximately 3.5% more likely to be licensed than their non-federally funded counterparts. While this difference is small, there is considerable variation when examining each funding source individually. For instance, patented inventions funded by the NIH are the most likely to be licensed (34%), while funded from the DOD are the least likely (26.5%) ones. In terms of dynamics, Table 2.1 shows that 43.2% of the patents that switched to LES, did so by the issue year and an additional 32%, 3.5 years after patent issuance. This finding is consistent with other case studies that find most academic inventions are licensed prior to patent grant or shortly thereafter (Wright et al., 2014; Elfenbein, 2007). One can observe that federally funded patents are licensed less frequently by issue year than non-federally funded patents. As before, there is significant variation across funding agencies. Patented inventions funded by the DOE are considerably less likely to be licensed early, while patented inventions funded by the NIH are the federally funded patents that are transferred fastest to the marketplace.

Patent characteristics of transferred university patents are analysed below. Table A.2 in the Appendix displays summary statistics for patents by renewal status. In general, patents that have switched to LES receive significantly more citations than those that have not. Such finding is consistent with Sampat and Ziedonis (2005), who find that citations are correlated with the economic value of patents as it is approximated by patent licensing. One can observe that LES patents have more backward patent (*BackwardCitesPat*) and non-patent citations (*BackwardCitesNonPat*) than those that do not. Furthermore, the scope of patent, captured by the four-digit International Patent Classification (*IPC4Digit*), is bigger, on average, for LES patents. All the differences in patent characteristics are statistically significant at the 1% level. With respect to university patenting experience, the likelihood of switching to LES is significantly associated with larger universities. Similarly, for the case of lead inventors, someone can observe LES patents to be associated with more experienced inventors. Finally, there is higher probability for a LES patent to be federally funded than a SES patent.

Table 2.2 below provides the summary statistics of status switching from SES to LES of federally funded university patents in six broad technological classes (sectors).

As Table 2.2 shows, the greatest proportion of university patents can be found in Chemical (24.2%) and Drugs (41.3%) related fields and federally funded patents are mainly in Chemical and Electronics sector. However, the difference is not big for patents in the rest of the fields except in Others. Finally, patents in Chemical, Computers, and Electronics have similar propensities of switching to LES, while patents in Drugs have slightly higher (36%) and patents in the Mechanical sector have a considerably lower likelihood (27.1%). The under-representation of Mechanical patents can be explained from the fact that patents are more essential in some fields, e.g. pharmaceutical, medical fields, than others; for instance,

Table 2.2: Large Entity Status (LES) and Federally Funded University Patents by Sector

	University Patents		
	All Patents	Federally Funded (share of All Patents)	Switch to LES (share of All Patents)
Chemical	5,059	41.2	33.7
Computers	1,724	36.3	34.6
Drugs	8,624	39.4	36.0
Electronics	3,314	41.2	33.4
Mechanical	1,178	36.8	27.1
Others	978	24.6	27.1

engineer, computer software (Levin et al., 1987, 1985). Moreover, while the most frequent route followed by inventions disclosed to the university OTT to pass to the marketplace is via patenting and licensing (Elfenbein, 2007), the main tool of transferring knowledge in the engineering discipline from the university to the marketplace is via consulting (Graff et al., 2002).

Finally, it is crucial to also report a complication that arose with the fee data. It was found that a large number of patents had not claimed SES for patent issue fees, while at the first maintenance renewal event the university claimed SES. In the sample, 3,063 university patents did not claim SES at issuance and also paid LES at the first renewal. However 2,014 patents did not claim SES at issuance, but later paid SES at the first renewal event 3.5 years after issuance. While it could be the case that some of them were indeed transferred to a corporation by issue year, by first maintenance fee event after grant, the license was revoked, it is more likely that for most of them the university did not claim SES at filing year and elected to pay the LES fees.[24] It is argued that this is the most likely case for the 2,014 patents that did not claim SES at filing, but paid SES 3.5 years after grant. This is consistent with the concern that claiming the incorrect filing status may affect the enforceability of the patent. If an office of technology transfer had been engaged in discussions with any organization or individual on the potential to license a patent, universities, will most likely, let the patent issue with LES in an abundance of caution. The concern is that if they claim SES status at issue and the patent is later subject to any kind of invalidity action, then they will run the risk of the patent being declared unenforceable because a claim of the wrong entity status is viewed as inequitable conduct. When the patent comes up for renewal, particularly, if there is

[24]Note that the internal data were actually collected at filing and therefore it could be the case that patent applicants later claimed SES.

no licensing agreement or associated revenue, the university is clear to claim SES. To provide some evidence towards this argument, from Table A.3 in the Appendix, someone can observe that patents that did not claim SES at filing, but paid SES at the first maintenance event after grant are similar in characteristics to patents that never switched to LES. However, patents that did not claim SES at filing and paid LES at the first maintenance event after grant are actually quite different from the previous two sets of patents. Hence, the former group is treated as patents that never switched to LES.

2.4 Empirical Results

This section presents the results. First, the study examines if the federally funded university patents are more or less likely to be transferred to the marketplace than the non-federally funded ones, and, second, for the patents that were licensed, their speed of technology transfer to the marketplace.

2.4.1 Are Federally Funded University Patents More (Less) Likely to be Transferred to the Marketplace than Non-Federally Funded?

The first objective of the chapter is to assess, along with other important patent characteristics, whether a patent, which discloses federal support, has different propensity of switching to LES, and consequently passing to the marketplace, compared to a non-federally funded patent. Table 3 reports probit estimates (marginal effects) of equation (1). Estimates of all university patents accounting for federal funding and for different types of funding are presented in columns (1) and (2), respectively. To control for outlier effects, specifications in columns (1) and (2) are re-estimated this time excluding the two largest, in patent activity, US universities, which behave as outliers, the Massachusetts Institute of Technology (MIT) and the University of California.

Column (1) shows that the propensity of federally funded patents of switching to LES is not any different from that of non-federally funded patents. Holding all other variables at their means, a patent that is federally funded (*Federal*) is only 0.68% less likely to be licensed than a non-federally funded patent but this difference is not statistically significant. This findings concurs with findings of past literature, for instance with that of Wright et al. (2014). Although the latter study compares the likelihood of licence of federally sponsored inventions with that of sub-categories of other, non-federally sponsored inventions (e.g., corporate funded inventions, other types of sponsors and inventions that are not tied to specific research grants), this study merely distinguishes between federally funded and subgroups of all other patents. Wright et al. (2014) in their online supplement material show that the average licensing propensity of all types of sponsors is very similar to the licensing propensity of federally funded inventions (24.1% vs. 25.9%); a result similar to the chapter's one.

Shifting the focus on the type of funding agency reported in column (2), one can observe that only the patents financed by the Department of Defence (*DODfunding*) are significantly less likely to be licensed than non-federally funded patents. Patents supported by the rest of funding agencies vary with respect to their difference in the likelihood of switching to LES; however, these differences are not statistically significant. This difference with respect to the Department of Defence funded patents, while significant, it is size-wise rather small (approximately 6%). In any case, this difference could be attributed to the fact that the DOD funded research is usually highly specialized and can only be developed by a limited number of firms. In addition, the DOD technology transfer program is unique in the federal government, because DOD itself is the primary customer of the military technology being developed. Therefore, while other federal departments develop technologies for private sector consumers, for DOD funded research there may be less opportunity for commercialization.[25]

In their majority, patent characteristics also seem to be associated with statistically significant propensities of switching to LES. All kinds of citations, backward (*BackwardCitesPat*, *BackwardCitesNonPat*) and forward (*ForwardCites*) are positively related to the propensity of switching to LES, with forward citations to be the ones associated with the highest predicted probability in switching to LES. Namely, holding all other variables at their means, an additional forward citation is associated with 0.4% greater likelihood of licensing. This finding is consistent with Harhoff et al. (1999), Sampat and Ziedonis (2005), and Bessen (2008). As citation metrics are approximations to patent quality, one can infer that patents which eventually switch to LES are higher quality patents. Furthermore, the number of inventors (*Inventors*) involved in the patent, the number of assignees (*Assignees*) the patent belongs to, and the 4-digit International Patent Classification (IPC4Digit), which proxies for patent scope (Lerner, 1994) are significantly and positively associated with the propensity to switching to LES.

In addition, the (lead) inventor's prior patenting activity is associated with significant increases in the likelihood of having the patent licensed. First, holding all other variables at their means, when the lead inventor has between 1 and 3 prior patents, her current patent is approximately 6% more likely to be transferred than a lead inventor's patent that has no past patents. When the lead inventor has more than three prior patents, she is between 11.1% and

[25] "Report to Congress on the activities of Department of Defence Office of Technology Transition" (August 2006).

Table 2.3: Propensity of Switching to Large Entity Status (LES)

	All University Patents		Excluding University Outliers (*)	
Federal	-0.0069		-0.0017	
	(0.007)		(0.008)	
DODfunding		-0.0591***		-0.0587***
		(0.015)		(0.019)
DOEfunding		-0.0103		-0.0261
		(0.014)		(0.020)
NIHfunding		0.00573		0.0095
		(0.0101)		(0.0108)
NSFfunding		-0.0200		-0.009
		(0.016)		(0.018)
Otherfunding		0.0145		0.020
		(0.014)		(0.014)
ForwardCites	0.0043***	0.0043***	0.0044***	0.0044***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
BackwardCitesPat	0.0015***	0.0015***	0.0015***	0.0016***
	(0.0003)	(0.0003)	(0.0004)	(0.0004)
BackwardCitesNonPat	0.0007***	0.0007***	0.0006***	0.0006***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
ApplicationLength	-0.0045	-0.0045	-0.0061*	-0.0062*
	(0.003)	(0.003)	(0.004)	(0.004)
Claims	0.0003	0.0003	0.0004	0.0004
	(0.0002)	(0.0002)	(0.0003)	(0.0003)
IPC4Digit	0.0345***	0.0343***	0.0342***	0.0340***
	(0.003)	(0.003)	(0.003)	(0.003)
USC3Digit	-0.0040	-0.0040	0.0015	0.0015
	(0.003)	(0.003)	(0.003)	(0.003)
Inventors	0.0152***	0.0152***	0.0139***	0.0141***
	(0.003)	(0.003)	(0.003)	(0.003)
$InventorActivity_{Medium}$	0.0600***	0.0608***	0.0596***	0.0601***
	(0.009)	(0.009)	(0.010)	(0.010)
$InventorActivity_{High}$	0.1250***	0.1260***	0.1110***	0.1120***
	(0.009)	(0.009)	(0.010)	(0.010)
Assignees	0.0486**	0.0469**	0.0572***	0.0553***
	(0.021)	(0.021)	(0.021)	(0.021)
$AssigneeActivity_{Medium}$	0.0904***	0.0903***	0.0743***	0.0747***
	(0.009)	(0.009)	(0.010)	(0.010)
$AssigneeActivity_{High}$	0.1600***	0.1620***	0.1360***	0.1350***
	(0.009)	(0.009)	(0.010)	(0.010)
Observations	20,877	20,877	17,286	17,286

All columns report probit estimates (marginal effects). In all estimations time dummies (*GrandYear*) and technology field dummies (*TechnologyDummy*) are included, but for brevity not reported here. Heteroskedastically robust standard errors are reported in parentheses.

(*) The MIT and the University of California are excluded (outliers) due to their exceptional patenting performance.

12.6% more likely to have her current patent licensed than a lead inventor's patent that has no prior patents. This finding is consistent with Elfenbein (2007).[26]

The university patenting activity is also associated with greater propensities of patents switching to LES. Holding all other variables at their means, a medium-sized university in terms of prior patent stock ($AssigneeMedium = 1$) is 7.4% to 9% more likely to have its current patent licensed than a less patenting active university. For the largest universities ($AssigneeHigh = 1$) their patents are 13.5% to 16.2% more likely. This positive correlation between university patenting activity and likelihood of licensing is consistent with Jensen et al. (2003) and Belenzon and Schankerman (2009).

A number of robustness checks are performed. To verify that the results are not driven by just a handful of large universities, the two biggest universities in terms of patenting activity are excluded: the University of California and Massachusetts Institute of Technology. Results are displayed in Columns (3) and (4). As before, government sponsorship of research (column (3)) does not seem to be associated with different propensity of licensing compared to non-federally funded patents. When one distinguishes by funding source (column (4)), estimates are very similar to those in column (2). Results remain unchanged. For further robustness, the patents that had not claimed SES for patent issue fees, while at the first maintenance renewal event the university claimed SES, are dropped from the analysis. Table A.4 in the Appendix, re-estimates the propensities of switching to LES given government sponsorship and types of funding agencies, along with patent characteristics, for all universities (columns (1) and (2)) and when excluding the University of California and the MIT (columns (3) and (4)). Results are qualitatively similar with those discussed so far. Overall, results did not change in any significant way.

In sum, federal funding does not matter for technology commercialization of university patents. The results have shown that government sponsored patents do not appear to be systematically associated with different propensity of being licensed compared to non-federally funded patents. The only notable exception is the DOD funded patents, which are less likely, compared to non-federally sponsored counterparts, to be licensed. Among the patent characteristics considered, it is found that the prior and posterior art base (citations), the number of patent inventors and assignees, along with the size of their patenting activity, and, finally, the scope of the patent are positively related with the propensity of a university patent being commercialized.

[26]The study of Thursby et al. (2001) also finds a negative relationship between frequency of sponsored research agreements in a license and faculty quality.

2.4.2 Are Federally Sponsored University Patents Faster Transferred to the Marketplace than Non-Federally Funded?

In the previous section, the conclusion was that there are hardly any differences in the licensing propensity between federally and non-federally funded patents. The second objective of this study is to examine whether federally sponsored university patents are licensed faster compared to their non-federally funded counterparts and further whether the source of funding makes any difference in the speed of technology transfer to the marketplace. Hence, there is no longer interest in patents that were not licensed.

Table 2.4 above shows the estimation results from the ordered probit model as it is described in equation (2).

Column (1) shows the average effect and columns (2) to (5) the marginal effects of a patent switching to LES at issue, at the first, at the second and at the third maintenance event, corresponding to 3.5, 7.5, and 11.5 year after patent grant, without differentiating by the source of funding. Analogously, columns (6) to (10) display average and marginal effects by funding agency.

As the coefficient of federally funded patents ($Federal$) in column (1) indicates, there is a positive association between federal sponsorship of a university patent and switching to LES at a late stage. Indeed, federally funded patents are more likely to be licensed later in time, as it can also be seen in columns (2) to (5). In particular, holding all other variables at their means, federally funded patents, as is shown in column (2), are 11.3% less likely to be licensed by the issue year than non-federally funded university patents. In contrast, the propensity of the federally sponsored patents to be licensed at a late stage, for example, at 7.5 or at 11.5 year (columns (4) and (5)), is about 5% higher compared to their non-federally sponsored counterparts. This finding comes as no surprise, as a set of the non-federally funded patents are corporate funded. In general, when the research funder is a corporation it, usually, licenses the invention early as it has information in advance for the research project.

Next, the study accounts for different funding agencies. Column (6) distinguishes by type of funding agencies and presents the average effects. The coefficients of the funding agencies ($DODfunding$, $DOEfunding$, $NIHfunding$, $NSFfunding$, and $OTHERfunding$) show that the switch is more probable to take place at a late stage, with the DOE funded patents to be the latest in being licensed and the NIH the first.

Table 2.4: Timing of Switching to Large Entity Status (LES)

	All University Patents					Excluding University Outliers (*)				
		by grant year	at 3.5 year	at 7.5 year	at 11.5 year		by grant year	at 3.5 year	at 7.5 year	at 11.5 year
		Marginal Effects					Marginal Effects			
Probability		0.4278	0.3326	0.1670	0.0725		0.4258	0.3355	0.1685	0.0702
Federal	0.2910***	-0.1133***	0.0215***	0.0500***	0.0418***					
	(0.0277)	(0.0107)	(0.0022)	(0.0049)	(0.0042)					
DODfunding						0.3188***	-0.1199***	0.0119***	0.0553***	0.0527***
						(0.0619)	(0.0220)	(0.0015)	(0.0104)	(0.0122)
DOEfunding						0.8554***	-0.2853***	-0.0288***	0.1265***	0.1876***
						(0.0622)	(0.0158)	(0.0093)	(0.0068)	(0.0192)
NIHfunding						0.1353***	-0.0526***	0.0094***	0.0238***	0.0194***
						(0.0375)	(0.0144)	(0.0022)	(0.0066)	(0.0057)
NSFfunding						0.2801***	-0.1061***	0.0121***	0.0488***	0.0452***
						(0.0620)	(0.0224)	(0.0012)	(0.0106)	(0.0118)
Otherfunding						0.2044***	-0.0784***	0.0113***	0.0359***	0.0312***
						(0.0501)	(0.0187)	(0.0017)	(0.0088)	(0.0086)
ForwardCites	0.0042***	-0.0016***	0.0003***	0.0007***	0.0006***	0.0041***	-0.0016***	0.0003***	0.0007***	0.0006***
	(0.0005)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0005)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
BackwardCitesPat	-0.0045***	0.0018***	-0.0004***	-0.0008***	-0.0006***	-0.0046***	0.0018***	-0.0004***	-0.0008***	-0.0006***
	(0.0010)	(0.0004)	(0.0001)	(0.0002)	(0.0001)	(0.0010)	(0.0004)	(0.0001)	(0.0002)	(0.0001)
BackwardCitesNonPat	-0.00004	0.00016	-0.00003	-0.00007	-0.00006	0.00002	-0.000008	0.000002	0.000003	0.000003
	(0.0006)	(0.0003)	(0.0001)	(0.0001)	(0.0001)	(0.0006)	(0.0003)	(0.0001)	(0.0001)	(0.0001)
ApplicationLength	0.0050	-0.0020	0.0004	0.0009	0.0007	0.0073	-0.0029	0.0006	0.0013	0.0010
	(0.0134)	(0.0053)	(0.0011)	(0.0023)	(0.0018)	(0.0135)	(0.0053)	(0.0011)	(0.0024)	(0.0018)
Claims	-0.0009	0.0004	-0.0001	-0.0002	-0.0001	-0.0010	0.0004	-0.0001	-0.0002	-0.0001
	(0.0008)	(0.0003)	(0.0001)	(0.0001)	(0.0001)	(0.0008)	(0.0003)	(0.0001)	(0.0001)	(0.0001)
IPC4Digit	-0.0015	0.0006	-0.0001	-0.0003	-0.0002	0.0017	-0.0007	0.0002	0.0003	0.0002
	(0.0083)	(0.0033)	(0.0007)	(0.0014)	(0.0011)	(0.0083)	(0.0033)	(0.0007)	(0.0015)	(0.0011)
USC3Digit	0.0251**	-0.0099**	0.0021**	0.0043**	0.0035**	0.0268**	-0.0105**	0.0022**	0.0047**	0.0036**
	(0.0107)	(0.0042)	(0.0009)	(0.0019)	(0.0015)	(0.0108)	(0.0042)	(0.0009)	(0.0019)	(0.0015)
Inventors	-0.0275***	0.0108***	-0.0023***	-0.0047***	-0.0038***	-0.0255**	0.0100**	-0.0021**	-0.0045**	-0.0034**
	(0.0103)	(0.0040)	(0.0009)	(0.0018)	(0.0014)	(0.0103)	(0.0040)	(0.0009)	(0.0018)	(0.0014)
$InventorActivity_{Medium}$	-0.0241	0.0095	-0.0020	-0.0042	-0.0033	-0.0317	0.0125	-0.0027	-0.0056	-0.0042
	(0.0368)	(0.0145)	(0.0031)	(0.0064)	(0.0050)	(0.0369)	(0.0145)	(0.0032)	(0.0065)	(0.0049)
$InventorActivity_{High}$	-0.1490***	0.0585***	-0.0125***	-0.0257***	-0.0203***	-0.1694***	0.0664***	-0.0143***	-0.0296***	-0.0225***
	(0.0358)	(0.0140)	(0.0031)	(0.0062)	(0.0048)	(0.0360)	(0.0141)	(0.0032)	(0.0063)	(0.0048)
Assignees	0.3356***	-0.1317***	0.0275***	0.0579***	0.0463***	0.3760***	-0.1474***	0.0309***	0.0659***	0.0506***
	(0.0540)	(0.0212)	(0.0047)	(0.0094)	(0.0075)	(0.0547)	(0.0215)	(0.0049)	(0.0098)	(0.0074)
$AssigneeActivity_{Medium}$	-0.2114***	0.0832***	-0.0192***	-0.0362***	-0.0278***	-0.1947***	0.0766***	-0.0177***	-0.0339***	-0.0250***
	(0.0367)	(0.0145)	(0.0038)	(0.0063)	(0.0047)	(0.0369)	(0.0146)	(0.0038)	(0.0064)	(0.0046)
$AssigneeActivity_{High}$	-0.0682*	0.0268*	-0.0057*	-0.0118*	-0.0093*	-0.0799**	0.0313**	-0.0067**	-0.0140**	-0.0106**
	(0.0366)	(0.0144)	(0.0031)	(0.0063)	(0.0050)	(0.0369)	(0.0145)	(0.0032)	(0.0065)	(0.0049)
Observations	7,095	7,095	7,095	7,095	7,095	7,095	7,095	7,095	7,095	7,095

Columns (1) and (7) report estimates of average effects and the rest of the columns marginal effects of ordered probit. In all estimations time dummies (*GrandYear*) and technology field dummies (*TechnologyDummy*) are included but for brevity not reported here.
Heteroskedastically robust standard errors are reported in parentheses.
(*) The MIT and the University of California are excluded (outliers) due to their exceptional patenting performance.

More specifically, when examining the marginal effects, in columns (7) to (10), two noteworthy findings emerge. First, as column (7) shows, not only all federally funded patents are less likely to switch to LES by the issue year than non-federally supported patents, but also the funding agency greatly matters, as differences in the probability of a patent being licensed depends on the source of funding.

For example, the DOE funded patents are the least likely among the federally funded patents to be licensed by issue year, whereas the NIH funded are the most. In particular, holding all other variables at their means, DOE funded patents are 28.5% less likely to switch to LES by issue year than non-federally funded patents. In the other extreme, NIH funded patents are only 5.3% less likely to be licensed by issue than non-federally funded patents. This difference could be partially explained by the nature of the funded patents. Second, at later stages, and in particular by the 7.5th and 11.5th year, federally funded patents compared to their non-federally counterparts are more likely to be licensed, with patents being funded by the DOE to now exhibit the highest propensity (about 19% in column (10)) and the NIH the smallest (about 2% in column (10)). The large difference between the DOE and NIH funded patents can be attributed to various reasons. Link and Ruhm (2009) argue that commercialized technologies that result in improvements in health are particularly likely to have high rates of return, which results in higher incentive for an early license. This may not be true for patents funded by the DOE. According to Herzog and Kammen (2002), the sparse federal investment in energy technologies has resulted in financial and policy uncertainty, which, in turn, discourages energy technology from early development.

With respect to the rest of the patent characteristics, there is no important difference between estimates reported in columns (1) to (5) and the corresponding ones, in columns (6) to (10). Given government sponsorship, it is further found that patents with a larger prior art base ($BackwardCitesPat$) are more likely to be licensed early, while patents with larger posterior art base ($ForwardCites$) are more likely to be licensed at a later stage. In contrast, the number of prior non patent citations (BackwardCitesNonPat) is not significantly associated with the speed of switching to LES. Large number of backward citations may indicate that the invention is in a relatively mature technology area. The resulting patent presumably suggests that the cited innovation is economically valuable Hall et al. (2005), giving the incentive to profit seeking organizations for faster transfer in the marketplace. The opposite could be the case for the forward citations, which indicate a later incentive to protect the property's rights Lanjouw and Schankerman (2001).

Furthermore, patents which have more inventors ($Inventors$) are licensed early, while the opposite seems to be the case for patents that belong to many co-assignees/universities (*Assignees*). Inventor's patenting experience, also shapes the speed of licensing. Patents, whose inventors have substantial prior patenting experience show 5.8% to 6.6% greater likelihood to be licensed early than patents whose inventors have no prior patenting experience. This finding is consistent with Elfenbein (2007). In terms of university's patenting experience, it is found that medium-sized universities are more likely to have their patents licensed early than small-sized universities by, approximately, 8%. While large universities are also more likely to have their patents licensed early than small-sized universities, the difference is about 3%. Finally, the number of 3-digit US classifications ($USC3Digit$), which proxies patent scope, is positively associated with delayed licensing.

Overall, it is found that federally funded university patents are more likely to be licensed at later years over their lifecycle compared to non-federally funded patents with the DOE funded patents to take the most time to be licensed and the NIH funded patents the least. The greater the prior art base of a patent, the more inventors involved, the larger their patent experience, and the larger the size of the patent stock of the university, the earlier a patent is commercialized. In contrast, the higher the posterior art base, the larger the number of assignees a university patent belongs to, and the smaller the patent experience of the inventor and stock of patents in a university, the higher the propensity of a university being licensed at a later stage.

For robustness purposes, alternative model specifications and techniques have also been applied.[27] The findings remain robust and do not alter in any significant way.

2.5 Conclusion

The present chapter addresses two questions that thus far have not been approached in a comprehensive manner in the literature, mainly due to data limitations: (i) Are federally funded university patents more (less) likely to be transferred to the marketplace than non-federally funded? and (ii) Are federally sponsored university patents faster transferred to the marketplace than non-federally funded?

[27] There are two dynamic alternatives to an ordered probit. A 'pseudo' dynamic (in lack of better term) and a more appropriate one, the hazard rate model. The first model is expressed as $T_i = X_i^{'}\beta + u_i$ where, $X_i^{'}\beta$ is defined as in Section 2.1; T_i is the number of years that patent i takes to be licensed and takes the values of 0, 4, 8, or 12. The second alternative dynamic model would be a hazard rate model, where one, models the probability of a patent being licensed at year t given that it has not been licensed up until year $t-1$. To estimate how each variable is associated with the hazard rate of licensing, the Cox proportional hazards model is used: $h_{License}(t, X_i) = h_0(t)\exp(X_i^{'}\beta)$ where, $h_{License}$ is the probability that patent i is licensed at period t (counted in years), given that it has not been licensed up until $t-1$; $X_i^{'}\beta$ is defined as in Section 2.1. A patent enters the dataset at year 0 and exits on the year that pays LES fees. Hence, it can exit at year zero, four, eight or twelve. Estimates of the two alternative dynamic models are similar with those of the ordered profit, used in the chapter.

To answer these questions, this study exploits a unique facet of the US patent system that has been overlooked so far, the fee payment data scheme associated with statutory rules on how and when university patent holders pay these fees. Based on this observation, someone is able to determine the propensity and time of technology transfer from the university to the marketplace of both federally sponsored - distinguishing also by funding agency - and non-federal funded patents and the associated characteristics of transferred patents.

Based on a large sample of 20,877 university patents issued between 1990 and 2000, the study finds, with respect to the first question, that government sponsorship of research does not seem to be associated with a systematically different propensity of licensing compared to non-federally funded patents. The only notable exception is the Department of Defense funded patents, which are less likely compared to non-federally sponsored counterparts to be licensed.

Furthermore, and with respect to the second question, it is found that federally funded university patents are more likely to be licensed at later years over their lifecycle compared to non-federally funded patents, with the Department of Energy funded patents to take the most time to be licensed and the National Institute of Health funded patents the least.

Finally, patent characteristics, such as the prior and posterior art base of a patent, the number of inventors and assignees involved in a patent along with the size of their patenting activity, and the scope of a patent are significantly associated with both the propensity and the speed of patent transfer to the marketplace.

Chapter 3

Individual Inventors and Market Potentials: Evidence from US patents

This chapter examines the commercialization propensities of individual inventors' patents. Exploiting a peculiarity of the US patent system, concerning patent renewal fees in order to obtain small or large entity status, someone is able to distinguish patents that become part of a large corporation's patent portfolio. Using an extensive dataset of US patents, both for domestic and foreign individual inventors, one finds that patent characteristics, size of research teams, prior patenting experience and past corporate patenting activity are positively associated with increased likelihood of transferring patent rights to large corporations.

3.1 Introduction

An "invention" is defined as the activity directed toward the discovery of new useful knowledge about products and processes, as described by Schmookler (1957) and it is most frequently protected by the use of patents which grant exclusive rights to the owner of the invention for a limited time in exchange for full disclosure. Users of this type of Intellectual Property (IP) can be corporations, small businesses, nonprofit organizations or even individual or independent inventors.[1].

Patented inventions by individual inventors constitute approximately 15% of total patents, according to United States Patent and Trademark Office (USPTO). While this may not seem as a big share, scholars have shown that individual inventors' inventions play a significant role in large firms' R&D strategies. Large corporations will often look for complementary

[1]According to the United States Patent and Trademark Office (USPTO), an independent inventor is defined as one whose patent at the time of grant is unassigned (i.e., patent rights are held by the inventor) or assigned to an individual:(http://www.uspto.gov/web/offices/ac/ido/oeip/taf/cbcby_in.html)

inventions outside their research labs to enhance their innovative performance. One of the main places they will seek for such complementary assets are individual inventors.[2] Individual inventors, on the other hand, in many occasions would prefer not to fully develop their inventions; instead, they would prefer to license or sell them to corporations that they will be in charge with dealing with all the development and production challenges (Arora and Gambardella, 2010; Gambardella et al., 2007).

Therefore, a market for technology can function as an efficient mechanism of allocating innovative labor which can be beneficial for all parties involved, including large corporations, inventors and society (Conti et al., 2013). In an interesting case study, in 1936, Eugene Houdry, a French engineer who invented catalytic cracking of petroleum feed stocks moved to the United States with a purpose to commercialize his invention. His invention was then developed by Standard Oil of New Jersey, now ExxonMobil (for more see Arora and Gambardella (2011)). This invention was one of the building blocks of refining technology.

Given the significance of individual inventors as an integral part of economy-wide innovation process, governments, and nonprofit organizations have developed programs to promote innovation by individuals. They provide consulting and evaluation services to inventors who want to transfer their inventions to the marketplace. Astebro and Gerchak (2001), in a case study of the Canadian Innovation Centre and its Inventor's Assistance Program, found significant social benefits in consulting independent inventors on how they can best manage and/or commercialize their inventions. However, such programs are not always successful. Spear (2006), for example, indicates that the National Research Development Corporation (NRDC) in the UK had low success rates in independent inventors' patent commercialization. [3]

The objective of this study is to examine commercialization and market potential of individual inventors' patented inventions. In particular, there is an interest on how the patent's characteristics, the size of the research team, the prior patenting experience of the inventor, the inventor's previous corporate ties, as well as some state macroeconomic factors are associated with commercialization of inventor owned US patents. Although, it is difficult to observe commercialization, one can infer to this concept in this study by exploiting a particular facet of the US patent system, namely switches from Small Entity Status (SES) to Large Entity Status (LES) for renewal fee purposes.

It is found that approximately twelve percent of individual inventors' patents have switched to LES. In addition, the patent characteristics, such as citations, claims and application length, are positively associated with the likelihood of a patent to be commercialized

[2] The other two main sources are startups and universities.

[3] NRDC started in 1948 to help inventors in UK transform inventions into innovations. For an in-depth analysis of the program see Crawley (1993) and Lavington (2011)

to a large corporation. Furthermore, it is discovered that the size of the inventive team is a positive indicator of commercial potential, a result that coincides not only with Chassagnon and Audran (2011) who emphasize the noteworthy influence of collaborations on inventors' innovativeness but also with Singh and Fleming (2010) who show that patent quality is on average higher from research teams' than single inventors' efforts. Prior patenting experience is also positively related with commercialization. Moreover, patents, where at least one inventor has prior corporate ties, have higher probability of being commercialized, a result that agrees with findings of Lawson and Sterzi (2014), where they have indicated that such patents are of higher quality, approximated by more forward citations. All of the above mentioned results are similar across the location of the inventor and technology fields.

This study contributes to the literature of commercialization of individual inventors' technological advancements and the market for technology literature by employing patent-level data contrary to the vast majority of scholarly work that has relied on primarily survey based evidence. For instance, for surveys in the US, see Weick and Eakin (2005) and Wilkins et al. (2008), in Canada, see Amesse et al. (1991) and Dagenais et al. (1991), in Sweden, see Ejermo and Gabrielsson (2007) and Braunerhjelm and Svensson (2010) and in Italy, see Schettino et al. (2013) among others. Additionally, Gambardella et al. (2007) employed the PatVal-EU survey to examine the licensing determinants of patents in six different European countries. However, their sample included a small percentage (2.5%) of individual inventors' patents. To our knowledge, this is the first study that uses such an extensive dataset of individual inventors' patents, combining information from several sources and examining patent characteristics in the propensity of transferring patented inventions to the marketplace.

In terms of policy implications, a number of insights is offered. A first policy recommendation would be to motivate cooperation amongst inventors as inventions by research teams are more likely to be commercialized. Additionally, encouraging open channels of communication between firms and inventors can enhance a market for technology as prior ties by inventors appears to increase the likelihood of technology transfer to large corporations.

It should be noted that a causality explanation between inventor, patent, regional characteristics and commercialization to large corporations is not offered. Given the importance of markets for technology, providing insights on how the above dimensions are associated with the likelihood of transfer of rights (sale or licensing) to large corporations is still informative with respect to policy.

The remainder of this chapter is organized as follows. Section two describes the concept of commercialization by individual inventors and how it is approximated. Section three presents the econometric specification and describes how the data is constructed. Section four outlines the data and empirical results, whereas the final section concludes.

3.2 Commercialization

There are two different ways for an individual inventor to achieve commercialization. He can either develop the invention to an end user product/service in-house or to license (or sell) the invention to a third party, usually to an established firm; see Braunerhjelm and Svensson (2010). The former is considered as an internal (direct) while the latter as an external (non-direct) method of commercialization; see O'Connor and Hewitt-Dundas (2013).

The study infers commercialization activity to large corporations from publicly available data, based on the following procedure. In the USPTO a patent applicant pays renewal fees in order to maintain the enforceability of a US patent at 3.5, 7.5 and 11.5 after the patent is granted. Individuals, small business and nonprofit organizations are defined as "small entities" in the Code of Federal Regulations (CFR) register. [4] Patents issued to one of those entities have the right to pay SES fees, which are approximately half the fees of LES.[5,6] Transfer of right (such as sale and licensing) to a large corporation of a certain patent drives to loss of SES and leads to mandatory payment of LES fees for that particular patent. This switch from SES to LES implies commercialization to a large corporation. It should be noted in this study large corporations are defined as those that are obliged to disclose LES. According to CFR, firms which have, including their affiliates, 500 employees are LES for USPTO fee purposes (13 CFR §121.802). These are the large corporations in the sample.

The above switch can be observed in any of the following two main scenarios. First, the inventor may sell or license the patented invention to a large corporation. Alternatively, the inventor may grow this patented invention and then transfer it to his own or a third party startup. Then that startup may itself grow to a large corporation or even achieve an Initial Public Offering (IPO) which will facilitate growth. Once the firm no longer qualifies for SES, then any remaining renewal fees have to be paid under LES. For case studies of these alternative scenarios see Meyer (2005).

While the payment of LES fees by individual inventors' patents reveals transfer of right to large corporations, two important caveats need to be mentioned. First, this switch cannot distinguish between the above two scenarios. Therefore, while via this switch one can infer transfer of rights to a large corporation, they are not aware the exact path that it took place.

[4] For further information see 37 U.S. Code §1.27 "Definition of small entities and establishing as small entity to permit payment of small entity fees; when a determination of . . . shall be considered as a fraud practiced or attempted on the Office."

[5] Under 35 U.S Code 41 (h)(1), fees charged under 35 U.S Code. 41 (a),(b)and (d)(1):
". . . shall be reduced by 50 percent with respect to their application to any small business concern as defined under section 3 of the Small Business Act, and to any independent inventor or nonprofit organization as defined in regulations issued by the Director".

[6] For extensive and detailed information on fee schedules, visit the USPTO official Gazette notices (http://www.uspto.gov/go/og/index.html).

Second, this switch cannot capture patents that may have been profitable by either further development or transfer to a medium sized firm. In other words, someone cannot capture patents that may have been successful in generating income but did not become part of a large corporation's portfolio. Therefore, even though this switch cannot capture the above instances, it still captures an important aspect of the technology market which is transfer of rights from individual inventors to large corporations.

Finally, it should be noted that renewal data have been extensively used to infer the private economic value of patents, since the pioneer work of Pakes (1986) and Schankerman and Pakes (1986), whereas Bessen (2008) and Liu et al. (2008) were the first to examine renewal data of US patents. Furthermore, Bessen (2008) and Rassenfosse and van Pottelsburghe de la Potterie (2012) have also explicitly accounted for whether the patent fees paid correspond to large or small entity status, but their sole motivation was to infer the economic value of patents in money-metric variables and did not focus on switches from SES to LES and what that might indicate.

3.3 Empirical Specification and Data

This section presents the empirical specification and the way the dataset was constructed.

3.3.1 Empirical Specification

The likelihood of a certain patent switching to LES can be described by a probit model defined as follows:

$$Prob(LES = 1|Xi) = \Phi(Xi\beta) \tag{3.1}$$

where the dependent variable LES takes the value 1, if patent i, has paid LES fees during its patent life, and 0 otherwise; Φ is the standard normal cumulative distribution function and Xi is a set of covariates defined as:

$$\begin{aligned} \mathrm{X}_i\beta = {} & \beta_0 + \beta_1\mathrm{Citations}_i + \beta_2\mathrm{Scope}_i + \beta_3\mathrm{Inventors}_i + \beta_4\mathrm{PastPatExperience}_i \\ & + \beta_5\mathrm{PriorTies}_i + \beta_6\mathrm{StateCharacteristics}_i + \beta_7\mathrm{GrantYear}_i + \varepsilon_i \end{aligned} \tag{3.2}$$

where $\varepsilon \sim$ N(0, 1). The set of variables $Citations_i$ for patent i includes the variables $ForwCites_i$, which is the number of patent citations patent i receives by 2010, the variable $BackCitesPat_i$, which is the number of citations patent i makes to the patent literature and the variable $BackCitesSci_i$, which is the number of citations patent i makes to the scientific literature. The set of variables $Scope_i$ includes the number of claims, $Claims_i$, the application length, $AppLength_i$ and technology fields dummies $TechnologyDummy_i$. For the last variable, each patent i is assigned to a broad technology field according to its primary US Classification (Hall et al., 2001). As there are 37 broad technology fields, the number of technology field dummies is 36 to avoid the dummy variable trap.

The set of variables $Inventors_i$ capture the collaborations of individuals.$InventorLow_i$ takes the value of 1 when there is only one inventor in patent i and 0 otherwise. $InventorMed_i$ takes the value of 1, if there are two inventors in patent i and 0 otherwise. $InventorHigh_i$ takes the value of 1, if there are more than two inventors in patent i and 0 otherwise. As before, to avoid the dummy variable trap, $InventorLow_i$ is excluded.

The past patenting experience of the inventors of a certain patent is denoted as $PastPat-Experience_i$, which is a set of four dummies. $PastPatsNo_i$ takes the value of 1, if all inventors in the patent have no previous patenting experience and 0 otherwise. $PastPatsLow_i$ takes the value of 1, if at least one inventor in the patent has previously one patent as an inventor and 0 otherwise. $PastPatsMed_i$ takes the value of 1, if at least one inventor in the patent has between 2 and 9 past patents and 0 otherwise. $PastPatsHigh_i$ takes the value of 1, if at least one inventor in the patent has 10 or more past patents and 0 otherwise. $PastPatsNo_i$ is not included in the estimation.

$PriorTies_i$ is a set of two variables which capture whether the inventor has had any patents under a corporation or a university: $PastCorp_i$ takes the value of 1, if at least one inventor of the patent was an inventor in a previous patent that was owned by a corporation and 0 otherwise, whereas $PastUniv_i$ takes the value of 1, if at least one inventor of the patent was an inventor in a previous patent that was owned by a university and 0 otherwise.

$StateCharacteristics_i$ is a set of two variables that control for state characteristics: $StateHigh_i$ takes the value of 1, if the lead inventor of patent i is located in a state that has produced the year that patent i was granted more than a thousand patents and 0 otherwise and $ShareTechState_i$ is the share of the technology field that the patent i belongs to, at the grant year in the specific state and takes values between 0 and 100. These two dummy variables are similarly constructed at the country level for foreign inventors. $GrantYear_i$ is a set of dummies that captures the year that patent i was granted. Table A.1 includes the definitions of all variables used in the present analysis.

The choice of using dummy variables instead of continuous is strictly for a more intuitive exposition of the results. Therefore, to provide further robustness, certain dummies are replaced with their continuous variables counterparts. Specifically, $InventorsMed$ and $InventorsHigh$ are replaced with the number of inventors (#$Inventors$); $PastPatsLow$, $PastPatsMed$, $PastPatsHigh$ with the number of past patents (#$PastPats$); $StateHigh$ with the number of patents in the state or country (#$StatePats$).

3.3.2 Data Construction

The first source of data is the Patent Data Project, sponsored by the National Bureau of Economics Research (NBER), hereafter NBER dataset, in which all patents are categorized by assignee type.[7] The sample of interest includes all patents that are assigned to a "US individual" or "Foreign individual" or are unassigned, which means that they are owned by the patent inventors, and are issued between 1990 and 2000. Overall, 197,407 inventor-owned patents are obtained.

From the NBER dataset information was directly obtained concerning the dummy variables *TechnologyDummy* and *GrantYear*. In addition, from the same dataset the variable *ShareTechState* was constructed, since the location information for each patent assignee was available as well as the variable *StateHigh*, and therefore the number of patents for each state or country per year could be calculated. The variables *ForwCites*, *BackCitesPat*, $BackCitesSc_i$, *Claims*, and *AppLength* are obtained from Lai et al. (2011). More importantly, in this dataset, the authors have disambiguated inventor names and have assigned a unique identifier to each inventor. Using this information one is able to acquire information for *PastPatExperience* variables. To construct *PriorTies* information is combined from both NBER and the dataset by Lai et al. (2011). From the latter, somenone can obtain the inventor's patenting activity and from the former can identify which prior patents were owned by corporations or universities.

Next, information was obtained about recorded maintenance fee events for the above patents from Google Bulk downloads, a dataset maintained weekly by USPTO.[8] The event codes in this dataset enable the distinguishment for these patents whether SES or LES fees have been paid. If LES fees have been paid for a patent, this observation is considered as an indication for successful technology transfer to a large corporation. Specifically, according to the Code of Federal Regulations (37 CFR §1.27 paragraph a(1)) an individual is entitled in paying SES fees as long as he/she has:

> ... not assigned, granted, conveyed, or licensed, and is under no obligation under contract or law to assign, grant, convey, or license, any rights in the invention.[9]

It should be noted that this regulation applies to each individual patent. Hence, an inventor with more than one patent may pay LES fees for some and SES fees for others depending on their commercial status.

[7] https://sites.google.com/site/patentdataproject/

[8] http://www.google.com/googlebooks/uspto-patents-maintenance-fees.html

[9] It should be noted that the regulation further states that an inventor:
"... who has transferred some rights in the invention to one or more parties ... can also qualify for small entity status if all the parties who have had rights in the invention transferred to them also qualify for small entity status either as a person, small business concern, or nonprofit organization". In other words if an inventor transfers any rights or licenses the patent another Small Entity, then the owner is still eligible to pay SES fees.

Failure to comply with the above regulations, i.e., not pay LES fees when required, will deem the patent invalid and therefore the rate of compliance is likely to be very high. On the contrary, while there could be inventors that pay LES fees, even though they do not have to do so, this is not very likely, since SES fees are approximately half of the LES fees and therefore inventors have significant incentive to take advantage of this regulation. Even though there are still cases where there may be noise in the data, any faulty renewal payments are most likely random and therefore will not bias the results.

3.4 Empirical Results

This section presents the probit estimations' results after presenting some descriptive statistics of the data used.

3.4.1 Descriptive Statistics

Before the empirical analysis is considered,worth presenting some interesting aspects of the dataset. First, as can be seen from Fig. 3.1, the share of inventor-owned patents issued per year in the USA during the period 1990−2000 remained roughly constant at about 15% of the total number of patents issued. In addition, the share of inventor-owned patents issued per year in the US during the same period that were switched to LES for renewal purposes was in the range 11−13%, (see Fig. 3.2). Overall, out of 197,407 individual inventors' patents, 23,871 (12%) switched their status to LES, as Table 3.2 depicts.

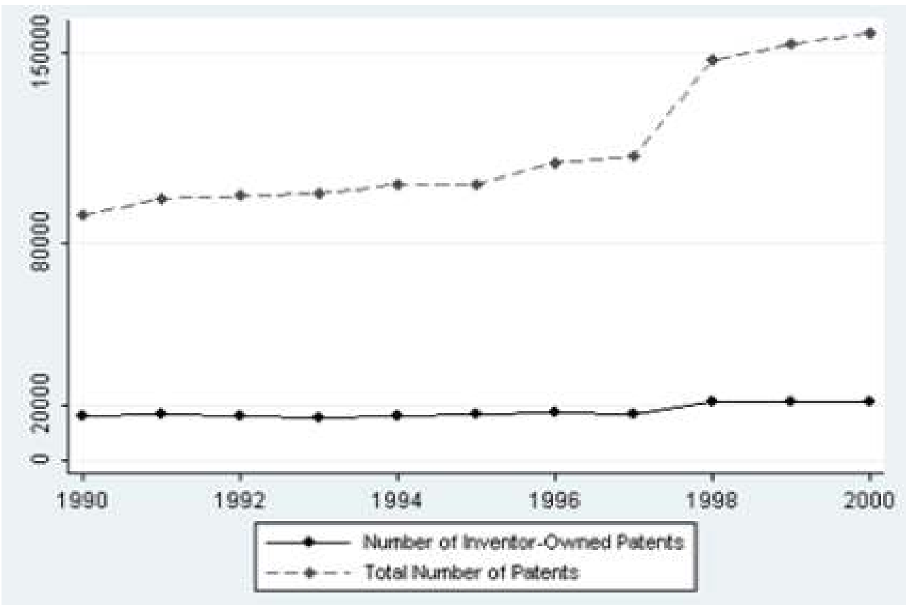

Figure 3.1: Total number of patents and inventor-owned patents per year.

Table 3.1: Definitions of variables

Variable	Definition
Citations	Set variable including: *ForwCites*, *BackCitesPat*, *BackCitesSci*
ForwCites	Number of citations patent *i* receives by 2010
BackCitesPat	Number of patent citations made by patent *i*
BackCitesSci	Number of citations of scientific literature made by patent *i*
Scope	Set variable including: *Claims*, *AppLength*, *TechnologyDummy*
Claims	Number of claims
AppLength	Application length
TechnologyDummy	Technology fields dummies
Inventors	Set variable including: *InventorsLow*, *InventorsMed*, *InventorsHigh*
InventorsLow	Dummy variable that takes value 1 when there is only one inventor in patent *i* and 0 otherwise
InventorsMed	Dummy variable that takes value 1 if there are two inventors in patent *i* and 0 otherwise
InventorsHigh	Dummy variable that takes value 1 if there are more than two inventors in patent *i* and 0 otherwise
PastPatExperience	Set variable that denotes past patenting experience of a certain patent's inventors including: *PastPatsNo*, *PastPatsLow*, *PastPatsMed*, *PastPatsHigh*
PastPatsNo	Dummy variable that takes value 1 if all inventors in the patent have no previous patenting experience and 0 otherwise
PastPatsLow	Dummy variable that takes value 1 if at least one inventor in the patent has one past patent and 0 otherwise
PastPatsMed	Dummy variable that takes value 1 if at least one inventor in patent already has $2-9$ patents and 0 otherwise
PastPatsHigh	Dummy variable that takes value 1 if at least one inventor in patent already has 10 or more patents and 0 otherwise
PriorTies	Set variable including: *PastCorp*, *PastUniv*
PastCorp	Dummy variable that takes value 1 if at least one inventor in patent was an inventor in a previous patent that was owned by a corporation and 0 otherwise
PastUniv	Dummy variable that takes value 1 if at least one inventor in patent was an inventor in a previous patent that was owned by a university and 0 otherwise
StateCharacteristics	Set variable that controls for state/country characteristics including: *StateHigh*, *ShareTechState*
StateHigh	Dummy variable that takes value 1 if lead inventor of patent *i* is located in a state/country that has produced more than 1,000 patents in year that patent *i* was granted and 0 otherwise
ShareTechState	Share of technology field that patent *i* belongs to, at grant year in specific state/country and takes value in range $0-100$
GrantYear	Set variable of dummies that captures year in which patent *i* was granted

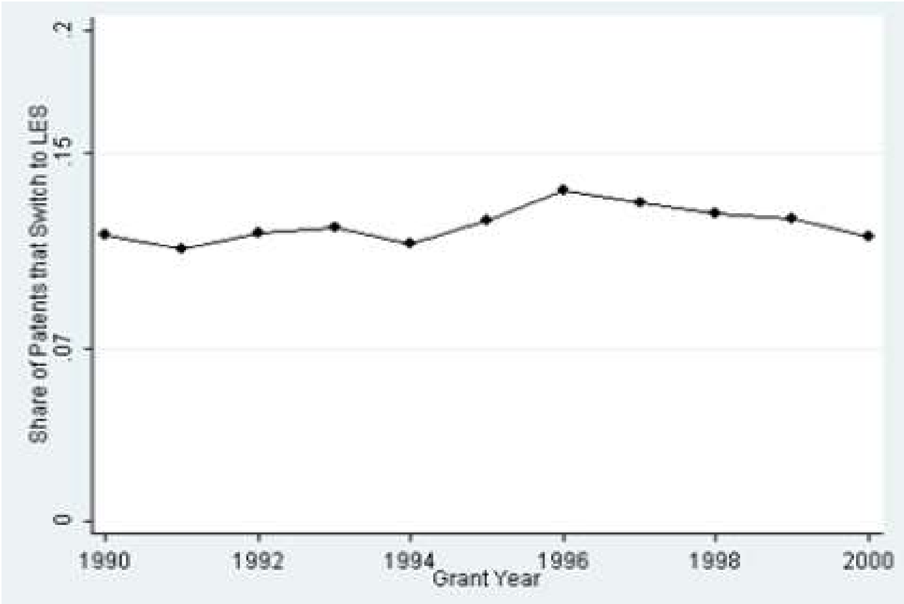

Figure 3.2: Share of inventor-owned patents that switch to LES for renewal purposes by grant year.

In particular, Table 3.2 displays the share of patents switching to LES according to six major technological fields. Computer patents have the highest likelihood (25%) of switching to LES followed by Drugs, Chemicals and Electronics. Contrary, Mechanicals and Other technology fields have the lowest likelihoods of switching to LES, even though these technological fields have the highest number of inventor owned patents. One possible explanation for observing this low propensity of switching to LES for Mechanicals is the fact that this technological field relies on consulting as the main tool for technology transfer (see for example Elfenbein (2007)).

Table 3.2: Allocation of individual inventors' patents by technology field

	Total No. of patents	Switch to LES	Switch to LES (%)	Patents by domestic inventors	Domestic switch to LES	Switch to LES (%)	Patents by foreign inventors	Foreign switch	Switch to LES (%)
Chemical	16,934	3,307	19.53	12,039	2,064	17.14	4,895	1,243	25.39
Computers	11,984	3,003	25.06	9,495	2,251	23.71	2,489	752	30.21
Drugs	21,665	4,416	20.38	17,243	3,272	18.98	4,422	1,144	25.87
Electronics	18,854	3,475	18.43	13,227	2,323	17.56	5,627	1,152	20.47
Mechanical	45,470	4,304	9.47	33,683	2,629	7.81	11,787	1,675	14.21
Others	82,500	5,366	6.50	65,000	3,470	5.34	17,500	1,896	10.83
Observations	197,407	23,871	12.09	150,687	16,009	10.62	46,720	7,862	16.83

Table 3.3: Summary statistics of independent inventors' patents by LES

Variable	Patents by domestic inventors (150,687)			Patents by foreign inventors (46,720)		
	No. LES 134,678	LES 16,009	p-value	No. LES 38,858	LES 7,862	p-value
ForwCites	7.65	13.93	0.00	6.13	8.24	0.00
	(0.03)	(0.20)		(0.05)	(0.17)	
BackCitesPat	9.48	13.11	0.00	6.43	6.93	0.00
	(0.02)	(0.13)		(0.03)	(0.08)	
$BackCitesSc_i$	0.74	3.08	0.00	0.45	1.50	0.00
	(0.01)	(0.10)		(0.02)	(0.07)	
Claims	12.58	17.56	0.00	9.77	12.93	0.00
	(0.03)	(0.12)		(0.04)	(0.11)	
AppLength	1.72	2.02	0.00	1.72	2.00	0.00
	(0.002)	(0.01)		(0.003)	(0.02)	
InventorsLow	0.81	0.60	0.00	0.84	0.59	0.00
	(0.001)	(0.004)		(0.001)	(0.01)	
InventorsMed	0.15	0.23	0.00	0.12	0.21	0.00
	(0.001)	(0.003)		(0.001)	(0.004)	
InventorsHigh	0.03	0.18	0.00	0.04	0.20	0.00
	(0.0005)	(0.003)		(0.001)	(0.004)	
PastPatsNo	0.56	0.21	0.00	0.59	0.34	0.00
	(0.001)	(0.003)		(0.002)	(0.005)	
PastPatsLow	0.13	0.11	0.00	0.13	0.12	0.02
	(0.001)	(0.002)		(0.001)	(0.004)	
PastPatsMed	0.22	0.38	0.00	0.21	0.31	0.00
	(0.001)	(0.004)		(0.002)	(0.01)	
PastPatsHigh	0.09	0.30	0.00	0.07	0.22	0.00
	(0.001)	(0.004)		(0.001)	(0.005)	
PastCorp	0.18	0.57	0.00	0.15	0.45	0.00
	(0.001)	(0.004)		(0.001)	(0.006)	
PastUniv	0.03	0.09	0.00	0.02	0.06	0.00
	(0.0004)	(0.002)		(0.001)	(0.003)	
StateHigh	0.70	0.75	0.00	0.61	0.74	0.00
	(0.001)	(0.003)		(0.002)	(0.005)	
ShareTechState	0.21	0.19	0.00	0.19	0.19	0.63
	(0.0002)	(0.001)		(0.004)	(0.001)	

Numbers in parentheses are standard errors

In addition, Table 3.2 distinguishes the share of inventor owned patents for each technological field according to the location of the inventors by considering two groups of patents, i.e., first when all inventors are within the US (domestic) and second when all inventors reside outside the US (foreign). It should be noted that 1,316 patents have already been excluded from the analysis, of which at least one inventor is located within the US and at least one is located outside the US.[10] Foreign inventors' patents have higher commercialization rates than domestic inventors on average, i.e., 16.8% versus 10.6% respectively. Given this difference, which seems to be significant, these two groups will be analyzed separately. Although, it is not intuitive why this difference is observed, perhaps one possible explanation is the fact that some foreign inventors are not aware of the SES and LES renewal schemes.[11] For an individual to pay SES fees needs to explicitly disclose it during the application or renewal payment phases; therefore paying LES fees is the default option. Hence, a foreign inventor may simply pay the default LES option simply because he/she is unaware of the existence of SES scheme. However, this large difference cannot be wholly attributed to faulty payments and probably indicates that foreign inventors' patents are more likely to be commercialized via a large corporation than domestic inventors' patents.

Table 3.3 presents the summary statistics for the variables of interest decomposing by type of inventor and renewal status. First, one can observe that *ForwCites* are higher in the case of patents that switched to LES. This finding is consistent with literature which has used forward citations to approximate patent quality (see Trajtenberg (1990)), private economic value (see Harhoff et al. (1999)) and firm's market value (see Hall et al. (2005)). Similar behavior is observed for *BackCitesPat*, $BackCitesSc_i$, *Claims* and *AppLength*. These variables have also been used to approximate patent quality; even though such metrics have been shown to be noisy (see Harhoff et al. (2003) and Bessen (2008)). Note that for all the above patent metrics, differences between commercialized and non-commercialized patents are bigger in the case of domestic than foreign inventors' patents. This observation could support the previous reasoning that a group of foreign inventors may not be aware of the renewal schemes and therefore pay LES fees even though they do not have to.

Patents that have switched to LES are more likely to have more than two inventors as *InventorMed* and *InventorHigh* show. For instance 18% of domestic inventors' patents that switch to LES have more than two inventors, while only 3% of patents that do not switch have more than two inventors. Similar results are also obtained when examining foreign inventors' patents. These observations are consistent with Singh and Fleming (2010) where they found that the more valuable patents are likely to be a product of inventor collaboration.

[10]While results for this group are qualitatively similar, they are not always significant due to the sample size. Results are not displayed for brevity but are available upon request.

[11]For instance, the European Patent Office has only a single payment scheme.

With respect to inventor's previous patenting experience, a variable that has been used as a proxy for inventor skill (see Conti et al. (2014)), one can observe that patents that switch to LES are more likely to have inventors that have had significant patenting experience. In particular, 68% of domestic inventors' patents that switch to LES have at least one inventor that has more than one prior patent, while the respective percentage of patents that do not switch is only 31%. Similar behavior is observed for foreign inventors' patents. Furthermore, patents that switch to LES are more likely to have inventors that have a previous patent under a corporation or under a university.

Finally, with respect to the US state or the country profile that the lead inventor is located, it is examined whether the size and the type of activity are associated with the likelihood of switching to LES. In the case of domestic inventors, 75% of patents that switch to LES their lead inventor is located in a state with more than a thousand patents annually. Contrary, 70% of patents that never switch to LES their lead inventor is located in such a state. This type of difference is considerably bigger when examining countries for foreign inventors' patents; 74% versus 61% respectively. Further, for patents that switch to LES the lead inventor is located in a state that on average has 19% of the patents in the same broad technology field as the focal patent; the percentage for patents that do not switch to LES is slightly higher at 21%. Overall, someone can observe that state characteristics do not seem to be associated significantly with patents that have switched to LES. However, the size of the inventive activity of the country seems to make a difference when examining foreign inventors' patents.

3.4.2 Probit Results

The next step was to study these relationships simultaneously. Table 3.4 reports the results of probit estimations that declare marginal effects estimated at the means of the variables for domestic inventors' patents, as shown in Columns 1−3, and for foreign inventors' patents, as shown in Columns 4−6. Column 1, which includes all domestic inventors' patents, shows that all patent characteristics, such as $ForwCites$, $BackCites$, $BackCitesSc_i$, $Claims$, and $AppLength$, have a positive and statistically significant relationship with patents switching to LES. These findings are consistent with studies (Bessen, 2008; Harhoff et al., 2003) that have shown that these metrics can be used as proxies for the value of the patent.

Someone can also observe from the coefficients of $InventorMed$ and $InvetorHigh$ that, the larger the group of inventors in a patent, the higher the likelihood of a patent switching to LES. Specifically, keeping all other variables at their means, a patent with two inventors is 3.3 percentage units more likely to switch to LES than a patent with just one inventor, whereas a patent with more than two inventors is 13.8 percentage units more likely to switch to LES than a patent with just one inventor. This finding is consistent with the results of

Table 3.4: Probit estimations for patents by domestic and foreign inventors

	Patents by domestic inventors			Patents by foreign inventors		
Variable	All patents	No. low/ med patents	No. outliers	All patents	No. low/ med patents	No. outliers
ForwCites	0.0009***	0.002***	0.0008***	0.002***	0.003***	0.001***
	(4.85e−05)	(0.0001)	(4.72e−05)	(0.0002)	(0.0004)	(0.0001)
BackCitesPat	0.001***	0.003***	0.001***	0.0009***	0.002***	0.001***
	(8.62e−05)	(0.0002)	(8.12e−05)	(0.0003)	(0.0006)	(0.0003)
$BackCitesSc_i$	0.0008***	0.001***	0.0007***	0.001***	0.0007	0.001**
	(0.0002)	(0.0003)	(0.0002)	(0.0005)	(0.0006)	(0.0004)
Claims	0.001***	0.002***	0.001***	0.002***	0.002***	0.002***
	(6.10e−05)	(0.0001)	(6.10e−05)	(0.0002)	(0.0004)	(0.0002)
AppLength	0.0048***	0.0078***	0.004***	0.0180***	0.0162***	0.0183***
	(0.0008)	(0.0018)	(0.0007)	(0.0021)	(0.0044)	(0.0021)
InventorsMed	0.0328***	0.0617***	0.0331***	0.0681***	0.0967***	0.0668***
	(0.0021)	(0.0048)	(0.0020)	(0.0054)	(0.0110)	(0.0054)
InventorsHigh	0.138***	0.239***	0.126***	0.191***	0.257***	0.184***
	(0.0048)	(0.0078)	(0.0049)	(0.0094)	(0.0143)	(0.0097)
PastPatsLow	0.0315***		0.0283***	0.0162***		0.0154***
	(0.0027)		(0.0025)	(0.0055)		(0.0053)
PastPatsMed	0.0542***		0.0481***	0.0287***		0.0276***
	(0.0025)		(0.0024)	(0.0052)		(0.0051)
PastPatsHigh	0.104***	0.0594***	0.0885***	0.100***	0.0875***	0.0731***
	(0.0042)	(0.0040)	(0.0048)	(0.0088)	(0.0087)	(0.0101)
PastCorp	0.0667***	0.0957***	0.0679***	0.115***	0.146***	0.110***
	(0.0025)	(0.0036)	(0.0026)	(0.0064)	(0.0079)	(0.0067)
PastUniv	−0.0023	−0.0112*	0.0015	0.0188*	0.0429***	0.0112
	(0.0031)	(0.0061)	(0.0034)	(0.0104)	(0.0156)	(0.0111)
StateHigh	0.0064***	0.0116***	0.0054***	0.0498***	0.0658***	0.0478***
	(0.0015)	(0.0039)	(0.0014)	(0.0036)	(0.0084)	(0.0035)
ShareTechState	0.0008***	0.002***	0.0006***	0.0002	−0.0002	0.00036*
	(9.29e−05)	(0.0002)	(9.13e−05)	(0.0002)	(0.0004)	(0.0002)
Observations	150,687	52,786	143,223	46,720	15,176	44,625

All columns report probit estimates (marginal effects). Time variables (*GrantYear*) and technology field dummies (*TechnologyDummy*) are included in all estimates but for sake of brevity are not reported here
Heteroskedastic robust standard errors are reported in parentheses
*** p <0.01, ** p<0.05, * p<0.1.

Singh and Fleming (2010) and Schettino et al. (2013) who found that inventors who work in teams produce patents that are of higher quality.

With respect to past patenting experience, patents with inventors with prior experience are more likely to switch to LES, as can be seen from the estimates of the coefficients of $PastPats$ variables. Specifically, patents where at least one inventor has one prior patent, are 3.2 percentage units more likely to switch to LES than patents where no inventor has a prior patent. Similarly, patents for which at least one inventor has two or more prior patents are 5.4 and 10.4 percentage units more likely to switch to LES than patents where no inventor has a prior patent respectively. This finding is also consistent with studies by Amesse et al. (1991) and Harison and Koski (2009) among others. Moreover, patents where the inventor had a patent registered under a corporation are 6.7 percentage units more likely to switch to LES. This finding shows that prior corporate ties are important and is consistent with results by Lawson and Sterzi (2014) who found that prior corporate ties are associated with higher quality patents, as indicated by more forward citations. It is not found a statistically significant relationship with inventors who had a prior patent under a university.

Further, patents whose lead inventors are located in highly innovative states are more likely to switch to LES than patents whose lead inventors are located in less innovative states, even though the difference is virtually zero (i.e. a difference of 0.6 percentage units). With respect to $ShareTechState$, one can observe that holding all variables at their means, a 10 percentage unit increase in $ShareTechState$ increases the likelihood of switching to LES by 0.8 percentage units. Overall, the aforementioned characteristics of the state where the lead inventor is located do not seem to be substantial.

Column 2 of Table 3.4 excludes patents where their inventors have little to no prior patenting experience. In particular, patents in which at least one inventor already has more than one patent are only considered and the results remain similar to Column 1, indicating that the above findings are not driven simply by the cases where inventors have little to no prior patenting experience. Column 3 checks for the robustness of the results for outliers by dropping patents where at least one inventor already has more than 20 patents. As previously, the results remain qualitatively similar.

Column 4 examines the above relationships in the context of foreign inventors. As before, the patent characteristics are positively associated with the propensity to switch to LES. The results with respect to the size of the research team, past patenting experience and prior ties, are by and large similar to the results for the patents by domestic inventors. A different result arises when exploring the patenting activity of the country in which the lead inventor is located. Specifically, a patent whose lead inventor is located in a country that produces more than 1,000 patents annually is five percentage units more likely to be switched to LES than a patent whose lead inventor is not located in such an innovative country. This result contrasts with the patents by domestic inventors, where the level of innovative activity in a state did not have a sizeable relationship with the commercialization potential. This comparison implies that while the location of domestic inventors may play little role in commercialization, after controlling for other factors, it is important for foreign inventors to be located within a country that is highly innovative. Although it is difficult, with the data at hand, to identify the large corporations who acquire or license the patents, the above finding implies that for patents by foreign inventors, the most likely candidates are firms within the same country as the lead inventor.

To ensure the robustness of the previous results similar estimations were performed as for the case of patents by foreign inventors. Column 5 of Table 3.4 only considers patents where at least one inventor already has more than one patent while Column 6 excludes patents where at least one inventor already has more than 20 patents. As before, the results remain similar.

To provide further robustness, certain dummies were replaced with their continuous variable counterparts: namely the size of the inventive team, the past patenting experience and the number of patents in the state or country. A replication of Table 3.4 after replacing these dummies is given in the Appendix (see Table B.1). The results are qualitatively similar.[12]

Finally, it is examined how the aforementioned results vary by technology fields without distinguishing domestic versus foreign inventors, since any substantial differences were not found (see Table 3.5). First, *ForwCites* are positively associated with the propensity of switching to LES across all technology fields, as well as other patent characteristics with the exception of $BackCitesSc_i$ which is not significant. Second, with respect to the size of the research team, one can observe that a larger group of inventors is associated with higher propensity to switch to LES for all technology fields. The smallest coefficient is observed in Others and the largest in Chemicals and Computers. In terms of past patenting experience, the positive relationship still holds for all technology fields. However, by far the largest positive relationship occurs for Drugs, indicating that past patenting experience in this field is more necessary to commercialize a patent by an individual inventors than is the case in all other fields. When examining prior ties it is found that, as before, those patents with inventors who had previous patents, under corporate assignees, have a higher likelihood of

[12] Further robustness is provided by considering other measures of prior patenting activity. Specifically, in separate specifications, the number of past patents of the most productive inventor is replaced with the average number of patents produced by the team, the total number of patents produced by all inventors, and prior patents of the lead inventor. The results are qualitatively similar to those in Table B.1 and are available upon request to the present authors.

switching to LES regardless of technology field. Patents in the Computers technology field with prior corporate ties have the highest likelihood of switching to LES.

Overall the results show that the characteristics of the patent are important predictors of it switching to LES. The size of the research team and prior experience are positively associated with the likelihood of commercialization by large corporations. In contrast to prior university patenting experience, prior corporate patenting experience is also a positive and significant indicator of the successful transfer of a patent. Results are similar for both domestic and foreign inventors as well as across different technology fields. Finally, only country level, and not state, innovative activity makes a difference when considering the market potential of patents by individual inventors.

Table 3.5: Patents by individual inventors by technology field

Variable	Chemicals	Computers	Drugs	Electronics	Mechanical	Others
ForwCites	0.002***	0.001***	0.002***	0.0009***	0.001***	0.0009***
	(0.0003)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(7.74e−05)
BackCitesPat	0.0005	0.001***	0.002***	0.0008**	0.001***	0.0007***
	(0.0003)	(0.0004)	(0.0003)	(0.0004)	(0.0001)	(0.0001)
$BackCitesSc_i$	0.002***	0.004***	0.001***	0.001	−0.0001	0.0005
	(0.0006)	(0.0007)	(0.0003)	(0.0008)	(0.0006)	(0.0006)
Claims	0.002***	0.001***	0.002***	0.002***	0.0007***	0.00109***
	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0001)	(7.74e−05)
AppLength	0.0135***	0.0124***	0.0165***	0.0058**	0.0046***	0.0079***
	(0.0029)	(0.0034)	(0.0028)	(0.0022)	(0.0016)	(0.0009)
InventorsMed	0.0917***	0.0975***	0.0306***	0.0755***	0.0333***	0.0229***
	(0.0086)	(0.0111)	(0.0073)	(0.0083)	(0.0041)	(0.0024)
InventorsHigh	0.265***	0.269***	0.177***	0.240***	0.139***	0.105***
	(0.0136)	(0.0166)	(0.0122)	(0.0146)	(0.0101)	(0.0068)
PastPatsLow	0.0135	−0.0054	0.0355***	0.0152	0.0260***	0.0232***
	(0.0107)	(0.0133)	(0.0098)	(0.0098)	(0.0047)	(0.0029)
PastPatsMed	0.0353***	0.0180	0.0768***	0.0122	0.0465***	0.0400***
	(0.0098)	(0.0130)	(0.0084)	(0.0086)	(0.0043)	(0.0028)
PastPatsHigh	0.0727***	0.0769***	0.178***	0.0730***	0.105***	0.0803***
	(0.0134)	(0.0178)	(0.0125)	(0.0120)	(0.0077)	(0.0057)
PastCorp	0.137***	0.188***	0.0883***	0.155***	0.0579***	0.0492***
	(0.0096)	(0.0135)	(0.0082)	(0.0093)	(0.0046)	(0.0033)
PastUniv	−0.0212**	0.0250	−0.0184*	0.0231*	0.0098	0.0090
	(0.0105)	(0.0203)	(0.0095)	(0.0124)	(0.0086)	(0.0063)
StateHigh	0.0236***	0.0181*	−0.0027	0.0306***	0.0212***	−0.0097***
	(0.0064)	(0.0102)	(0.0062)	(0.0059)	(0.0025)	(0.0019)
ShareTechState	0.0028***	0.0023***	0.0024***	−0.00095***	0.0025***	−0.0015***
	(0.0004)	(0.0006)	(0.0005)	(0.0003)	(0.0002)	(0.0001)
Observations	16,934	11,984	21,665	18,854	45,470	82,500

All columns report probit estimates (marginal effects)
Time variables (*GrantYear*) and technology field dummies (*TechnologyDummy*) are included in all estimates but for sake of brevity are not reported here. Heteroskedastically robust standard errors are reported in parentheses
*** p<0.01, ** p<0.05, * p<0.1.

3.5 Conclusion

Individuals have contributed diachronically to many great inventions. Thus, scholars have examined the pathways and determinants of the commercialization of such independent inventions in depth (Conti et al., 2013). Further, policies in many countries have been set to promote patenting and commercialization activity by individual inventors.

While individual inventors can potentially produce inventions of great potential, it is large firms who are equipped to develop such inventions to end-user products. Transactions of technology assets can therefore be beneficial to both inventors and large firms in addition to society. To this end, the objective of this study was to examine the population of individual inventors' US patents in the period 1990−2000 and analyze the factors that are associated with commercialization by large corporations. In particular, it exploits a peculiarity of the US patent system regarding the two different schemes for the payment of maintenance fees to infer commercialization activity by large corporations.

The results are potentially relevant in terms of policy as a market for technology between inventors and corporations is important in facilitating the timely development of promising innovations. Indeed, policies in different countries have already explored ways which can enhance this type of commercialization. This study provides insights into a series of dimensions that appear to be strongly associated with the propensity for commercialization.

The results show that individual inventors' patent characteristics, including forward citations, are positively associated with the likelihood of switching to LES, whereas the likelihood of commercialization also increases by the size of the team of inventors. Thus, policies that encourage collaboration among researchers/inventors can yield patented inventions with greater potential for commercialization. Past patent experience and prior corporate ties are also positively associated with the likelihood of switching to LES. Similarly, policies that encourage open channels of communication between firms and inventors can also yield promising opportunities for both parties. In the case of patents whose inventors are located in the USA, the state's inventive activity is not significantly associated with the likelihood of commercialization. However, if the inventors are located in a foreign country, the inventive activity of a country is positively and significantly associated with the likelihood of switching to LES. This finding probably indicates a cooperation by inventors with firms from the same country. Lastly, all the above results are similar across technology fields with subtle but noteworthy differences for past patenting experience and prior corporate ties.

Finally, is should be noted that while this observation on paying LES fees is a useful indicator for inferring commercialization by large corporations from publicly available data it still comes with three important caveats. First, there may be erroneous payments. While this may cause noise in the data, the noise is likely to be small. There are strong monetary incentives to claim SES whenever possible and high penalties if one falsely claims SES. Second, the payment for LES does not identify the exact path whereby an individual inventor's patent became part of a large corporation's portfolio. Finally, payment of LES will not capture patents that still generate revenues or have been commercialized on a smaller scale but never became part of a large corporation's portfolio. Given all these caveats, however, such a methodology can still capture a large part of the technology market that takes place between individual inventors and corporations.

Chapter 4

Mobility of Highly Skilled and Ordinary Individuals and Local Innovation Activity

This chapter studies what moves highly skilled individuals across space as well as their impact for local innovation activity. It focuses on patent inventors, as they are deeply involved in the production of innovation and are important vehicle of knowledge transmission. Employing patent data to track their moves, a gravity model is used to examine whether proximity, namely geographic, technological, economic, and cultural between countries and country level factors shape the flows of these talented individuals. As a comparison, in the same framework, the flows of ordinary, less skilled individuals are also analyzed. The evidence shows that proximity matters for migration flows. Gravity emerges everywhere; in the mobility of the highly skilled workers as well as in the ordinary migrant workers.It is found, however, that inventors are less geographically restricted and, therefore, their effective reach is beyond that of the average workers. Similarity in technological structure of production between countries is the main driver of inventor moves - especially for inventors from the most innovative countries, whereas social proximity matters more for the average migrant flows. Attractive country features for inventor mobility are the level of economic and financial development, the size of inventors' community and the trade linkages between origin and host country. Most of these factors as well as the tertiary education level of the host country appear to be also important for the less skilled migrant flows. Finally, knowledge and skills that move with the inventors have a positive impact on local innovation production.

4.1 Introduction

In an open economy immigration is a natural process. It certainly poses challenges for the host countries, but it also brings benefits, especially if immigrants are highly skilled. The mobility of these "talented" migrants has significant impact on the innovation capabilities and economic growth of the host country. In contrast, the loss of high skilled workers deprives their home countries of the scientists, entrepreneurs and other professionals who drive their economies to higher levels of efficiency and productivity.

Evidence based on the World Intellectual Property Organisation (WIPO) data shows that highly skilled individuals appear to be more mobile than the general population, which is consistent with a positively documented relation between skill and mobility. The fear of a "brain drain" and the exodus of economically valuable agents has led the revival of the interest on what determines the mobility of such individuals and what policies could influence these flows.

The goal of this chapter is twofold. First, it aims to study the role of proximity, along with a number of attraction factors in shaping international flows of highly skilled individuals. The focus lies on patent inventors - a specific class of highly skilled workers which is more homogeneous, as a whole, than the tertiary educated workers.[1] Although inventors are just a small proportion of skilled labour, they have a significant economic contribution: they are deeply involved in the production of innovation, which in turn is the main driver of economic growth and well-being (Dahl and Sorenson, 2009). They are also important vehicle of knowledge transmission; when skilled workers move from place to place, their knowledge and skills move as well (Breschi and Lissoni, 2009; Glaeser et al., 1995; Lucas, 1988).In order to track inventor moves, patent data is used. Using a gravity model it is analyzed how geographic, technological, economic, and cultural proximity among countries along with other relevant factors shape the flows of talented individuals. Second, using the same framework of analysis, it is also examined how these proximities can influence the mobility of ordinary individuals. Furthermore, the flow of people between firms, industries and locations has been proposed as an important mechanism for transferring knowledge and is argued as significant for innovation and firm demography (Audretsch and Keilbach, 2007; Agarwal et al., 2006).Therefore,the impact of highly skilled migrants on a country's innovation activity is explored.

The analysis relates and adds to a number of important works in the literature. It adds to the literature of spatial spillovers of knowledge flows and geographical distribution of

[1]Tertiary education movers can be individuals with non-university tertiary degrees, undergraduate university degrees, and postgraduate and doctorate degrees; however, these degrees may not always be fully comparable across different countries.

innovation and economic activity (Biagi et al., 2011; Lewer and der Berg, 2008; Moreno et al., 2005; Verspagen, 1999).[2] It mainly relates to the works of Miguélez et al. (2010), Miguélez and Moreno (2012), and Miguélez (2016) on the mobility of patent inventors and the knowledge they carry across space. Additionally, using a common framework it examines the mobility of less skilled, ordinary individuals. Furthermore, an attempt is made to assess the economic impact of inventor moves on local production of innovation activity, proxied by the number of patents produced in country. The study also closely affiliates to a rather recent branch of literature that documents evidence on learning via the mobility of highly skilled personnel. The focus on job moves of patent inventors is based on the assumption that ideas and knowledge are embodied in the minds of individuals (Feldman, 2000) and, consequently, job movements enable an inventor to take advantage of knowledge - not only codified, but also tacit - accumulated by other inventors in inventors' past jobs and share it in later jobs. A number of studies, in this literature, have extensively investigated the migration of inventors as a potential channel of market-generated knowledge diffusion. For example, Kim and Marschke (2005) explore the linkages between inventors' mobility and knowledge flows in the nanotechnology sector confirming that the mobility of inventors enhances the citations across patents of firms that the inventor was previously employed. Similar conclusions are also drawn by Agarwal et al. (2006), who document that knowledge flows to an inventor's prior location are approximately 50% greater than if the inventor had never lived there, suggesting that social relationships, not just physical proximity, are important for determining flow patterns.[3] Rather than studying citations exchanged between inventors, Giuri and Mariani (2013) focus on the interactions between inventors that were important for the development of a patent, using survey data for european patent inventors. It also remotely relates to an emerging literature on the economic consequences of immigration. The literature has been mostly concerned with the labor market impact of immigration and emigration in Europe (Docquier et al., 2014).

The modelling approach is applied to thirty countries over the period 2000-2012 with three key questions in mind: (i) What shapes the international mobility of inventors? (ii) What shapes the international mobility of the average, less skilled migrants? (iii) What is the impact of inventor migration flows on local innovation activity?

The evidence shows that proximity matters for migration flows. Gravity emerges everywhere, in the mobility of the very talented and highly skilled worker as well as in the average worker; the former group stretches farther in space than the latter. It is found, however, that technological proximity, i.e., the similarity in production structure, is the main driver

[2] For a detailed review of the different channels of knowledge flows and their impact on local innovation activity, see Drivas et al. (2016).

[3] See Miguélez et al. (2010) for an excellent survey of the literature.

for the mobility of a very talented individual; a finding that emerges particularly strong for inventors originating from the top innovating countries. Geographic closeness and social similarity, though significant, play a less important role, especially the latter. In contrast, social proximity matters more for the average migrant flows. Attractive country features for inventor inflows are the level of economic and financial development, the number of inventors and the trade linkages between origin and host country. Most of these factors as well as the tertiary education level of the host country appear to be also important for the less skilled migrant flows. Finally, the knowledge that moves with the inventors positively contributes to local innovation production.

The implications of the findings for the growth literature are potentially relevant. Although theoretical studies (Grossman and Helpman, 1991; Rivera-Batiz and Romer, 1991) emphasise the important consequences of disembodied knowledge flows over knowledge embodied in the trade of goods, there has been little effort, on the empirical side, to thoroughly explore this issue. Along with other important studies, this one makes an effort toward analysing knowledge diffusion via the channel of highly skilled individuals mobility and its impact on local innovation activity. It is found that knowledge flows are relevant to a country's innovation production, as external accessible R&D gained through mobility of inventors has a positive effect on a country's innovation activity, confirming thus the importance of embodied knowledge flows for technology transfer and economic growth.

The results further highlight the importance of policies and factors conductive to attract patent inventors. High level of economic and financial development, presence of other inventors for synergies and knowledge creation and exchange, and a strong trade activity could pave the ground for more inflows of talented people.

The remainder of the chapter proceeds as follows. Section 4.2 introduces the framework for analyzing migration flows and the estimation technique applied. Section 4.3 discusses the data. Section 4.3 presents the results. Finally, Section 4.5 summarises the findings and concludes.

4.2 Framework of Analysis

This section presents the framework of the analysis. After determining a gravity-like equation to model migration flows, the estimation approach is described.

4.2.1 Modelling Migration Flows

The decision of inventors to move is influenced by the comparison between expected utilities of the origin and destination locations. Migrating across countries has costs, monetary and non-monetary. The geographical separation between countries proxies some of the distance-related costs, such as the sunk cost of re-location that are difficult to measure empirically. Technological distance also proxies for costs of adjusting in a different (or similar) technological environment. Similarly, social differences in culture, language and religion, can impose additional challenges and costs for the migrants.

A gravity-like equation is used to model migration flows, as conventionally has been proposed in the literature (Drivas et al., 2016; Miguélez and Fink, 2013). As F_{ijt} are indicated the flows of inventors between two countries, i (destination) and j (origin) at year t. Therefore, for any country-pair i and j, the mobility of inventors is modeled to depend on geographic, technological, economic, and cultural (social) closeness, along with county-level attractive factors, as follows:

$$\begin{aligned} F_{ijt} = \beta_i + \beta_j + \beta_1 NeighbouringCountries\,[> 300\,km]_{ij} + \beta_2 Distance\,[< 1,110\,km]_{ij} + \\ \beta_3 Distance\,[1,110 - 1,500\,km]_{ij} + \beta_4 Distance\,[> 1,500\,km]_{ij} + \beta_5 Density_i + \beta_6 Density_j \\ + \beta_7 Inventors_i + \beta_8 Inventors_j + \beta_9 TechnologicalCloseness_{ijt} + \\ \beta_{10} CulturalCloseness_{ijt} + \beta_{11} EconomicCloseness_{ijt} + \beta_{12} Z_{ijt} + \varepsilon_{ijt} \end{aligned} \tag{4.1}$$

where β_i and β_j are origin and destination, respectively, country fixed effects; $Neighbouring-Countries\,[> 300\,km]$ takes the value of 1 for flows exchanged between countries that share a common border and their geographical centres are located in a distance more than 300 km, and 0 otherwise; the generic term $Distance\,[\,]$ denotes various distance classes and takes the value of 1 for flows exchanged between countries i and j that are located within a certain distance class, and 0 otherwise; $Density$ is population over country's area; $Inventors$ is the number of total inventors within a country; $TechnologicalCloseness$ is a vector that contains controls relevant to technological proximity between two countries; $CulturalCloseness$ is a vector of variables that capture aspects of social and cultural affinities of two countries; $EconomicCloseness$ captures the proximity of the economic performances between each country pair; Z is a control vector that contains factors that characterise the economic environment of the destination country i; and, finally, ε is an iid error term.

An inventor will decide to move to another country if the expected utility of the destination country is greater than the expected utility of the origin country plus the costs of moving,

both monetary and non-monetary. As is customary in the related literature, the costs of migrating across two countries are proxied by the geographical separation between them. The coefficients β_1 to β_4 provide a characterisation of how geographic factors shape inventor flows across countries. By model construction, each geographic coefficient captures the difference between knowledge flows diffused in geographic space to knowledge flows diffused within an area of 300 km.[4] The neighbouring area of a country is used as a benchmark to perform comparisons of inventor mobility flows across various distance classes. This distance taxonomy was chosen for the following reason: The longest distance between two neighbouring countries in the sample is approximately 1,110 km and this is the distance between the most populated cities of France and Italy, as the crow flies. There are also neighbouring countries that their geographic centres are located in less than 1,110 km; for instance Belgium (Brussels) and the Netherlands (Amsterdam) are 174 km apart (as the crow flies). Therefore, neighbouring countries are broken down into two groups: $NeighbouringCountries\,[<300\,km]$ and $NeighbouringCountries\,[>300\,km]$, which take the value of 1 for flows exchanged between countries that do share a common border but their geographical centres are located in a distance less (more) than 300 km, and 0 otherwise. The cut-off value of 300 km was chosen simply because it gives equal number of neighbouring countries within these two distance classes. The study proceeds till the distance between the two farthest located countries in the sample is exhausted.[5] The proposed classification, $Distance\,[<1,110\,km]$, $Distance\,[1,110-1,500\,km]$, and $Distance\,[>1,500\,km]$, allocates about equal number of countries in each distance class, which are not neighbours, meanwhile keeping the number of classes as low as possible.[6] The benchmark distance class is the $NeighbouringCountries\,[<300\,km]$, and therefore not included in the model. All geographic coefficients, consequently, will be compared to that benchmark. For example, β_1, the coefficient of $Neighbouring$
$Countries\,[>300\,km]$ captures the effect of geographic nearness of countries that share common borders, but are located in more than 300 km away, compared to flows exchanged in less than 300 km. Each one of the coefficients of the rest of the distance dummies, examines whether countries, located at a specific distance class exchange less (more) flows in comparison to flows that take place in an area of less than 300 km. One would expect

[4] As there is no data on the mobility of inventors within a country, the study uses as a benchmark the 300 km 'neighbouring' area of a country.

[5] The longest pair-country distance in the sample is the distance between Portugal and Japan: about 11,200 km and the shortest pair-country distance is between Slovakia and Austria: about 60 km.

[6] Alternative division of geographic space is not expected to modify results in any significant way. Continuous definitions of distance (e.g. polynomials) are not considered in this analysis as the aim is to stay close to the relevant literature (Mancusi, 2008; Peri, 2005), and further great loss of information is not expected.

that increasing geographic distance would reduce exchange among countries, signalling that migration flows are bounded in space and characterized by spatial declining effect.[7]

As in any typical gravity model, the size and population of a country may influence the exchange of the flows (Frankel and Romer, 1999). Glaeser et al. (1995) argue that low density areas are highly attractive to immigrants. One should expect, then, a negative influence of density on inventors' inflows. However, it could be also argued that dense, urban areas may have a larger supply of producer and consumer amenities (Perugini and Signorelli, 2010), so a positive effect of density (*Density*) might be observed for the destination country and negative for the origin. Furthermore, the total number of inventors (*Inventors*) acts as a proxy for the size of the host labour market for inventors, and consequently as a proxy for job opportunities and synergies. Therefore, one can expect a positive sign for the destination and a negative for the origin country.

Countries, however, located near each other may exchange more migration flows with each other simply because they have, for instance, similar technological efforts and/or technology specialisation of production structures or because they share common culture and roots. Not accounting for technological differences may lead to an overestimation of the geography effect. Therefore, along with the geographic proximity, the effect of the technological closeness (*TechnologicalCloseness*) between two countries is also considered. The latter is a vector that contains two indices, the technological effort (*TechEffortDistance*) proximity and technological (*TechSpecialisationSimilarity*) proximity.

More specifically, distance in the technological effort, *TechEffortDistance*, between two countries i and j for a given year, t, is proxied as[8]:

$$TechEffortDistance = \left| \ln \frac{R\&D_i}{Scientists_i} - \ln \frac{R\&D_j}{Scientists_j} \right|$$

One would expect that countries with high technological activity are also those with most intense inventor flows.

[7] The localisation of knowledge flows - exemplified by a variety of mechanisms such as citation, trade, and inventor flows - has been considerably tested in the knowledge spillover literature, which has unanimously documented the geographic confinement of knowledge diffusion (Belenzon and Schankerman, 2013; Alcacer and Gittelman, 2006; Thompson, 2006; Peri, 2005; Jaffe et al., 1993).

[8] The level of technological capability of a region is often proxied in the literature (Peri, 2005) by the level of R&D activity and human capital (number of researchers). According to innovation-driven models of growth (Aghion and Howitt, 1998; Grossman and Helpman, 1991), R&D stimulates innovation and facilitates the imitation of others' discoveries. Apart from contributing directly to invention, human capital also accounts for aspects of innovation not captured by the R&D sector, including 'learning-by-doing' and 'on-the-job-training' (Redding, 1996; Romer, 1989).

The similarity in the technological specialisation of production sectors, $TechSpecialisa-tionSimilarity$, between two countries i and j for a given year t is proxied by the (uncentered) correlation of their patent profiles and calculated as:[9]

$$TechSpecialisationSimilarity = \frac{sh_i^{'}\ sh_j}{\sqrt{\sum_{s=1}^{8} sh_{is}^2 \sum_{s=1}^{8} sh_{js}^2}}$$

where, sh are shares of patents issued in a technology field (out of eight, in total, fields) in countries i and j.

The constructed index ranges from zero (minimum similarity), which implies that the production structures are orthogonal, to one (maximum similarity), which denotes identical sectoral structure (patenting in exactly the same sectors) in two countries. Researchers are expected to benefit more from other researchers who work in the same or related sectors (Bode, 2004). Consequently, one expects to find a positive association between intensity of migration flows between two countries specialised in similar sectors.

The (dis)similarity in economic performances could be another reason that people move across countries. The economic similarity between two countries i and j for a given year t is proxied by the absolute difference of the log levels of real GDP as follows:

$$EconomicCloseness = \mid lnGDP_i - lnGDP_j \mid$$

One would expect countries with high economic activity to attract more migration flows; however, intense flows could also be observed between countries with similar (high) economic activities. In a similar fashion and for robustness, economic closeness could also be proxied by the absolute difference of top marginal tax rates or by the absolute difference of the log levels of real wages between two countries. The latter two could test whether there are monetary motives to the inventors' mobility (Akcigit et al., 2016).[10]

A less explored type of proximity that could shape inventor flows is cultural closeness between countries. Culture is history, religion, language, attitudes and values, beliefs and assumptions learned in early childhood that distinguish one group of people from another and can be critical to innovation (Beck and Moore, 1985). The dominant view in the literature is that national culture has a strong impact on organizational culture (Hofstede, 2001, 1980). Certain cultural norms and behaviours, for instance, trust and openness, awards and rewards,

[9] Structural proximity between two countries is measured as in Jaffe (1986). First, each patent is classified, according to their primary international patent classification, in one of 8 technology fields (Human Necessities; Performing Operations, Transporting; Chemistry, Metallurgy; Textiles, Paper; Fixed Constructions; Mechanical Engineerings, Lighting, Heating, Weapons, Blasting; Physics; and Electricity). Then, for each country, a patent profile is created by taking the vector of shares of patents issued in technology field, $Sh_i = (sh_{i1}, sh_{i2}, ..., sh_{i8})$, for a given year.

[10] The study examines the effect of top tax rates on "superstar" inventors' international mobility since 1977 using panel data on inventors from the US and European Patent Offices concluding that superstar inventors' location choices are significantly affected by top tax rates.

autonomy and flexibility may facilitate an innovative climate in organizations and help the organization to innovate more quickly, to be agile in changing times, and to get products to market faster than competition, while other aspects can impede innovation process.[11]

People whose languages and religions share common roots may also share similar cultural backgrounds. The study, therefore, computes indices of language and religion similarity. To construct the former index (*LinguisticSimilarity*), each language of every country in the sample is assigned to one of the six dominant Indo-European subfamilies, i.e., Germanic, Romance, Slavic, Baltic, Celtic and Greek, and one non Indo-European, the Uralic - the latter, includes Estonian, Finnish, and Hungarian.[12]

The index gets the value of 1 if the country pair belongs in the same subfamily, and zero otherwise.

To construct an index of religion similarity (*ReligionSimilarity*), the analysis follows Miguélez (2016) and proxies religion similarity for each country pair with an index built as follows:

$$ReligionSimilarity = (\%muslim * \%muslim) + (\%catholic * \%catholic) + (\%orthodox * \%orthodox) + (\%protestant * \%protestant) + (\%hinduism * \%hinduism) + (\%buddhist * \%buddhist) + (\%eastern * \%eastern) + (\%judaism * \%judaism)$$

The index ranges from 0 (no believers in common) to 1.

Culture similarities tend to facilitate the formation of trust and mutual understanding of individuals, smooth out communication problems, ease the screening of potential partners, help the managing and administration of a common project. Inventors can operate better in environments which are familiar to them and supportive of innovation. Therefore, one

[11] In his seminal study, Hofstede (1980) and subsequent studies (Efrat, 2014; Jones and Davis, 2000; Herbig and Dunphy, 1998) examine four dimensions of culture: power distance (acceptance of social stratification), individualism versus collectivism, masculinity, and uncertainty avoidance (the degree to which the members of a society feel uncomfortable with uncertainty and ambiguity) and examines the effect of each dimension on innovation activity. For example, the presence and level of social or organizational hierarchy, centralized power, formal vertical communication flows, top down control, formal rules and procedures, and resistance to change impedes innovation. Further, individualistic societies value freedom more than collectivist societies and freedom is necessary for creativity. Characteristics associated with strong uncertainty avoidance, such as the need for consensus, formal rules and procedures, are believed to inhibit innovation and an acceptance of competition and colleague dissent relate positively to innovative capabilities.

[12] Germanic languages are spoken in central and northern Europe and include Danish, Dutch, English, German, and Swedish. Romance languages are spoken in western, southern European regions; they include French, Italian, Portuguese, Romanian, and Spanish. The Slavic languages are to be found in the central Europe and the Balkans in southern Europe. They include Bulgarian, Croatian, Czech, Polish, Slovak, and Slovene. The Baltic languages are Latvian and Lithuanian. The Celtic languages include Irish. Finally, the Greek language is spoken in Greece and Cyprus. Outside the Indo-European family, Estonian, Finnish and Hungarian are Uralic languages. For further details, see www.ethnologue.com.

can expect a positive association between cultural closeness between countries and inventor mobility.

The vector Z contains a number of variables that could be relevant to inventor flows and related to financial, labor, and knowledge institutions. For example, the level of standards of living ($GDPcapita$) is included. The higher the standards of living in a country, the higher the level of education and innovation (and vice versa), as well as the number of inventors. The analysis further includes the level of financial development (FD)[13], research and development spending ($R\&D$)[14], public spending on tertiary education ($Tertiary$)[15] and labor market policies - stringency in employment protection regulation (EPL)[16] in both origin and destination country. The study also accounts for the stock of foreigners ($Foreigners_i$) at the destination country[17] and the intensity of trade linkages between origin and destination country ($Trade_{ij}$).[18]

4.2.2 Estimation Approach

The first step of the analysis consists of estimating the coefficients of equation (4.1). As the response variable of equation (4.1) is a discrete one with distribution that places the probability mass at non-negative integer values and with data concentrated in a few small discrete values skewed to the left, count data models are more suitable in this framework

[13] The level of financial development and its effect on economic growth and investment has been largely investigated in the finance-growth literature (Robinson, 1952; Schumpeter, 1911). More recently, a newly grown literature has switched its focus on finance-innovation nexus. For instance, Hsu et al. (2014) study the importance of financial development to innovation activity.

[14] A strong R&D environment in the destination and origin is expected to provide job and research opportunities for knowledge workers and is the main driver of economic growth according to R&D-driven growth models (Grossman and Helpman, 1991; Romer, 1990).

[15] Policies related to higher (tertiary) education could also be relevant for influencing the direction of inventor flows as higher level of education leads to more economic growth. Aghion et al. (2009), for instance, examine whether investments in education could raise growth. They find positive growth effects of exogenous shocks to investments in four-year college education in the U.S.

[16] The theoretical effects of labor regulations, such as employment protection legislation on innovation is rather ambiguous. EPL increases job security and the greater enforceability of job contracts may increase worker investment in innovative activity. But EPL increases firms' adjustment costs, which may lead to underinvestment in activities that are likely to require adjustment, including technologically advanced innovation. See Griffith and Macartney (2014) for an updated review of this literature and empirical evidence.

[17] The stock of immigrants in the destination country may also play a role in attracting migration flows as common values and culture smooths out may ease the settlement and connect the new comers both with the origin and the host country (Miguélez, 2016).

[18] Trade is a conduit of information which may also foster technological partnerships (Drivas et al., 2016). I also intended to use the share of FDI inflows over host country's FDI inflows but lack of FDI data for many countries prevented it.

(Cameron and Trivedi, 2013).[19] The most basic type of count data model is derived from the Poisson distribution and one can use a Poisson pseudo-maximum likelihood method of estimation. However, the Poisson distribution assumes equi-dispersion; that is to say, the conditional variance equals the conditional mean. However, in the case of over-dispersion, which often appears due to the presence of individual unobserved heterogeneity in the data generating process, the Poisson regression may lead to consistent, but inefficient estimates (Burger et al., 2009), with standard errors biased downward (Cameron and Trivedi, 2013). Therefore, the study applies negative binomial regression and maximum likelihood estimation techniques.

The second stage of the analysis consists of assessing the impact of inventor flows on local innovation activity. Therefore, an innovation function is estimated having two arguments: local activity/knowledge and the external (foreign) activity/knowledge that reaches a country via the flows of inventors. Having obtained the fitted values of the coefficients after estimating the inventor flows equation (4.1) in the first stage, the study uses them to weight the external knowledge that reaches a country. Country-year fixed effect estimators are used.

4.3 Data Description and Analysis

The empirical analysis is based on 30 OECD countries for the period 2000 to 2012.[20] Data are obtained from a range of sources.

Information on inventors' mobility ($InventorFlows$), defined as the number of countries a patent inventor changes during the lifetime, every time s/he files for a new patent, is obtained from the World Intellectual Property Organisation (WIPO) Database, which is publicly available and described in detail by Miguélez and Fink (2013).[21] An occurrence of inventor mobility is counted only if an inventor files for a patent either under a different owner (firm) or under the same owner but in a different country. Inventors' mobility flows are constructed by counting the number of occurrences in every year.[22]

[19]The logarithmic transformation of the data and OLS estimation techniques, often applied in gravity models, would lead to inconsistent estimates, as for some pairs of countries there is exchange of inventors, making the logarithmic transformation of these observations impossible.

[20]Countries in the sample are presented in Table C.1 in the Appendix.

[21]The WIPO maps migratory patterns of inventors extracted from information contained in patent applications filed under the Patent Cooperation Treaty (PCT). The database contains bilateral counts of "migrant inventors" for a large number of years as well as a considerable number of "sending" and "receiving" countries. Information on the data is provided at http://www.wipo.int/publications/en/series/index.jsp?id=138&sort=code.

[22]Mobility of inventors is measured in the analysis through patent data. Clearly, the proposed measure does not include of inventors that only patented one or a few patents in a single organisation or areas, but might have changed position in a period during which they did not patent.

Information on immigrant flows (*$ImmigrantFlows$*), defined as the number of immigrants moving from partner to reporting country , is obtained from the Organisation of Economic Cooperation and Development (OECD), *International Migration Database*.[23]

Geographical closeness ($NeighbouringCountries\,[>300Km]$ and various distance classes (of non-neighbouring countries) denoted by $Distance\,[\,]$) is measured by the geographic distance (in kilometres) between two countries' geographical centres as the crow flies. This information is obtained from Mayer and Zignago (2011).[24] Data on the geographical surface and population to construct country's density (*Density*) - measured in millions of people per hundred thousands square km - are obtained from the World Bank, *World Development Indicators* (WDI).

Information on a country's standards of living, proxied by the gross domestic product (GDP) per capita ($GDPcapita$), comes from the WDI.[25] Data on total number of inventors ($Inventors$) in each country come from the WIPO.

Technological closeness between countries is proxied by the technological effort distance ($TechEffortDistance$) and technological specialisation similarity ($TechSpecialisationSimilarity$). To construct the former, information on R&D expenditure and number of scientists (science, engineering, and health researchers) from the National Science Foundation *Science and Engineering State Profiles* is used. To construct the latter, patents are allocated into eight technological fields based on international patent classification (IPC) system. Patents' primary IPCs as well as patent file data are extracted from the OECD patent database, *Science, Technology and Patents*.[26]

Economic closeness ($EconCloseness$) is proxied by the difference in GDP between two countries. For robustness, the study also considered economic closeness between countries based on marginal income tax rate (*Tax*) and average wage (*Wage*) differences. Information on marginal personal income tax rate as well as on average wage is derived from the Organisation of Economic Cooperation and Development (OECD) *Tax Database* and *Employment Database*, respectively.[27]

[23] Only 22 (out of 30) countries have full information on bilateral migration flows.

[24] See "Notes on CEPII's distances measures: The GeoDist database," CEPII Working Paper 2011-25, December 2011.

[25] For robustness, the analysis also used the growth rate of GDP, which proxies the market dynamics and the level of GDP, which measures the sheer economic size of a country. The source of these two variables is the WDI.

[26] Available at https://stats.oecd.org/Index.aspx?DataSetCode=PATS_IPC.

[27] Average wage is defined as national-accounts-based total wage bill divided by the average number of employees in the total economy, which is then multiplied by the ratio of the average usual weekly hours per full-time employee to the average usually weekly hours for all employees. Marginal income tax rate is the combined central government and sub-central government marginal personal income tax rate at the earnings threshold where the top statutory personal income tax rate first applies. It is calculated as the additional central and sub-central government personal income tax resulting from a unit increase in gross wage earnings.

Cultural closeness is proxied by language and religion similarities. To construct the *LinguisticSimilarity* information is derived from the Ethnologue Project [28], while for the *ReligionSimilarity* the CIA World Factbook Dataset provides the percentage of population adhering to one of eight major religions[29].

Information for the variables in the control set Z is derived from the following sources: To measure the financial development (FD) of a country, a newly constructed financial development index (FD) proposed by the International Monetary Fund (IMF) is employed.[30] The index aims to describe the multidimensional process and multifaceted nature of contemporary financial sector by capturing the key features of financial systems - depth (size and liquidity of markets), access (ability of individuals and companies to access financial services), and efficiency (ability of institutions to provide financial services at low cost and with sustainable revenues, and the level of activity of capital markets). Data on public spending on tertiary education (% GDP) are obtained from the WDI, while total R&D spending (% GDP), as well as its components public R&D and industry R&D (%GDP), are derived from the EUROSTAT. Information on the strictness of employment protection legislation(EPL) for overall, regular and temporary employment comes from the OECD *Employment Database*.[31] The scale of the EPL is 0-6 from least to most restrictive. Bilateral merchandise trade flows ($Trade$) are derived from the OECD STAN *Bilateral Trade Database*. Data on foreign-born people including refugees (over country's population), who have residence in one country but were born in another country (*Foreigners*) per country are obtained from the WDI.

For the second stage of the analysis, information on a country's innovation activity is needed. Commonly in the literature, innovation activity is proxied by patents. Information on the number of patent applications ($Patents$) per country is derived from the WIPO database, *WIPO Patent Report: Statistics on Worldwide Patent Activity*.

All variables in monetary terms are expressed at constant US dollars (purchasing power parity).

Table 4.1 below, provides summary statistics of the variables.

According to Table 4.1, for every pair of countries, in a given year, there are, on average, 18 occurrences of inventors' mobility. On average, there are 9,300 inventors in each country. Each pair of countries is, on average, 5.5% likely to be neighbouring with each other and

[28] Available at www.ethnologue.com.

[29] Available at https://www.cia.gov/library/publications/the-world-factbook/.

[30] Available at: https://www.imf.org/external/pubs/cat/longres.aspx?sk=43621.0. For a description, see, Svirydzenka (2016), *Introducing a New Broad-based Index of Financial Development*, Strategy, Policy, and Review Department, IMF Working Paper, WP/16/5, 2016.

[31] The employment protection legislation measures the procedures and costs involved in dismissing individuals or groups of workers and the procedures involved in hiring workers on fixed-term or temporary work agency contracts. EPL refers a dimension of a complex set of factors that influence labour market flexibility.

to be located in more than 300 km away from each other, 22.5% within a distance of 300 to 1,110 km, 16% in a distance of 1,110 to 1,500 km, and 5.4% further than 1,500 km. The average country's density is 13.6 million people per hundred thousands square km. In terms of technological effort, countries, on average, appear to be less distant than the maximum potential distance, but not quite close in terms of technological specialisation in their productions.

On average, for a given pair of countries there are large economic (in terms of GDP, marginal tax rate and wage) and cultural differences (in terms of language and religion). The trade intensity between any two countries is about 4% of their total trade. On average, the yearly GDP per capita is about 29,000 US dollars and the average growth rate is about 2%, while about 10% of a country's population consists of foreigners (immigrants). Countries spend on average on R&D about 1.7% of their GDP - 1.1% of their GDP is R&D performed by the business sector and 0.2% by the public sector - and 1.3% of their GDP on tertiary education. The average country has a fair level of labor market strictness (2.5 out of 4.1) and financial level (0.65 out of 1) .

Figure 4.1, below, shows the inventor inflows for the period 2000-2012.

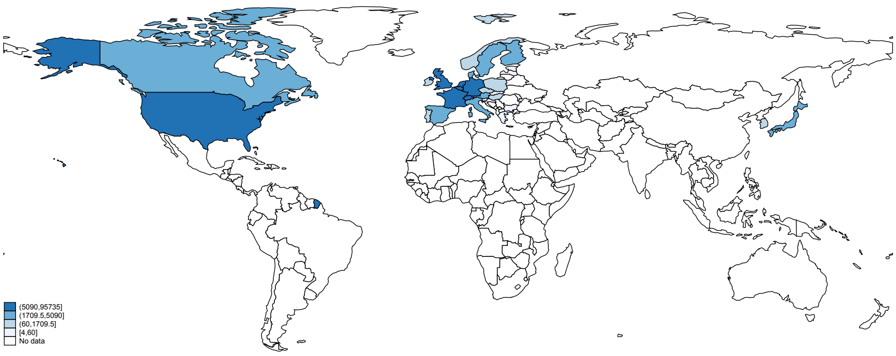

Figure 4.1: Inventor Flows

As Figure 4.1 shows, intense inventor flows are concentrated in few OECD countries; US, Germany, France and the UK attract large flows of inventors, whereas Greece, Portugal and Spain the least.

Figure 4.2, shows the country pairs with the highest exchange of inventors across all countries and over the study's time span.

There are 68 (out of 870) country pairs that inventor mobility between them is very high - at the top 5% of the inventor mobility distribution - that is more than 70 occurrences per

Table 4.1: Summary Statistics, 2000-2012

Proximity	Variable	Obs	Mean	St. Dev.	Min	Max
Inventor Flows	$InventorFlows$	11,310	18.071	100.934	0	2,415
Immigrants Flows	$ImmigrantFlows$	5,967	2082,28	7074.27	0	177758
Geographic						
	$NeighbouringCountries\,[< 300Km]$	11,310	0.0276	0.164	0	1
	$NeighbouringCountries\,[> 300Km]$	11,310	0.0552	0.228	0	1
	$Distance\,[< 1,110Km]$	11,310	0.225	0.418	0	1
	$Distance\,[1,110-1,500Km]$	11,310	0.156	0.363	0	1
	$Distance\,[> 1,500Km]$	11,310	0.536	0.499	0	1
	$Density$	11,310	13.614	11.840	0.308	49.930
Inventors' community	$Inventors$	11,310	9,308.079	21,627.28	3	133,960
Technological						
	$TechSpecialisationSimilarity$	11,310	0.795	0.150	0.130	0.997
	$TechEffortDistance$	11,310	0.968	0.779	0.00003	3.569
Economic						
	$EconCloseness$	11,310	0.785	0.612	0.000221	3.110
	$TaxCloseness$	8,450	0.114	0.0927	0	0.589
	$WageCloseness$	8,450	0.454	0.362	0.00003	1.517
Cultural						
	$LinguisticSimilarity$	11,310	0.0483	0.214	0	1
	$ReligionSimilarity$	11,310	0.174	0.208	0	0.873
Control set (Z)						
	$GDPcapita$	11,310	29,310	15,804	2,751	69,095
	$GDPgrowth$	11,310	2.221	3.418	-14.7	11.902
	FD	11,310	0.651	0.202	0.236	1
	$R\&D$	11,310	1.70	0.945	0.228	4.026
	$R\&D_{industry}$	7,569	1.107	0.793	0.06	3.14
	$R\&D_{public}$	7,569	0.208	0.964	0.02	0.45
	$Tertiary$	11,310	1.341	0.513	0.54	2.71
	EPL	9,367	2.467	0.576	1	4.1
	$Trade$	11,310	0.0414	0.0860	0.00001	1.428
	$Foreigners$	11,310	9.771	5.844	0.528	27.66
Innovation Activity	$Patents$	10,962	39,289.8	104,536	8	542,815

Note: $Flows$ are occurrences (non-negative integers); $NeighbouringCountries\,[< 300Km]$ is a dummy (1 if countries share common border and are located within 300 km, 0 otherwise) and the benchmark distance class; $NeighbouringCountries\,[> 300Km]$ is a dummy (1 if countries share common border and are located more than 300 km away, 0 otherwise); the generic term $Distance\,[\,]$ refers to different distance classes and is a dummy (1 if countries are located within the class, 0 otherwise); $Density$ (=population/area) of a country's population is expressed in millions of people per hundred thousands square km; $Inventors$ is the total number of patent inventors within a country (plus net flows); $GDPcapita$ is expressed in constant 2005 US dollars (ppp) and proxies for the market size and quality of living, while its growth rate, $GDPgrowth$ captures the market dynamics; $TechEffortDistance$ ranges from 0 (close) to 3 (away) and $TechSpecialisationSimilarity$ ranges from 0 (dissimilar) to 1 (similar); $GDPCloseness$ is the absolute difference of the log GDP between two countries; Tax is the absolute difference of the the top marginal tax rates between two countries; $Wage$ is the absolute difference of the log of average wages between two countries; $LinguisticSimilarity$ is a dummy, 0 (dissimilar) and 1 (similar); $ReligionSimilarity$ is the percentage of population adhering to one of eight major religions ranging from 0 (dissimilar) to 0.873 (more similar); FD is IMF index of financial development; $R\&D$ is research and development spending (share of GDP); $R\&D_{industry}$ is business (industry) R&D (share of GDP); $R\&D_{public}$ is public R&D (share of GDP); $Tertiary$ is public spending on tertiary education (share of GDP); $Trade$ is trade intensity between recipient and partner country over recipient country's total trade; $Foreigners$ is stock of immigrants in a country; and EPL is index of the stringency of employment protection legislation - proxies the flexibility in the labor market; ranges from 1 (less strict) to 6 (very strict); $Patents$ is total number of patents filed in a country.

year. Large inventor flows are observed from Canada to the US (21,837 occurrences), UK to US (17,424), and Germany to the US (12,040). In Europe, the highest inventor flows are observed from Germany to the Switzerland (9,719), France to Switzerland (3,341), Austria to Germany (3,169), and France to Germany (3,074).

Table 4.2, depicts the inventor flows in the top destination countries as well as the top countries of origin of these flows for the sample period, 2000-2012.

Overall, countries that exhibit the highest inflows of inventors are also the ones with the highest outflows. Inventors, and subsequently the knowledge they carry, move across a small number of developed countries. Finally, from the summary statistics per country, reported in Table C.1 in the Appendix, a consistent finding that emerges is that countries, which are top ranked in patents, and R&D spending are also the ones that have high inventor mobility, with the US to be by far an outstanding performer in attracting inventor flows.

4.4 Empirical Results

This section presents the results. First, the study examines the effect of various types of proximities in shaping the international flows of inventors, and, second, whether these flows and the knowledge they carry, have an impact on a country's innovation activity.

4.4.1 What Shapes the Moves of Highly Skilled Individuals?

Different specifications that correspond to the effects of various types of proximities are estimated. Table 4.3 shows the results. Columns (1) to (5) report estimates of the inventor migration flows of equation (4.1). Geographic proximity estimates are reported in column (1), technological proximity in column (2), social proximity in column (3), economic proximity in column (4), and, finally, all types of proximities together along with other factors included in Z-set are shown in column (5). Finally, column (6) tests for the effect of the global financial crisis.

Before embarking on analyzing the results, one can note that once other proximities are controlled for, the role conferred on geographic distance slightly alters, confirming the concerns that a bias is introduced if they are neglected. Certainly, geographical and other distances may partially overlap, but each feature may have a different, independent effect on mobility that must be isolated correctly.

One can focus on the estimates of column (5), which contains estimates of all proposed proximities and, additionally, control variables of the recipient as well as of the origin country and are relevant to inventor flows. Each geographic coefficient in Table 4.3 captures the

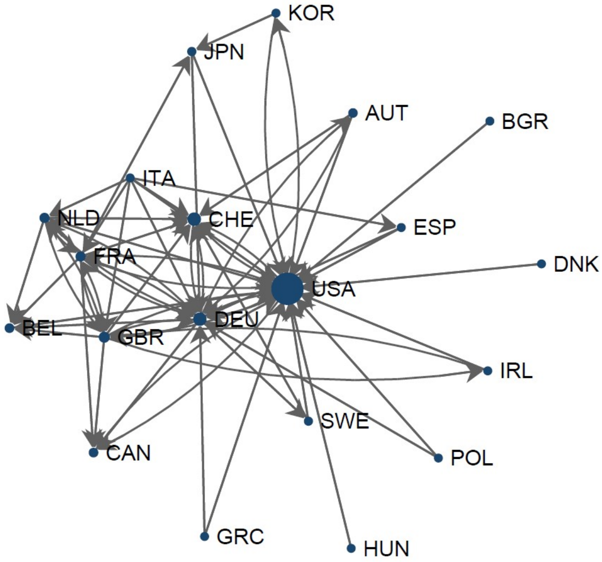

Figure 4.2: Top 5% Inventor Flows

Table 4.2: Inventors' Top Destinations

Top Destination Countries	Origin of Largest Flows	Number of Inventors	% out of total
USA		95,735	
	Canada	21,837	22.81%
	UK	17,424	18.20%
	Germany	12,040	12.58%
Germany		22,453	
	Austria	3,169	14.11%
	France	3,074	13.69%
	UK	2,429	10.82%
Switzerland		22,198	
	Germany	9,719	43.78%
	France	3,341	15.05%
	Italy	1,824	8.22%
UK		13,008	
	France	2,372	18.23%
	Germany	1,917	14.74%
	Italy	1,425	10.95%
Nederlands		8,400	
	Germany	2,515	29.94%
	UK	1,633	19.44%
	Italy/France	656	7.81%

difference between knowledge flows diffused in geographic space to knowledge flows within an area of 300 km, which is the benchmark area. Given that the estimation method is negative binomial, all coefficients can be interpreted as elasticities once they are exponentiated. The exponential formula is used, to convert each value to percentage change.[32] For example, the coefficient of $NeighbouringCountries\,[> 300Km]$ implies that neighbouring countries that their geographic centres are located in more than 300 km apart, exchange about 54% (=1 - $e^{-0.775}$) less inventors to what they would exchange within a distance of 300 km. In other words, on crossing a distance of 300 km, knowledge, based on inventor flows, diminishes to about 46%. Further, the coefficient of $Distance\,[< 1,110Km$ shows that non-neighbouring countries that their geographic centres are located within 1,110 km exchange about 67% (=1 - $e^{-1.098}$) less knowledge than what neighbouring countries with their geographic centres located less than 300 miles apart would exchange. The coefficients of $Distance\,[1,110 - 1,500Km]$ and $Distance\,[> 1,500Km]$ show that as distance grows the flows of inventors are further dissipated; the exchange of inventors between countries that their geographic centres are located between 1,110 and 1,500 km (more than 1,500 km apart) drops to 29% (16%) compared to what they would exchange if their geographical centers were located within a distance of 300 km.

In sum, geographic proximity plays an important role in shaping flows. The general finding of geographic localisation of flows, documented in the literature (Drivas et al., 2016; Miguélez and Fink, 2013), also finds support in this study. To get a better sense of the size of the coefficients, the findings are compared with prior evidence reported in the literature. Cross-study comparisons are not always easy due to different measures of distance and different level of analyses employed; however, one can still recover some effects that can be compared with the ones of the present study.

Although most studies in the literature have studied the geographic reach of patent citations and merchandise trade, there is recent but still thin evidence in the literature related to the geographic spread of inventors.[33]

For example, the studies of Miguélez and Moreno (2012) and Drivas et al. (2016) examine the effect of geographic proximity on inventor flows in Europe and the US, respectively. Both

[32] The coefficient, β, of a negative binomial regression with dependent variable Y and regressor X is read as follows: If X changes by 1%, then Y changes by e^{β} times, i.e., $(1 - e^{\beta})\%$, if α, is smaller than 1 or $(e^{\beta} - 1)\%$ if α is greater than 1. In case regressors are in logarithmic terms, $log(X)$, then β expresses the percentage change of 1% change of X on Y. See Cameron and Trivedi (2013, p. 95).

[33] Patent-citation literature, initiated by the seminal work of Jaffe et al. (1993) and followed by numerous subsequent studies (Mancusi, 2008; Peri, 2005; Branstetter, 2001), traces-out technological learning via citations of patents. The principal assumption is that a citation from a patent to another indicates that inventors of the latter patent knew and used the former. A separate volume of literature has documented the negative impact of geographic distance and borders on the flows of physical trade (Chen, 2004; Wolf, 2000; McCallum, 1995).

Table 4.3: Estimates of International Inventor Mobility

	(1)	(2)	(3)	(4)	(5)	(6)
$NeighbouringCountries\,[>300Km]$	-0.877***	-0.817***	-0.800***	-0.783***	-0.775***	-0.775***
	(0.252)	(0.251)	(0.229)	(0.231)	(0.228)	(0.228)
$Distance\,[<1,110Km]$	-1.547***	-1.402***	-1.173***	-1.170***	-1.098***	-1.098***
	(0.218)	(0.215)	(0.218)	(0.223)	(0.224)	(0.224)
$Distance\,[1,110-1,500Km]$	-1.697***	-1.501***	-1.422***	-1.324***	-1.228***	-1.228***
	(0.229)	(0.225)	(0.225)	(0.229)	(0.231)	(0.231)
$Distance\,[>1,500Km]$	-2.440***	-2.420***	-1.975***	-1.955***	-1.815***	-1.815***
	(0.248)	(0.244)	(0.241)	(0.244)	(0.248)	(0.248)
$Density_i$	-0.033	-0.041	-0.056	-0.058	-0.055	-0.055
	(0.051)	(0.051)	(0.051)	(0.051)	(0.052)	(0.052)
$Density_j$	-0.045	-0.020	-0.034	-0.037	-0.029	-0.029
	(0.045)	(0.045)	(0.045)	(0.046)	(0.046)	(0.046)
$lnInventors_i$	0.894***	0.915***	0.907***	0.915***	0.877***	0.877***
	(0.067)	(0.068)	(0.068)	(0.069)	(0.073)	(0.073)
$lnInventors_j$	0.227***	0.231***	0.228***	0.227***	0.218***	0.218***
	(0.055)	(0.056)	(0.055)	(0.056)	(0.062)	(0.062)
$TechEffortDistance$		-0.031	-0.013	-0.144	-0.137	-0.137
		(0.097)	(0.098)	(0.116)	(0.117)	(0.117)
$TechSpecialisationSimilarity$		1.156***	1.005***	1.018***	0.985***	0.985***
		(0.298)	(0.295)	(0.294)	(0.294)	(0.294)
$LinguisticSimilarity$			0.637***	0.642***	0.592***	0.592***
			(0.117)	(0.116)	(0.115)	(0.115)
$ReligionSimilarity$			0.780***	0.768***	0.761***	0.761***
			(0.209)	(0.210)	(0.209)	(0.209)
$EconClossness$				0.274	0.299	0.299
				(0.192)	(0.202)	(0.202)
$Trade_{ij}$					0.701**	0.701**
					(0.351)	(0.350)
$Foreigners_i$					0.050*	0.050*
					(0.026)	(0.026)
$lnGDPcapita_i$					1.701***	1.701***
					(0.464)	(0.464)
$lnGDPcapita_j$					0.139	0.139
					(0.343)	(0.343)
FD_i					0.840*	0.840*
					(0.450)	(0.450)
FD_j					0.318	0.318
					(0.407)	(0.407)
$R\&D_i$					0.055	0.055
					(0.108)	(0.108)
$R\&D_j$					0.047	0.047
					(0.093)	(0.093)
$Tertiary_i$					0.007	0.007
					(0.119)	(0.119)
$Tertiary_j$					0.149	0.149
					(0.116)	(0.116)
$crisis$						0.422*
						(0.230)
Observations	11,310	11,310	11,310	11,310	11,3 10	11,310

All regressions include origin and destination country and year fixed effects; Coefficient of constant term is omitted for brevity; Robust standard errors in parentheses; (***): p<0.01, (**): p<0.05, (*): p<0.1 significance at 1%, 5% and 10%, respectively.

studies document a strong geographic effect on the stretch of inventors' flows.[34] Distance could be seen as informational barrier, and serves as proxy for all types of informational frictions. Agents within a close geographical distance tend to know much more about each other and each other's business, technologies, and cultures because of higher direct interactions between their citizens.

Irrespective of the geographic distance, the presence of inventors in the origin and, most important, in the destination country associates with inventor moves. Holding all other variables constant, a 1% increase in the number of inventors in the host country ($lnInventors_i$) would lead to about 0.88% increase in the inventor inflows to the host country. This is because the size of the inventors' community reflects on job opportunities and synergies among inventors and is an attractive feature of the recipient country (Miguélez, 2016; Miguélez and Fink, 2013; Maggioni and Uberti, 2009). Countries that have a large pool of inventors, attract more inventors as well as send more inventors out (about 0.22% for a 1% increase in the number of inventors at home), as the estimate of the number of inventors in the origin country ($lnInventors_j$) indicates, compared to countries that they do not. Further, the density (*Density*) of the population in the destination or origin country appears to be negatively related with the flows of inventors. As the literature argues (Glaeser et al., 1995), low in population density areas are highly attractive to migrants and therefore one should expect a negative influence of density on inventors' inflows. However, it could also be argued that dense, urban areas may have a larger supply of producer and consumer amenities, and therefore a positive association could also be observed. The density estimates, however, are statistically insignificant.

Nevertheless, countries located close may exchange more knowledge with each other simply because of the technological effort they pour and/or technological similarity specialisation in their production. As the literature has argued, investment in R&D and human capital makes a region attractive to talented individuals (Lucas, 1988). The results show, a one unit decrease in technological effort distance, $TechEffortDistance$, between countries, increases the exchange of flows between countries by about 13%. The estimate, however, is not statistically significant.[35] A country may also receive more inventor flows from another country with technological sector specialisation as itself than from a country with completely dissimilar technological specialisation production structure. Specifically, a unit increase in

[34] For example, the study of Miguélez and Moreno (2012) find the geographic impact to range from -1.45 to -1.54, which is somewhat larger than this study's one (-0.775 to -1.815; -1.23 on average) and Drivas et al. (2016) show that only 1.7% of knowledge embodied in inventors, crosses the vicinity of 500 miles and this percentage remains unaltered for any farther travelled distance implying that the die-out effect is large and sharp.

[35] It should be noted here that the technological effort indicator, by construction, does not capture quality or productivity differences in R&D or human capital across countries.

structural similarity, *TechSpecialisationSimilarity* (i.e., countries become perfectly identical with respect to their patent portfolio), increases the exchange of inventors by about 168% compared to countries with completely mismatched patent portfolio. As expected, technological specialisation is important for inventors' flows as inventors are expected to benefit more from other inventors who work in the same or related technologies (Peri, 2005; Bode, 2004).

Social closeness between origin and destination country greatly shapes the flows of inventors. As the coefficient of the *LinguisticSimilarity* shows, countries that share common language are about 81% more probable to attract inventor flows than countries that do not. Even greater is the effect of religion similarity. The estimate of *ReligionSimilarity* shows that countries with identical religion composition exchange about 114% more inventors than countries that have virtually no common religion background. Religious and language heritage of countries is a critical element of their culture and identity (Guiso et al., 2009). Countries with similar religious and linguistic roots are culturally closer and likely to interact more.[36] Cultural affinities and social connectedness facilitate the development of trust and networks of economic agents, mutual understanding of individuals, smooth out communication problems and help the managing and administration of a common project. Inventors can operate better in environments which are familiar to them and supportive to innovation.[37]

Economic (dis)similarity of countries, in contrast, seems to have no effect at all. Even when economic similarity is defined in terms of tax rate or wage differences, still results remain statistically insignificant.[38]

Further, specific characteristics of the recipient and/or origin country could also shape the flows of inventors. Among them (at 1% level of significance), the level of life quality (*GDPcapita*) at the host country positively and significantly associates with more inventor inflows; a 1% increase in GDP per capita of the host country associates with an increase in the number of inventor inflows of about 1.7%. Better economic conditions at the home country could also lead some inventors to move out from the country. Having acquired education, skills and experience in a good economic environment, they increase their probability to fly-out to an even better place. The bilateral trade intensity (*Trade*) also associates (at 5% level of significance) with higher inventor inflows as one unit increase in the trade intensity

[36] The trade literature, see, among others, De Groot et al. (2004) has considered the impact of religious bonds between trading partners on shaping trade flows across countries.

[37] Social proximities have been identified in the literature (Saxenian, 1994) as important factors for knowledge exchange. For example, Breschi and Lissoni (2009) apply a social network analysis to derive maps of social connectedness among patent inventors. The authors find that the probability to observe a citation is positively influenced by social proximity of the inventors. A more recent work by Miguélez (2016) finds that social connectivity fosters cross-country co-inventorship as well as R&D offshoring.

[38] See Robustness Section that follows.

between two countries associates with a 106% increase. Further, the presence of foreigners in the destination country has a positive but nuance (at 10% level of significance) association with more inventor moves. An open multicultural society, presence of home fellows or synergies with researchers from different (or same as the origin of the inventor) countries could be attractive features of the host country.[39] It is found that a 1% increase in the number of foreigners (*Foreigners*) in the host country associates with a 5% increase in the flows of inventors. The level of financial development of the recipient country is also an important factor as is positively associated with inventor inflows. The level of financial development (FD_i) at the host country positively relates (at 10% level of significance) to more inflows; as one unit increase of financial development associates with an increase of 132% in the flows of the inventors. The innovation activity of the host ($R\&D_i$) and origin ($R\&D_j$) country, as well as their public spending on tertiary education ($Tertiary_i$ and $Tertiary_j$) are positively associated with the mobility of inventors. Countries that invest in R&D and in higher education, attract more inventors, but also send more inventors out compared to countries that they do not. These estimates, however, are statistically insignificant.

Finally, it is explored whether the global financial crisis in 2007 had an effect on the international mobility of inventors.The *Ex post* 2007 crisis flows of inventors are larger by 52.5% compared to the *ex ante* crisis flows, as the coefficient of the dummy, *crisis*, (column 6) shows. Apparently, after the 2007 crisis, some countries were hit hard and their economic and financial level have deteriorated; that influenced the reallocation of inventors across space.

Summing up, geographic proximity and technological and social similarity across countries appear to greatly shape the flows of inventors with the technological similarity in the production structure to exert the largest influence. In contrast, economic proximity does not appear to play any role. Furthermore, the level of economic and financial development along with intense bilateral trade linkages between inventor's origin and destination country are highly conductive to attracting highly skilled migrants. The size of inventors community at the host country and multicultural environments could also work into this direction.

Robustness

A battery of checks have been performed to sharpen the robustness of the findings. Results are shown in Table C.2 in the Appendix. To ease comparisons, column (i) reports estimates of the baseline specification in column (5) of Table 4.3.

[39] The analysis's measure does not account for ethnicity composition of the foreign population in the host country. Neither for the educational background of the foreigners.

First, it was considered whether wage and taxation differences across countries associate with higher (lower) inventor flows. Therefore, in place of economic proximity (measured by GDP differences) in column (i), the analysis used the proximity in average wages (*WageCloseness*, column ii) and in the top marginal tax rates (*TaxCloseness*, column iii) across countries. Although large (small) wage and tax rates differences are associated with also large (small) inventor inflows, results are statistically insignificant. Perhaps, such differences would matter for just a share of inventors, the very top ones (Akcigit et al., 2016).

Second, it was also explored whether the market dynamics can shape inventor flows. Therefore in place of GDP per capita, the growth rate of the GDP (*GDPgrowth*) was used. Column (iv) reveals that when there are growth opportunities at home, outflows are reduced by 1.4%.

Third, the study allowed for different categories of total R&D spending; industry (*R&Dindustry*, column vi) and public R&D (*R&Dpublic*, column v). An increase in the public spending on R&D at the recipient country, increases the inventor inflows by 49%, while an increase in the business R&D at the home country decreases the outflows by 32%.

Fourth, labour market policies and institutions on shaping inventors' mobility were also explored. Column (vii) re-estimates specification in column (i) but also controlling for employment protection legislation (*EPL*). In doing so, the number of observations fall, as EPL data are not available for all countries in the sample. It is found that the stricter the EPL in the host country is, the larger the inflow of inventors is. For example, a one unit increase in the stringency of the EPL, associates with a 58% increase in the inventors' inflows in the recipient country.[40] This finding appears rather surprising at first glance, as strict hiring and firing policies could impede the mobility of workers, including that of inventors. However, different patterns of innovation specialisation could require different types of labour market regulations. For instance, in incremental innovation patterns (as it is mainly the case in Germany), stable and cooperative relationships between employers and employees are functional to the incremental path, while in countries which specialise in emerging radically new technologies (for instance, UK and US) more relaxed EPL is conductive to this path (Soskice, 1997). EPL increases the cost of adjustment, but it also has positive effects on both types of innovation by increasing workers' effort to further increase the productivity of innovations. Empirical evidence by Griffith and Macartney (2014) shows that the optimal level of investment in radical innovation decreases with EPL, but the optimal level of investment in incremental innovation increases with EPL.

[40] There is a burgeoning literature on EPL and productivity growth with implications to innovation activity. For an updated review of the literature, see Bassanini et al. (2008).

Finally, different taxonomies of distance have also been considered.[41] Results change mildly, but rather insignificantly.

Overall, results do not change in any significant way across different specifications, sub-samples and alternative definitions.

As stated earlier, inventor mobility is also associated with knowledge diffusion. As inventors move across countries they carry knowledge with them. Concerns, however, have been expressed in the literature for potential caveats of using inventor mobility as a potential measure of knowledge flows. One concern could be that the mobility of inventors measure was employed here is based on patent data and so it does not catch the move of inventors that do not patent. However, by solely focusing on the patenting scientists this measure captures the moves of the "high quality" scientists and, therefore, represents a lower bound of the "true" inventor mobility effect. Overall, it was not expected this measure to be biased across countries; however, it was expected to find a very strong effect of distance - confirmed by the estimates - as the way inventors' movement defined here, requires significant patenting to be observed.[42]

4.4.2 What Shapes the Moves of Highly Skilled Individuals from the Most and Least Innovative Countries?

An interesting issue to explore is whether the importance of the aforementioned proximities and other country related factors alter when one investigates subsets of flows. The study considers two types of inventors: those who come from the most innovative countries, i.e., US, Japan, Korea, Germany and Canada - these countries rank very high in R&D spending and number of patents (together count for more than 90% of WIPO patents) - and those who come from the rest of the countries in the sample.

Table 4.4 , presents the results. The first two columns report estimates of inventor flows only from the top five most innovative to the rest of the countries (column 1) and from the top five most innovative to all countries (column 2), while the last two, report estimates of inventor flows from the least innovative countries to only to the top five most innovative (column 3) and to all countries in the sample (column 4).

[41] Results are not shown here, but are available upon request.

[42] Instead of using inventors' job moves, one could use a more refine measure such as informal meetings and exchange of ideas of inventors during the inventive process (or probability to enter into local/international networks of research based on inventors' characteristics during the inventive process) as the study of Giuri and Mariani (2013) does. The latter, relies on survey data by interviewing european patent inventors about interactions that were important for the development of a patent. Such data, although very useful, is not yet available for large population of the US patent inventors.

Estimates in columns (1) and (2) in Table 4.4 show that an inventor from a top innovative country is less geographically restricted than an inventor from the "average" country of the sample (see geographic estimates of column 5 in Table 4.3). This finding becomes even stronger for inventors from the least innovative countries. As estimates in column (3) reveal, technologically frontier countries are attractive places to an inventor from a less technological advanced country irrespective of the distance. In contrast, geography exerts the heaviest toll on the inventors' moves from the least innovative countries to all countries in the sample, as estimates in column (4) show.

The main driver of an inventor from a top innovative country to relocate herself is the technological proximity, i.e., the technological similarity. In fact, technological similarity in the production structure between host and inventor's country of origin exerts about five times more impact on the mobility of an inventor from a top innovative country compared to the mobility of an inventor from the "average" country. Apparently, job similarity ranks very highly in the preferences of this set of inventors. Furthermore, quality of life, and financial development are significant mobilisers for inventors from top innovative countries. In contrast, R&D investment activity at inventors' home makes them less probable to move abroad.

Coming to the other set of inventors, those from the less technologically advanced countries, what mobilises them is again the technological proximity - the technological similarity in the production structures of home and host country. Its effect is about three times stronger than that on an inventor from the "average" country. Social proximity, in terms of language similarity, appears to be more important to this group of inventors than to any other group. Intense trade linkages between inventor's country of origin and destination are also great shapers of this set of flows. Public spending on tertiary education, either at the host or origin country, increases the chances for this set of inventors to move to other countries. So does the high level of domestic GDP per capita. Innovation activity (R&D) at home, in contrast, lessens the motivation for migration to frontier places.

Summing up, splitting the flows of inventors by the technological performance of the country of inventor's origin, it is the technological proximity, and specifically technological similarity, which greatly shapes both sets of flows - particularly that of inventors from technologically frontier countries. Social proximity is more important to inventors from less innovating than to inventors from more innovating countries. Inventors from top innovative countries are less geographically restricted than inventors from the "average" country; for inventors who originate from less prosperous in innovation backgrounds and aim to move to frontier countries, gravity does not matter at all. Economic similarities among countries do not seem to play any particular role in almost all subgroups.

Table 4.4: Estimates of International Inventor Mobility from Most and Least Innovative Countries

	From Top5 innovative to[a]		*From Low25 innovative to*[b]	
	Low25	*All*	*Top5*	*All*
	(1)	(2)	(3)	(4)
$NeighbouringCountries\,[> 300Km]$	-0.384	-0.020	-0.097	-0.843***
	(0.308)	(0.397)	(0.410)	(0.238)
$Distance\,[< 1,110Km]$	-0.756**	-0.864**	-0.111	-1.123***
	(0.300)	(0.377)	(0.434)	(0.239)
$Distance\,[1,110-1,500Km]$	-0.100	-0.057	-0.063	-1.303***
	(0.269)	(0.381)	(0.429)	(0.246)
$Distance\,[> 1,500Km]$	-1.288***	-1.578***	-0.549	-1.379***
	(0.363)	(0.462)	(0.475)	(0.262)
$Density_i$	-0.035	-0.019	-0.417	-0.057
	(0.118)	(0.093)	(0.389)	(0.062)
$Density_j$	0.775**	0.652***	-0.060	-0.135**
	(0.349)	(0.239)	(0.095)	(0.061)
$lnInventors_i$	0.777***	0.788***	0.583	0.876***
	(0.155)	(0.137)	(0.367)	(0.085)
$lnInventors_j$	0.614*	0.521**	0.069	0.177**
	(0.314)	(0.230)	(0.094)	(0.069)
$TechEffortDistance$	-0.212	-0.016	-0.290	-0.117
	(0.256)	(0.263)	(0.220)	(0.120)
$TechSpecialisationSimilarity$	2.213***	2.337***	1.782***	1.782***
	(0.735)	(0.608)	(0.452)	(0.273)
$LinguisticSimilarity$	0.477***	0.479***	0.851***	0.664***
	(0.166)	(0.174)	(0.189)	(0.136)
$ReligionSimilariry$	0.047	1.178	0.735	0.523***
	(0.816)	(0.961)	(0.774)	(0.199)
$EconCloseness$	0.523	0.692	0.859	0.034
	(0.410)	(0.435)	(0.681)	(0.198)
$Trade_{ij}$	0.284	0.544	1.049	0.676***
	(0.378)	(0.431)	(2.398)	(0.283)
$Foreigners_i$	-0.017	0.001	0.143	0.059**
	(0.042)	(0.046)	(0.097)	(0.029)
$lnGDPcapita_i$	4.655***	3.888***	0.120	0.345
	(1.674)	(1.256)	(0.589)	(0.382)
$lnGDPcapita_j$	0.777***	0.788***	0.583	0.876***
	(0.155)	(0.137)	(0.367)	(0.085)
FD_i	1.348**	0.627*	0.558	0.404
	(0.630)	(0.363)	(1.287)	(0.513)
FD_j	-0.222	0.175	-0.271	-0.068
	(1.416)	(1.115)	(0.580)	(0.440)
$R\&D_i$	0.152	0.038	0.216	0.029
	(0.195)	(0.152)	(0.323)	(0.128)
$R\&D_j$	-0.666*	-0.595**	-0.256*	-0.018
	(0.374)	(0.279)	(0.141)	(0.118)
$Tertiary_i$	0.201	0.185	0.537**	0.133
	(0.199)	(0.182)	(0.254)	(0.135)
$Tertiary_j$	0.089	0.073	0.150	0.234*
	(0.344)	(0.282)	(0.160)	(0.130)
Observations	1,625	1,885	1,625	9,425

All regressions include origin and destination country and year fixed effects; Coefficient of constant term is omitted for brevity; Robust standard errors in parentheses; (***): p<0.01, (**): p<0.05, (*): p<0.1 significance at 1%, 5% and 10%, respectively.

[a] : Inventor flows only from the top five most innovative countries were included as senders (origin). Top innovative countries are US, Japan, Korea, Germany and Canada. The remaining 25 countries were included as receivers (destination) in column (1) and all countries of the sample in column (2).

[b] : Inventor flows only from 25 - less innovative countries, compared to the top five - were included as senders (origin). Column (3) reports estimates when the destination is one of the top five most innovative countries, while column (4) reports estimates when destination is all countries in the sample.

At this point, one can visualise some of the results with the use of a graph. Figure 4.3 depicts the estimated (dashed line) along with the actual values (bold line) of the geographic distance on inventor flows. The first panel shows the actual and estimated decay of inventor flows moving out of a nearby area of 300 Km, out of 1,110 Km, and out of 1,500 Km. In similar fashion, the second and third panel present inventor flows originating only from the most and the least innovative countries, respectively.

The graphical evidence confirms the significant drop in mobility of inventors for distances larger than 700 km. Within a distance of 700 km there are four pairs of countries (Czech Republic and Germany, USA and Canada, Germany and Austria, and Germany and France) that exchange large flows of inventors and drive upwards the graph. Overall, knowledge flows exemplified by the mobility of inventors are rather geographically confined in space. From the figure one can also observe that actual and estimated values are very close to each other indicating a good fit of the model.

4.4.3 What Shapes the Moves of Ordinary Individuals?

As an exercise, in one common framework described by equation (4.1), the role of proximity is also examined along with other country related factors in shaping the flows of the less skilled individuals, the ordinary immigrants. As not all 30 countries in the sample provide information on immigration flows, the analysis is narrowed down to 22 countries.[43]

Before embarking on the analysis, it is important to discuss some descriptives of these flows. Over the sample period 2000-2012, an average pair of countries has exchanged about 2,082 migrant individuals. As shown in Table C.3 in the Appendix, the countries with the largest inflows are Germany (3,540,019), the UK (1,313,663) and Spain (962,090) in Europe and the US (1,183,853) and Japan (938,482) elsewhere.

High mobility (top 5% of the immigrant mobility distribution) is observed in 38 (out of 459) country pairs - that is more than 9,974 occurrences per year. Large immigrant flows are reported from Poland to Germany (1,577,493), Korea to Japan (326,161), Italy to Germany (300,308), US to Japan (286,365) and Korea to the US (280,900). Figure C.1 in the Appendix graphs country interactions (network) with the largest migrant moves.

Estimates of immigrant flows are presented in column (3) of Table 4.5, below. For comparison purposes, column (1) reports estimates of equation (4.1) of inventor flows but for the new sample of 22 countries. Columns (2) and (4) further account for labour institution factors (*EPL*).

[43]Due to lack of data, eight countries were dropped out: Bulgaria, Cyprus, France, Estonia, Greece, Hungary, Ireland and Portugal.

There are few things worth noting in this exercise. The geographic stretch of the less skilled (column 3) is about 50% smaller than that of the highly skilled individuals (column 1). For example, the flows of ordinary migrants on crossing neighbouring countries that their geographic centres are located more than 300 km apart diminish to 22% (= $e^{-1.492}$) compared to in-300 km area level, whereas the flows of inventors diminish to 47% for the same distance, as the coefficients of $NeighbouringCountries\,[> 300Km]$ indicate. Similarly, the flows of ordinary individuals (inventors) that cross a distance of 1,500 km drop to 6% (12%) to what would flow within a distance of 300 km.

Technological proximity, as expected, matters more for the mobility of inventors than for the simple immigrants; nevertheless it is also relevant for the latter. Specifically, technological effort distance is important only for the inventors: the results show, a one unit decrease in technological effort distance between countries, increases the exchange of inventor flows by 21%. Further, a unit increase in structural similarity increases the flows of inventors by 118%, while the flows of immigrants by 16% compared to countries with completely mismatched patent portfolio. Apparently, the technological level of the destination country and its similarity to the origin is relevant for the immigrants as in this set there are individuals who are technically skilled (scientists, researchers, engineers, medical doctors among others) and therefore the technological effort and technological production similarity matter. So does the number of inventors in the host countries. The size of inventors at the host country is also relevant for the immigrants, although its estimate is four times bigger for the inventors, as a large inventor community offers more opportunities for synergies for a subset of immigrants. In addition, a large community of inventors reflects on the innovation capability of the country and economic growth potential.

Social proximity, in contrast, is more important for the simple immigrants than for inventors. Religion similarity, which captures a broad set of beliefs and attitudes important for shaping local culture and in turn the innovative performance, is more important than linguistic similarity to both inventors and immigrants: two countries with exactly the same language exchange 58% (48%) more immigrants (inventors) than countries with dissimilar languages. Also, two countries with exactly the same religion exchange 270% (81%) more immigrants (inventors) than countries that they do not.

With respect to country amenities, GDP per capita, bilateral trade intensity, quality of education (tertiary spending) and strict labor policies (EPL) at the host country associate with high migrant moves. The first two factors are also important for the mobility of inventors. Additionally, financial development attracts inventors, but not necessarily ordinary immigrants. The latter, appear to be less mobile when the level of financial development increases at home.

Finally, economic closeness plays no role. However, as one can see from the robustness analysis in Table C.4 in the Appendix, economic closeness proxied by the top marginal tax rate differences is important for the immigrant flows (column v), as a one percent change in the top marginal tax rate at the host country, associates with a 17% drop in the immigrant flows. Wage closeness, though, has no impact at all. In addition, all other equal, the growth perspectives of the origin country motivate more individuals (about 1.6%) to stay in the country (column iv), while has no impact on inventor flows (column i). The economic growth of the destination country positively affects both types of flows but its effect is not statistically significant.

One can also graphically show the geographic stretch of inventors and immigrants in this set of 22 countries. Figure 4.4 depicts the estimated (dashed line) along with the actual values (bold line) of geographic resistance factors on inventor and ordinary migrant flows. As before, it shows the actual and estimated decay of inventor and immigrant flows moving out of a nearby area of 300 Km, out of 1,110 Km, and out of 1,500 Km.

The graph confirms the dramatic drop in the mobility of inventors and immigrants alike for distances larger than 700 km. Within the distance of 700 km, however, there are strong inventor flows between Czech Republic and Germany, USA and Canada, Germany and Austria, and Germany and France, and large immigrant flows between Poland and Germany, Austria and Germany, and Czech Republic and Germany that drive the patterns upwards. After the distance of 700 km there is a sharp drop in both flows. An important difference, however, is that for long distances, higher than 1,500 km, while the flows of immigrants continue to significantly decay, there is a small increase in the inventors flows - most probably European countries (UK and Germany) and the US or between Asian countries and the US - as other factors, such as technology, could be prove to have a stronger effect than that of gravity.

4.4.4 Does Inventor Mobility Contribute to Local Innovation Activity?

The study has established thus far that inventor (and immigrant) flows across countries are shaped by various proximities along with other country level factors. The existence of these flows, however, does not necessarily support presence of externalities of knowledge on local innovation. Available knowledge originating from other countries may bring, along with new ideas, a reduction in innovation possibilities, thus generating a zero or even negative net effect on the productivity of researchers in innovation.

Therefore, the next task of this study is to assess the effect of external available knowledge on country's innovation activity. In doing so, a function of innovation production is estimated

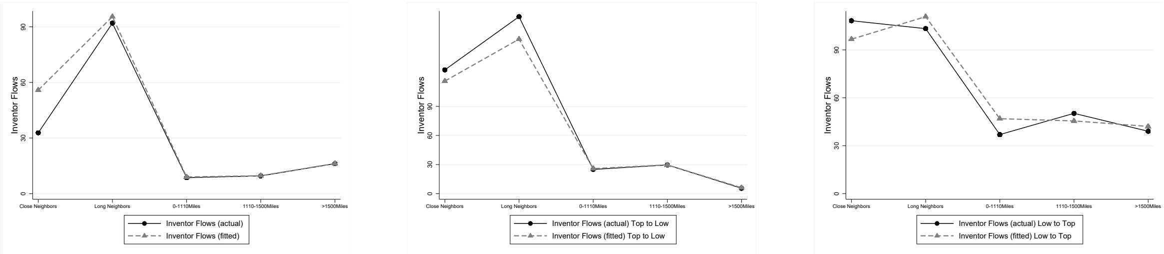

Figure 4.3: Decay of Inventor Flows Due to Geographical Distance

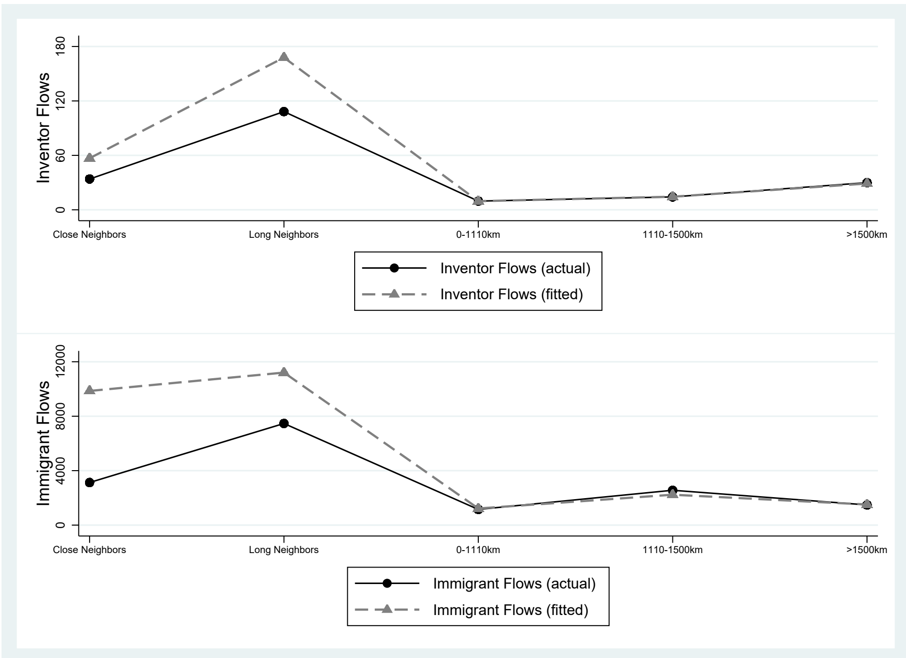

Figure 4.4: Decay of Inventor & Immigrant Flows Due to Geographical Distance

Table 4.5: Estimates of International Inventor and Immigrant Flows

	$Inventor\,Flows$[a]		$Immigrant\,Flows$[a]	
	(1)	(2)	(3)	(4)
$NeighbouringCountries\,[>300Km]$	-0.754***	-0.732***	-1.492***	-1.526***
	(0.267)	(0.271)	(0.334)	(0.339)
$Distance\,[<1,110Km]$	-1.149***	-1.131***	-1.863***	-1.964***
	(0.244)	(0.247)	(0.320)	(0.312)
$Distance\,[1,110-1,500Km]$	-1.217***	-1.193***	-2.151***	-2.205***
	(0.249)	(0.253)	(0.319)	(0.314)
$Distance\,[>1,500Km]$	-2.115***	-2.104***	-2.814***	-2.917***
	(0.278)	(0.281)	(0.334)	(0.331)
$Density_i$	-0.067	-0.116*	-0.009	-0.029
	(0.059)	(0.062)	(0.047)	(0.047)
$Density_j$	-0.013	-0.028	-0.099***	-0.086**
	(0.050)	(0.053)	(0.038)	(0.039)
$lnInventors_i$	0.715***	0.708***	0.227***	0.275***
	(0.081)	(0.0821)	(0.041)	(0.050)
$lnInventors_j$	0.272***	0.273***	0.146***	0.137***
	(0.077)	(0.079)	(0.047)	(0.060)
$TechEffortDistance$	-0.241*	-0.254*	-0.00001	-0.111
	(0.143)	(0.148)	(0.130)	(0.143)
$TechSpecialisationSimilarity$	0.778**	0.820**	0.146***	0.137***
	(0.358)	(0.372)	(0.041)	(0.035)
$LinguisticSimilarity$	0.391***	0.398***	0.455***	0.435***
	(0.144)	(0.145)	(0.159)	(0.159)
$ReligionSimilarity$	0.591**	0.592**	1.308***	1.110***
	(0.277)	(0.280)	(0.248)	(0.250)
$EconClossness$	0.151	0.141	0.188	-0.051
	(0.252)	(0.256)	(0.179)	(0.210)
$Trade_{ij}$	0.810*	0.752*	1.002**	1.001*
	(0.470)	(0.440)	(0.504)	(0.504)
$Foreigners_i$	0.044	0.037	0.021*	0.033*
	(0.034)	(0.035)	(0.012)	(0.017)
$lnGDPcapita_i$	2.205***	2.253***	1.331***	1.219***
	(0.416)	(0.426)	(0.380)	(0.304)
$lnGDPcapita_j$	-0.210	-0.059	-0.151	-0.345
	(0.464)	(0.484)	(0.309)	(0.419)
FD_i	1.106**	1.204**	0.284	0.490
	(0.527)	(0.600)	(0.372)	(0.367)
FD_j	-0.230	-0.309	-0.083	-0.633*
	(0.501)	(0.505)	(0.328)	(0.350)
$R\&D_i$	0.024	0.011	0.036	0.032
	(0.116)	(0.117)	(0.072)	(0.070)
$R\&D_j$	0.126	0.151	0.0320	0.003
	(0.001)	(0.102)	(0.069)	(0.078)
$Tertiary_i$	0.029	0.065	0.603***	0.592***
	(0.138)	(0.140)	(0.092)	(0.096)
$Tertiary_j$	0.0113	0.014	0.0273	0.132
	(0.132)	(0.133)	(0.088)	(0.090)
EPL_i		0.538		0.511**
		(0.342)		(0.247)
EPL_j		0.024		0.338*
		(0.319)		(0.183)
Observations	5,967	5,179	5,967	5,179

All regressions include origin and destination country and year fixed effects; Coefficient of constant term is omitted for brevity; Robust standard errors in parentheses; (***): p<0.01, (**): p<0.05, (*): p<0.1 significance at 1%, 5% and 10%, respectively.

[a] : Estimates are based on a sample of 22 countries (original sample, excluding Bulgaria, Cyprus, France, Estonia, Greece, Hungary, Ireland and Portugal due to lack of data).

and the effect of this channel of knowledge flows is assessed, i.e., inventors' mobility on local production of innovation.

In its simple form, a region's (country in this case) output of production of innovation is determined by the homegrown as well as by the external, but accessible (or "borrowed") to the region technological knowledge of other regions (Drivas et al., 2016; Peri, 2005; Griliches, 1992) and can be expressed as follows:

$$Q_{it} = (A_{it})^{\beta}(A_{it}^{\alpha})^{\mu} \tag{4.2}$$

where Q is the innovative output, proxied by the number of patents produced in country i; A is own, homegrown knowledge stock, proxied by R&D stock accumulated from past and current R&D investments in country i; and A^{α} is the stock of external and accessible (hence the α superscript) to country i knowledge stock, proxied by R&D accumulated in countries other than i at time t.

Knowledge flows take place when an idea, generated in a region, country or institution, is learned by another region, country or institution. If knowledge flows manage to perfectly and completely spill over, then the amount of external knowledge that eventually reaches country i is simply the summation of all borrowed knowledge that comes from all other countries. In reality, however, the diffusion of knowledge flows across countries may be less than complete; only a share of research results from other countries reaches country i. Therefore, the external accessible to country i R&D activity can be described by:

$$A_{it}^{\alpha} = \sum_{j \neq i} \phi_{ij} A_{jt} \tag{4.3}$$

where ϕ_{ij} is the share of knowledge learned in country i.

Substituting equation (4.3) into equation (4.2) and by taking logs, equation (4.2) yields:

$$lnQ_{it} = \beta lnA_{it} + \mu ln(\sum_{j \neq i} \phi_{ij} A_{jt}) \tag{4.4}$$

The dependent variable of equation (4.4) is the innovation output Q, which is the log of number of patents filed in a country in year t and is a count variable. Negative binomial estimator techniques are applied controlling for time effects.

Table 4.6 reports estimated coefficients of country's own R&D stock and external accessible to a country flow-weighted R&D stock gained via the mobility of inventors channel. Column (ii) reports innovation elasticities, in similar fashion, but when external accessible flow-weighted R&D stock originates only from the top five innovator countries in the sample. In fact, the second column includes in the regressions only the top five countries as senders of knowledge flows and the remaining 25 countries as receivers. Consequently, A_{it}^{α} in equation (4.4) is defined as A_{it}^{α}=$\sum_{j\in Top5}(\phi_{ij}A_{jt})$. This allows someone to minimise potential endogeneity in estimating the coefficient μ of A_{ij}^{α}.

As Table 4.6 shows, the estimates of flows reported in columns (i) and (ii) are very close to each other. This alleviates concerns about endogeneity. Despite of the potential worsening of the endogeneity problem, when external accessible R&D stock originates from all countries, estimates are overall quite close across different specifications.

More specifically, results support that country's own ($lnR\&D_{own}$) as well as external accessible R&D stock are contributors to country's innovation production. Their effect size-wise is small; nevertheless statistically significant. It is found that a 100% percent increase of country's own R&D is associated with an increase in the local production of innovation by 0.004% (column 1). This effect drops to one forth when top innovator countries are the only source of relevant knowledge flows. Apparently, the most innovative countries in the sample invest heavily on home-produced technological knowledge.

Other countries' R&D effort has also a positive effect on local production of patents and appears to be greater than country's own R&D effect. A 100% percent increase of external accessible inventor-weighted R&D ($lnR\&D_{external}$) is associated with an increase in the production of innovation by 0.005%; however, the effect is statistically insignificant. The external inventor-weighted R&D stock when only flows that originate from the top innovator countries are considered, is positive and statistically significant and almost double in size compared to the effect of homegrown R&D stock.[44]

Summing up, it is found that knowledge flows, are relevant to local innovation production as external accessible R&D, gained through the inventors mobility channel, has a positive, (though small) effect on a country's innovation activity and the effect is as large as country's homegrown R&D stock.

The innovation elasticities of inventor mobility across the world appear smaller compared to innovation elasticities reported for the US (Drivas et al., 2016). A consistent finding across literature is that either across or within a country, inventors moves are geographically restricted.

4.5 Conclusion

The flows of individuals between firms, industries and locations has been proposed as an important mechanism for transferring knowledge and is argued as important for innovation.

[44] As a further check, all regressions in Table 4.6 were run, lagging all variables on the right-hand side by one period to overcome potential immediate feedback effect. Results did not change in any significant way.

Table 4.6: Elasticities of Innovation Production Function

	Flows from All Countries[a] (1)	*Flows from Top 5 Innovative Countries*[b] (2)
$lnR\&D_{own}$	0.00004***	0.000125***
	(0.000002)	(0.0000007)
$lnR\&D_{external}$	0.00005	
	(0.00003)	
$lnR\&D_{top}$		0.00002***
		(0.00002)
Constant	4.783**	8.071***
	(1.956)	(0.266)
Observations	378	313

All regressions include year fixed effects. All variables are in logs. Standard errors reported in parentheses; $lnR\&D_{own}$ is country's own R&D stock; $lnR\&D_{external}$ and $lnR\&D_{top}$ are external available to a country inventor-weighted external R&D stocks that originate from the rest of the countries or only from the top five most innovative countries, respectively; (***), (**), and (*): significance at 1%, 5%, and 10% level, respectively.

[a] All countries were included as senders (origin) of knowledge flows. All countries were included as receivers (destination) of knowledge flows.

[b] Only the top 5 innovative countries were included as senders (origin) of knowledge flows. Only the remaining 25 countries were included as receivers (destination) of knowledge flows. The top 5 most innovative countries in the sample are: the US, Japan, Korea, Germany and Canada.

The present analysis has studied the factors that shape the international mobility of the economically highly valuable agents as they are critical conduits of knowledge diffusion and key drivers of economic growth: the inventors.

Employing patent data to track inventor moves, a gravity model is used to examine whether proximity, namely geographic, technological, economic, and cultural between countries along with relevant country level factors shape the flows of these talented individuals. As a comparison, within the same framework, the flows of simple, less skilled migrants are also analyzed. Then, potential benefits of inventors' mobility on local innovation production are evaluated. Thus far, only a scant few studies have examined the mobility of highly skilled individuals and even fewer assessed their impact on innovation performance.

The findings support that proximity matters for migration. Gravity emerges everywhere; in the mobility of the highly skilled workers as well as in the average migrant worker. It is found, however, that inventors are less geographically restricted and, therefore, their effective reach is beyond that of the average migrant worker. Similarity in technological structure of production is the main driver of inventor moves - especially for inventors from the most innovative countries, whereas social proximity matters more for the average migrants. Attractive country features for inventor inflows are the level of economic and financial development, the size of inventors' community and the trade linkages between origin and host country. Most of these factors as well as tertiary education at the host country appear to be also important for the less skilled migrant flows. Finally, knowledge that moves with the inventors has a positive impact on local innovation production which is almost as large as that of domestic knowledge.

The implications of the findings for the literature are potentially relevant. Theoretical trade-growth studies (Grossman and Helpman, 1991; Rivera-Batiz and Romer, 1991) have long emphasized the important consequences of knowledge flows for technology transfer and economic growth. Along with other important studies, this study makes an effort toward this direction and empirically confirms the geographic scope of embodied knowledge flows as well as their economic impact.

Chapter 5

Conclusion

The present thesis investigates the transfer of the patented knowledge to the market and across space, and to effectively tackle this issue, it is organized into three essays.

The first essay focuses exclusively on patents created by academic institutions and addresses two questions that thus far have not been approached in a comprehensive manner in the literature, mainly due to data limitations: (i) Are federally funded university patents more (less) likely to be transferred to the marketplace than non-federally funded? and (ii) Are federally sponsored university patents faster transferred to the marketplace than non-federally funded? To answer these questions, this study exploits a unique facet of the US patent system that has been overlooked so far, the fee payment data scheme associated with statutory rules on how and when university patent holders pay these fees, namely switches from Small Entity Status (SES) to Large Entity Status (LES) for renewal fee purposes. Based on this observation, someone is able to determine the propensity and time of technology transfer from the university to the marketplace of both federally sponsored - distinguishing also by funding agency - and non-federal funded patents and the associated characteristics of transferred patents. Based on a large sample of 20,877 university patents issued between 1990 and 2000, the study finds, with respect to the first question, that government sponsorship of research does not seem to be associated with a systematically different propensity of licensing compared to non-federally funded patents. The only notable exception is the Department of Defense funded patents, which are less likely compared to non-federally sponsored counterparts to be licensed. Furthermore, and with respect to the second question, it is found that federally funded university patents are more likely to be licensed at later years over their lifecycle compared to non-federally funded patents, with the Department of Energy funded patents to take the most time to be licensed and the National Institute of Health funded patents the least. Finally, patent characteristics, such as the prior and posterior art base of a patent, the number of inventors and assignees involved in a patent along with the size of their patenting activity, and the scope of a patent are significantly associated with both the propensity and the speed of patent transfer to the marketplace.

The second essay studies the commercialization propensities of individual inventors' patents. Diachronically, individuals have contributed to many great inventions. Thus, scholars have examined the pathways and determinants of the commercialization of such independent inventions in depth (Conti et al., 2013). Further, policies in many countries have been set to promote patenting and commercialization activity by individuals inventors. While individuals can potentially produce inventions of great potential, it is large firms who are equipped to develop such inventions to end-user products. Transactions of technology assets can therefore be beneficial to both inventors and large firms in addition to society. To this end, the objective of this study was to examine the population of individual inventors' US patents in the period $1990-2000$ and analyze the factors that are associated with commercialization by large corporations. In particular, it exploits the same peculiarity of the US patent system regarding the two different schemes for the payment of maintenance fees to infer commercialization activity by large corporations. The results show that individual inventors' patent characteristics, including forward citations, are positively associated with the likelihood of switching to LES, whereas the likelihood of commercialization also increases by the size of the team of inventors. Thus, policies that encourage collaboration among researchers/inventors can yield patented inventions with greater potential for commercialization. Past patent experience and prior corporate ties are also positively associated with the likelihood of switching to LES. Similarly, policies that encourage open channels of communication between firms and inventors can also yield promising opportunities for both parties. In the case of patents whose inventors are located in the USA, the state's inventive activity is not significantly associated with the likelihood of commercialization. However, if the inventors are located in a foreign country, the inventive activity of a country is positively and significantly associated with the likelihood of switching to LES. This finding probably indicates a cooperation by inventors with firms from the same country. Lastly, all the above results are similar across technology fields with subtle but noteworthy differences for past patenting experience and prior corporate ties.

The third essay studies the factors that shape the international mobility of the economically highly valuable agents as they are critical conduits of knowledge diffusion and key drivers of economic growth: the inventors. The flows of individuals between firms, industries and locations has been proposed as an important mechanism for transferring knowledge and is argued as important for innovation. Employing patent data to track inventor moves, a gravity model is used to examine whether proximity, namely geographic, technological, economic, and cultural between countries along with relevant country level factors shape the flows of these talented individuals. As a comparison, within the same framework, the flows of simple, less skilled migrants are also analyzed. Then, potential benefits of inventors' mobility on local innovation production are evaluated. Thus far, only a scant few studies have examined the mobility of highly skilled individuals and even fewer assessed their impact on innovation performance. The findings support that proximity matters for migration. Gravity emerges everywhere; in the mobility of the highly skilled workers as well as in the average migrant worker. It is found, however, that inventors are less geographically restricted and, therefore, their effective reach is beyond that of the average migrant worker. Similarity in technological structure of production is the main driver of inventor moves - especially for inventors from the most innovative countries, whereas social proximity matters more for the average migrants. Attractive country features for inventor inflows are the level of economic and financial development, the size of inventors' community and the trade linkages between origin and host country. Most of these factors as well as tertiary education at the host country appear to be also important for the less skilled migrant flows. Finally, knowledge that moves with the inventors has a positive impact on local innovation production. The implications of the findings for the literature are potentially relevant. Theoretical trade-growth studies (Grossman and Helpman, 1991; Rivera-Batiz and Romer, 1991) have long emphasized the important consequences of knowledge flows for technology transfer and economic growth. Along with other important studies, this study makes an effort toward this direction and empirically confirms the geographic scope of embodied knowledge flows as well as their economic impact.

Overall, the empirical analysis of technology transfer to the market and around the world undertaken in the present thesis, offers useful and novel insights to important policy issues surrounding technology transfer of university and individual inventors' patents which are also relevant beyond US borders as a number of European countries consider or have already adopted policies to facilitate the efficient transfer of technologies to the marketplace. Further, by studying the mobility of patent inventors, important factors that make a region an attractor of talented individuals can be identified and relevant policies can be suggested into that direction.

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Appendix A

Table A.1: Variable Overview

Variable	Definition	Aim & relevance to the literature
Federal	1 if patent discloses federal support; 0 otherwise	Whether federally funded patents differ from non-federally funded ones (Pressman et al., 2006; Drivas and Economidou, 2013)
Citations		The following citation metrics approximate patent quality and value (Harhoff et al., 1999; Bessen, 2008)
ForwardCites	# of patent citations a patent receives	A high *ForwardCites* implies that the focal patent has been cited and may have influenced a large number of follow-up patents.
BackwardCitesPat	# of backward patent citations a patent makes	A high *BackwardCitesPat* implies that the focal patent builds on a large number of patents. While this could imply that the patent is in a saturated field, it could also imply the significance of the field itself
BackwardCitesNonPat	# of backward non-patent citations a patent makes	A high *BackwardCitesNonPat* implies that the focal patent makes a lot of citations to the scientific literature and could mean that it is more basic in nature than with no scientific references.
Scope		The following metrics illustrate a patent's complexity (usage and scope)
ApplicationLength	time (in years) from application date to grant date	A large *ApplicationLength* has been of special policy in examining how quickly ideas are appropriated (Johnson and Popp, 2003; Regibeau and Rockett, 2010)
Claims	# of claims the patent makes	See Popp et al. (2004).
IPC4Digit	# of four-digit International Patent Classification codes	Both *IPC4Digit* and *USC3Digit* show how many
USC3Digit	# of three-digit US classification codes	technology fields a patent is related to. Both capture different technology classification schemes (*USC3Digit* is more academic, while *IPC4Digit* is more industry classification scheme (Lanjouw and Schankerman, 2001). The larger the number of the fields could imply increased complexity of the patent.
Inventors	# of (patent) inventors; lead inventor: first named inventor	Examines whether patents from teams are more valuable than from individual inventors. Captures the difficulty and economic importance (Singh and Fleming, 2010)
InventorActivity	To explore non-linearities, we break down prior inventor activity into three classes:	Conti et al. (2014) showed that patents that come from inventors with previous patenting activity are on average more valuable than patents by first time inventors.
$InventorActivity_{Low}$	1 if patent i's lead inventor has no past patenting activity; 0 otherwise	
$InventorActivity_{Medium}$	1 if patent i's lead inventor has ,between 1 and 3 past patents; 0 otherwise	
$InventorActivity_{High}$	1 if patent i's lead inventor has more than 3 past patents; 0 otherwise	
Assignees	The number of assignees in the patent	More patent assignees imply larger likelihood of a technology transfer. Sapsalis et al. (2006) showed that the number of assignees, in a patent is correlated positively to its value.
AssigneeActivity	To explore non-linearities, we break down prior assignee activity into three classes:	Scholars argue that larger universities are better equipped in managing the technology transfer process (Merrill and Mazza, 2011)
$AssigneeActivity_{Low}$	1 if patent i's assignee has ,less than 123 patents; 0 otherwise	
$AssigneeActivity_{Medium}$	1 if patent i's assignee has between 123 and 583 past patents; 0 otherwise	
$AssigneeActivity_{High}$	value of 1 if patent i's assignee has more than 583 past patents	
GrantYear	set of dummies for the grant (issue) year of the patent	To control for macroeconomic shocks
TechnologyDummy	set of dummies for the technology field of the patent	To control for macroeconomic shocks

Notes: Assignee Activity was broken down into three classes. Classifications performed in such a way that sample sizes of the classes are fairly even ($AssigneeActivity_{L}ow$=1 for 6,957, $AssigneeActivity_{Medium}$=1 for 6,909, and $AssigneeActivity_{High}$=1 for 7,011 patents). In the regressions we exclude $AssigneeActivity_{Low}$ to avoid the dummy variable trap. Analogously, for the Inventor's activity, classifications performed in such a way that sample sizes of different inventor activity classes are fairly even ($InventorActivity_{Low}$=1 for 6,222, $InventorActivity_{Medium}$=1 for 7,040, and $InventorActivity_{High}$=1 for 7,615 patents). In the regressions we exclude $InventorActivity_{Low}$ to avoid the dummy variable trap.

Table A.2: Summary Statistics of University Patents issued between 1990 and 2000 by Large Entity Status (LES)

	Never Switch to LES	Switch to LES	p-value
$Federal$	0.38	0.42	0.00
	(0.48)	(0.49)	
$ForwardCites$	9.87	16.82	0.00
	(15.34)	(25.15)	
$BackwardCitesPat$	8.83	10.69	0.00
	(10.26)	(14.65)	
$BackwardCitesNonPat$	12.21	16.47	0.00
	(18.21)	(23.38)	
$ApplicationLength$	2.30	2.38	0.00
	(1.04)	(1.08)	
$Claims$	17.27	18.73	0.00
	(13.43)	(16.49)	
$IPC4Digit$	2.97	3.41	0.00
	(1.25)	(1.65)	
$USC3Digit$	3.19	3.29	0.00
	(1.19)	(1.28)	
$Inventors$	2.33	2.55	0.00
	(1.27)	(1.38)	
$InventorActivity_{Low}$	0.33	0.23	0.00
	(0.47)	(0.42)	
$InventorActivity_{Medium}$	0.34	0.33	0.01
	(0.47)	(0.47)	
$InventorActivity_{High}$	0.32	0.45	0.00
	(0.47)	(0.50)	
$Assignees$	1.02	1.03	0.00
	(0.13)	(0.19)	
$AssigneeActivity_{Low}$	0.38	0.25	0.00
	(0.48)	(0.43)	
$AssigneeActivity_{Medium}$	0.33	0.34	0.09
	(0.47)	(0.47)	
$AssigneeActivity_{High}$	0.30	0.41	0.00
	(0.46)	(0.49)	
Observations	13,782	7,095	

Table A.3: Summary Statistics of University Patents by Different Entity Status Behavior

	Not Switching to LES	Not claiming SES at grant but at the 1st renewal	Not claiming SES at filing and LES claimed at the 1st renewal
$Federal$	0.38	0.36	0.35
	(0.49)	(0.48)	(0.48)
$ForwardCites$	9.84	10.03	14.19
	(15.02)	(17.05)	(20.23)
$BackwardCitesPat$	8.82	8.91	11.00
	(10.16)	(10.83)	(15.27)
$BackwardCitesNonPat$	12.05	13.16	16.66
	(18.13)	(18.67)	(23.35)
$ApplicationLength$	2.25	2.60	2.35
	(0.97)	(1.34)	(1.13)
$Claims$	17.29	17.20	18.18
	(13.20)	(14.67)	(16.20)
$IPC4Digit$	2.95	3.06	3.36
	(1.24)	(1.28)	(1.53)
$USC3Digit$	3.18	3.22	3.23
	(1.19)	(1.18)	(1.21)
$Inventors$	2.33	2.33	2.56
	(1.27)	(1.22)	(1.36)
$InventorActivity_{Low}$	0.34	0.31	0.21
	(0.47)	(0.46)	(0.41)
$InventorActivity_{Medium}$	0.34	0.34	0.31
	(0.47)	(0.48)	(0.46)
$InventorActivity_{High}$	0.32	0.35	0.47
	(0.47)	(0.48)	(0.5)
$Assignees$	1.02	1.03	1.02
	(0.13)	(0.16)	(0.13)
$AssigneeActivity_{Low}$	0.38	0.37	0.25
	(0.48)	(0.48)	(0.43)
$AssigneeActivity_{Medium}$	0.33	0.31	0.37
	(0.47)	(0.46)	(0.48)
$AssigneeActivity_{High}$	0.29	0.32	0.38
	(0.45)	(0.46)	(0.48)
Observations	11,768	2,014	3,063

Numbers in parentheses are standard errors.

Table A.4: Propensity of Switching to Large Entity Status (LES) Excluding Patents Not Claiming Small Entity Status (SES) at grant, but at 1st Renewal

	All University Patents		Excluding University Outliers (*)	
	Funding	Type	Funding	Type
Federal	-0.0121		-0.0089	
	(0.008)		(0.009)	
DODfunding		-0.0677***		-0.0686***
		(0.016)		(0.020)
DOEfunding		-0.0137		-0.0328
		(0.016)		(0.021)
NIHfunding		-0.0016		0.0005
		(0.011)		(0.012)
NSFfunding		-0.0239		-0.0147
		(0.017)		(0.019)
Otherfunding		0.0144		0.0181
		(0.015)		(0.016)
ForwardCites	0.0046***	0.0046***	0.0047***	0.0047***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
BackwardCitesPat	0.0017***	0.0017***	0.0018***	0.0018***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
BackwardCitesNonPat	0.0006***	0.0006***	0.0005**	0.0005**
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
ApplicationLength	0.0077**	0.0076*	0.0049	0.0047
	(0.004)	(0.004)	(0.004)	(0.004)
Claims	0.0004	0.0004	0.0004	0.0004
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
IPC4Digit	0.0365***	0.0363***	0.0367***	0.0366***
	(0.003)	(0.003)	(0.003)	(0.003)
USC3Digit	-0.0051	-0.0051	0.0007	0.0008
	(0.003)	(0.003)	(0.003)	(0.003)
Inventors	0.0149***	0.0148***	0.0138***	0.0140***
	(0.003)	(0.003)	(0.003)	(0.003)
$InventorActivity_{Medium}$	0.0658***	0.0667***	0.0650***	0.0656***
	(0.010)	(0.010)	(0.010)	(0.010)
$InventorActivity_{High}$	0.138***	0.138***	0.124***	0.125***
	(0.009)	(0.009)	(0.010)	(0.010)
Assignees	0.0657***	0.0644***	0.0744***	0.0726***
	(0.023)	(0.023)	(0.023)	(0.023)
$AssigneeActivity_{Medium}$	0.0956***	0.0955***	0.0798***	0.0802***
	(0.010)	(0.010)	(0.010)	(0.010)
$AssigneeActivity_{High}$	0.177***	0.179***	0.147***	0.146***
	(0.010)	(0.010)	(0.011)	(0.011)
Observations	18.863	18.863	15.609	15.609

All columns report probit estimates (marginal effects). In all estimations time dummies (*GrandYear*) and technology field dummies (*TechnologyDummy*) are included but for brevity not reported here. Heteroskedastically robust standard errors are reported in parentheses.
(*) The MIT and the University of California are excluded (outliers) due to their exceptional patenting performance.

Appendix B

Table B.1: Robustness check of Table 3.4 results in the chapter. Replace the Dummies with their continuous counterparts.

Variables	Domestic Inventors' Patents			Foreign Inventors' Patents		
	All Patents	No Low /Med Patents	No Outliers	All Patents	No Low /Med Patents	No Outliers
ForwCites	0.0009***	0.0016***	0.0008***	0.0016***	0.0029***	0.0014***
	(5.01e−05)	(0.0001)	(4.81e−05)	(0.0002)	(0.0004)	(0.0002)
BackCitesPat	0.0013***	0.0027***	0.0011***	0.0012***	0.0021***	0.0014***
	(9.21e−05)	(0.0002)	(8.39e−05)	(0.0003)	(0.0006)	(0.0003)
$BackCitesSc_i$	0.0008***	0.0013***	0.0008***	0.0012**	0.0006	0.0011**
	(0.0002)	(0.0003)	(0.0002)	(0.0005)	(0.0006)	(0.0005)
Claims	0.0013***	0.0017***	0.0010***	0.0026***	0.0019***	0.0026***
	(6.46e−05)	(0.0001)	(6.28e−05)	(0.0002)	(0.0004)	(0.0002)
AppLength	0.0054***	0.0081***	0.0042***	0.0180***	0.0162***	0.0183***
	(0.0009)	(0.0018)	(0.0008)	(0.0021)	(0.0045)	(0.0021)
#Inventors	0.0326***	0.0649***	0.0297***	0.0438***	0.0607***	0.0438***
	(0.0013)	(0.0034)	(0.0013)	(0.0025)	(0.0051)	(0.0024)
#PastPats	9.52e−05***	5.37e−05*	0.0040***	0.0009***	0.0013***	0.0042***
	(1.64e−05)	(3.06e−05)	(0.0002)	(0.0001)	(0.0002)	(0.0005)
PastCorp	0.1240***	0.1090***	0.0854***	0.1540***	0.1650***	0.1210***
	(0.0024)	(0.0036)	(0.0027)	(0.0059)	(0.0077)	(0.0063)
PastUniv	0.0142***	−0.0033	0.0054	0.0288***	0.0479***	0.0229*
	(0.0038)	(0.0064)	(0.0037)	(0.0112)	(0.0160)	(0.0120)
#StatePats	3.79e−05**	3.28e−05	2.01e−05	0.0004***	0.0004***	0.0004***
	(1.48e−05)	(3.68e−05)	(1.44e−05)	(2.17e−05)	(4.94e−05)	(2.13e−05)
ShareTechState	0.0008***	0.0018***	0.0006***	0.0002	−0.0004	0.0004**
	(9.43e−05)	(0.0003)	(9.20e−05)	(0.002)	(0.0004)	(0.0002)
Observations	150,687	52,786	143,223	46,720	15,176	44,625

All columns report probit estimates (marginal effects).
In all estimations time variables (*GrantYear*) and technology field dummies (*TechnologyDummy*) are included but for brevity not reported here.
Compared to Table 4, we replace *InventorsMed* and *InventorsHigh* with *#Inventors*; *PastPatsLow*, *PastPatsMed*, *PastPatsHigh* with *#PastPats*; *StateHigh* with *#StatePats*. Heteroskedastic robust standard errors are reported in parentheses.
***p<0.01, ** p<0.05, * p<0.1.

Appendix C

Table C.1: Summary Statistics per Country, 2000-2012

Country	Inventor Flows		Inventors		R&D		Researchers		GDPcapita		Density	
	mean	Std.	mean	Std.	mean	Std.	mean	Std.	mean	Std.	mean	Std.
AUT	8.703	32.150	2,275.615	779.886	2.388	0.302	32,092.74	4,819.12	38,858.556	1,850.41	9.820	0.159
BEL	13.886	31.603	2,468.692	830.961	1.953	0.158	35,532.44	4,510.19	36,897.277	1,453.62	34.751	0.920
BGR	0.027	0.191	59.462	17.444	0.493	0.055	10,530.08	923.713	4,006.857	752.371	6.905	0.233
CAN	13.501	30.717	5,947.077	1,883.29	1.915	0.075	138,814.5	17,860.19	35,739.11	1,365.01	0.327	0.012
CHE	58.881	154.448	4,818.308	1,578.76	2.681	0.178	28,176.56	4,455.68	55,821.98	2,553.16	18.264	0.619
CYP	0.111	0.429	12.231	4.532	0.365	0.076	673.000	212.234	24,290.84	1,266.25	11.276	0.629
CZE	0.225	0.937	331.846	153.413	1.274	0.193	23,473.60	6,903.81	13,419.84	1,503.25	13.081	0.154
DEU	59.557	79.810	41,498.385	12,133.23	2.546	0.166	2.97e+05	30,907.18	35,956.81	1,806.90	22.990	0.155
DNK	6.393	11.564	2,326.38	706.370	2.614	0.282	31,101.92	6,438.78	48,066.26	1,458.44	12.659	0.187
ESP	5.966	11.633	3,299.15	1,486.18	1.148	0.169	1.10e+05	21,206.01	26,045.25	961.117	8.725	0.452
EST	0.050	0.253	74.385	51.371	1.185	0.519	3,594.04	631.702	10,026.24	1,644.57	2.992	0.052
FIN	5.610	7.419	3297.615	741.656	3.416	0.179	39,653.57	1,872.07	38,767.12	2,352.31	1.560	0.022
FRA	22.061	37.784	13,617.38	4,376.82	2.119	0.067	220,530.1	28,175.73	34,856.37	889.943	11.557	0.274
GBR	34.504	50.030	12,336.46	3,370.47	1.680	0.039	233,029.3	29,765.25	39,132.85	1,659.73	25.053	0.642
GRC	0.159	0.468	186.231	61.213	0.594	0.052	19,996.87	3,724.85	21,500.19	1,897.16	8.397	0.065
HRV	0.064	0.366	125.923	51.893	0.866	0.103	6,759.51	727.329	10,101.69	1,003.19	7.795	0.104
HUN	0.231	0.861	626.692	166.851	1.007	0.135	17,798.14	3,155.22	10,749.77	897.148	10.829	0.088
IRL	3.830	10.260	762.077	284.742	1.295	0.208	12,056.75	2,350.05	48,837.34	2,913.98	6.047	0.401
ITA	5.239	10.350	56,49.53	1,818.94	1.124	0.082	86,078.19	15,603.04	31,483.16	807.097	19.315	0.307
JPN	8.825	22.215	54,338.76	16,792.62	3.265	0.150	6.62e+05	16,036.31	35,531.73	1,126.74	33.791	0.091
KOR	2.297	8.866	15,261.46	8,944.96	2.907	0.573	2.06e+05	61,731.92	19,378.36	2,589.06	48.611	0.790
LVA	0.011	0.103	64.46	30.779	0.495	0.134	3,738.41	358.665	7,436.171	1,515.27	3.424	0.156
NLD	22.281	50.957	6,104.846	2,158.669	1.779	0.081	50,520.47	7,373.12	42,268.87	1,764.86	39.400	0.576
NOR	3.310	6.483	1,249.15	339.036	1.591	0.072	23,845.82	2,864.88	65,688.25	2,234.94	1.221	0.044
POL	0.233	0.831	447.692	198.800	0.632	0.096	60,144.77	3,121.73	8613.706	1,351.41	12.202	0.022
PRT	0.538	1.526	217.000	132.189	1.066	0.347	28,989.94	10,411.93	18,824.99	390.254	11.384	0.088
SVK	0.074	0.334	85.308	29.599	0.565	0.100	11,956.06	2,150.68	12419.782	2,210.913	10.978	0.021
SVN	0.027	0.229	268.231	110.441	1.673	0.410	6,033.71	1,706.66	18,237.17	1,706.243	9.948	0.119
SWE	11.602	18.330	5,361.84	1,413.70	3.476	0.206	49,453.85	3085.740	42,903.98	2,615.38	2.030	0.049
USA	253.939	447.572	96,130.15	37,287.26	2.640	0.104	1,135,913	87563.202	43,437.81	1,567.56	3.073	0.080

Country's three-letter abbreviation reported in first column; *InventorFlows* are occurrences (non-negative integers); *Inventors* is total number of inventors in a country (+ net flows); *R&D* is research and development spending (constant prices, ppp)as a share of GDP; *Researchers* is the number of scientists (science, engineering, and health researchers); *GDPcapita* is GDP per capita (constant prices, ppp); *Density* is a country's total population (in millions) over country's surface area (in hundreds thousands of sq. km).

Table C.1: Summary Statistics per Country, 2000-2012 (continued)

Country	Foreigners		Wage		Tax		Tertiary		EPL		Patent applications	
	mean	Std.	mean	Std.	mean	Std.	mean	Std.	mean	Std.	mean	Std.
AUT	14.116	1.120	40,576.92	5,310.86	43.431	0.447	1.478	0.138	2.682	0.114	2474.692	172.494
BEL	8.916	0.788	44,148.28	6,047.38	46.485	2.573	1.357	0.063	2.837	0.049	3735.846	84.323
BGR	0.845	0.193	.	.	.	.	0.754	0.097	.	.	505.231	331.843
CAN	19.351	1.018	33,163.13	2,858.70	46.638	0.560	2.415	0.141	1.510	0.000	38610.231	2294.621
CHE	24.757	1.742	49,956.82	7,670.07	36.731	0.519	1.312	0.105	2.180	0.000	2248.538	264.124
CYP	12.863	3.071	.	.	.	.	1.682	0.334	.	.	40.875	35.659
CZE	3.168	0.551	16,909.81	3,659.86	24.977	3.829	0.957	0.139	2.880	0.100	2097.462	1789.756
DEU	12.980	1.211	46,045.23	6,612.14	48.200	2.897	1.205	0.100	2.950	0.000	60180.538	1261.627
DNK	8.304	0.817	41,563.35	6,057.62	55.631	2.866	2.456	0.165	2.453	0.100	1827.846	117.807
ESP	9.688	3.137	29,684.87	4,586.53	45.615	2.592	1.045	0.106	2.743	0.040	3428.154	274.835
EST	16.993	0.585	14,597.94	4,098.76	23.108	2.357	1.088	0.151	2.250	0.172	267.615	299.372
FIN	3.846	0.751	35,809.50	6,652.86	49.885	1.596	2.041	0.104	2.070	0.060	2134.154	323.504
FRA	11.098	0.338	35,298.83	4,723.05	40.162	5.280	1.256	0.061	2.691	0.038	16862.769	445.505
GBR	10.353	1.492	47,182.03	3,973.95	42.308	4.219	1.008	0.178	1.720	0.000	26918.154	4043.6
GRC	10.847	0.414	30,816.23	4,065.68	35.546	2.777	1.352	0.174	2.861	0.163	551.615	137.919
HRV	13.262	0.054	.	.	.	.	0.772	0.124	.	.	658.385	358.245
HUN	3.754	0.511	15,939.76	3,815.36	48.877	10.839	1.092	0.079	2.400	0.000	2337.385	2036.897
IRL	13.585	2.224	31,202.89	5,767.84	45.785	2.743	1.243	0.139	1.871	0.061	893.462	171.062
ITA	7.184	2.052	31,308.05	4,387.144	43.138	2.736	0.810	0.044	3.150	0.000	9616.857	276.083
JPN	1.561	0.108	39,315.16	4,419.38	46.938	0.617	0.643	0.078	2.034	0.115	3.94E+05	34977.951
KOR	1.270	0.532	37,330.44	6,335.96	36.285	1.129	2.254	0.145	2.230	0.000	1.49E+05	29929.079
LVA	16.387	1.219	.	.	.	.	0.927	0.134	2.990	0.000	179.769	33.008
NLD	10.617	0.446	46,355.86	7,056.61	51.400	2.727	1.520	0.121	2.905	0.023	2755.923	136.015
NOR	8.809	1.806	45,109.41	7,323.28	43.154	3.559	2.095	0.178	2.380	0.000	4898	1899.96
POL	1.855	0.166	16,706.11	3,031.31	27.462	4.087	1.072	0.077	2.456	0.069	4976.538	1828.563
PRT	7.105	0.346	22,019.60	3,926.51	37.854	3.006	0.998	0.090	3.828	0.306	338.923	195.565
SVK	2.497	0.227	13,958.47	3,526.90	19.615	14.662	0.862	0.070	2.692	0.178	772.385	740.604
SVN	10.497	1.301	22,390.43	3,772.11	35.723	3.544	1.280	0.060	2.844	0.020	386.5	51.783
SWE	13.176	1.384	36,189.68	5,058.10	56.277	0.458	1.961	0.098	2.585	0.011	3235	806.376
USA	13.433	0.685	40,142.35	4,907.11	42.531	1.855	1.305	0.090	1.000	0.000	4.14E+05	74916.256

Country's three-letter abbreviation reported in first column; *Foreigners* is foreign-born population - people who have residence in one country but were born in another country, including refugees; *WAGE* is average market wage that is national-accounts-based total wage bill divided by the average number of employees in the total economy, which is then multiplied by the ratio of the average usual weekly hours per full-time employee to the average usually weekly hours for all employees; *Tax* is the marginal tax rate; is the additional central and sub-central government personal income tax resulting from a unit increase in gross wage earnings; *Tertiary* is public spending on tertiary (higher) education; *EPL* is stringency of a country's employment protection legislation; *Patentapplications* is total country's patent applications.

Figure C.1 shows the country pairs with the highest exchange of immigrants across 22 countries and over 2000-2012:

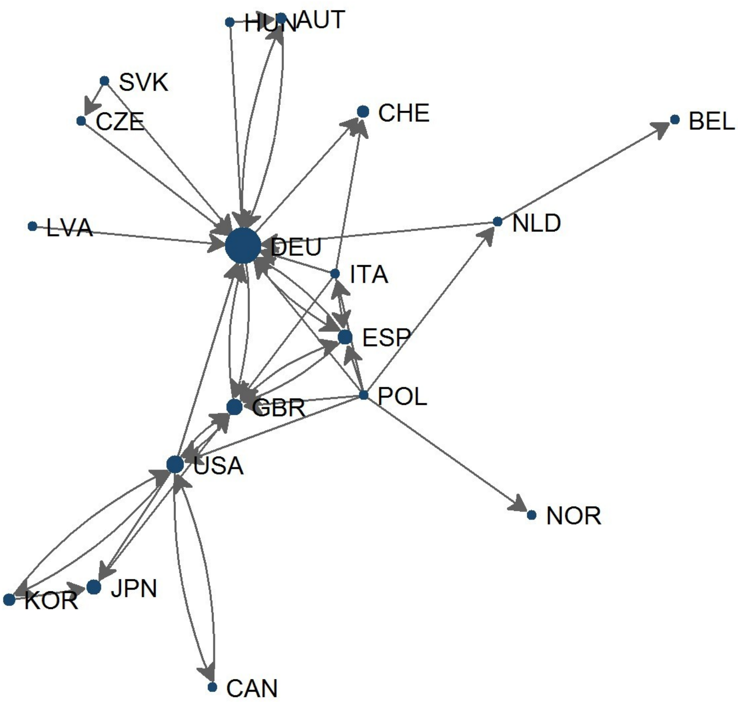

Figure C.1: Top 5% Immigrant Mobility Flows

Table C.2: Determinants of International Inventor Mobility (Robustness)

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)
$NeighbouringCountries\,[>300Km]$	-0.775***	-0.818***	-0.813***	-0.777***	-0.756***	-0.752***	-0.776***
	(0.228)	(0.216)	(0.221)	(0.230)	(0.235)	(0.236)	(0.226)
$Distance\,[<1,110Km]$	-1.098***	-1.143***	-1.143***	-1.097***	-1.098***	-1.098***	-1.138***
	(0.224)	(0.214)	(0.216)	(0.225)	(0.237)	(0.237)	(0.224)
$Distance\,[1,110-1,500Km]$	-1.228***	-1.264***	-1.253***	-1.227***	-1.186***	-1.185***	-1.181***
	(0.231)	(0.219)	(0.224)	(0.232)	(0.242)	(0.243)	(0.229)
$Distance\,[>1,500Km]$	-1.815***	-1.909***	-1.903***	-1.817***	-1.781***	-1.781***	-1.832***
	(0.248)	(0.241)	(0.245)	(0.249)	(0.269)	(0.269)	(0.249)
$Density_i$	-0.055	-0.087	-0.086*	-0.046	-0.085	-0.049	-0.132**
	(0.052)	(0.052)	(0.052)	(0.052)	(0.065)	(0.063)	(0.056)
$Density_j$	-0.029	-0.035	-0.028	-0.038	0.038	0.008	-0.0421
	(0.046)	(0.046)	(0.046)	(0.047)	(0.056)	(0.056)	(0.048)
$lnInventors_i$	0.877***	0.856***	0.859***	0.922***	1.109***	1.064***	0.885***
	(0.073)	(0.075)	(0.075)	(0.074)	(0.093)	(0.091)	(0.075)
$lnInventors_j$	0.218***	0.269***	0.268***	0.208***	0.229***	0.206***	0.254***
	(0.062)	(0.070)	(0.070)	(0.060)	(0.072)	(0.071)	(0.071)
$TechSpecialisationSimilarity$	-0.137	-0.0756	-0.059	-0.140	-0.121	-0.114	-0.166
	(0.117)	(0.117)	(0.118)	(0.116)	(0.135)	(0.135)	(0.129)
$TechEffortDistance$	0.985***	1.013***	1.005***	0.989***	1.081***	1.077***	1.032***
	(0.294)	(0.327)	(0.327)	(0.293)	(0.382)	(0.384)	(0.337)
$LinguisticSimilarity$	0.592***	0.567***	0.567***	0.590***	0.482***	0.484***	0.465***
	(0.115)	(0.118)	(0.118)	(0.115)	(0.143)	(0.143)	(0.117)
$ReligionSimilariry$	0.761***	0.705***	0.705***	0.712***	0.713***	0.711***	0.719***
	(0.209)	(0.122)	(0.125)	(0.109)	(0.218)	(0.218)	(0.224)
$EconClossness$	0.299			0.273	0.311	0.306	0.296
	(0.202)			(0.193)	(0.225)	(0.225)	(0.230)
$Trade_{ij}$	0.701**	0.710**	0.705**	0.746**	0.728***	0.707***	0.730**
	(0.351)	(0.336)	(0.342)	(0.371)	(0.223)	(0.206)	(0.316)
$Foreigners_i$	0.050*	0.060**	0.058**	0.031	0.129***	0.108***	0.052*
	(0.026)	(0.027)	(0.027)	(0.026)	(0.039)	(0.038)	(0.028)
$lnGDPcapita_i$	1.701***	1.685***	1.632***		1.537***	1.664***	1.762***
	(0.464)	(0.449)	(0.424)		(0.350)	(0.425)	(0.409)
$lnGDPcapita_j$	0.139	0.285	0.445		0.433	0.560	0.061
	(0.343)	(0.362)	(0.379)		(0.494)	(0.482)	(0.399)
$GDPgrowthi$				0.011			
				(0.009)			
$GDPgrowthj$				-0.014*			
				(0.007)			
FD_i	0.840*	0.820**	0.817**	0.873**	0.825	0.851	0.857***
	(0.450)	(0.414)	(0.411)	(0.440)	(0.619)	(0.618)	(0.244)
FD_j	0.318	0.395	0.516	0.330	0.138	0.141	0.316
	(0.407)	(0.412)	(0.431)	(0.399)	(0.526)	(0.520)	(0.425)
$R\&D_i$	0.055	0.016	0.015	0.024			0.026
	(0.108)	(0.109)	(0.108)	(0.107)			(0.114)
$R\&D_j$	0.047	0.066	0.069	0.049			0.110
	(0.093)	(0.094)	(0.094)	(0.092)			(0.001)
$Tetriary_i$	0.007	0.016	0.029	0.006	0.255*	0.198	0.021
	(0.119)	(0.119)	(0.120)	(0.118)	(0.151)	(0.148)	(0.121)
$Tetriary_j$	0.149	0.016	0.028	0.135	0.101	0.071	0.039
	(0.116)	(0.105)	(0.104)	(0.119)	(0.138)	(0.137)	(0.109)
$WageCloseness$		0.094					
		(0.213)					
$TaxClossness$			0.513				
			(0.494)				
$R\&Dpublic_i$					0.397**		
					(0.705)		
$R\&Dpublic_j$					-0.357		
					(0.557)		
$R\&Dindustry_i$						0.122	
						(0.157)	
$R\&Dindustry_j$						0.280**	
						(0.133)	
EPL_i							0.457*
							(0.238)
EPL_j							-0.136
							(0.212)
Observations	11,310	8,450	8,450	11,310	7,308	7,308	7,718

All regressions include origin and destination country and year fixed effects; Coefficient of constant term is omitted for brevity; Robust standard errors in parentheses; (***): p<0.01, (**): p<0.05, (*): p<0.1 significance at 1%, 5% and 10%, respectively.

Table C.3: Top Destination and Origin Countries (Immigrant Flows)

Mean	St. Dev.	Min	Max
2,082.281	7,074.274	0	177,758

Top Destination Countries	Origin of Major Flows	Number of immigrants	Share
Germany		3,540,019	
	Poland	1,577,493	44.56%
	Italy	300,308	8.48%
	Hungary	278,914	7.88%
UK		1,313,663	
	Poland	226,361	17.23%
	USA	202,022	15.38%
	Germany	170,656	12.99%
USA		1,183,853	
	Republic of Korea	280,900	23.73%
	Canada	209,969	17.74%
	UK	190,316	16.08%
Spain		962,090	
	UK	300,198	31.31%
	Italy	164,289	17.08%
	Germany	151,954	15.79%
Japan		938,482	
	Republic of Korea	326,161	34.75%
	USA	286,365	30.51%
	UK	79,672	8.49%

Table C.4: Determinants of International Mobility of Inventors & Immigrants (Robustness)

	Inventor Flows			Immigrant Flows		
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
$NeighbouringCountries\,[>300Km]$	-0.761***	-0.740***	-0.740***	-1.494***	-1.352***	-1.427***
	(0.269)	(0.267)	(0.264)	(0.332)	(0.304)	(0.313)
$Distance\,[<1,110Km]$	-1.152***	-1.141***	-1.141***	-1.859***	-1.692***	-1.757***
	(0.245)	(0.240)	(0.238)	(0.317)	(0.283)	(0.297)
$Distance\,[1,110-1,500Km]$	-1.224***	-1.205***	-1.204***	-2.147***	-1.995***	-2.064***
	(0.251)	(0.247)	(0.245)	(0.316)	(0.279)	(0.294)
$Distance\,[>1,500Km]$	-2.126***	-2.113***	-2.112***	-2.810***	-2.752***	-2.835***
	(0.280)	(0.276)	(0.271)	(0.332)	(0.296)	(0.311)
$Density_i$	-0.0550	-0.0775	-0.0774	-0.0313	-0.0238	-0.00989
	(0.0602)	(0.0589)	(0.0589)	(0.0454)	(0.0432)	(0.0422)
$Density_j$	-0.0231	-0.0198	-0.0192	-0.108***	-0.0890**	-0.0679*
	(0.0528)	(0.0502)	(0.0500)	(0.0383)	(0.0386)	(0.0381)
$lnInventors_i$	0.807***	0.713***	0.714***	0.137***	0.232***	0.226***
	(0.0844)	(0.0815)	(0.0816)	(0.0393)	(0.0477)	(0.0475)
$lnInventors_j$	0.241***	0.287***	0.287***	0.163***	0.194***	0.191***
	(0.0739)	(0.0792)	(0.0790)	(0.0484)	(0.0574)	(0.0564)
$TechEffortDistance$	-0.245*	-0.192*	-0.191*	-0.0029	-0.0404	-0.0694
	(0.146)	(0.139)	(0.142)	(0.131)	(0.110)	(0.143)
$TechSpecialisationSimilarity$	0.760**	0.795**	0.794**	0.224***	0.243***	0.261***
	(0.357)	(0.366)	(0.365)	(0.097)	(0.055)	(0.052)
$LinguisticSimilarity$	0.392***	0.399***	0.399***	0.455***	0.468***	0.476***
	(0.144)	(0.145)	(0.145)	(0.159)	(0.160)	(0.157)
$ReligionSimilariry$	0.579**	0.538**	0.539**	1.307***	1.140***	1.166***
	(0.275)	(0.268)	(0.267)	(0.248)	(0.247)	(0.249)
$EconClossness$	0.140			0.172		
	(0.242)			(0.182)		
$Trade_{ij}$	0.773*	0.781*	0.781*	0.988**	0.790*	0.840**
	(0.443)	(0.459)	(0.460)	(0.480)	(0.441)	(0.468)
$Foreigners_i$	0.0124	0.0438	0.0437	-0.0233	0.0342*	0.0327*
	(0.0322)	(0.0336)	(0.0335)	(0.0178)	(0.0177)	(0.0176)
$lnGDPcapita_i$		2.190***	2.187***		1.174***	0.987***
		(0.623)	(0.617)		(0.312)	(0.313)
$lnGDPcapita_j$		-0.184	-0.192		-0.157	-0.348
		(0.478)	(0.457)		(0.355)	(0.341)
$GDPgrowthi$	0.00371			0.00141		
	(0.0107)			(0.00451)		
$GDPgrowthj$	-0.00319			-0.0165***		
	(0.00906)			(0.00541)		
FD_i	1.020**	1.020**	1.019**	0.382	0.463	0.237
	(0.511)	(0.508)	(0.507)	(0.381)	(0.374)	(0.365)
FD_j	-0.270	-0.247	-0.239	-0.163	-0.539	-0.343
	(0.509)	(0.519)	(0.493)	(0.328)	(0.365)	(0.337)
$R\&D_i$	0.0267	0.0457	0.0454	0.0000363	0.00483	0.0104
	(0.118)	(0.116)	(0.115)	(0.0695)	(0.0724)	(0.0702)
$R\&D_j$	0.111	0.110	0.110	0.0125	0.0461	0.0454
	(0.100)	(0.0986)	(0.0988)	(0.0708)	(0.0716)	(0.0718)
$Tetriary_i$	0.00530	0.0314	0.0305	0.609***	0.606***	0.584***
	(0.138)	(0.137)	(0.139)	(0.0910)	(0.0965)	(0.0960)
$Tetriary_j$	0.0113	0.00277	0.00190	0.0571	0.141	0.153*
	(0.133)	(0.131)	(0.133)	(0.0887)	(0.0907)	(0.0923)
$TaxClossness$		-0.0264			-0.182**	
		(0.550)			(0.081)	
$WageClossness$			-0.00642			0.124
			(0.239)			(0.211)
	5,967	5,460	5,460	5,967	5,460	5,460

All regressions include origin and destination country and year fixed effects; Coefficient of constant term is omitted for brevity; Robust standard errors in parentheses; (***): p<0.01, (**): p<0.05, (*): p<0.1 significance at 1%, 5% and 10%, respectively.