Faculteit Bedrijfseconomische Wetenschappen

master in de toegepaste economische wetenschappen

Masterthesis

Inventor mobility and the innovative performance of former employers

Sibert Thijs

Scriptie ingediend tot het behalen van de graad van master in de toegepaste economische wetenschappen, afstudeerrichting innovatie en ondernemerschap

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Preface

This research is conducted to achieve a master's degree in applied economics with a specialization in innovation and entrepreneurship at Hasselt University. During the realization of this master thesis, I was supervised by Prof. Dr. Bart Leten and Ngoc Han Nguyen. Bart Leten is associate professor innovation management at the University of Hasselt, the KU Leuven, and previously at the Vlerick Business School. I would like to praise both for the advice they have offered me during the realization of my master thesis.

This master thesis was written during the COVID-19 crisis in 2020. This global health crisis might have had an impact on the (writing) process, the research activities, and the research results that are at the basis of this thesis.

Sibert Thijs

Hasselt, 2020

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Chapter 1: Introduction

1. Introduction

Due to a general increase in availability and mobility of skilled workers, the growth of the venture capital market, the external options for unused ideas, and the increasing capability of external suppliers, the market of knowledge is changed into an open innovation process (Chesbrough & Bogers, 2014). As a result, it becomes difficult to develop all the required knowledge for technological innovations inside the firm since it is less expensive and faster to tap into externally available knowledge than develop all the necessary knowledge internally. More specifically, firms need to tap into external sources of knowledge, such as suppliers, buyers, universities, consultants, and competitors. However, given the tacit and complex nature of knowledge, the acquisition of valuable knowledge can be challenging. A large part of the knowledge that firms look for is embedded in inventors. When these inventors move between organizations, they can apply their knowledge to a new context and thereby effectively transfer the knowledge between firms. Therefore, hiring inventors from another firm can perform as a knowledge spillover channel, namely a mechanism to effectively acquire external knowledge (Song, Almeida, & Wu, 2003).

Prior research has mainly emphasized on the fact that labor mobility could function as a key channel of knowledge spillovers to the receiving firm. On the contrary, labor mobility may also affect the firm that has been abandoned. Losing inventors brings a firm into a situation of losing possible crucial knowledge of the inventors and consequently damaging the competitive position of the firm (Campbell, Coff, & Kryscynski, 2012). Although, Corredoira and Rosenkopf (2010) find evidence in the semiconductor sector of reverse knowledge spillovers, especially, they find that semiconductor firms that lose an employee becomes mare aware of the firm that hires the employee. Namely, an increase occurs in the application of the knowledge of the hiring firm. Besides, research in the context of the Danish labor market by Kaiser, Kongsted, and Rønde (2015) found that labor mobility stimulates the total innovation performance of both: the firm losing an inventor and the firm receiving the inventor. Moreover, inventor mobility is seen as a contributor to the knowledge creation among firms and regions.

Only a small number of studies is focusing on the effect of leaving inventors on the firm's innovation output. This research aims to clarify the potential impact of leaving inventors in the pharmaceutical industry. In this industry, innovation is of the highest importance and the mobility of inventors between firms is especially vital in high-technology industries, such as the pharmaceutical industry (Di Lorenzo & Almeida, 2017). Therefore, this research copes with the following central question: "How does inter-firm inventor mobility influence the innovation performance of former employers in the pharmaceutical industry?" A literature review gives a broad insight into the concept of inventor mobility. Next, an answer if formulated by the conduction of a quantitative study with a correlational and causal-comparative research design.

On the one hand, the literature review is focusing on the different aspects of inventor mobility. Firstly, a broad insight is provided about the main concept of the central research question, namely inventor mobility. Various types or dimensions of mobility events are explained. Within the empirical part of the study, inventor mobility is reflected as an independent variable. More specifically, this research examines the effect of a change in the share of leaving inventors on the innovation output of the former employers within the pharmaceutical industry context.

Secondly, the effect of mobility on the intellectual capital and competitive advantage of a firm is studied. The inventors within a pharmaceutical firm and their underlying knowledge shape a part of the knowledge asset of a particular firm, which plays an essential role in the creation of a sustained competitive advantage (Campbell et al., 2012). Inventor mobility could change the knowledge asset of a firm and thus influence the competitive position. Therefore, firms may try to limit leaving inventors and the potential effect on the firm. Moreover, the determinants of inventor mobility are mentioned.

Thirdly, the effect of inventor mobility is being investigated. The impact of inter-firm inventor mobility is observed in various ways. In this research, a distinction is made between the effect of inventor mobility on a macro-perspective, micro-perspective, and the inventor himself. The macro-perspective reflects the impact of inventor mobility at a broad perspective, namely the effect at a regional level. The micro-level focusses on the effect of inventor mobility on the firm that loses the inventor and the firm that hires the inventor.

On the other hand, the empirical study is done by analyzing a panel data set of 276 pharmaceutical firms, including the 50 largest R&D spending pharmaceutical firms in the world. This study uses patent data, as many prior studies to examine inventor mobility. Currently, most of the conducted studies are using patent citations as an indicator of knowledge spillovers, although patent citations do not expose the firm-level effect on innovation output, which is the main interest of the present paper. This research examines the impact of a change in the share of leaving inventors on the firm's innovation output. Also, this research examines how the innovation output of a firm is affected by the productivity of the leaving inventor, the technological distance between the hiring and losing firm, and the geographical proximity after the mobility event of the leaving inventor.

Chapter 2: Literature review

2. Literature review

To ultimately fulfill the research question and to conduct an empirical study, a theoretical framework based on existing academic literature is composed. The theoretical framework consists of three major parts. The first part aims to answer the central question: "What is inventor mobility?" The second part explains inventor mobility as a driver to generate knowledge, whereby different kinds of knowledge of a firm are clarified. Besides, this part focuses on the impact of inventor mobility on the possibility of a firm to generate a sustained competitive advantage. The third part of the theoretical framework focuses on the effect of inventor mobility. This part is divided into three parts, specifically the effect of inventor mobility at the regional level, the firm level, and the inventor. Besides,

2.1. What is inventor mobility?

Labor is characterized by many economists as an input for production. Adam Smith, for instance, discussed the advantages of labor specialization extensively in his well-known work "The Wealth of Nations". Moreover, he suggested that by educating and training of employees, later on, determined as improving the human capital of an employee, a firm will become more profitable. Ultimately, this fosters the collective wealth of a society (Smith, 1776). However, labor mobility, determined as a change in location, affects the input factor labor of an organization. For the reason that mobility is essentially a change in location, inventor mobility is identified as an input for production (Latham et al., 2011).

As illustrated in *figure 1* by Latham et al. (2011), it is possible to create a specific career path of an inventor within a cube. The cube depicts inventor mobility over three distinctive dimensional spaces. The first dimension is the geographic space. Depending on the scale of measurement, mobility indicates a movement within a city or between cities, within a region or between regions, within a country or between countries. The second-dimensional space is the industrial structure of an economy. A mobility event within this space can be an industrial movement, an intra-firm movement, or an inter-firm movement. Intra-firm mobility is a movement within a firm between divisions or branches, inter-firm mobility or firm-to-firm mobility indicates a movement between firms of the same industry, and industry-to-industry mobility is a movement between firms of different industries. The third-dimensional space is a technological space. This dimension indicates a

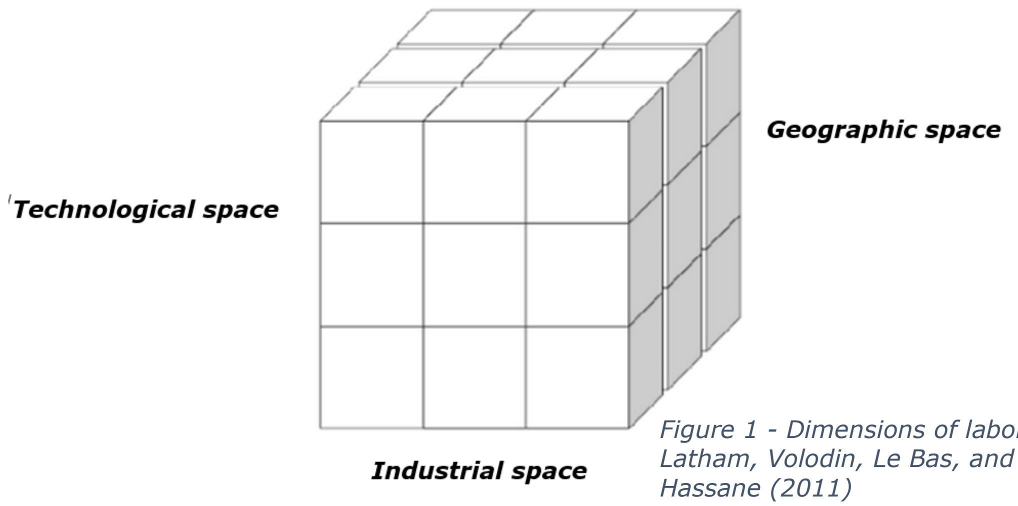

Figure 1 - Dimensions of labor mobility by Latham, Volodin, Le Bas, and Bouklia-Hassane (2011)

movement over different technologies. For example, an inventor may invent in a broad technological area as biotechnology. If the inventor develops something related to pharmaceutical technology, namely another distinctive technological area, mobility occurs. Technological areas are retrievable on patents in the form of International Patent Classification (IPC). Technological mobility is possible to measure from one specific technological class to another specific technological class or from one broad technological class to another one (Latham et al., 2011).

If a movement is identified as a movement between regions (geographic space), between firms in the same industry structure (industrial space), between broad patent technology classes (technology space), an immobile inventor is one who remains at the current firm he is working for, stays in the same region and will patent in the same broad patent class (Latham et al., 2011).

2.2. The relationship between inventor mobility and intellectual capital of a firm

Important is to understand when inventor mobility is more likely to occur. Song et al. (2003) suggested two motives for hiring experienced inventors. Firstly, some firms that miss a specific technological trajectory or firms that are still developing their technological areas may try to tap into external knowledge by hiring inventors. Secondly, firms may employ experienced inventors to build a high-quality human capital environment. In both cases, the motive for hiring an inventor is to expand the firm its knowledge assets.

Di Lorenzo and Almeida (2017) highlighted the importance of knowledge generation mechanisms in science-driven industries to the competitiveness of firms. In these industries, knowledge of inventors is seen as a potential source to boost the competitiveness of firms. Therefore, hiring or losing an inventor influences the knowledge assets of the "source firm", the firm that loses an inventor, and the "recipient firm", the firm that employs the inventor. When an inventor leaves the source firm to join the recipient firm, it is possible to transfer valuable knowledge of the source firm. Inventors within the pharmaceutical industry, create new knowledge which is often difficult to transfer to another person. Song et al. (2003) refer to tacit knowledge, defined as "sticky" knowledge that is complicated to diffuse across firms unless the individuals owning the tacit knowledge will move. An often-used example is knowledge of state-of-the-art technologies. Mostly, the assets of a firm that establishes the competitive advantage are built internally through experience or by learning-by-doing. However, some knowledge cannot be transferred through inventor mobility, such as a firm routine, culture, and norms. To understand the impact of inventor mobility on the source firm and recipient firm, it is important to distinguish different kinds of knowledge assets a firm possesses and how the mobile inventor these assets influences. Further in this section, various types of knowledge are distinguished.

According to McCracken, McIvor, Treacy, and Wall (2017), intellectual capital or knowledge capital is the intangible value of a firm. It consists out of three specific capital values: the labor value (human capital), network value (social capital), and the intangible organizational assets such as organizational processes, patents, and trademarks (structural capital) of a firm. These three components discussed hereafter shapes the knowledge asset of a firm that in the right circumstances may generate a sustained competitive advantage. Moreover, these three components are interdependent.

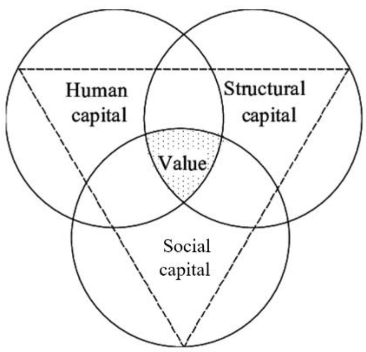

Figure 2 – Illustration of the dimensions of intellectual capital by Mahmoud (2016)

2.2.1. Human capital

Human capital is often seen as the foundational part of intellectual capital because it has a fundamental role in the creation of new knowledge. The creation of new knowledge by an inventor often results in a patent (McCracken et al., 2017). Acemoglu and Autor (2016) define human capital as any stock of knowledge or characteristic that an inventor possesses (either innate or acquired) that contributes to the productivity of the firm. Besides, Campbell et al. (2012) show that different kinds of human capital change the potential market value of the inventor, and hence the probability of inventor mobility. Therefore, a firm may be willing to oppose being vulnerable to employee mobility and to generate in that manner a sustained competitive advantage. Observing inventor mobility from a human capital perspective reveals a theory for firms to limit inventor mobility. However, three boundary conditions are limiting the applicability of this theory and, thus, to conduct a sustained competitive advantage.

Human capital can be distinguished into two types. On the one hand, an inventor possesses general human capital. General human capital contains skills and knowledge that an inventor can use in other firms, as with the competition. For example: basic reading skills, writing skills, and lower mathematics. On the other hand, firm-specific human capital refers to the skills, knowledge, and abilities of an inventor with limited application options outside the source firm. For example, the knowledge of the technology or social structure of a firm. Inventors who understand the source firm's unique innovation system can introduce this knowledge to the recipient firm, although it is challenging to apply in practice because the knowledge is cospecialized to a broad mix of assets unique to the source firm (Campbell et al., 2012).

Technology is a determinant of human capital. A high level of technology ensures a high demand for high-skilled work, whereas skills are one of the determining factors of human capital. Consequently, a higher level of technology requires a larger stock of human capital than a low-technology company. This means that there exists a positive relationship between the level of technology and the demand for human capital (Dobbelaere & Vancauteren, 2014). The pharmaceutical industry is seen as a high technological industry where innovation, measured by patents, is especially important (Di Lorenzo & Almeida, 2017). According to Hoisl (2007), mobility is more likely to occur in an industry with a higher patent propensity.

Extensive research demonstrates that human capital can be a source of sustained competitive advantage for firms. A sustained competitive advantage is created when a firm can generate more economic value than the marginal (breakeven) competitor. However, human capital is not fully controlled by a firm due to inventor mobility. Consequently, firms may try to isolate human capital only to the extent that inventors have a little ability to leave the source firm. Firm-specific human capital seems to act as an isolating mechanism, a mechanism that will hinder inventors from taking their vital knowledge and skills to competing firms. When an inventor possesses much firm-specific human capital, the inventor becomes more valuable to the current firm, and even the labor-market value of the inventor does not increase. This stems from the fact that the knowledge of the inventor is not applicable to other firms. In this way, firm-specific human capital limits inventor mobility, whereas general human capital is perfectly applicable to other firms and consequently will not limit inventor mobility. For this reason, firm-specific human capital is considered to support sustained competitive advantage, while stimulation of general human capital will not always have a positive influence on sustained competitive advantage. Although, if an inventor is willing to accept lower wages, mobility can still occur. Nevertheless, the source firm-specific knowledge will not be affected because it is not easy to implement this elsewhere. It can be concluded that firm specificity acts as an isolation mechanism to develop a sustained competitive advantage (Campbell et al., 2012). This is also confirmed in the study conducted by Hoisl in 2007. She states that inventors who are specialized in particular small technical areas and thus possess more firm-specific human capital are less likely to move. However, this theory seems not always to work accurately. Three boundary conditions constrain the applicability of this theory. Namely, heterogeneous skills, heterogeneous knowledge, demand-side information asymmetries, and Supply-side constraints.

2.2.1.1. Heterogeneous skills and knowledge

Firstly, the value of the skills and knowledge of an inventor is heterogeneous. This indicates that the general human capital value of an inventor is not valued the same for each firm, because firms possess unique portfolios of resources and capabilities. The valuation of general human capital may differ over product markets, complementary assets, and different technologies. For example, a software developer who is working for a small insurance company can be more valuable for a big firm like Google. This follows on the fact that the general skills of the employee are valued higher at Google than at the small insurance company. Consequently, Google may be willing to compensate the software developer more than the current employer. Therefore, firm-specific skills may not restrict mobility if the general skills of an employee are differently valued by different product markets, complementary assets, and different technologies. This leads to the condition that the real market value of the general human capital of the inventor cannot exceed the valuation of the market value by the firm where the inventor currently works. Otherwise, the inventor is more valuable to other firms and thus more likely to leave the current firm and start a new job elsewhere (Campbell et al., 2012).

Besides, it is critical to analyze the nature of the entire portfolio of skills of an inventor, rather than observing a single skill in isolation. For example, a unique skill with low applicability outside the current context has a low exchange value, thus potential employers will not compensate workers for that skill. In reality, the inventor possesses a portfolio of skills, namely the accumulation of general and firm-specific human capital. Thus, to understand the market demand for an inventor, it is important to consider all skills of an inventor simultaneously, rather than any isolated skill individually. (Campbell et al., 2012).

2.2.1.2. Demand-side information asymmetries

Second, labor markets are fraught with information asymmetries. This makes it very difficult for hiring firms, namely the demand-side, to assess the human capital portfolio of an inventor. Especially, the possession of mostly firm-specific human capital may be overvalued, and portfolios consisting mainly of general human capital may experience less external demand. Overvalued human capital by the market damages a firm its ability to create a sustained competitive advantage for two reasons. Namely, a firm must pay more money to retain the inventor and the inventor has more outside options and will be more likely to leave. On the contrary, undervalued human capital may act as a source of sustained competitive advantage. Therefore, the theory of firm-specific capital as an isolating mechanism requires a second condition. Namely, the value of the skills of the inventor and the valuation of those skills by the market must be tightly coupled (Campbell et al., 2012).

Labour mobility is more likely to occur in a competitive labor market (Kaiser et al., 2015). As a result of legal regulations, firms are obligated to make patent information publicly available. Information about inventors is hereby available at low costs and turns the market in an "open job market". The "open job market" leads to a better match quality between inventor and employer, more productive inventors, and an increase of social welfare (Hoisl, 2007).

Besides, pharmaceutical firms have an information advantage over their inventors. The current employer uses comparative mechanisms to better understand the performance and subsequent actions of inventors. For example, pharmaceutical firms use reference points, such as co-patentors, to determine the relative performance of an inventor. This means that inventor productivity relative to an inventor its co-patentors has a meaningful influence on the valuation of an inventor and, thus on the probability of inter-firm mobility. If an inventor is performing above its reference group, an increase in relative performance (the difference between individual performance and the co-inventors their performance) lowers the probability of mobility. This results from the fact that the current employer has an information advantage over the inventor its performance and can efficiently allocate rewards and other incentives to retain the relatively strong performing inventor. In contrast, when an inventor is performing below its reference group, a decrease in relative performance lowers the probability of mobility. This is explained by the opportunity to learn from other relatively better performing inventors.

Competing firms are only capable of investigating the overall patent performance of inventors. Nevertheless, the within-group performance of an inventor located in another firm is much harder to identify. To improve the job market prospects of an inventor, he or she must provide intra-group information to potential employers (Di Lorenzo & Almeida, 2017). Finally, Hoisl (2007) found that an increase in productivity lowers the probability that an inventor will leave its current firm. This confirms the view that the firms have an information advantage over their employees.

To limit the information asymmetries, firms use several mechanisms to determine if the inventor is suitable for the job. Research sponsored by the European Commission, involving six European universities, found that the cumulative knowledge of the inventor and the value of its patents are crucial factors in the decision of firms concerning recruitment (Giuri et al., 2007).

According to Di Lorenzo and Almeida (2017), firms observe an inventor its research collaboration network to lower the doubts over the inventor its capabilities prior to employment. Besides, firms also take the level of education into account as a signal for the qualification of the skillset of an inventor. It is proven that an increasing level of education of the inventor increases the likelihood that an inventor will switch from an employer. To attract an inventor, firms can use financial rewards and career advancement offerings (Hoisl, 2007).

Ultimately, research conducted by Hoisl (2007) shows that the level of inventor mobility also depends on the frequency of innovations executed by the inventor. This means that inventors who invent continuously during their life are more visible and are more likely to move towards another firm. On the other hand, inventors who developed all their innovations within a short period, are less likely to move to another firm.

2.2.1.3. Supply-side constraints

Third, mobility is also limited by the supply-side of the labor market, due to information asymmetries and the mobility costs for the inventor. These two imperfections constrain the movement of inventors with valuable human capital and consequently ease to build and sustain a firm-specific human capital based competitive advantage (Campbell et al., 2012).

Supply-side information asymmetries occur when an inventor does not know its value in the labor market. When an inventor underestimates its value, no direct incentive is given to search for another job or bargain for a higher wage. If an employer can determine the value of an inventor its portfolio better than the inventor himself, a possibility occurs for the current firm to leverage this knowledge-advantage to reduce inventor mobility (Campbell et al., 2012). According to Di Lorenzo and Almeida (2017), pharmaceutical firms are providing intensive performance feedback and are rewarding high-performing inventors to maximize the probability of retaining them. Frequent performance feedback and making the inventors constantly aware of their standing in the organization increases the awareness of the inventor its value towards the firm. However, in science-based industries, the success of an inventor is partly driven by the existing routines, relationships, and complementary assets represent in the firm. This decreases the willingness of inventors to be mobile and to leave the organization.

An inventor can increase its knowledge about its own market value by membership in social and professional communities. External communities are influential in technology and science-intensive areas, like the pharmaceutical industry. These communities will increase knowledge about emerging ideas as well. Inventors who have a bigger network are more likely to have better insight into job opportunities elsewhere, and can better assess the fit with another firm. Thus, if an inventor is performing above its reference group, external professional collaborations increase the likelihood of inter-firm mobility (Di Lorenzo & Almeida, 2017).

Furthermore, switching from an employer generates extra costs for the mobile inventor. For example, search, negotiation, and switching costs limit inventors changing from an employer or negotiating for a higher wage. In the first place, idiosyncratic inventor preferences for a given firm may increase higher the costs of mobility. Firms can design this by unique inimitable compensation packages, for instance, medical benefits packages and economic externalities such as proximity to family. Besides, firms can offer unduplicatable nonpecuniary rewards such as a particular social network or a unique firm culture. In contrast with financial compensations and market-based benefits, these benefits are not easily imitable by other firms and make it unlikely for inventors to quit (Campbell et al., 2012). On the contrary, inventors prefer job security and opportunities to grow. This is more likely when an inventor is working for a large firm. Namely, large firms are commonly early adopters of new technologies and the R&D departments possess more resources to employ and retain high-quality researchers. As a consequence, Hoisl (2007) found a negative correlation between firm size and inventor mobility. Moreover, Ganco, Campbell, Franco, and Agarwal (2012) found that an inventor its earnings are negatively correlated with mobility. This indicates that a raise of an inventor its earnings lowers the probability that an inventor will leave the firm. Furthermore, the years of tenure of an inventor is negatively correlated with mobility. This demonstrates that an inventor who works longer for a firm becomes more connected with the firm and, consequently, he is less likely to leave the firm. Finally, the age of the inventor interacts negatively with inventor mobility. This is since older inventors could be promoted into management positions and therefore have less incentive to leave the firm.

Secondly, an inventor that has an intense geographic preference is not likely to switch from an employer to join the competition in less desirable regions. As a result, monopsonists in attractive regions can appeal and keep inventors at a discount due to the nonpecuniary benefits associated with the region (Campbell et al., 2012). Additionally, when an inventor is living in a small city, a switch from an employer often forces an interregional move which increases the cost of mobility as well (Hoisl, 2007).

Thirdly, employers will try to stimulate the commitment of their valuable inventors by legal institutions such as non-compete agreements and patent enforcement. Noncompete agreements Reduce the application of firm-specific human capital and general human capital by rivals. Consequently, firms with aggressive patent enforcement character discourage inventor mobility. Even when legal restrictions are unenforceable, they have an impact since inventors must bear the legal and emotional costs of confronting the agreement (Campbell et al., 2012).

It can be concluded that the demand-side factors and supply-side factors determine the willingness of an inventor to leave the firm. Low desirability supply-side factors stimulate inventors to leave the firm. When these factors overweight the supply side factors to remain in the same firm, an inventor is likely to leave the firm, even when it results in a financial loss. Consequently, the logic of firm-specific human capital as an isolation mechanism will only remain if the third condition applies, namely, the supply-side factors should not compel workers to leave the firm (Campbell et al., 2012).

2.2.2. Social capital

Other studies highlight the importance of professional social networks in the knowledge creation process. Social capital reflects an inventor its network, which is seen as a resource to stimulates the generation of human capital and structural capital. On the one hand, social capital facilitates the development of human capital by increasing an inventor its current knowledge with new knowledge embedded inside a network. On the other hand, social capital promotes the development of structural capital by adapting the tacit knowledge of inventors into explicit knowledge to be shared within the firm. This fosters organizational capital development. Moreover, it promotes the distribution of ideas resulting in structural capital outputs such as patents, which fosters the creation of knowledge capital and competitive advantage (McCracken et al., 2017).

Kostova and Roth (2003) documented that building social capital as a private and public good is a valuable method for multinational corporations to facilitate the management of trans-border activities. Social capital as a private good reflects the personal benefits that an inventor receives out of their social relations, while social capital as a public good is seen as a feature that benefits the individual and an organization as a whole. Social capital becomes a public good if all members can tap into and consequently can benefit from the resources derived from a person its social relationships without necessarily having engaged in the formation of these relationships. The research highlights the importance of boundary spanner, namely inventors employed by subsidiaries who got in touch with the headquarters representative in the past. More specifically, these interactions should be meaningful, fruitful, and supervised toward mutually valuable job-related objectives. This is a prerequisite to collect value out of the interactions, thus social capital, in the future. In addition to this, Choudhury (2010) shows that frequently traveling to the headquarters benefits local inventors to look for resources for knowledge creation projects. Especially, frequent travel to the headquarters by local inventors leads to a higher probability of patenting, namely inventor productivity. Also, he stated that personal events such as childbirth and inventor marriages create a shock that will constrain traveling in the short-term.

Rost (2011) investigated which type of professional network is more willing to increase knowledge generation. On the one hand, a close network is more willing to provide solidarity benefits, like sharing their tacit knowledge. On the other hand, a thin network with a few redundant ties offers much information and control advantages. Moreover, a thin network architecture without strong relationships creates no value. If strong network ties are present, thin network architecture will leverage the strength of strong ties in the creation of innovation. Besides, Miguelez and Moreno (2013) investigate the importance of inventors their collaborative research networks on regional innovation outcomes. This research stated that research partnerships across firms and regions are crucial for collecting external knowledge and for promoting the creation of new knowledge. The promotion of remote, thin ties embracing as many actors as possible is thus a reasonable and beneficial policy alternative from a regional perspective. However, they found that the strength of relationships (measured as the network density) is negatively correlated with innovation. This is explained by the fact that extremely tense interpersonal relations may restrict innovation because, at some point, the knowledge should be borne in mind and becomes redundant. Taken together, the social capital of an inventor is seen as a resource to stimulates the generation of human capital and structural capital and consequently positively influence the value to a particular firm.

2.2.3. Structural capital

Structural capital represents the supportive infrastructure, mechanisms, and databases of a firm that facilitate human capital and social capital to perform and vice versa. In Particular, structural capital consists of intangible organizational assets such as organizational processes, patents, and trademarks. Further, structural capital indicates the firm its appearance, culture, internal structures, etc. Structural capital consists out of three categories: organizational capital, process capital, and innovation capital (McCracken et al., 2017).

Firstly, organizational capital is often associated with the philosophy and systems of an organization for leveraging the organization its capability. For example: databases, information technology structures, organization culture, and structures (McCracken et al., 2017). An organizational culture reflecting the characteristics of diversity and equality positively impacts the firm its human capital, social capital, and organizational results such as the creation of innovation. In an equal and diverse environment, communication barriers are removed between employees from different races which facilitates knowledge sharing and knowledge creation. For instance, the diversity and equality management system[1] (DEMS), leads to higher labor productivity, workforce innovation, lower employee turnover, and greater success in attracting high-productive employees which fosters the generation of a sustainable competitive advantage (Armstrong et al., 2010).

Besides, Han, Han, and Brass (2014) showed by a sample of MBA teams composed of students from different industrial backgrounds that the composition of teams can impact upon the development of social capital. Moreover, a team composition of employees with diverse backgrounds leads to a knowledge diverse team which stimulates the team creativity. Team creativity is seen as a critical aspect to encourage the creation of innovation. Moreover, team structures limit the potential impact of a loss of valuable human capital, as if a high performing inventor does leave, the damage is reduced because the remaining team members will still possess the firm-specific human capital (Campbell, Saxton, & Banerjee, 2014).

Secondly, process capital refers to the procedures, techniques, and programs that implement and improve the delivery of goods and services. It is a collective knowledge that links the resources of a firm together into a system, for example, databases and data depositories. In high technological industries, the specificity of the technology of a firm influences the attitude of certain employees. Namely, a firm could use specific equipment or technology that not everyone would like to use (McCracken et al., 2017). Toh (2014) Found that high-productive inventors influence the adoption of certain technologies over others.

Thirdly, innovation capital indicates to intellectual property and alternative intangible assets. The intellectual property of a firm contains commercial rights such as copyrights, trademarks, and patents. Existing patents contribute to the creation of new patents and knowledge. Building up the

[1] Diversity and equality management systems (DEMS) provide challenges to the way people conceptualize and tackle issues that are related to equality, sameness, difference, discrimination, and injustice in employment (Armstrong et al., 2010).

existing organizational knowledge infrastructure facilitates the creation of human capital and organizational capital. Moreover, innovation capital contributes is crucial to reinvent a firm in challenging times (McCracken et al., 2017).

Structural capital is interdependently associated with human and social capital. For instance, if an inventor of the pharmaceutical industry produces a new patent (innovation capital), the knowledge of the inventor (human capital), the knowledge of its co-workers (social capital) and the existing firm intellectual assets (structural capital) are combined (McCracken et al., 2017).

2.3. Implications of inventor mobility

This section outlines the importance of inventor mobility, particularly the effect of inventor mobility. The consequences of a knowledge transfer can be separated into two perspectives, namely the macro-perspective (regions) and the micro-perspective (firms). Besides, inventor mobility has some complications for the inventor himself.

2.3.1. Implications of inventor mobility at a regional level

The macro-perspective focuses on the effect of knowledge transfer due to employee mobility on regional innovation performance. Previous studies found that mobility at a regional level has a positive influence on regional innovation intensity. Regional innovation intensity is measured by the total patent applications per capita of a given region (Miguelez & Moreno, 2013). This is supported by the "job matching theory" in which mobility is perceived as a search and sorting process to improve the employer-inventor match. Inventors will change from an employer if their productivity is small and will stay by their current employer when their productivity seems to be relatively high. It can be concluded that mobility leads to an increase of the match quality, resulting in higher inventor productivity (Hoisl, 2007).

Besides, inter-regional mobility stimulates innovation in regions, filling labor shortages in particular sectors, producing absorptive capacity, and supporting significant knowledge diffusion. Moreover, cross-regional mobility creates a broader culturally diverse region. Individuals originating from diverse regions have various complementary skills that can activate the creation of new ideas in the receiving regions (Cappelli, Czarnitzki, Doherr, & Montobbio, 2019).

An example is the "job-hopping" culture of Silicon Valley. This culture is characterized by strong knowledge transfers due to highly coupled social networks, high labor turnover, and localized knowledge sharing among firms in the semiconductor industry. Job hopping has been stimulated by prohibiting the use of non-compete agreements by the law of California. This spurred a "brain drain", namely the migration of employees working in regions where non-compete contracts are enforceable to regions where these were unenforceable. Especially the most valuable employees and the employees who are more collaborative were more mobile. This resulted in a high innovation rate and strong economic growth in Silicon Valley (Marx, Singh, & Fleming, 2015). In general, Kaiser et al. (2015) supported the notion that labor mobility increases the overall innovation of a country or region as a result of an enlargement of knowledge transfer. Besides, labor mobility is an effective method for developing markets that try to reduce the technological gap with advanced markets (Song et al., 2003).

Cappelli et al. (2019) investigated inter-regional mobility and international mobility of inventors in Italy, and its impact on the total factor productivity (TFP). At an inter-regional scale of measurement, an inflow of high-skilled inventors in a region increases the TFP. However, an outflow of inventors in a region lowers the TFP. A decrease in TFP is explained by a reduction of the total human capital in a particular region. Compared to international mobility, inter-regional mobility faces lower barriers that foster mobility that consequently leads to an extensive geographical reallocation of human capital across regions in the same country.

As a result, regional growth patterns within the same country can differ. Notable is that regions focus on keeping and appealing high-skilled inventors. Failing to attract high-skilled inventors can lead to a vicious circle or "brain drain" where wealthy regions can attract more high-skilled inventors than more impoverished regions. For example, wealthy regions can offer higher wages and major investments in knowledge-intensive activities compared to impoverished regions.

2.3.2. Implications of inventor mobility at firm level

A more specific perspective, namely the micro-perspective focuses on the effect of knowledge transfer due to employee mobility on the innovation activities of individual firms. In general, within this perspective, two main impacts of inventor mobility can be distinguished: the effect on the source firm and the recipient firm.

2.3.2.1. Implications of inventor mobility for the source firm

When an inventor leaves a firm, a straightforward conclusion would be that it negatively impacts the source firm. This conclusion is in line with the human capital theory; namely, the source firm will lose the general human capital and firm-specific human capital of the leaving inventor. The general human capital consists of the skills and knowledge learned by education and training. The firm-specific human capital is difficult to replicate in other firms and will not negatively impact the source firm (Campbell et al., 2012). For example, knowledge about the culture of the source firm. More important is the fact that the source firm will lose access to the tacit knowledge of the inventor. This knowledge often forms the competitive advantage of a firm (Song et al., 2003).

In addition, research on mobility in a Dutch accounting firm stipulated that employees who leave the source firm in a group, namely co-mobility, will impact the source firm even more. In that case, the source firm is disturbed by a concentrated loss of social capital as well. Co-mobility can lead to a loss of clients and within-firm connections (Corredoira & Rosenkopf, 2010). Research by Marx and Timmermans (2017) added that social relationships transfer not only information but also jointly-held human capital across organizational boundaries. Moreover, employees moving in a group instead of independently collected a superior wage bonus. More specifically, wages are the greatest between co-movers with related expertise but not identical. This could indicate that firms are hiring employees in a group to capture shared knowledge across the co-workers that may difficult and time-consuming to obtain if the firm employs the workers separately form various firms.

In contrast with the human capital theory that only predicts a loss for the source firm, the social capital theory forecasts advantages for the source firm. Namely, inventor mobility creates a communication channel between the source and recipient firm. This channel becomes part of the social capital of both firms involved. Research by Corredoira and Rosenkopf (2010) found that the source firm increases the application of the knowledge of the recipient firm. A study based on the Danish labor market, characterized as a "flexicurity" system fostering employee mobility, confirmed the existence of this channel. This is shown by the source and recipient firm citing each other patents more frequently, which implies that inventor mobility leads to a mutual knowledge transfer between the source and recipient firm. On the one hand, the behavior of the recipient firm can be explained by the application of previous knowledge of the inventor. On the other hand, a reverse knowledge transfer, indicating a knowledge transfer towards the source firm, occurs too. This is the result that the inventor stays in contact with former co-workers, resulting in a knowledge transfer among the firm's inventors. Also, the source firm awareness towards the behavior of the recipient firm may be more intensive than before (Kaiser et al., 2015). According to Corredoira and Rosenkopf (2010), the effect of the source firm citing the recipient firm is powerful for geographically distant firms, implying that the developed communication channels are more valuable if they hand over remote, non-redundant knowledge.

Singh and Agrawal (2011) stipulate that the generated previous ideas of the mobile inventor by the source firm will increase in value after the mobility event. This is due to the increased attention and usage of those ideas by the recipient firm, namely, exploitation by the mobile inventor himself and its immediate collaborative network. However, the source firm could benefit from an increased value of these innovations through licensing mechanisms or a strategic partnership. Moreover, this connection develops an opportunity to create a channel that enables easier access to external ideas.

Furthermore, Ganco et al. (2012) investigated the different effects on the source firm if an employee moves to an established firm or starts their own venture, namely employee entrepreneurship. Each decision has another performance impact on the source firm. Employee entrepreneurship has a larger negative effect on the productivity of the source firm than when an employee moves to an established firm. Namely, when employees are leaving for a venture, it is more likely that the recreation or transfer of the complementary assets of the source firm will happen. Consequently, it is more important to reduce spin-out generation than traditional inventor mobility to established firms. This is in line with "Schumpeterian forces of creative destruction" indicating that the development of new ventures probably results in greater destruction of value at a source firm in comparison to inter-firm mobility.

Particularly, the negative impact on the source firm innovation performance is driven by three factors: quantity, quality, and other factors of the leaving inventor. Firstly, if more inventors leave the source firm, the impact will be more substantial. Secondly, the effect on the source firm its performance increases with the exiting inventor its quality, the ability to generate value. Namely, highly productive inventors appear to be the ones most likely to start a new venture. Third, employees with higher wages are less willing to join another firm relative to employees with lower wages, but if an employee with a high wage leaves, he is more likely to create a new venture. Besides, it is important to identify inventors who can convince other inventors to leave the firm and replicate networks at new ventures is essential for sustained long-term firm performance (Ganco et al., 2012).

2.3.2.2. Implications of inventor mobility for the recipient firm

The advantage for the recipient firm by hiring a new inventor depends on the match of the inventor its knowledge with the current knowledge base and capabilities of the recipient firm. Besides, the total value of the inventor relies upon the nature of the knowledge the inventor possesses (Boschma, Eriksson, & Lindgren, 2009).

One the one hand, the resources and capabilities of the recipient firm are of superior importance to analyze the effect of labor mobility on innovation. Namely, to benefit from newly hired inventors, the recipient firm needs to enable the exploitation of the external knowledge of the inventor as a part of their strategy by actively combining potential and realized absorptive capacities. Potential absorptive capacities refer to the competence of firms to identify and acquire external knowledge and next to analyze and understand the external knowledge. Besides, realized absorptive capacities indicate the capability to merge external knowledge with the internal capabilities and to utilize the knowledge into a profitable product or services (Crescenzi & Gagliardi, 2018).

On the other hand, the value of the inventor depends on the amount of useful knowledge towards the recipient firm. For example, the recipient firm may try to gain knowledge of vital information and experiences such as advanced technologies by making use of inventor mobility. However, gaining access to advanced technologies is extremely challenging because these often consist out of tacit knowledge. Therefore, advanced technologies often form a crucial source of competitive advantage for firms. Moreover, some knowledge can be at low levels of codifiability which makes knowledge transfer even more difficult. In these circumstances, inventor mobility fosters learning-by-hiring, which is a solution to transfer tacit knowledge, the otherwise immobile knowledge (Song et al., 2003). In the science-based industries, such as the pharmaceutical industry, evidence exists that the mobility of star-scientists and key-engineers operate as a key-method to diffuse knowledge among firms (Boschma et al., 2009). In fact, Singh and Agrawal (2011) found that the use of the inventor its prior innovations, measured by patent citations, increased by 219% on average. Thus, hiring inventors seems an attractive manner to adopt external knowledge. However, this effect can be nuanced. The gigantic increase in patent citations is due to the inventor exploiting its prior innovations and the immediate co-workers exploiting the innovations of the mobile inventor. According to Song et al. (2003), three aspects stimulate the inter-firm knowledge transfer through a learning-by-hiring mechanism.

First, learning-by-hiring is more effective when the recipient firm is less path-dependent. If a firm is performing well, it may be satisfied with their ongoing innovation programs and less likely to tap into the knowledge of other firms to stimulate their performance. Moreover, the products and routines of successful firms often become a standard, and thus more challenging to integrate external knowledge. Consequently, it becomes more difficult for new inventors to introduce new distant knowledge. This means that strong-dependent firms that are adopting external knowledge are less open to new knowledge and less successful in obtaining knowledge of the mobile inventor (Song et al., 2003).

Second, inventors who work in non-core technological areas in the recipient firm are less likely to transfer knowledge of the previous firm. Within the core technical areas of a firm, innovation continues along well-trodden paths. Consequently, firms are less likely to be receptive to the influence of an incoming inventor and will, therefore, offer fewer opportunities to adopt external knowledge (Song et al., 2003).

Third, learning-by-hiring is stronger when an inventor possesses technological expertise distant from that of the recipient firm. When an inventor its knowledge match with the core-technological area of the recipient firm, the inventor is more probably to work within this field. Consequently, the inventor is expected to continue innovation programs in the core technological area of the recipient firm. When an inventor its skills do not match with the core-technological area of the recipient firm, the recipient firm can extend their knowledgebase with skills distant from their own (Song et al., 2003).

However, Boschma et al. (2009) state that mobility does not always positively impact the performance of the recipient firm when the inventor its expertise is distant from that of the recipient firm. Namely, the effect of mobility depends on two aspects, the conformity of the knowledge of the inventor with the recipient firm and the geographic proximity. On the one hand, if the knowledge of the inventor is identical to the recipient firm, it is possible to absorb that knowledge, although this will not add an extra value to the firm. For instance, if the recipient firm hires an inventor with only work experience in the same sector. In contrast, if the knowledge of the inventor is entirely new, thus unrelated to the current knowledge of the recipient firm, it also becomes difficult to absorb the distinctive knowledge of the inventor, resulting in no contribution to recipient firm performance. For example, an inventor joining the recipient firm with work experience in unrelated sectors. However, when the inventor possesses knowledge related (not similar) to the current knowledge base of the recipient firm, a great economic impact occurs.

On the other hand, Boschma et al. (2009) investigated the effect of the geographical proximity of the recipient firm. It turns out that unrelated knowledge only contributes positively to plant performance when these are recruited in the same region. This is explained by a communication problem that is more likely to happen when an inventor originates from another region. Besides, Labor mobility across regions only contributes positively to the productivity growth of the recipient firm, if this concerns new inventors possessing related skills.

2.3.3. Implications of inventor mobility for the inventor

A research conducted by Hoisl (2007), investigated the causality between inventor mobility and productivity and their underlying determinants. This research identifies a simultaneous relationship between inventor mobility and inventor productivity. On the one hand, if an inventor leaves a firm the inventor its patent productivity, namely the rate of newly invented patents, is been affected. Mobile inventors are seen to be 14.5% more productive than inventors who do not move. This is explained by the development of a better match quality between the inventor and its employer. Moreover, the skills and experiences of an inventor could be increased by the mobility event. Remarkable, Kaiser et al. (2015) found that an inventor leaving a patent source firm has six times higher patent productivity that an inventor that stays with the firm.

On the other hand, more productive inventors are less motivated to switch from an employer. Namely, an increase in productivity by one unit of an inventor decreases the probability of a move by 18%. Thus if an inventor leaves a firm, the chance that he will leave the recipient firm again is reduced. This is explained once again by the fact that if an inventor moves to another firm, the match quality between the inventor and employer is increased and the inventor is less stimulated to move again. Besides, incentive systems of a firm may encourage the inventor to remain within the firm, such as bonuses and a variable pay system. Also exclusive contracts or agreements, for example, a non-compete agreement between the inventor and employer is restricting employment options of the inventor outside the firm which limits the bargaining power of the inventor over the employer (Hoisl, 2007).

Consequently, it is important to determine the aspect that influences the inventor its productivity. Firstly, the size of a firm is positively associated with the inventor its productivity. This is explained by the fact that large firms are mostly early adopters of state-of-the-art technologies. Also, large firms have more resources at their disposal to hire and retain high valuable inventors. Secondly, the inventor its age is negatively correlated with productivity, namely if the inventor its age increases by 10%, the productivity reduces by 8.2%. This could be a result due to a decrease in motivation, risk-taking, and brand-new knowledge of the inventor over time. Moreover, inventors could be promoted into management positions over time and have less time to invent new patents. Thirdly, inventors who are making use of external knowledge sources, namely the use of scientific research, are more productive. For example, patent documents are containing state-of-the-art technologies and relevant information that contributes to an inventor its productivity (Hoisl, 2007).

2.4. Hypotheses

The goal of this research is to determine the impact of leaving inventors to another firm on the innovation performance of former employers in the pharmaceutical industry. According to the intellectual capital theory, the main effect depends on three factors: human capital, social capital, and structural capital (McCracken et al., 2017). If an inventor leaves a firm, its knowledge and skills, namely its human capital will be lost for the source firm (Campbell et al., 2012). More important is the fact that firms hire inventors to access external knowledge, inclusive the tacit knowledge which is otherwise immobile. Consequently, the source firm will lose access to the tacit knowledge of the inventor which often contributes to the competitive advantage of a firm (Song et al., 2003). Although, this size of the effect seems to depend on the kind of human capital the inventor possesses, from a human capital perspective a leaving inventor will only lead to a negative impact on the source firm. Therefore, the first hypothesis reflects this point of view:

Hypothesis 1a: "The effect of an increase in the share of the firm's leaving inventors has a negative impact on the innovation performance of the source firm."

However, firms may try to create a sustained competitive advantage by reducing the potential amount of leaving inventors and the potential impact a leaving inventor may have on the firm. In line with the human capital view, inventors that are possessing more firm-specific knowledge, namely knowledge that difficult is to replicate in other firms, are consequently less valuable to other firms and will less damage the source firm (Campbell et al., 2012). Moreover, the social capital theory predicts a reverse knowledge transfer, a knowledge transfer from the leaving inventor to the source firm. Namely, the leaving inventor could stay in contact with former co-workers, and the source firm awareness towards the behavior of the recipient firm may be more intensive than before the leaving event (Corredoira & Rosenkopf, 2010). Additionally, the structural capital of a firm could reduce the amount of leaving inventors and their impact on the source firm. On the one hand, the success of an inventor is partly driven by the structural capital of a firm, namely existing routines, team structures, relationships, and complementary assets represent in the firm. A good capital structure contributes to more productive inventors and consequently decreases the willingness of inventors to be mobile and to leave the organization (Di Lorenzo & Almeida, 2017). On the other hand, inventors working in team structures reduces the impact of the leaving inventor because the remaining team members will still possess the firm-specific human capital (Campbell et al., 2014; Han et al., 2014). Therefore, the impact of a leaving inventor could also turn out positive for a firm.

Hypothesis 1b: "The effect of an increase in the share of the firm's leaving inventors has a positive impact on the innovation performance of the source firm."

Besides, the effect of leaving inventors could vary across certain characteristics of the inventors who leave. Namely, the impact of the leaving inventor on the source firm may differ based on the productivity of the leaving inventors. High-productive inventors are more valuable to the source firm because they contribute more to the firm's innovation output. If a high-productive inventor leaves a firm, the source firm may be more aware of the recipient firm. However, no significant difference in social capital between high and low productive inventors is expected. Consequently, this research expects that if the share of high-productive leaving inventors increases, it will have a negative impact on the source firm's innovation performance. High-productive inventors possess more human capital which could impact on the source firm's innovation performance. Therefore, the second hypothesis is:

Hypothesis 2: "The effect of an increase in the share of high-productive leaving inventors has a negative impact on the innovation performance of the source firm."

Furthermore, the effect of a leaving inventor could also depend on the technological equality between the recipient and source firm. A potential relation may exist between the core-technology of the source firm and the core-technology of the recipient firm. According to Boschma et al. (2009), the distance of knowledge between the inventor and the recipient firm determines the absorption capacity of the recipient firm to acquire the knowledge of the inventor. Especially, if an inventor its knowledge is unrelated to the current knowledge base of the recipient firm, it is difficult for the recipient firm to understand the inventor its knowledge. Consequently, the competition between the two firms is not increased and no great economic impact may occur on the source firm innovation performance. However, this theory may also be relevant to the distance of the knowledge between the source firm and the recipient firm. Namely, if the core-knowledge of the source firm is not the same as the core-knowledge of the recipient firm, it is difficult to transfer knowledge from the source firm to the recipient firm. Additionally, the social capital view predicts that if inventors leave to a firm with another core-technology than the source firm, a reverse-knowledge transfer would be more valuable because they hand over distant non-redundant knowledge which consequently could contribute to the source firm innovation performance (Corredoira & Rosenkopf, 2010). Taken these arguments together, it seems that leavers to another core-technology firm will impact the source firm less than leavers to the same core-technology firm. As a result, the third hypothesis expresses:

Hypothesis 3a: "The effect of an increase in the share of leaving inventors to another core-technological expertise firms than the source firm has a positive impact on the source firm innovation performance."

However, if the inventor possesses identical knowledge to the recipient firm, the recipient firm can absorb that knowledge, although no extra value will be added to the firm (Boschma et al., 2009). Besides, Song et al. (2003) state that a learning-by-hiring opportunity for the recipient firm is more likely if an inventor possesses technological expertise distant from that of the recipient firm. This may also be relevant to the distance of the knowledge between the source firm and the recipient firm. Compared to the source firm core-technology expertise, if the recipient firm possesses another core-technology, a knowledge spillover may still increase the competition between the two firms. As a result, this research also expects that if the core-knowledge of the source firm is not the same as the recipient firm, the knowledge of the source firm may be an opportunity for the recipient firm to tap into and strengthen the competition between the two firms. Therefore, this research expects the opposite of the previous hypothesis as well.

Hypothesis 3b: "The effect of an increase in the share of leaving inventors to another core-technological expertise firms than the source firm has a negative impact on the source firm innovation performance."

Besides, the effect of leavers on the innovation performance of the source firm could depend on the geographical proximity of the inventor. Namely, if an inventor moves to a firm closely located to the source firm the potential negative effect may be greater than if an inventor moves further away. In line with the social capital theory, Corredoira and Rosenkopf (2010) found that if an inventor moves further away a reverse knowledge spillover channel becomes more valuable because they hand over distant, non-redundant knowledge. Moreover, it is already proven that the source firm generally cites more often geographically distant recipient firms. However, evidence on the difference of the impact on the firm source firm innovation performance of leaving inventors to another country or the same country is still missing. Therefore, it is interesting to examine this last hypothesis:

Hypothesis 4: "The effect of an increase in the share of leaving inventors to another country than the source firm has a positive impact on the source firm innovation performance."

Chapter 3: Empirical research

3. Empirical research

This section manages the empirical part of the research. The empirical section is divided into three parts. The first part outlines the approach of the empirical study. Thereafter, the implemented variables are described and followed by the descriptive statistics of these variables.

3.1. Empirical research approach

3.1.1. Reliability of patent data

Among all the types of knowledge that could be moved, scientific and technological knowledge creates a trace on paper when these become granted as a patent. In other words, a patent represents a physical record of the transfer or creation of knowledge to a firm. Additionally, patent data has been well documented in databases. For that reason, patents are extensively used in scientific research to measure the innovation performance of a firm (Corredoira & Rosenkopf, 2010). Moreover, patents are a trustworthy source of information to identify the performance of an inventor. The number of patents an inventor made and the number of citations the inventor its patent receives, is a proxy for the inventor its productivity. Five till ten years after the application date of a patent, citation counts are accessible and trustworthy. This is due to a decrease in attractiveness after this period. By contrast, patents are published 18 months after the priority date which turns them into a valuable signal for ingenuity (Hoisl, 2007). Furthermore, previous research suggests that patent data is a reliable way to track inventor mobility, and it is possible to combine different indicators with patent data. For example, patent citations are suitable to define the orientation and geographical scope of knowledge flows among inventors and patent holders (Di Lorenzo & Almeida, 2017; Giuri et al., 2007). Taken together, the use of patent data creates a wide range of research options. However, research by patent data also has some drawbacks.

On the one hand, patents describe only to particular types of innovations. To patent a particular innovation great costs for the firm occurs. Moreover, the innovation will become publicly known in detail. Additionally, when the patent expires everyone is free to use the knowledge. Therefore, some firms may not patent a particular innovation and will use other mechanisms to protect their innovation. For example, some innovations may never be patented but will be kept as a secret. This also has some drawbacks, namely if other firms discover the technical solution they can use and even patent it. Another mechanism to protect an innovation is that a firm will publish the innovation on a publishing platform or writing an article about it in a journal. Subsequently, no one can patent the innovation anymore, though the innovation can be used by everyone (Swiss Federal Institute of Intellectual Property). However, according to (Kelchtermans, Leten, & Belderbos, 2013), this problem is solved by focussing on patent analyses to industries with high patent firms and examining firm-level patent time series. In the pharmaceutical industry are nearly all innovations protected by a patent and the firm-specific patent policies are relatively balanced over time.

On the other hand, there exist limitless differences across countries, industries, and firms in the way how patents measure innovation output. Moreover, there is still uncertainty about the accuracy of the indicators of a patent. For instance, previous research demonstrates that patent citations are a noisy measure of information flows, especially due to citations that are not added by applicants, but by the patent officer or just to avoid infringements. Furthermore, it is difficult to determine whether patent claims are a measure of the patent scope, the degree of protection, or its value. Similarly, citations interact with various aspects of the patent and not only with its value (Giuri et al., 2007).

3.1.2. Data and sample

This research uses the same panel dataset of patents as in the study of (Kelchtermans et al., 2013). This panel dataset contains patent data from the 50 largest R&D spending pharmaceutical firms in the world observed for a period of eight years (1995-2002). The patent data is taken from the European Patent Office's (EPO's) Worldwide Patent Statistical Database, henceforth (Patstat). Moreover, data from over more than 200 firms over a greater period (1995 – 2015) are added to the dataset. Ultimately, the dataset consists of 256 international firms that are all operational in the context of the Pharmaceutical industry. The dataset provides data on each patent published between 1995 and 2015. Namely, the applicant firm name, inventor name, the International Patent Classification[2] (IPC) technology class, and the number of citations the patent received in a 5-year window.

The database is an unbalanced panel, indicating that for some firms data is missing for at least one year. Therefore, multiple adjustments are needed. Additionally, a matching problem occurs because the spelling of the names of the inventor is not standardized. Namely, the inventor names are written in different ways which occurs a name matching problem. Moreover, the patent data includes duplicate cases because some inventors are multiple times linked to the same patent. This will complicate the examination of inventor mobility and it will automatically lead to an incorrect research outcome.

In total, three corrections are made to decrease the name matching problem. This is done by removing all special punctuation marks from the inventor names, such as dots, commas, hashtags, etc. Thereafter, all the inventor names are put in capital letters and the inventor title, namely "DR" is removed. The last correction removed all the duplicate cases from the file. However, it is not possible to remove all duplicated cases. For example, some names are written differently but may refer to the same inventor. Additionally, to measure the effect of the leaving inventors, only the patents with the firm name and the name of the inventor can be measured.

In this research, the hypotheses are tested through two kinds of regression analysis. On the one hand, a simple OLS model is conducted where the dependent variable, the innovation output, is transformed into a logarithm. This is done to improve the fit of the model. Namely, it reduces the skewness of the variable which transforms the variable into a more normalized dataset. Besides, after checking the assumptions of Ordinary Least Squares (OLS) a heteroskedasticity-consistent standard error is calculated. This is done by following the procedure that Hayes and Cai (2007) described. On the other hand, a negative binomial model is made containing the dependent variable as a count of the innovation output. Particularly, this model allows over-dispersion in the data.

[2] The International Patent Classification (IPC), is established by the Strasbourg Agreement 1971 which provides for a hierarchical system of language independent symbols for the classification of patents and utility models according to the different areas of technology to which they pertain (World Intellectual Property Organization, n.d.).

3.2. Description of the variables

3.2.1. Dependent variables

The dependent variable is the innovation performance of a firm. A requirement to patent a particular technology, it needs to be novel and not obvious. Namely, an innovation must not be already known from publication in the past. Therefore, patents offer a credible measure of state-of-the-art knowledge. Within academic research, patent data is taken for granted as a measure of the innovation performance of a firm. In this research, on the one hand, the innovation performance of the source firm is measured in a negative binomial model by a count of the number of patent applications filed by the source firm in a given year. This is in line with the research method of the research conducted by Kaiser et al. (2015). On the other hand, a second simple OLS model is conducted measuring the innovation output of the firm as a logarithm. This type of research model is in line with the research of Rahko (2017).

3.2.2. Independent variables

Inter-firm mobility is determined as a firm-to-firm movement in the same industry. According to Di Lorenzo and Almeida (2017), an inter-firm move is observed at the midpoint between the date of application of the last patent by the source firm and the first patent at the recipient firm. Therefore, inventor mobility is a dummy variable that takes the value 1 if the inventor moves and 0, otherwise. Particularly, a move is established if the applicant firm changes on the inventor its next patent. The assumption is made that the applicant firm on a patent is the employer of the inventor. As reported by Hoisl (2007), 92% of the inventors are effectively working by the applicant firm. This assumption should not lead to remarkable biases if it is assigned to each patent application in a model.

Table 1: Example of the determination of inter-firm mobility

Year	Patent Number	Inventor	Applicant firm	Inter-firm mobility
1998	23008348	Aaron Siegmund	Johnson & Johnson	0
1999	7910041	Aaron Siegmund	Neurocrine Biosciences	1
2000	4852201	Aaron Siegmund	Neurocrine Biosciences	0

To measure the effect of leaving inventors on the innovation output of the source firm, leavers are determined as inventors who were working by a given firm in the previous year (t-1) but patented a particular patent in a year (t) by another firm (Kaiser et al., 2015). For example, in table 2, a leaver is determined in the year 1999 for the firm Johnson & Johnson. Since with this method, it is not possible to identify the exact date when an inventor leaves the firm, the time of the mobility event is taken to occur in the year of the inventor its first patent application at the recipient firm. Consequently, inventors that are appearing on a single patent, mobility cannot be observed. Moreover, mobility is only determined between two consecutive years. Taken together, an inventor is considered to leave a firm if he or she appears on a patent application by another firm in the first year after an appearance on a patent application by the source firm (Corredoira & Rosenkopf, 2010).

3.2.2.1. The ratio of the total leaving inventors

The first independent variable, the ratio of the total leavers, is created to answer hypothesis one. It is conducted by first making a sum of all the leavers for a particular firm in a particular year. Thereafter, this number is divided by the sum of all the inventors of the previous year (t-1). It is divided through the number of inventors of the previous year because prior research has shown that it takes time before investment in R&D translates into new patents and a time lag of one year provides the best fit between R&D investments and innovations. The number of inventors in the previous year (t-1) proxies for the size of the R&D labor force in the previous year (t-1) which includes both stayers and leavers. The sample included only the cases that had at least 1 leaver.

3.2.2.2. Ratio high-productive leaving inventors

For the second hypothesis, the independent variable the ratio of high-productive leavers is construed. High-productive leavers are defined as the leavers with more patent applications in the last year by the source firm (t-1) than the mean of patent applications per inventor in the previous year (t-1). In the sample, each patent contains one or more inventor names. Firstly, a count of high-productive leavers per firm and per year is conducted by comparing the inventor productivity with the mean inventor productivity of all the inventors of the sample. Thereafter, this number is divided by the total number of leavers to become the ratio of the high-productive leavers. This ratio indicates the percent of leavers of a firm in a year that was highly productive in the previous year.

3.2.2.3. Ratio leaving inventors to another core-technological expertise firm.

The third independent variable, leavers to another core-technological expertise firm than the source firm, is made to answer the third hypothesis. Therefore, the core-technological area for each firm each year is calculated. For most patents, the technological International Patent Classification (IPC) code is fully given in eight-digits and used to conduct the variable. Each code represents a particular technological function or application (World Intellectual Property Organization, n.d.). This is done by counting the applied patents per technology class. The technology class in which the most patents are applied is the core-technology class of a firm. Next, a count of the leavers to a different core-technological expertise firm is done (Rahko, 2017). Furthermore, the Ratio of the leavers to different technological expertise firms than the source firm is conducted by dividing the total leavers to a different core-technological expertise firm by the total leavers.

3.2.2.4. Ratio leaving inventors to another country

The fourth independent variable, leavers to firms located in another geographical area, is made to answer the fourth hypothesis. This is done by first counting the total leavers whose residence changed on their first patent application by the recipient firm (Cappelli et al., 2019). On most patents, the geographical location of the inventor is given in terms of the country the inventor currently lives. Consequently, it is possible to measure only the geographical inventor mobility within countries. Therefore, a ratio is conducted by dividing the total leavers to another country through the total leavers of the firm with no missing geographical data. Because of the lack of missing geographical data for some patents, a dummy variable 'no geographical data' is created which takes the value 1 if a firm has a leaver to the same or another country and 0 if there are no leavers detected to the same or another country. This is done to restrict the sample to non-missing observations.

3.2.3. Control variable

To control for alternative explanations than the influence of inventor mobility on the source firm's innovation output, control variables are added. On the one hand, it may be favorable to add the total yearly inventors for each firm of the previous year. This because a time lag of one year provides the best fit between R&D investments and innovations. The variable is created by counting the inventors that patented for a particular firm in the previous year (t-1).

Furthermore, the control variable technology diversity is calculated. This variable is made by first shorten the eight-digit IPC code to only the first four digits. Thereafter, The Herfindahl–Hirschman Index is calculated which measures the degree of concentration of patents among patent classes. The Herfindahl index can range from 0 to 1. It will take the value 1 if a firm only patent in 1 single patent class and will approach the value 0 if the patents of the firm are evenly dispersed over a large number of technology classes.

The Herfindahl–Hirschman Index (HHI) is reflected in the denominator and determined per year per firm. Namely, it is calculated by taking the sum of squares of the numbers of patents in a particular technological field (N_i) divided by the total number of patents (N).

Equation 1: Calculation of technological diversity

$$DIV = \frac{1}{\sum_i \left(\frac{N_i}{N}\right)^2}$$

According to Leten, Belderbos, and Van Looy (2007), the Herfindahl–Hirschman Index is a more precise assessment of the technological diversification of a firm than a simple count of the different technologies in a firm's knowledge base because it correlates less with the. Moreover, the index is less sensitive to missing IPC information for some patents.

The variable DIV transforms the Herfindahl–Hirschman Index (HHI) into a measure of technology diversification by taking the inverse. The ratio is described as the equal distribution number equivalent of the Herfindahl index: The value represents the number of technology fields over which patents would have to be equally distributed to generate the same value of the equal distribution number equivalent. According to Leten et al. (2007), an inverted U-shaped relationship exists between technological diversification and technological performance. Therefore, the square of technological diversification (DIV^2) is also included in the regression models to test for a nonlinear relationship. A positive sign is expected for the DIV and a negative sign is expected for DIV^2.

Lastly, two dummy variables are created to do a robustness check. A firm dummy controls for time-invariant differences of the innovation performance across firms. This can pick up differences across firms in things such as the quality of management and operational systems. Besides, a year dummy is added to the model which controls for time effects on innovation performance, e.g. the impact of the financial crisis (Di Lorenzo & Almeida, 2017).

Table 2: Summary of the variables

Variable		Measure	Explanation
Dependent variable			
1.	The innovation output	Discrete	The count of the firm its patent applications in a given year (t).
1a.	Logarithm of the innovation output	Logarithm	The logarithm of the innovation output.
Independent variable			
1.	Total Leavers	Discrete	The count of the inventors of a firm who were present in the firm in the previous year (t-1) but applicated a patent in the current year (t) by another assignee firm.
1a.	Ratio total leavers	Ratio	Total leavers dived by the sum of the total inventors of the previous year (t-1).
2.	High-productive leavers	Discrete	The count of the leavers with more patent applications in the last year by the source firm (t-1) than the mean of patent applications per inventor in the previous year (t-1).
2a.	Ratio high-productive leavers	Ratio	High-productive leavers divided by the total leavers.
3.	Leavers to another core-technology firm	Discrete	The count of the leavers when the core-technology class of the source firm is not the same as the core-technology class of the recipient firm.
3a.	Ratio of the leavers to another core-technology firm	Ratio	Leavers to different technological expertise firms than the source firm divided by the total leavers.
4.	Leavers to firms located in another region	Discrete	The count of the leavers whose residence changed on their first patent application by the recipient firm.
4a.	Ratio leavers to firms located in another region	Ratio	Leavers to firms located in another region divided by the total leavers
Control variable			
1.	Total firm patent inventors previous year	Discrete	Count of all the inventors that patent in for a firm in the previous year (t-1).
2.	Technology diversity	Ratio	The inverse of the Herfindahl index that measures the degree of concentration of patents among patent classes.
2a.	Technology diversity squared	Ratio	The square of the technology diversity variable
3.	Year dummy	Binary	For each year a binary variable is created which turns 1 if t = that year and 0 if t ≠that year.
4.	Firm dummy	Binary	For each Firm a binary variable is created which turns 1 if the firm = firm of the dummy and 0 if the firm ≠ the firm of the dummy variable.

3.3. Descriptive statistics

3.3.1. General descriptive statistics

The descriptive statistics of the dependent and explanatory variables are illustrated in Table 3. On the one hand, the discrete variables are depicting a high maximum value combined with an extremely low mean value. Moreover, the median of those variables is, even more, lower than the mean. This is an indication that those variables have a right-skewed distribution. On the other hand, the logarithmic and the ratio variables have a mean and median closer to each other. A remarkable finding is that firms with at least one leaver have on average 24% leaving inventors, based on the number of inventors working by a firm in the previous year. The leavers of a firm are on average: 57% high-productive, 41% leaves to a firm which has another core-patent technology class, and 36% leaves to another country. Besides, the mean of the technology diversity measure is 9.76. This indicates that a general firm patent in 9.76 patent technology classes in which patents would have to be equally distributed to generate the same value of the equal distribution number equivalent.

Table 3: General descriptive statistics

	N	Min.	Max.	Mean	Median	Std. Dev.
Firm’s innovation output	1782	1	7530	117,73	11.00	472.39
Logarithm of the innovation output	1782	0	8.93	2.62	2.40	1.93
Total leavers	1782	1	6296	108.60	16.00	361.52
Ratio total leavers	1782	0.01	1	0.24	0.18	0.19
High-productive leavers	1782	0	2451	56.99	8.00	169.62
Ratio high-productive leavers	1782	0	1	0.55	0.58	0.34
Leavers to another core-technology firm	1782	0	2674	40.75	5.00	127.77
Ratio leavers to another core-technology firm	1782	0	1	0.48	0.37	0.42
Leavers to another country	1782	0	2246	35.78	5.00	127.96
Ratio leavers to another country	1782	0	1	0.59	0.67	0.33
Dummy no geographical data	1782	0	1	0.92	1	0.273
Total firm patent inventors previous year	1782	1	34953	682.47	95.50	2367.37
Technology diversity	1782	1	57.70	9.76	9.00	6.06
Technology diversity squared	1782	1	3329.61	131.96	80.86	200.57

3.3.2. Descriptive statistics of the dependent variable

The dependent variable is the firm's innovation output per year. Annex 1 illustrates the total innovation output of all firms per year. Namely, per year a count is made of all the patents in the sample. This figure shows the spread of the patents of the sample over different years. After taking a closer look at the figure, the dependent variable seems a little to fluctuate over the years. Only the first four years (1995 -1999) seems to have fewer patent applications than the other years. In the sample, the year 2007 contains the most patent applications. An explanation of the difference in the number of patent applications could be the nature of the data set, namely in the used panel dataset for some firms data is missing for at least one year.

3.3.3. Descriptive statistics of the independent variable

3.3.3.1. Total leavers

The distribution of the first independent variable, total leavers, is illustrated per year in annex 2. The figure seems to fluctuate in the same trend as the dependent variable total innovation performance. Besides, the ratio of the total leavers is shown in annex 3. The ratio of total leavers remains steady till 2003 with a value fluctuating between 20-25% leaving inventors per year. However, after 2003 the ratio begins to fluctuate heavenly and decreases to 11% in 2015.

3.3.3.2. Leavers with high and low past patent behavior

The trend of high-productive leaving inventors over 19 years is illustrated in annex 4. Moreover, the figure shows a comparison between high and low productive leaving inventors. The number of highly productive leaving inventors is in the most years slightly more than the number of low productive leaving inventors. Consequently, the trend of these variables is similar to the trend of the total leavers. Besides, annex 5 shows the trend of the ratio of high-productive leavers. Although the number of total leavers decreases, this graph shows a stable trend of share high-productive leaving inventors.

3.3.3.3. Leavers to similar and distinctive core-technology firms

The distribution of the variables leavers to the same and another core-technology class firm is illustrated in annex 6. Besides, in annex 7 the ratio of total leaving inventors to another core technology is depicted in a line graph. Remarkably, after 2002 the number of leavers who leave to a firm with the same core-technology class, substantial increases till 2011. Moreover, the number of leaving inventors to another core-technology firm is after 2002 less than the number of leaving inventors to the same core-technology firm as the source firm.

3.3.3.4. Leavers to another country

The fourth independent variable leavers to another country, illustrated in annex 8 and annex 9, seems to fluctuate in the same way with the first independent variable total leavers. Remarkable, by comparing the leavers to another country with the leavers to the same country, their relationship has changed over time. Namely, until the year 2002, the number of leavers to the same country is slightly more than leavers to another country. However, after 2002, the leavers to another region is approximately the double of the leavers to the same region. A possible explanation could be the globalization of the world due to advances in transportation and communication. Besides, it can also be explained by the amount of missing geographical data, provided in annex 10. On average, the leavers their geographical location is missing in 48% of the cases over 20 years. Although the percentage of missing data is only increasing slightly over the years, the number of leavers to the same and another country may be different.

3.3.4. Correlations between the variables

The Pearson's correlation coefficient of the variables is given in table 5. The coefficient is a measure of the strength of the association between two variables. The value of the correlation can range between -1 and +1. It takes the value +1 if there is a perfect positive linear relationship and -1 if there is a perfect negative linear relationship, the value 0 indicates no linear correlation.

The correlation coefficients between the independent ratio variables and the dependent variables are strongly lower than the correlation coefficients between the discrete independent variables and the dependent variables. Besides, no extreme high or low correlation coefficients are found between the dependent variables and the other variables. The logarithm of the innovation output of a firm is significant for all variables. Remarkably, the logarithm and the discrete variable of firm's innovation output has a negative correlation coefficient with the ratio of total leavers and the ratio of leavers to a core-technology firm. Besides, the ratio of high-productive leavers and leavers to another country is positively correlated with the dependent variables. As expected, also the control variables: total firm patent inventors of the previous year and technology diversity are positively correlated with the dependent variable. The asterisks indicate whether the correlation between the two variables is significant at 1% (**) or 5% (*). A significant correlation 1% indicates that there is only 1% chance that the relationship does not exist.

Table 4: Correlation table

	Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1)	Firm's innovation output	1												
(2)	Logarithm of the innovation output	0.52**	1											
(3)	Total leavers	0.45**	0.44**	1										
(4)	Ratio total leavers	-0.07**	-0.10**	-0.07**	1									
(5)	High-productive leavers	0.53**	0.50**	0.96**	-0.03	1								
(6)	Ratio high-productive leavers	0,03	0.09**	-0.03	0.46**	0.05	1							
(7)	Leavers to another core-technology firm	0.36**	0.43**	0.67**	-0.06**	0.69**	-0.02	1						
(8)	Ratio leavers to another core-technology firm	-0.07**	-0.08**	-0.08**	0.04	-0.08**	0.02	0.14**	1					
(9)	Leavers to another country	0.43**	0.41**	0.98**	-0.05*	0.94**	-0.01	0.61**	-0.09**	1				
(10)	Ratio leavers to another country	0.03	0.07**	0.04	0.12**	0.06*	0.13**	0.00	-0.10**	0.08**	1			
(11)	Total firm patent inventors previous year	0.54**	0.44**	0.95**	-0.12**	0.88**	-0.07**	0.64**	-0.07**	0.91**	0.01	1		
(12)	Technology diversity	0.22**	0.44**	0.17**	-0.35**	0.19**	-0.19**	0.17**	-0.05*	0.16**	0.08**	0.17**	1	
(13)	Technology diversity squared	0.19**	0.35**	0.11**	-0.20**	0.13**	-0.08**	0.10**	-0.05*	0.11**	0.08**	0.11**	0.90**	1

** Correlation is significant at the 0.01 level (2-tailed).

* Correlation is significant at the 0.05 level (2-tailed).

Annex 11 represents the variance inflation factor (VIF) of the variables of the intended regression models. The VIF coefficient indicates whether multicollinearity is present between two or more variables. According to Rutherford (2002), the VIF index needs to be lower than 4. However, the control variables technology diversity and technology diversity squared is exceeding the value 4. Therefore, this variable is only represented in the first regression model. Besides, the independent variable leavers to another core-technology firm has a VIF of 4.385, although, this variable is included in regression table 4. Consequently, this variable may bias the regression outcomes. Annex 12 contains the variance inflation factor (VIF) of the variables that are used in the ultimate regression models.

Chapter 4: Empirical Results

4. Empirical Results

This section manages the empirical results of the research. In total ten regression models, to be found in five regression tables, are conducted to answer the hypotheses. Each regression table provides two types of regression models. In the first regression table are only the control variables added. Thereafter, the second regression table contains the independent variable ratio of the total leavers. The following three models elaborate on this model. Namely, each table separately adds one ratio independent variable: high-productive leaving inventors, leaving inventors to another core-technology firm, and leaving inventors to another country. In all regression tables are the year and firm dummies added, however, due to the great extent of these variables are the coefficients and standard errors are not shown.

Regression table 1: Regression model between the control variables and the source firm's innovation output

	Simple OLS		Negative binomial	
	Coeff.	SE	Coeff.	SE
(constant)	1.9691*	0.3441	2.126*	0.3581
Total firm patent inventors previous year	0.0002*	0.0000	0.000*	0.0000
Technology diversity	0.1813*	0.0110	0.177*	0.027
Technology diversity squared	-0.0014*	0.0003	-0.002*	0.0004
Year dummies (1996 – 2015)	*Year dummies included*			
Firm dummies (276 firms)	*Firm dummies included*			
Dependent variable	*ln(innovation output)*		*Innovation output*	
Adjusted R^2	*0.5389*			

* Indication of a significance at 1% level

The first regression table contains only the control variables. Each coefficient is significant at a 1% level. Both research model types, the simple OLS model and the negative binomial model have similar results. The first control variable, total firm patent inventors of the previous year, has surprisingly almost no effect on the innovation output of the source firm. According to the simple OLS model, an increase of one inventor would stimulate the total innovation output of the firm by 0.0002%. Although the negative binomial model identifies no effect of an increase of one inventor on the dependent variable. Besides, the control variable technology diversity reacts as expected. An increase of one unit in technology diversity has a positive impact on the innovation output of a firm. Furthermore, the control variable technology diversity squared is negative which confirms the existence of an inverted U-shape relationship between the technological diversification and technological performance of firms. However, these results could be biased because the variance inflation factor (VIF) is higher than 4 for the control variables technology diversity and technology diversity squared. Therefore, those variables are not used in the next regression tables. Besides, the coefficient of determination (R^2) shows that a variance in the innovation output of a firm in the simple OLS model can be explained for 53,89% by the chosen control variables per regression respectively.

Compared with the coefficients of the control variable total firm patent inventors of the previous year in the following regression tables, are the results of regression table 1 approximately identical. The second regression handles the first hypothesis, namely it investigates the effect of the ratio of the leaving inventor of a firm on the innovation output. The added variable is negative and significant in both regression models at a 1% level. This indicates that an increase in the share of leavers has a negative impact on the source firm's innovation output. More specifically, if the share of leaving inventors, based on the total inventors of the previous year, increases by 1%, the innovation output of a firm will reduce by 1.32% or decrease by 1.402 patent. In other words, if the share of leaving inventors decreases by 1%, the innovation output of the firm increases by 1.32% or 1.402 patents. Besides, the coefficient of determination (R^2) shows that a variance in the innovation output of a firm in the simple OLS model can be explained for 41.44% by the chosen control variables per regression respectively. Compared with the following regression tables, the ratio of total leavers is comparable and significant in all next regression tables at a 1% level. Regression table 3 even shows that if the share of the leaving inventors increases with 1%, the innovation output of a firm will fall with 1.43% or decrease with 1.589 patent. Taken together, these results support hypothesis 1a: *"The effect of an increase in the share of the firm's leaving inventors has a negative impact on the innovation performance of the source firm".*

Regression table 2: Regression model between the ratio of total leavers and the source firm's innovation output

	Simple OLS		Negative binomial	
	Coeff.	SE	Coeff.	SE
(constant)	3.5301*	0.3367	3.585*	0.3471
Ratio total leavers	-1.3230*	0.1778	-1.402*	0.2676
Total firm patent inventors previous year	0.0002*	0.0000	0.001*	0.0000
Year dummies (1996 – 2015)	*Year dummies included*			
Firm dummies (276 firms)	*Firm dummies included*			
Dependent variable	*ln(innovation output)*		*Innovation output*	
Adjusted R^2	0.4144			

* Indication of a significance at 1% level

Regression table three provides insight into the second hypothesis, namely it adds the variable ratio of high-productive leavers to investigate the effect of the increase in the share of high-productive leavers on the firm's innovation output. Again, all the variables are positive and significant at a 1% level. An increase in the share of high-productive leavers of the total leaver stimulates the firm's innovation output by 1.07 % or 1.733 patent. Consequently, the second hypothesis is rejected: *"The effect of an increase in the share of high-productive leaving inventors, has a negative impact on the innovation performance of the source firm."* Moreover, the results show that an increase in the share of low-productive leavers the firm's innovation output decreases. Compared with regression table 2, the coefficient of determination (R^2) increases to some extent.

Regression table 3: Regression model between ratio high-productive leavers and the source firm's innovation output

	Simple OLS		Negative binomial	
	Coeff.	SE	Coeff.	SE
(constant)	3.2825*	0.3377	3.239*	0.3490
Ratio total leavers	-1.4293*	0.1781	-1.589*	0.2630
Ratio high-productive leavers	1.0691*	0.1086	1.733*	0.1519
Total firm patent inventors previous year	0.0003*	0.0000	0.000*	0.0000
Year dummies (1996 – 2015)	*Year dummies included*			
Firm dummies (276 firms)	*Firm dummies included*			
Dependent variable	Ln(innovation output)		Innovation output	
Adjusted R2	0.4290			

* Indication of a significance at 1% level

The fourth regression table, which provides an answer for hypothesis 3, contains the ratio of leavers to another core-technology firm. Within the regression table, all the coefficients are significant at a 1% level. The ratio leavers to another core-technology firm is negative which indicates that an increase of 1% in the share of leavers to another country, decreases the innovation output of the source firm by 0.94% or 1.473 patent. Consequently, these results support hypothesis 3b: *"The effect of an increase in the share of leaving inventors to another core-technological expertise firms than the source firm, has a negative impact on the source firm innovation performance".* However, as illustrated in annex 12, the variance inflation factor (VIF) of the variable ratio of the leavers to another core-technology firm is greater than 4 which indicates that the variance of the estimated coefficients is more than four times higher because of correlation between two independent variables. Consequently, it is not possible to reject or support hypothesis 3a and 3b.

Regression table 4: Regression model between leavers to another core-technology firm and the source firm's innovation output

	Simple OLS		Negative binomial	
	Coeff.	SE	Coeff.	SE
(constant)	4.5751*	0.3615	5.294*	0.4185
Ratio total leavers	-1.2099*	0.1783	-1.202*	0.3115
Ratio leavers to another core-technology firms	-0.9429*	0.1187	-1.473*	0.1885
Total firm patent inventors previous year	0.0002*	0.0000	0.000*	0.0000
Year dummies (1996 – 2015)	*Year dummies included*			
Firm dummies (276 firms)	*Firm dummies included*			
Dependent variable	Ln(innovation output)		Innovation output	
Adjusted R2	0.4239			

* Indication of a significance at 1% level

The fifth regression table provides insight into the fourth hypothesis. Namely, the variable leavers to another country can be found in the regression table. Also, in this table are all the variables significant at a 1% level. The ratio leavers to another country is negative in both regression models. Especially, an increase of the share of leavers to another country by 1% leads to a decrease in productivity of 0.52% or 0.628 patent. This indicates that an increase in the share of leavers to the same country will stimulate the productivity of a firm. Besides, the coefficient of determination (R^2) shows that a variance in the innovation output of a firm in the simple OLS model can be explained for 43.82% by the chosen control variables per regression respectively. Taken together, the last hypothesis is rejected, namely: "*The effect of an increase in the share of leaving inventors to another country than the source firm, has a positive impact on the source firm innovation performance".*

Regression table 5: Regression model between leavers to another country and the source firm's innovation output

	Simple OLS		Negative binomial	
	Coeff.	SE	Coeff.	SE
(constant)	2.3523*	0.3497	2.271*	0.3686
Ratio total leavers	-1.3915*	0.1781	-1.443*	0.2641
Ratio leavers to another country	-0.5235*	0.1073	-0.628*	0.1665
Total firm patent inventors previous year	0.0002*	0.0000	0.000*	0.0000
Year dummies (1996 – 2015)	*Year dummies included*			
Firm dummies (276 firms)	*Firm dummies included*			
Dependent variable	Ln(innovation output)		Innovation output	
Adjusted R2	0.4382			

* Indication of a significance at 1% level

Chapter 5: Conclusion

5. Conclusion

The main purpose of this research is to determine how inter-firm inventor mobility influences the innovation performance of former employers in the pharmaceutical industry. The conduction of a literature review aims to give an insight into the concept of inventor mobility, its potential impact, and its underlying mechanisms on how it could impact a firm. Besides, an answer to the central research question is formulated by the conduction of a quantitative study.

Inventor mobility is defined as an input for production, depicted in a three-dimensional cube in which a specific inventor its career path can be represented (Latham et al., 2011). Research states that inventor mobility can have an impact on the intellectual capital of a firm, and vice versa. This can be explained by the fact that intellectual capital consists out of human capital, social capital, and structural capital. Furthermore, intellectual capital could also create a sustained competitive advantage for the firm (McCracken et al., 2017). Besides, inventor mobility has a distinguishable impact at various levels, namely, on macro-perspective, micro-perspective, and the inventor himself. The macro-perspective reflects the impact of inventor mobility at a broad perspective, namely the effect at regional level. Marx et al. (2015) highlight that a high rate of inventor mobility results in a high innovation rate and steady economic growth. Moreover, labor mobility is an effective method for developing markets that try to reduce the technological gap with advanced markets (Song et al., 2003). The micro-perspective focuses on the effect of inventor mobility on both the firm that loses the inventor and the firm that hires the inventor. Although extensive previous research stipulates that inventor mobility is positive for the recipient firm, the impact on the source firm is still inconclusive. Especially, a leaving inventor can have a positive and negative impact on the previous employer.

The empirical results are consistent with the negative perspective of leaving inventors on the source firm. Namely, an increase of 1% in the share of leaving inventors decreases the innovation output of a firm by 1.32% or by 1.402 patents. This is an indication that leaving inventors have a negative impact on the source firm's innovation output. A negative impact of leaving inventors could be explained by the changes in the knowledge asset of a firm. When an inventor leaves a firm, its knowledge and skills, namely its human capital, is lost for the source firm. As a result, daily processes could be disrupted (Campbell et al., 2012). Even more important is the fact that the source firm will lose access to the tacit knowledge of the inventor, which often contributes to the competitive advantage of a firm (Song et al., 2003). Moreover, this result indicates that reverse knowledge spillovers, an increase of knowledge of the source firm due to leaving inventors, do not over-compensate for the loss of skills and inventor expertise associated with outbound mobility (Corredoira & Rosenkopf, 2010). Furthermore, it is examined how the innovation output of a firm is affected by the productivity of the leaving inventor, the technological distance between the hiring and losing firm, and the geographical proximity after the mobility event of the leaving inventor.

Firstly, the productivity of the leaving inventor has a positive impact on the source firm's innovation output. Especially, high-productive leaving inventors contribute positively to the firm's innovation output. An increase of 1% in the share of high productive leavers of the total leavers will lead to an increase in the innovation output by 1.07% or 1.733 patents. This is a remarkable result since this indicates that a high-productive leaving inventor contributes more to the innovation output of a firm, than a low-productive leaving inventor. A possible explanation could be in line with the social capital theory which predicts a reverse knowledge transfer, a knowledge transfer from the leaving inventor to the source firm. Namely, the high-productive leaving inventor could stay in contact with former co-workers and the source firm's awareness towards the behavior of the recipient firm may be more intensive than before. Particularly, the adoption of the leaving inventor its previous ideas by the recipient firm could create an opportunity for the source firm to create a channel that enables easier access to external ideas of the recipient firm (Singh & Agrawal, 2011).

Secondly, this research investigates if there is a difference in the impact on the source firm's innovation output of leaving inventors to firms with another core-technology. The results show that leaving inventors to another core-technology firm have a negative impact on the source firm's innovation output. However, this result should be treated with caution because multicollinearity has been detected between the variables.

Thirdly, the impact of leaving inventors to another country is examined. An increase in the share of leavers to another country by 1% of the total leavers leads to a decrease in productivity of 0.52% or 0.628 patents. Again, this is a remarkable result because it indicates that a leaving inventor to the same country is less damaging for the source firm, than a leaving inventor to another country. A possible explanation is that inventors leaving to another firm within the same country maintain a better relationship with former co-workers. Moreover, the source firm's awareness towards the behavior of the recipient firm may be more intensive than before since the hiring firm is closely located to the source firm.

These results lead to some management implications, more specifically it is recommended that firms try to reduce the amount and impact of leaving inventors. For instance, firms should change their structural capital, such as, team working structures. Furthermore, high-productive leaving inventors have a positive impact on the firm's innovation output which means that investment in employees is no wasted money.

5.1. Research limitations and recommendations for future research

Future research is recommended to provide more insight into other aspects that could impact the effect of a leaving inventor on the source firm. For example, the effect of similarity between the inventor and the hiring firm, co-mobility, and leaving inventors to a new venture. Furthermore, additional studies are necessary to confirm whether our results also apply beyond the pharmaceutical industry where the mobility of inventors and innovation is an essential factor for a firm. Also, future research could investigate how the mobility of other knowledge workers besides patent inventors influence the innovation performance of a firm.

This research copes with some limitations. Firstly, a limited number of control variables are added to the regression models. Including more control variables, such as the inventor age, could strengthen the credibility of the results. Besides, the productivity of an inventor is determined by its patent productivity in the previous year. A more accurate measurement would be a determination of its patent productivity over a larger timeframe. Lastly, only inventors leaving for another firm are captured as a leaver if the time between the last patent created at the source firm and the first patent created at the hiring firm is less than one year.

Chapter 6: References

6. References

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Chapter 7: Annex

7. Annex

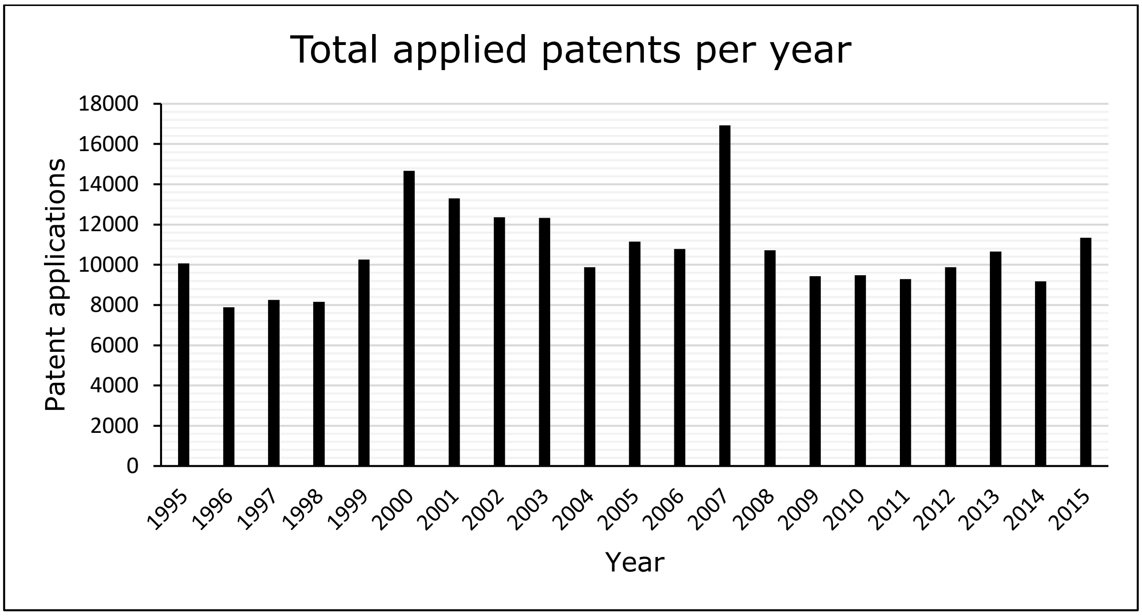
7.1. List of Sample firms

Abbott Laboratories	Chimerix Inc	Illumina
Abbvie	Chiron	Imclone Systems
Abgenix	Chr Hansen	Immunogen
Acadia Pharmaceuticals	Cipla	Impax Laboratories
Acambis	Clovis Oncology	Incyte
Acorda Therapeutics	Coherus Biosciences	Indivior
Actelion Pharmaceuticals	Crucell	Infinity Pharmaceuticals
Active Biotech	Csl	Innogenetics
Affymetrix Inc	Cti Biopharma	Insmed Incorporated
Agios Pharmaceuticals	Cv Therapeutics	Intercell
Ajinomoto	Dade Behring	Intercept Pharmaceuticals
Alexion Pharmaceuticals	Daiichi Pharmaceutical	Intermune
Alizyme	Daiichi Sankyo	Invitrogen
Alkermes	Dainippon Pharmaceutical	Ipsen
Allergan	Diversa Corp	Ironwood Pharmaceuticals
Almirall	Dr Reddy's Laboratories	Ivax
Alnylam Pharmaceuticals	Dynavax Technologies	Jazz Pharmaceuticals
Altana	Egis Pharmaceuticals	Johnson & Johnson
Amgen	Eisai	Juno Therapeutics
Amicus Therapeutics	Elan	Karo Bio Ab
Antisoma	Eli Lilly	Karyopharm Therapeutics
Applera	Emergent Biosolutions	Kissei Pharmaceutical
Arena Pharmaceuticals	Endo	Krka
Ariad Pharmaceuticals	Epigenomics	Kyorin
Array Biopharma	Epizyme	Kyowa Hakko Kirin Co, Ltd
Astellas Pharma	Evotec Ag	Kyowa Hakko Kogyo
Astrazeneca	Exelixis	Lfb
Aventis	Fibrogen	Lonza Ag
Axis-Shield	Flamel Technologies	Lupin
Axovant Sciences	Forest Laboratories	Mallinckrodt
Barr Laboratories	Fosun International	Martek Biosciences
Bavarian Nordic	Fujisawa Pharmaceutical	Maxygen Inc
Bayer	Galen	Medarex
Beckman Coulter	Galenica	Medicines
Becton Dickinson And	Gedeon Richter	Medigene
Company	Gen Probe Inc	Medimmune
Biogen Idec	Genelabs	Merck & Co
Biomarin Pharmaceutical	Genencor	Merck Kgaa
Biomerieux	Genmab	Merrimack Pharmaceuticals
Biotage	Genzyme	Merz
Biotest	Geron	Microscience
Biotie Therapies	Gilead Sciences	Millennium Pharmaceuticals
Bluebird Bio	Glaxosmithkline	Mitsubishi Pharma
Boehringer Ingelheim	Gpc Biotech	Mitsubishi Tanabe Pharma
Bristol-Myers Squibb	Green Cross Corp	Corp
British Biotech Plc	Grifols	Ml Laboratories
Btg	Grunenthal	Mochida Pharmaceutical
Cadila Healthcare	Guerbet	Momenta Pharmaceuticals
Cat	Gw Pharmaceuticals	Monsanto
Celgene	H Lundbeck A/S	Morphosys
Cell Genesys Inc	Hanmi Pharm	Mundipharma
Cell Therapeutics	Heska Ag	Mylan
Celldex Therapeutics	Hisamitsu Pharmaceutical	Myriad Genetics
Celltech	Human Genome Sciences	Nanogen Inc
Cephalon	Hybridon	Nektar Therapeutics
Cepheid	Icos Corp	Neurocrine Biosciences
Cerep	Idexx Laboratories	New England Biolabs Inc
Chiesi Farmaceutici Spa	Ignyta	Nicox S.A.

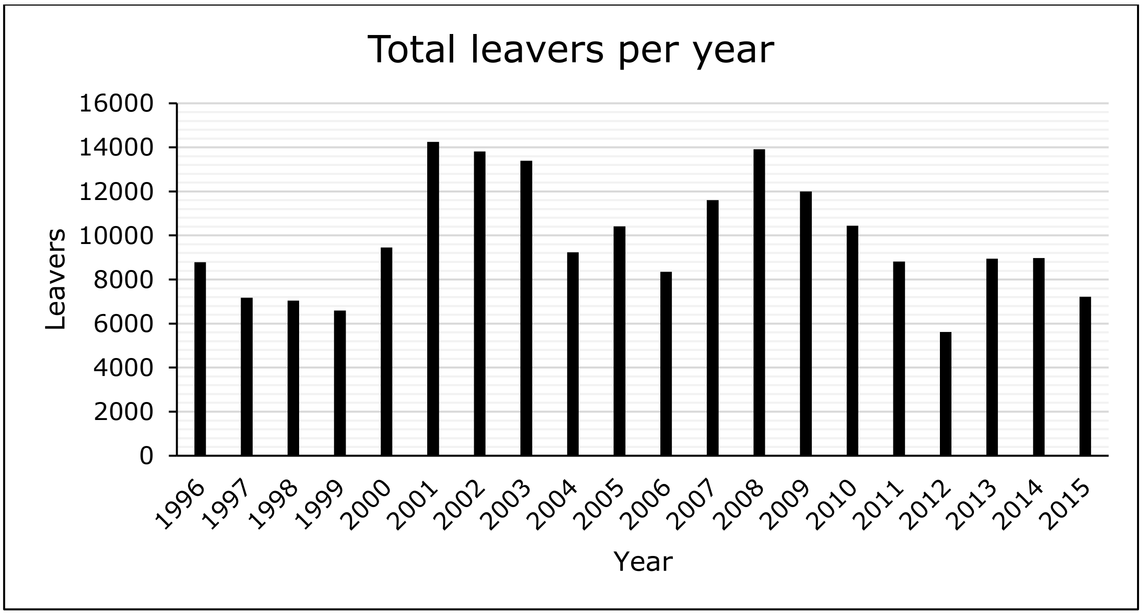
Nippon Shinyaku Northwest Biotherapeutics Novartis Novavax Novo Nordisk Octapharma Ono Pharmaceutical Ophthotech Corporation Opko Health Osi Pharmaceuticals Otsuka Oxford Biomedica Perrigo Co Pfizer Pharmexa Phytopharm Plc Pliva Portola Pharmaceuticals Promega Ptc Therapeutics Qiagen Q-Med Quintiles Recordati Regeneron Pharmaceuticals Relypsa Ribozyme Pharmaceuticals Richter Gedeon Roche Sankyo Sanofi Santen Pharmaceutical Sarepta Therapeutics Schering Schering Plough Schwarz Pharma Scios Inc Seattle Genetics Seikagaku Seikagaku Corporation Sepracor Sequenom Serono Servier Sas Shanghai Pharmaceuticals Shionogi Shire Sichuan Kelun Pharmaceutical Sino Biopharmaceutical Skyepharma Solexa Stada Arzneimittel Stratagene Sumitomo Dainippon Pharma Co, Ltd Sun Pharmaceutical Industries Synergy Pharmaceuticals Taisho Pharmaceutical Takeda Pharmaceutical Tanabe Seiyaku Tanox Inc Tesaro	Teva Pharmaceutical Industries Therapeuticsmd Theravance Towa Pharmaceutical Transgene Tularik Ucb Ultragenyx Pharmaceutical United Therapeutics Valeant Pharmaceuticals Vectura Limited Vertex Pharmaceuticals Watson Pharmaceuticals Wockhardt Wyeth Xenova Yamanouchi Pharmaceutical Zambon Zeltia Zeria Pharmaceutical Zhejiang Hisun Pharmaceutical Ziopharm Oncology Zoetis Zymogenetics

7.2. Visual representation of the description of the variables

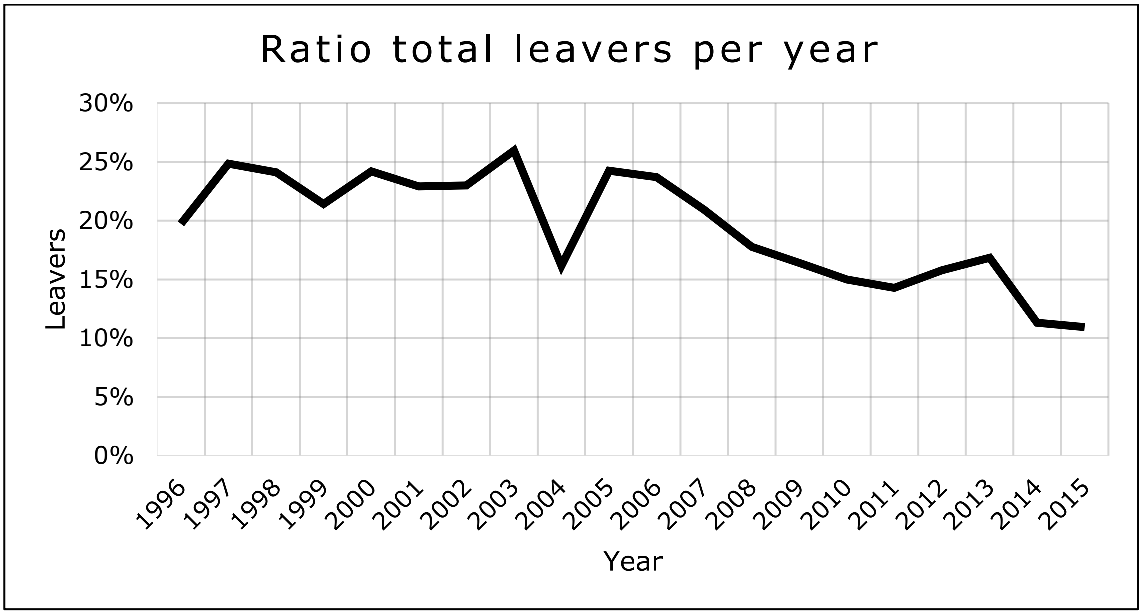
Annex 1: The innovation output of the sample over 20 years



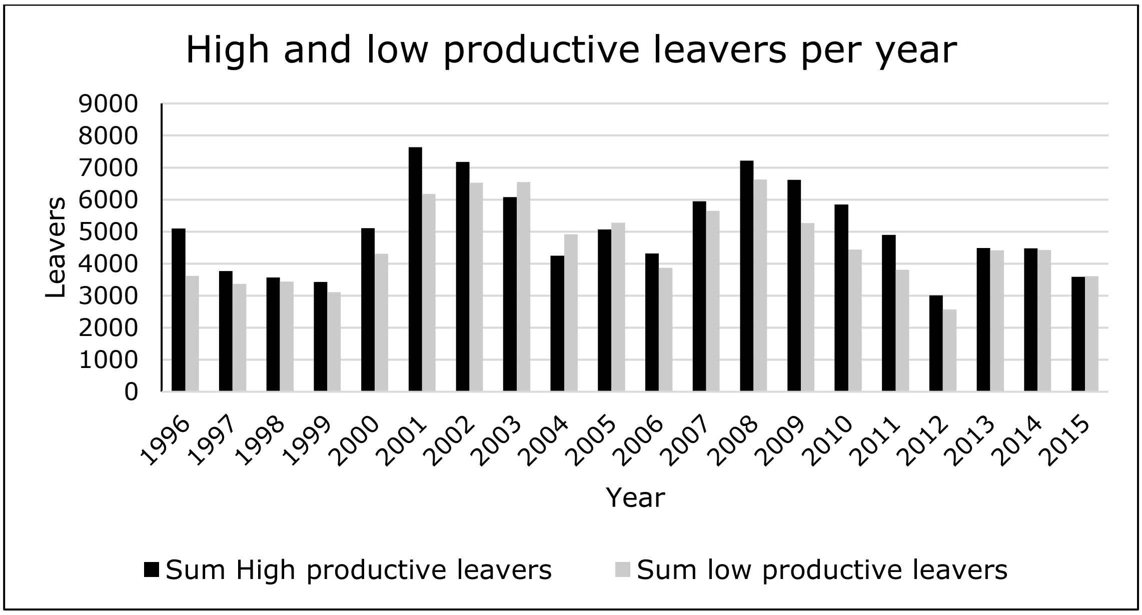
Annex 2: Mean total leavers over 19 years



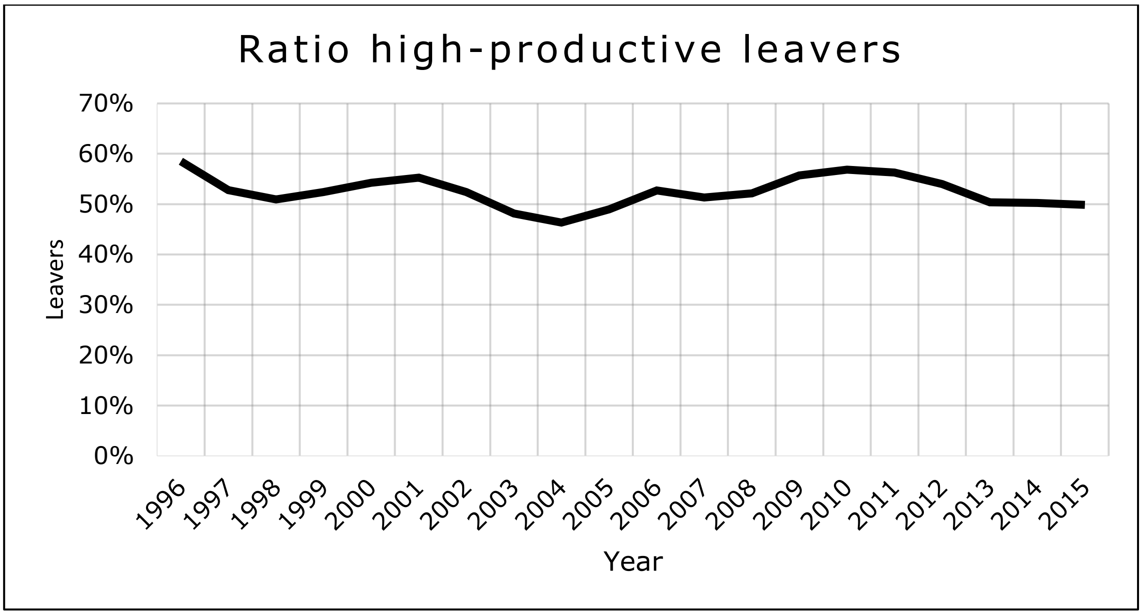
Annex 3: Mean ratio total leavers over 19 years



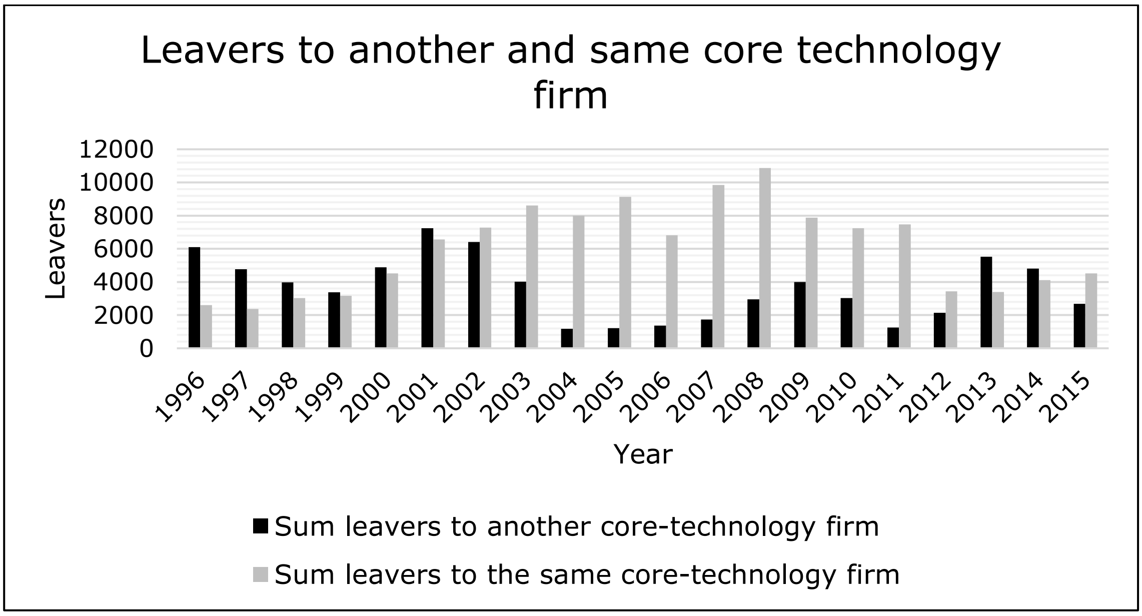
Annex 4: Comparison between total high and low productive leavers over 19 years



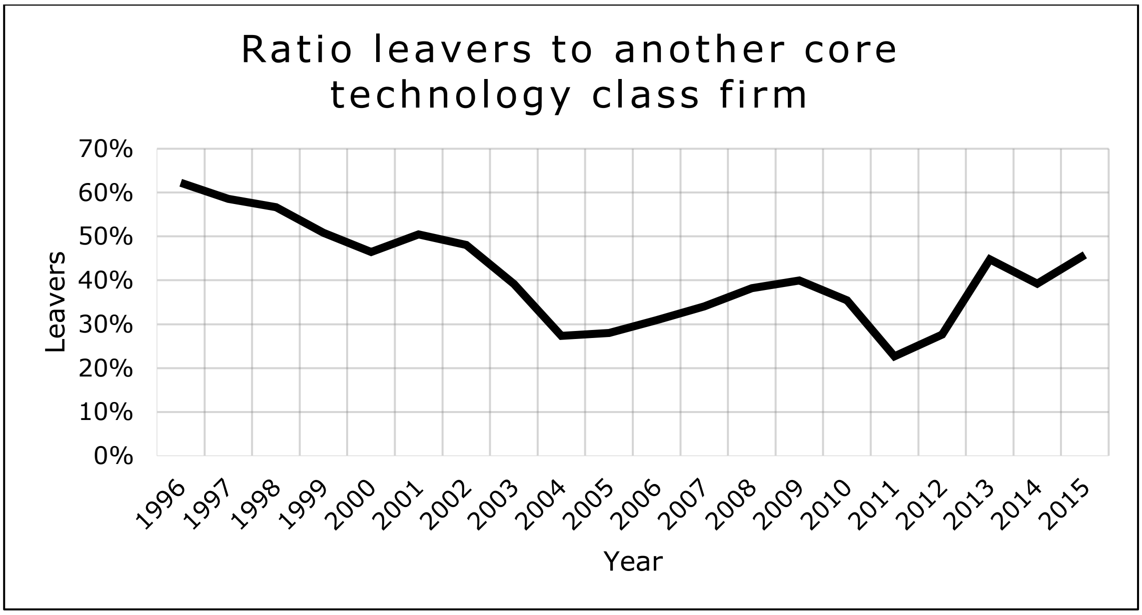
Annex 5: Ratio high-productive leavers over 19 years



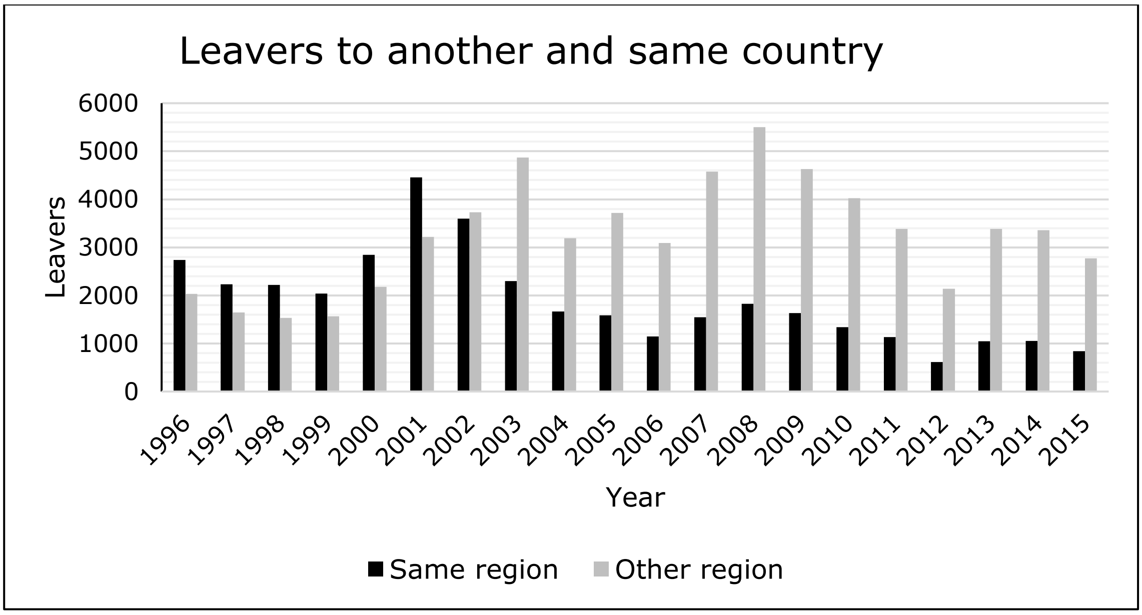
Annex 6: Comparison between leavers to another and same core-technology firm over 19 years



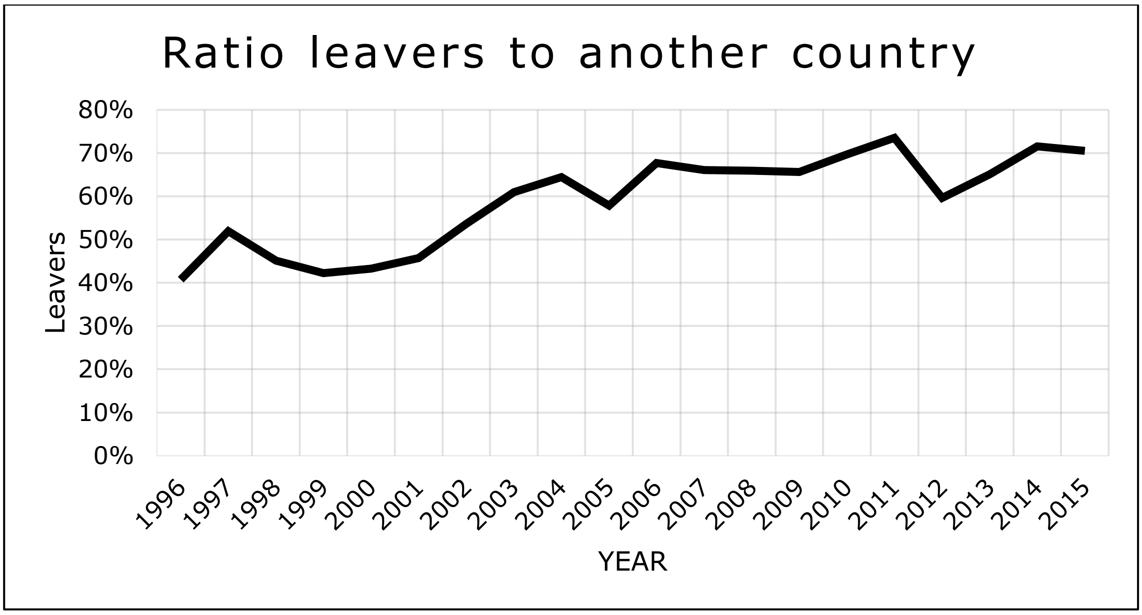
Annex 7: Ratio leavers to another core-technology class firm over 19 years



Annex 8: Comparison between leavers to the same and another country over 19 years



Annex 9: Ratio leavers to another country over 19 years



Annex 10: Missing geographical data of the leaving inventors to another country

Year	% Missing data
1996	46%
1997	46%
1998	47%
1999	45%
2000	47%
2001	46%
2002	47%
2003	46%
2004	47%
2005	49%
2006	49%
2007	47%
2008	47%
2009	48%
2010	49%
2011	49%
2012	51%
2013	50%
2014	51%
2015	50%
Mean	48%

7.3. Multicollinearity detection

Annex 11: VIF index of the intended variables

	Regression table				
	(1)	(2)	(3)	(4)	(5)
Ratio total leavers		2.149	2.153	2.157	2.188
Ratio high-productive leavers			2.447		
Ratio leavers to another core-technology firm				**4.385**	
Ratio leavers to another country					2.264
Missing geographical data					2.043
Total firm patent inventors previous year	1.227	1.232	1.233	1.235	1.236
Technology diversity	**7.855**	**8.568**	**8.584**	**8.570**	**9.047**
Technology diversity squared	**7.089**	**7.406**	**7.424**	**7.407**	**7.599**
Year dummies	< 4	< 4	< 4	< 4	< 4
Firm dummies	< 4	< 4	< 4	< 4	< 4

Annex 12: VIF index of the variables in the regression models

	Regression table				
	(1)	(2)	(3)	(4)	(5)
Ratio total leavers		1.932	1.939	1.944	1.939
Ratio high-productive leavers			2.441		
Ratio leavers to another core-technology firm				**4.367**	
Ratio leavers to another country					2.262
Dummy no geographical data					1.939
Total firm patent inventors previous year	1.227	1.212	1.214	1.216	1.219
Technology diversity	**7.855**				
Technology diversity squared	**7.089**				
Year dummies	< 4	< 4	< 4	< 4	< 4
Firm dummies	< 4	< 4	< 4	< 4	< 4