

Regional Innovation and Entrepreneurship

**Patents, Trade Marks, Entry and Entrants'
Growth in European Manufacturing Industries**



Michał Kazimierczak

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**Regional Innovation and Entrepreneurship
Patents, Trade Marks, Entry and Entrants' Growth in
European Manufacturing Industries**

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To my wife Kasia

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1 Introduction

1.1 The motivation for this study

The main topic of this thesis is the relationship between the regional stocks of technological knowledge, entry and performance of newly created firms.

The traditional entrepreneurship literature has emphasized various personality traits of entrepreneurs and their importance for the decision to start new ventures. However, the explanatory power of this strand of literature is limited, as personal features of individuals can hardly explain large differences in entry rates across countries or regions. Rather than treating the external context of entrepreneurial action as given, this research studies the variation of knowledge available in the local economic milieu, strategic behaviour of incumbents shielding this knowledge from competitors, and their effect on entry rates and newly established firms' growth performance.

Local (patented) knowledge stocks are studied as an important source of entrepreneurial opportunities, but also as a source of increased competitive pressures influencing entry and performance of entrants. Similarly, local trade mark stocks may represent a region's non-technological knowledge stock in terms of the ability to introduce new products that are not necessarily based on new technology. Trade marks are increasingly seen as indicators that can capture aspects of firm level innovation, in particular, incremental innovation in low-tech settings. New products signalled by trade mark registration may therefore also reflect innovative activity generating potential knowledge spillovers, which can spur entry and performance of newly created firms. Yet trade marks can also serve as entry barriers and as an instrument for appropriation by incumbents. As summarized by Castaldi (2018) *"trademark-based indicators can operationalize constructs that are complementary to constructs operationalized with patents. They can also provide alternative measures for constructs and contexts where patents are hardly helpful"*. In the dissertation we examine both aspects of trade marks.

Our work builds on a recent stream of research on knowledge-based entrepreneurship, in particular, the knowledge spillover theory of entrepreneurship (KSTE). The KSTE directly links the decision to create a new firm to the opportunities emerging from knowledge generated but not exploited commercially by incumbents (Ghio et al. 2015). It posits that *"a context which is rich in knowledge generates entrepreneurial opportunities from*

those ideas created” (Acs et al. 2013). This focus on local knowledge is motivated by evolutionary economic theory (Winter 1988; Nelson & Winter 1982) which sees business firms as repositories of society’s know-how. Distribution of knowledge among economic actors is uneven (Hayek 1945) and it is precisely this dispersion of information and knowledge that creates business opportunities (Venkataraman 1997). Variation in local knowledge stocks is therefore an important factor that conditions discovery and recognition of new entrepreneurial opportunities that can be pursued by new ventures. We posit that those specific repositories of know-how consist of the prior knowledge available to an entrepreneur in the local milieu, which she combines with her novel input. Individual entrepreneurs and newly established firms are crucial for introducing novelty into the economic system.

A territorial dimension of innovation is at the core of several related strands of literature: research on industrial districts, innovative milieus, clusters and Regional Innovation Systems (RIS). This literature emphasizes the region as the most appropriate level of analysis of location-specific innovation systems (Asheim et al. 2011). Specific regional resources, networks of private and public actors and institutional settings are of utmost importance for stimulating the innovative capability and competitiveness of individual firms, as they are the basis for long-term competitive advantage that can hardly be imitated by firms located in other regions (Asheim & Isaksen 2002).

Both among policy makers and entrepreneurship scholars entrants are generally thought to benefit from choosing regions and industries with higher stocks of relevant (technological) knowledge. However, research on territorial innovation models, such as industrial districts, innovative milieus or regional innovation systems, tends to overlook competitive aspects of innovation and strategic behaviour of incumbents that may shield their knowledge from potential rivals. The main motivation of incumbents to engage in innovation activity is the improvement of their market position, relative to their competitors (Porter 1990; Porter 2000; Delgado et al. 2010). Successful innovation efforts undertaken by incumbents may thus result in *market stealing* from rivals pursuing the same product market (Bloom et al. 2013; Belderbos & Mohnen 2013). Knowledge stocks are therefore not only generating positive knowledge spillovers and opportunities for entrants but may also discourage entry into the industries populated by strong incumbents, determined to defend their market position.

The influence of local knowledge stocks may differ depending on the appropriation strategies employed by incumbents to increase their profits from innovation. Entrepreneurs' incentives to exploit discovered opportunities are generally lower when confronted with incumbents' determination to pursue the same or similar entrepreneurial opportunities (Casson 1982; Plummer & Acs 2014) as "*the private reward to the exercise of entrepreneurial judgement depends crucially upon the absence of competition from like-minded individuals*" (Casson 1982). The possibility that knowledge-driven entrepreneurship may be negatively affected by the commercialization of knowledge by incumbents (Audretsch et al. 2006) and localized competition (Plummer & Acs 2014) has been discussed within the KSTE literature. However, so far, the role of competition has not received due attention in empirical work and there is little evidence if and how these factors affect the rate of formation of new firms and their growth perspectives.

Incumbents' trade mark stocks can also reflect strategic behaviour of incumbents shielding their knowledge stocks from spillovers. Trade marks can complement patents by strengthening protection of innovation and increasing the appropriation by incumbents of their innovation efforts. In this context, patent stocks represent pools of relevant technological knowledge, potentially available to the entering firm, while trade mark stocks are reputational and strategic assets of incumbents (Castaldi 2018) employed to fend-off potential competitors (Tirole 1988; Lipczynski et al. 2005; Belleflamme & Peitz 2010).

Market rivalry and incumbents' appropriation strategies may play a less critical role if entrants are not competing directly on the same market (Bloom et al. 2013). In the present dissertation we distinguish between knowledge stocks in *focal industries* (at the product market level) and *related industries* (knowledge held by firms active in different product markets) to examine which knowledge stocks are a more important driver of entry and growth. This approach builds on the concept of *related variety*. Within this concept, *cognitive proximity* is crucial to assess the extent to which knowledge can spill over or be transferred across industries. Learning and knowledge transfer are possible when cognitive distance is not too large (Bjorn T Asheim et al. 2011). While the concept has been used in prior research (Jaffe 1986; Bloom et al. 2013; Frenken et al. 2007) the comparative relationship of related knowledge stocks with new firm entry and growth in the presence of market rivalry has not been sufficiently studied so far.

In the present dissertation, we reckon that regional knowledge stocks and the strategic behaviour of incumbents may be important factors not only for the creation of new firms but also for their (growth) performance. Regions with high stocks of knowledge may increase growth potential among newly created firms, but also may pose challenges to compete against incumbents, adding to the large set of disadvantages faced by young firms, called the *liability of newness*. In highly innovative contexts, technological innovation and trade marking by young firms may be required to compete against incumbents. Entry with innovative or differentiated products or services, although potentially increasing entrepreneurial risks, may also increase the chances of young firms to perform well.

1.2 Research questions

In this dissertation we aim at enriching the extant literature on the relationship between local knowledge stocks and the creation and growth of new firms. The main research question is:

What is the influence of local knowledge pools on entry and growth of new manufacturing firms?

In addition, we aim to answer a number of more specific questions on entry:

Is the relationship between entry and knowledge stocks different for local knowledge stocks produced by incumbents active in the same industry and knowledge produced by firms in other industries using related technologies?

Are positive effects of local knowledge stocks in the focal industry on entry reduced by trade mark activity of incumbents?

Do the relationships above differ depending on the industry (technology intensity) and type of entry (new firms with or without patent or trade mark activity)?

On the growth of firms, we similarly aim to answer a set of specific question:

What is the relationship between innovations proxied by patents and trade mark activity of newly created firms and their turnover growth?

Is the relationship between growth of newly established firms and local knowledge stocks different for knowledge produced by incumbents active in the same industry and related knowledge produced by firms in other industries?

Are positive effects of local knowledge stocks in the focal industry on growth of new firms limited due to simultaneous trade mark activity of incumbents?

Those general research questions are further developed and extended in the empirical chapters 5 and 6. To answer these research questions, we construct an integrated database on manufacturing firms' entry, growth, and patent and trade mark activity in Europe. The analysis on entry employs data on entries and incumbents in the years 2001-2009 in 982 NUTS-3 regions representing 12 Member States of the EU and 230 NACE 4-digit product markets. The analysis on entry examines a cohort of 22 218 manufacturing firms created in the year 2000 and their turnover growth between 2003 and 2009. We also construct a new inter-industry technological similarity index facilitating the operationalization of the concept of technologically related knowledge stocks outside the focal 4-digit industry. This granularity, not available in previous research, enables us to better separate positive and negative externalities due to local knowledge pools.

1.3 The outline of the dissertation

The dissertation starts with a literature review (chapter 2). In the literature review, we focus on the place of knowledge in the classical and modern economic theories of the firm, research on knowledge spillovers, and the literature pointing to incumbents as a source of such spillovers for new entrepreneurial entry. We also discuss the literature on strategic tools incumbents may employ to limit spillovers and discuss to what extent trade mark data may serve as a useful proxy to examine such strategic behaviour of incumbents.

In chapter 3 we present the details of the dataset, created from various sources of information on individual firms. Financial data, data on establishment, growth and survival, and information on industry was taken from ORBIS, while patent and trade mark data was extracted from various IP registers at the European and national level. As the dataset has been built using novel matching algorithms to assign patents to industries, it is important to compare our approach with existing methods. In chapter 3 we provide such comparative analysis, in particular with concordances developed by Schmoch et al. (2003) and Dorner & Harhoff (2018).

Chapter 4 describes our method of determining technological relatedness between industries, which we use to distinguish between relevant and non-

relevant knowledge stocks. We also discuss how the similarity between knowledge stocks has been operationalized in prior work and compare our measure with other methods. The key advantage of our measure is its granularity at the product market level.

Chapter 5 examines the relationship between incumbents' knowledge stocks and entry of new firms, drawing on the granular database developed on new firm formation at the detailed industry (NACE 4 digit) and regional (NUTS 3) level for 12 EU countries. Poisson models with fixed effects for year, industry and regions are estimated relating the number of new firms in each NACE-NUTS to focal industry knowledge stocks and related knowledge stocks in other local industries, trade mark stocks, the interaction between focal industry patent and trade mark stocks, and a range of regional and industry covariates.

Chapter 6 investigates the role of local patent and trade mark stocks, as well as entrants' own patents and trade marks, on the growth of newly established manufacturing firms. We estimate quantile regression models to examine how these factors change the growth distribution of firms, with novel methods for panel structure and sample attrition.

We summarize our conclusions in chapter 7. In this chapter we also discuss limitations of our data and research, and indicate future research possibilities to address remaining gaps in our knowledge regarding entrepreneurship and local knowledge stocks.

2 Literature review

2.1 Knowledge and firms

Theoretical work of Solow (1956; 1957) and Romer (1990) enhanced the understanding of the sources of economic growth. An important insight of Solow's model and the more recent endogenous growth models is that the long term growth can be sustained only by technological progress (Acemoglu 2008). Technological progress stems from the activities of individuals and firms carried out in order to profit from the introduction of new, and the improvement of the existing, products and processes. New ideas and inventions are the engine of economic growth, because they improve the technology of production. In the most prevalent production function model proposed by Griliches (1979) firms engage in R&D activities in order to produce new knowledge, which results in higher output and productivity.

In contrast, knowledge has not been treated as an important determinant of growth in neoclassical microeconomic theories of firm (Nelson & Winter 1977). Although the firm is widely recognized as a crucial institution for technological change, in the neoclassical economics it remains a *black-box* when it comes to the understanding of the process of new product and services development and commercialisation (Teece 2010). In the increasingly rigorous analytical treatment of market processes in neoclassical economic models, there is a room only for a highly stylized characterisation of a firm.

The production function approach treats knowledge as costless and perfectly transferable. Capital is represented as infinitely elastic and can be easily moved from one production process to the other. Choices between homogenous capital goods are not complex and entrepreneurial judgment does not play any important role in such models (Bjørnskov & Foss 2013). The neoclassical approach, therefore, does not consider the firm as a *problem-solving institution* (Demsetz 1988). As a consequence, the theory of the firm remains in the periphery of economic analysis (Walker 2015). The most interesting contributions to innovation analysis and entrepreneurship theory were developed outside of the mainstream economics in the areas of Austrian economics, evolutionary economics and among management scholars.

Evolutionary economics sees firms as a repository of the productive knowledge embedded in routines (Winter 1988; Nelson & Winter 1982). Learning is a crucial aspect of a firm activity and performance. It consists of a constant process of updating of knowledge of the environment a firm

operates in. In this process, the firm relies on the search for alternative routines, adopting those which best matches the changing environment. The rate of discovery of new routines depends on the size of the pool available as well as the intensity and direction of search (Cohendet et al. 1998). The choices made by individuals are highly dependent on the specific historical and economic reality in which the firm operates (Spender 1996).

Evolutionary theories are not explaining very well how firms are established (Spender 1996) and what is the role of the entrepreneur (Cohendet et al. 1998). It is instead Austrian theorizing that provides some interesting hypotheses regarding the crucial role of knowledge, and especially the dispersion of knowledge, for entrepreneurship and new firms creation.

2.2 Knowledge and innovative entry

Austrian economists emphasize that in the real world the stationary state described in the neoclassical models can hardly be reached due to the disruptive impact of innovation (Schumpeter 1934). Market entry is often related to the introduction of new products or new ways of production of existing products, in which entrepreneurs may play an important role. This process is complicated as it requires stepping out of routine thinking while facing uncertainty related to the *“impossibility of surveying all the effects and counter-effects of the projected enterprise”* (Schumpeter 1934).

Learning is an important aspect of Austrian definition of entrepreneurship. Kirzner (1997) defines entrepreneurship in terms of profit opportunities, discovered and acted upon by routine-resisting agents who are constantly alert to such opportunities. Since Kirzner (1997), the conceptualization of entrepreneurship as alertness to profit opportunities has risen to prominence in the management literature. In their seminal article, setting the agenda for research on entrepreneurship, Shane & Venkataraman (2000) defined this field of research as *“the study of sources of opportunities, the process of discovery, evaluation, and exploitation of opportunities; and the set of individuals who discover, evaluate, and exploit them”*. In the Shane & Venkataraman (2000) framework, entrepreneurial opportunities are objective phenomena, although they are not known to all the economic agents and their recognition is non-trivial and subjective.

The uncertainty, information asymmetries, and high transaction costs inherent to knowledge induce divergent views as regards its value and its commercialization possibilities (Arrow 1962). Therefore, knowledge is harder

to trade than most other resources. The creation of a new firm is not the only option available for commercializing inventions. An invention may sometimes be commercialized more efficiently by incumbents. The inventor may be better off transferring rights to his inventions to existing firms. Therefore, a critical determinant of innovative entrepreneurship is whether the creation of a new firm is necessary to commercialize inventions. The inventor has an incentive to become an innovative entrepreneur when the costs of commercializing the invention through a new firm are lower than the cost of transferring information and rights to such inventions to incumbents (Spulber 2014).

The highest, and sometimes insurmountable, transaction costs are related to differences in the evaluation of the market prospects and the business ideas developed regarding the invention. Uncertainty regarding these prospects, defined in the Knightian terms as the situation where the distributions of future outcomes is not known (Knight 1921), creates entrepreneurial opportunities. *Entrepreneurs establish firms not because they have no knowledge of the future, but because their beliefs about the future cannot be easily articulated and communicated to existing resource owners* (Foss & Klein (2012)). This makes the entrepreneurial judgment so difficult for interpersonal agreement and market exchange (Langlois & Cosgel 1993). According to the theory of the experimentally organized economy (EOE) developed among Swedish scholars of entrepreneurship, every economic activity is in fact a market experiment due to the bounded rationality of economic agents and uncertainty related with new business ideas (Johansson 2010).

Due to the costs of knowledge transfers, prospective entrepreneurs may not be able to communicate their visions to the owners of critical assets and therefore have an incentive to seek their ownership. Capital goods are heterogeneous because they have different kinds of attributes, characteristics, functions, or possible uses as perceived by entrepreneurs (Foss & Foss 2001). Future attributes are discovered over time as a consequence of assets' usage in the production process. Internalisation of crucial resources within the boundaries of the newly created firm reduces costs in comparison with their acquisition in the market transactions (Coase 1937). New firms emerge therefore as a means of maximizing the returns from entrepreneurs' judgement (Foss & Klein 2012; Spulber 2014).

Austrian economists indicate the uncertainty of new business endeavours and asymmetry of information as regards entrepreneurial opportunities as a

prominent spur for entrepreneurial entry. Extant literature suggests that incumbent firms may be an important source of such opportunities explored by entrepreneurs in the form of new firms.

2.3 Incumbents as a source of entrepreneurial opportunities

The Knowledge Spillover Theory of Entrepreneurship (KSTE) (Audretsch & Belitski 2013) and related Knowledge Spillover Strategic Entrepreneurship theory (KSSE) posit that *“entrepreneurial opportunities do not appear to be exogenous but rather systematically created by a high presence of knowledge spillovers”* (Acs et al. 2009). The creation of new firms is related to the knowledge generated but not exploited commercially by incumbents (Acs et al. 2013).

The full spectrum of commercial exploitation possibilities of new knowledge is not always obvious even for the innovator engaged in its development. Even the most efficient incumbents will not exploit all the business opportunities stemming from their innovation. As discussed in section 2.1, a firm’s knowledge and previous experience are embodied in the routines, which help it navigate a complex economic environment. Routines could be seen as the centralised body of common knowledge guiding the learning process and guaranteeing its coherence (Cohendet et al. 1998). As noted by Loasby (2001) *‘competing visions within firms, unless very carefully managed, and limited in scope, cause trouble’* whereas *“competing visions between firms are necessary features of an evolutionary or experimental economy”*. One firm may be unable to embrace the whole spectrum of business opportunities related to innovation.

The boundaries of a firm may be explained by transaction costs (Coase 1937). The upper limits of incumbents’ expansion are set at the point where the advantages of *central planning* within a firm are offset by additional costs of coordination stemming from dispersed information. The knowledge management difficulties will limit the size of firms at some point. An incumbent firm may be better off adopting a narrow business strategy (Rotemberg & Saloner 1994). Such an approach means that the firm commits to consider only business ideas within a narrow, but highly profitable, set of business activities, while disregarding business opportunities outside that narrow domain.

Routines of the mature organizations are path-dependent and based on the refinement of their past experience. Ahuja & Morris Lampert (2001) identified three organizational pathologies that reduce the probability of incumbents to engage in the breakthrough inventions. The familiarity trap increases the odds of incumbents to simply refine the familiar solutions rather than developing new technologies. The maturity trap drives incumbents' search towards technologies that are relatively well-known and well-established within the industry. The propinquity trap tips incumbents' search towards technologies that are relatively close to the existing routines. Ahuja & Morris Lampert (2001) argue that those mental traps bring some immediate benefits, however, they constrain firms' abilities to engage in breakthrough inventions and therefore undermine their long term prospects. Incumbents may be also locked-in by their current customers' base. Existing customers favour established firms because they are more reliable than new ventures. However *"reliability reduces adaptability, because it is achieved by reducing variation in the organization's activities that otherwise would have provided opportunities to innovate"* (Eckhardt & Shane 2011). New firms are created and grow capitalizing on those unused opportunities.

KSTE focuses on the contextual variables that shape entrepreneurship, particularly local knowledge endowments, while keeping constant the individual features of entrepreneurs (Acs et al. 2013). According to KSTE, contexts rich in knowledge generate more entrepreneurial opportunities. As explained by Acs et al. (2013) *"what distinguishes this theory from other theories of entrepreneurship is that the source of the entrepreneurial opportunity involves knowledge spillovers. The knowledge spillover theory of entrepreneurship explains the entrepreneurial act – why certain people become entrepreneurs while others abstain from entrepreneurship – as a response to knowledge spillovers."* Acs et al. (2013) posit that heterogeneity between growth rates of regions and countries can be explained by knowledge endowments and the entrepreneurial capital which facilitates the conversion of those endowments into new entrepreneurial ventures. Technological change is facilitated by the stock of technological knowledge historically developed within a region (Acs et al. 2009).

KSTE links endogenous growth theory with the concepts of knowledge spillovers and entrepreneurship (Ghio et al. 2015). Proponents of endogenous growth theory argue that, besides a direct impact on the productivity of innovative firms, new knowledge may be a source of benefits for third parties as well. Romer (1990) defined technology as non-rival and only partially

excludable. Other agents do not have to replicate the inputs of the knowledge creator to enjoy the same or similar benefits from knowledge. Useful economic knowledge may be diffused among wider sets of economic agents with only a fraction of the costs associated with its creation, which makes knowledge crucial for overall productivity and economic growth.

Extant research indicates that incumbents' knowledge may be an important source of entrepreneurial opportunities leading to entry and commercialization of knowledge underutilized by incumbents. For a better insight of why and how this transfer of knowledge may occur, it is necessary to look into the literature on knowledge spillover and the factors facilitating and conditioning its strength.

2.4 Knowledge spillovers

The term knowledge spillovers has been used in the economic literature to describe the external benefits from knowledge that are enjoyed by parties other than the entity investing in the knowledge creation (Griliches 1991; Agarwal et al. 2010). A lack of direct compensation for the knowledge creator is the definitional aspect of the knowledge spillovers. Knowledge spillovers arise from two fundamental phenomena: the intangible character of knowledge and the uncertainty triggering divergent views on the market prospects of innovations. The non-rival and non-excludable character of knowledge linked to its intangible nature make it more likely to be subject to spillovers than other investments (Romer 1990; Arrow 1962). Due to the nonrival nature of knowledge, the incumbent is not able to appropriate the full value of its investment in intangible resources (Scotchmer 2004) but this value is shared among a broader set of economic agents and society as a whole. As a result, the productivity of those agents improves (Romer 1986, Grossman and Helpman, 1991).

Scholars distinguish between intra-industry spillovers that occur between firms active on the same product market and inter-industry spillovers that arise between firms active on different markets but engaged in some type of technological or knowledge interaction facilitating knowledge externalities (Kaiser 2002). The main mechanism of the diffusion of knowledge between firms active in the same and related industries are regional labour networks and interfirm mobility of the knowledge workers (Almeida & Kogut 1999; Agrawal et al. 2006; Song et al. 2003; Møen 2005).

As noted by Griliches (1979), research approaches based on the concept of inter-industry knowledge spillovers could be broadly classified into two types, which reflect two channels through which spillovers operate. The first channel operates through traded goods and is based on R&D intensive inputs from other industries. The spillover benefits for *receiving* industries have their source in the price of inputs that is lower than warranted by the quality improvements stemming from the R&D efforts of the *giving* industries. Among the most prominent examples of such spillovers are the benefits other industries gain from the progress in information technology. This type of spillovers from technological innovation is called in the literature *rent spillovers* or *pecuniary spillovers* (Verspagen 1997a).

Pure knowledge spillovers, on the other hand, are characterized by flows of ideas that are not necessarily related to the purchase of inputs. Seemingly unrelated industries that are not using each other products as an input to the production process, may work on related technical problems and may use solutions invented in one field as the input to solving their own problems. Thus, innovation by firms may create entrepreneurial opportunities for firms in other industries (Audretsch 1995a). Pure knowledge spillovers have a different nature from rent spillovers, as they are related to the public good character of knowledge. In an empirical context, the distinction between those two types of spillovers is however difficult. Proxies used to measure spillovers, to a lesser or greater degree cover both channels through which spillovers occur (Meijers & Verspagen 2010).

2.4.1 Geographical proximity

Despite rapid growth in communication and information technologies, knowledge spillovers remain to a large extent a local phenomenon. This is related to the difficulty to transfer (tacit) knowledge.

Information has been characterized by Kogut & Zander (1992) as “*knowledge which can be transmitted without loss of integrity once the syntactical rules required for deciphering it are known*”. Penrose (1959) called this type of information *objective knowledge*. However, to be useful, information must be embodied in humans. Such humanly embodied knowledge that cannot be explicitly described is called in the literature *know-how* or *tacit knowledge*. Know-how has been defined by von Hippel (1988) as “*accumulated practical skill or expertise that allows one to do something smoothly and efficiently*”. Know-how, in contrast to *information*, is to a large extent tacit, and difficult to codify and interpret (Polanyi 1966; Hidalgo 2015).

While the marginal cost of diffusing information across space is virtually zero, the marginal cost of transmitting tacit knowledge, rises with distance (Audretsch 2007). Transmission and accumulation of tacit knowledge require direct and regular interpersonal contacts (Maskell & Malmberg 1999) because individuals know more than they are able to explain (Polanyi 1966). Know-how is disseminated mainly among neighbouring firms through informal interactions between employees (Glaeser et al. 1992), who frequently develop a specific language code (Kogut & Zander 1992).

There is a growing recognition in recent research on entrepreneurship that opportunities explored by entrepreneurs are highly localized and path-dependent (Foss & Klein 2012). The limited ability of humans to embody knowledge and know-how (Hidalgo 2015) increases the importance of local networks for accumulating and preserving technological knowledge. The experiential and social character of learning drives knowledge accumulation towards the domains already present in close vicinity, which leads to a geographical bias in the accumulation of knowledge and know-how (Hidalgo 2015). Spatial proximity is, therefore, an important factor conditioning the direction of entrepreneurial search and selection (Kogut & Zander 1992).

An enduring competitive advantage of firms is local and arises from *“highly specialized skills and knowledge, institutions, rivals, related businesses, and sophisticated customers”* (Porter 1998). These specific, heterogeneous sources of competitive advantage are the cornerstone of the concept of the national (Freeman & Soete 1997; Lundvall 2010) and regional (Cooke et al. 1997) systems of innovation. As emphasized by Lundvall (2010) *“the most relevant performance indicators of national system of innovation should reflect the efficiency and effectiveness in producing, diffusing and exploiting economically useful knowledge”*.

By facilitating communication and learning between various parties located in close vicinity and sharing similar cultural norms, regional systems of innovation play an essential role in directing processes of searching for novelty and innovation. As noted by Porter (1998) *“the prevalence of clusters in economies, rather than isolated firms and industries, reveals important insights into the nature of competition and the role of location in competitive advantage (...) The presence of clusters suggests that much of competitive advantage lies outside a given company or even outside its industry, residing instead in the locations of its business units”*. According to Malmberg & Maskell (2002) clusters exist because co-location of firms reduces costs related to the identification, access and transfer

of knowledge, in particular, if firms undertake similar activities (Maskell 2001).

Empirical literature based on patent citations has confirmed that knowledge spillovers benefit mainly nearby locations, while international spillovers are much weaker (Branstetter 2001; Maurseth & Verspagen 2002; Verspagen 2010). Bottazzi & Peri (2003) concluded that spillovers are very localized and exist only within a distance of 300 km. Therefore, location is a key strategic parameter increasing the potential benefits from exposure to knowledge spillovers (Alcácer & Chung 2007).

However, the prospects of entrepreneurs are not only affected by the sheer availability of knowledge in the region but also by the nature of the technological regime predominant in a given region and/or industry (Winter 1984). In routinized innovative regimes favouring innovative activities by established firms, even large pools of knowledge may not be sufficient for spurring entrepreneurial entry and growth. In routinized regimes, access of potential entrepreneurs to the pool of innovative ideas relevant for commercial activity may be difficult due to the highly specialized or esoteric character of that knowledge (Winter 1984) or strategic behaviour of incumbents fencing-off their knowledge from potential rivals. Audretsch & Fritsch (2002) claim that such technological regimes are not only a feature of an industry but also of a region.

Recent theories emphasize the multifaceted nature of interconnections and competition between various regional agents and their impact on entrepreneurial activity in the region. Concepts related to entrepreneurial regions (Smith, 2016), entrepreneurial ecosystems (Spigel 2017) and collaborative innovation blocs (Elert & Henrekson 2019) built upon various intellectual traditions, emphasize that this network of various regional actors is not only important for knowledge creation and diffusion but also for entrepreneurial activity per se. The presence of crucial institutions and economic agents on the regional level enables an entrepreneur to tap into abundant knowledge pools and convert entrepreneurial ideas into successful firms with promising growth prospects. In this perspective, the Schumpeterian entrepreneur still plays the vital role in discovery of the new business opportunities, but she must rely on others to convert this idea into a profitable firm (Elert & Henrekson 2019).

2.4.2 Cognitive proximity and relatedness of knowledge stocks

Geographical proximity is not sufficient for knowledge spillovers to occur. Cognitive relatedness is another crucial factor facilitating knowledge spillovers, learning and knowledge exchange (Boschma 2005). Due to different competences and research interests, firms will be affected differently by the innovative activity of other entities (Jaffe 1986). For each technology and production process there is a certain level of knowledge that is required in order to comprehend and implement it. Cognitive proximity between two firms should be close enough to facilitate understating, communication and processing the new information. It has been argued that other dimensions of proximity, including institutional, cultural, social and, especially, cognitive are at least as necessary as geographic proximity per se (Van Oort & others 2013; Boschma 2005). While other dimensions of proximity may substitute for lack of geographical closeness, geographical proximity facilitates building and strengthening of all other types of proximities that are important for learning and knowledge transfer.

Since the possibilities to benefit from new technologies depend on the existing portfolio of technological knowledge and expertise, technological relatedness is considered to be a vital aspect steering the direction of knowledge spillovers (Boschma et al. 2015). Too much cognitive proximity could be however detrimental to innovation as creating new knowledge requires some complementary source of novelty. This may result in the *competency trap* stemming from routinized procedures and habits. Adoption of novelty often requires a costly departure from routines that have been used by the management in the past. As noted by Loasby (2001) unlearning can be cognitively and emotionally challenging. If firms face other firms that are very close in terms of cognitive scale, usage of similar production methods and procedures, this may confirm to the management that the routines used by them are *right* and there is no need to change this. Therefore, firms looking for breakthrough novelty may be better off if they source knowledge from firms operating in related industries, using similar technology but in a less familiar context.

In a similar vein, there are competing theories that formulate different predictions as to whether *homogeneity* of the clustering industries or rather their *diversity* promotes economic growth (Beaudry & Schiffrauerova 2009). Marshall (1920), Arrow (1971) and Romer (1986) hypothesize that the concentration of an industry enhances knowledge spillovers and promotes innovation in a region. In accordance with Marshall-Arrow-Romer model

formalized by Glaeser et al. (1992), knowledge externalities and spillovers occur mainly between firms active in the same or very similar industries. The arguments regarding the intra-industry strength of knowledge spillovers are shared by Porter (1990). Within this framework *localization* economies are crucial to economic development (Beaudry & Schiffauerova 2009) .

On the other hand, Jacobs (1970) claims that knowledge spillovers often occur between distinct industries and that they are more important to economic growth than intra-industry knowledge externalities. She argues that economic expansion occurs when novel features are added to existing technologies. A diverse economic structure in a given location fosters exchange of knowledge between seemingly different industries, which share and recombine each other's ideas. This hypothesis emphasizes the role of *urbanization* economies for regional economic prosperity (Beaudry & Schiffauerova 2009) and complementarities across heterogeneous firms (Ghio et al. 2015).

2.5 Knowledge spillovers and strategic behaviour of incumbents

KSTE theory suggests that spillover of knowledge is not an automatic process and some knowledge filters impede its operation (Acs et al. 2013; Braunerhjelm et al. 2010). KSTE motivated research has identified many possible knowledge filters such as the entrepreneurial climate, infrastructure, regulation, attitudes and knowledge appropriation mechanisms. Within the KSTE framework attention has been given to the Intellectual Property Rights (IPR) protection, as a key appropriation mechanisms for innovation firms that will restrict the use of knowledge by other firms (Acs & Sanders 2012). These studies found that the impact of the level of IPR protection on economic growth follows the inverted U-shaped pattern. Too strong IPR protection may shift the balance too much in favour of knowledge creators and may reduce incentives to knowledge commercialization.

The strategic behaviour of incumbents is another knowledge filter mechanism that may limit the spillover of knowledge. The strategic importance of new knowledge has been recognized in the management literature. Given the importance of knowledge for the competitive position of a firm, incumbents employ various strategies to limit outflows of knowledge, in particular to rival firms in the same industry. Patents may be used strategically by incumbents to erect a substantial barrier to entry (Cockburn & MacGarvie 2011; Jaffe & Lerner 2004; Hall & Ziedonis 2001). The catalogue

of strategic mechanisms used by incumbents includes reputation for toughness in patent enforcement (Agarwal et al. 2009), non-compete agreements reducing employee mobility (Marx 2011), internal linkages across R&D units (Belderbos & Somers 2015). This strategic behaviour of incumbents may have a negative effect on innovation within a region. Marx et al. (2015) documented a brain-drain effect in US states where non-compete agreements are more strictly enforced. The general conclusion from this literature stream is that *“knowledge spillovers are conditional on incumbent firms’ strategic behaviour”* (Belderbos & Somers 2015). However only recently, most prominent proponents of KSTE extended their theory to include localized competition and strength of incumbents as a possible mechanism moderating the relationship between new knowledge and entrepreneurial activity (Plummer & Acs 2014). One of the strategic mechanisms employed by incumbents to raise entry barriers and limit the effects of spillovers may be to use trade marks.

2.6 The role of trade marks

The economic theory of trade mark has been developed so far mainly within the *Law and Economics* domain (Landes & Posner 1987; Griffiths 2011). This school employs a comparative statics toolkit to evaluate the contribution of trade marks to overall social welfare. Within this perspective the main contribution of trade marks stems from reducing the *search costs* of consumers related to the purchase of the products with unobservable characteristics (Landes & Posner 1987; Economides 1988). This function of trade marks requires that producers of a trade marked goods or services maintain consistent quality over time (Landes & Posner 1987).

Through the consistent investment in the quality and distinctive characteristics of the product, a trade mark may acquire additional meanings and gain recognition among consumers. *“These additional meanings give the trade mark value in the minds of consumers both as information and as a safeguard against the various risks they may face, thereby strengthening demand for the marked products”* (Griffiths 2011). Advertising can add additional mental attributes to the product, which complement its physical characteristics (Economides 1988).

This additional meanings conveyed through trade marks have the potential to increase appropriability, allowing firms to reap the benefits of product innovation (Davis 2006). Trade marks provide legal protection for the expenditure necessary to build the brand. Branding is a key element for the

differentiation of a firm's products from competitors and providing information about the quality and *meaning* of a firm's unique offer (Belleflamme & Peitz 2010). Brands can be critical to the long-term success of innovation as they prevent the slide of the products into the commodity status, with related margin erosion (Aaker 2007).

Brand equity is one of the most powerful tools in creating entry barriers defined as "*any competitive advantage that established firms have over potential entrants*" (Spulber 2006). The potential competitor or entrant, whose strategy is built on the imitation of the innovator, will not only have to master all the technical aspects of innovation but will have to overcome "*the power of brand*" (Aaker 2007) by advertising more than existing firms or by offering some other competitive advantages (Demsetz 1982). Brands may thus be used by incumbents to increase entry costs for new firms and to act as an entry deterrent. A strong brand and its related reputation may facilitate the creation of a capability necessary for impeding imitation (Kogut & Zander 1992; Faria & Sofka 2010). With new offerings and the creation of many product subcategories protected by trade marks, a brand can become a moving target difficult to beat by competitors (Aaker 2010).

Davis (2006) draws some parallels between the signalling functions of patents and trade marks. She claims that trade marks serve not only as an instrument of reducing information asymmetries between firms and consumers but also between competitors. By registering trade marks, incumbents may signal to the potential competitors that they are determined to commercialize the efforts of their innovation and defend their market position. Trade marks may also be used by incumbents to prevent competitors from associating potentially attractive words or phrases with their products (Lemley 1998). More trade mark activity within a sector may be a sign of marketing intensity and the important role of reputation within industry. In such sectors, it may be difficult for newcomers to develop and expand their market position. The effectiveness of trade marking as a strategic tool for erecting entry barriers will be greatest in mature industries with less innovation activity (Davis 2006).

There are only few empirical papers that look at the strategic use of trade marks by incumbents. Empirical analysis has confirmed a positive relationship between trade mark activity and sales growth (Crass 2014) and a negative relationship with sales of competitors (Greenhalgh & Rogers 2012). Von Graevenitz (2013) analyse the phenomenon of *trade mark cluttering* by

which incumbents strategically register trade marks with no intention of their immediate use, or they register trade marks with a broader scope than needed to block entry of new products.

Incumbents may also increase costs of new entrants by opposing strategically to their trade marks registrations. Collette (2012), examining Canadian trade mark opposition cases between 1996 and 2009, documents that larger and more experienced companies are more likely to delay proceedings in trade mark applications strategically. The likelihood of successful opposition increases with size and firms' experience on the market and the inexperience of the applicant. A strong brand name of the firm may also be a barrier for employees to leave the firm (Walker 2010), reducing spillovers through employee mobility.

While all the arguments and studies above have treated trade marks as an instrument of appropriability and entry deterrence, recent contributions have also highlighted that trade marks can be seen as an indicator of innovative output in their own right. Trade marks may be a sign of niche entry based on novel product differentiation. It may be particularly suited to denote incremental innovation with a small inventive step not warranting patent protection. Since trade marks are cheaper to obtain than patents, they are more accessible to small and medium sized enterprises (Mendonca et al. 2004). The filing of new trade marks reflects the introduction of novel offerings on the market and an attempt to persuade consumers that this offering addresses their needs, not yet covered by existing products or services (Mendonca et al. 2004). Recent research found that trade marks may capture innovative activity not covered by patents, such as innovation in small firms as well as low tech and service innovation (Flikkema et al. 2014; Schautschick & Greenhalgh 2016; Castaldi 2018). Firms that meet the Community Innovation Survey (CIS) criteria for innovativeness, consistently use more trade marks than their non-innovative counterparts (Millot 2009).

In this dissertation, we will give due attention to the potential dual role of trade marks in facilitating or hindering new (innovative) firm entry and subsequent growth, by analysing stand-alone use of trade marks as well as their use in conjunction with patents and their capacity to negatively moderate effective knowledge spillovers from patent stocks.

3 Data and methods

3.1 Introduction

The main objective of the present dissertation is to study the relationship between local stocks of technological knowledge, entry rates and the post-entry performance of newly established firms. As knowledge spillovers are the strongest in close geographical vicinity, we focus our analysis on regions (NUTS3) of 12 Member States of the European Union. We study entry in respective industry/region combinations and relate that to knowledge stocks in this industry/region. Industry/region combinations are the unit of analysis. In the study of post-entry growth performance of new firms, by contrast, the unit of analysis is the firm, where we investigate the growth performance of the individual firm in relation to local knowledge stocks available in the industry/region.

The concept of knowledge stocks is operationalized in our research with the patent applications data (see section 3.2.3). The moderating effect of aggressive protection by incumbents, diminishing positive externalities from local knowledge stocks, is measured by trade mark stocks accumulated by incumbents. To address the core concepts of our research questions, we thus had to develop a fine-grained dataset linking firm level data about the firms' date of incorporation, sector of activity and sales evolution – derived from the ORBIS database – with data on patent applications and trade marking. This merging required extensive effort as the datasets contain very different structures and variables, but not one variable that could act as a unique identifier to merge the datasets. This chapter explains the various data sources used, their particular characteristics and how we merged the data.

A particular effort lies in assigning patents and trade marks to industrial classifications. We develop a new methodology to link patents and trade marks to NACE industries, at a more fine-grained level, namely NACE 4 digit, than done in the previous studies that attempt to link patents to industries. We compare and validate the results of our matching algorithm with patent-industry concordance tables developed by other scholars.

We subsequently explain the construction of our measures of local stocks of technological knowledge. Clearly, not all the knowledge stocks in a NUTS 3 region are equally relevant for prospective entrepreneurs willing to start up a business in that region in a particular industry. Entry in a region and in a particular industry will be more triggered by the presence of technological

knowledge in industries that are closer in the technological space than in industries sharing little technological knowledge. Consequently, in the analyses of entry and growth we do not only focus on the role of knowledge pools in the same industry/region, but also on the effect of knowledge in related industries. We devote chapter 4 to developing a method to construct better measures of relevant stocks of technological knowledge, taking into account patenting in technologically related industries.

In this chapter we present the main sources of data in section 3.2, discuss previous efforts to link IPRs and industries in section 3.3, followed by an explanation of the methodology we develop to establish IPR – industry links at a more fine-grained level and incorporating data from trade marks in section 3.4. In section 3.5, we validate our methodology against the concordance tables developed by other scholars to link IPRs and industries. Section 3.6 subsequently explains the calculation of local knowledge stocks, while section 3.7 presents some selected summary statistics. Section 3.8 discusses our contribution and 3.9 highlights the main limitations of the data.

3.2 Main sources of data

3.2.1 Business register data

Our main source of demographic and financial data on incumbents and entrants is Bureau van Dijk ORBIS dataset, April 2012 version. For the preparation of the final dataset, we used data on nearly 20 million firms. ORBIS is sourced from over 160 data providers worldwide¹. Contrary to other data sources, the majority of the firms available in ORBIS are private companies of all sizes, so it has a structure similar to the statistical census. ORBIS provides access to publicly available information revealed in the public registers, so confidentiality does not pose major problems for the data analysis.

Based on the ORBIS database, we constructed several datasets to answer the various empirical research questions as described in the subsequent chapters. In all these datasets we used the following core variables:

- NACE industry of incumbents and entrants has been determined based on *NACE Rev. 2 Core code (4 digits)* variable in ORBIS;

¹ <https://www.bvdinfo.com/en-gb/-/media/brochure.../orbis.pdf> accessed on 11/12/2018.

- Date of entry determined on the basis of *Date of incorporation* variable in ORBIS;
- Focal NUTS3 regions of the incumbents and entrants determined based on address information available in ORBIS (*Postcode* and *City* variables). Subsequently, those variables were matched with NUTS3 regions using Eurostat correspondence tables² and GeoNames geographical database.³

3.2.2 Industry classification

Nomenclature statistique des activités économiques dans la Communauté européenne (NACE) is the European standard classification of productive economic activities that is being developed in the European Union since 1970'. Its current version - NACE Rev. 2 was adopted in December 2006.

NACE is set up as the hierarchical structure in the following manner: a first level is defined by an alphabetical code (sections); a second level is defined by two-digit numerical code (divisions); a third level is defined by a three-digit numerical code (groups); a fourth level is defined by a four-digit numerical code (classes). NACE Rev. 2 contains 21 sections, 88 divisions, 272 groups and 615 classes.

NACE classes are designed so that the units grouped into each class will be as similar, in respect of the activities in which they engage, as possible. Activities are classified under the same class when they share a common process for producing goods and services using similar technologies.

A NACE industry code is assigned to each firm in our dataset based on the core activity of the company as reported in ORBIS (NACE Rev. 2 Core Code 4 digits). We do not take into account secondary NACE codes which may complement the main activity of the firm⁴. Our approach is similar to Dorner & Harhoff (2018), who took into account only the main industrial activity of the establishment at the time of a patent filing retrieved from the German

²currently (11/12/2018) available under the following link
<http://ec.europa.eu/eurostat/tercet/flatfiles.do>

³ www.geonames.org

⁴ In most countries, where firms are assigned one or more industry codes when they register with the relevant government office, ORBIS sources industry information on companies directly from the firms' register. In some cases, the relevant information is completed by information providers as they collect company data.

Institute of Employment Research. The core activity is defined as the activity which contributes most to the value-added of the unit (Eurostat 2007).

3.2.3 Patent data

We calculate the regional stocks of technological knowledge based on the number of patent applications associated with inventors with address in the focal region. A patent is a document, issued on the basis of application, which describes an invention and creates a legal situation in which the exploitation of the invention is possible only with the authorization of the patent owner. Invention is a solution to a specific problem in the field of technology and may relate to a product or a process (WIPO 2004). To be patentable an invention must be novel, not forming part of the *state of the art* and must involve an inventive step- quantitative advance on the *state of the art*. An additional requirement of patentability of an invention is its potential industrial application (Seville 2016). Therefore, not all inventions are patentable and for those that could be subject to patenting, inventors may prefer other forms of protection due to strategic considerations. Also, propensities to patent differ depending on structural features of industries. Finally, the value of patented inventions varies widely.

However, when the research interest covers a broad set of industries and regions, patent documents remain the most useful source of data for analysis. Patent data is available for firms representing almost all industries and active in most regions. Long series of patent information on individual assignees is available from patent offices in many countries. Therefore patent information is a valuable indicator of innovative output used in many empirical papers in diverse areas of research (Basberg 1987). The usefulness of patents as innovation indicators stems from the fact that they are granted to novel products and processes that have an industrial application and are non-obvious to a person knowledgeable in the relevant technological field (Stuart & Podolny 1996).

The EPO's Worldwide Patent Statistical Database (PATSTAT April 2013) was the source of patent application data. The PATSTAT database contains records of published European patent applications filed with EPO and national patent applications filed with the majority of national patent offices around the world.

There are several possibilities for obtaining patent protection in the European Union Member States. The European Patent Convention (EPC), adopted in Munich in 1973 provides for a single, centralized process of European patent

grants. First European patent applications were received by the European Patent Office (EPO) in 1978. Applicants, who use the EPC route benefit from a single application and search procedure. If successful, European patent application results in the grant of a bundle of national patents in each of the countries designated by the applicant. European patents granted under the EPC convention do not have the unitary character. Each patent from that bundle has the effect of the national patent in each country for which it was granted (Seville 2016). The scope of protection of such bundled patents differs under the patent legislation of each country. Patent protection may last up to 20 years from the filing date, subject to the renewal fees payable for the third and subsequent years.

For the calculation of patent stocks of industries, we use European patent applications. We use European applications rather than national ones, as the scope of information, particularly address information of inventors, available in PATSTAT, is much broader for European applications. As shown in Table 3.1, depending on the country, European patent stocks may be larger or smaller than national ones, but generally, the difference is less pronounced than for trade marks.

For establishing industry codes associated with patents, we used patent assignee data available in PATSTAT table *TLS206_PERSON* in conjunction with table *TLS207_PERS_APPLN*. Subsequently, we matched patent assignees' data with the business register dataset. This is not a straightforward task, as both data sets lack unique identifiers (such as VAT numbers) and the matching has to be done on the basis of the name string of patent assignees (from PATASTAT) and the name of the company (ORBIS), after careful cleaning and processing as we explain in section 3.4. We use patent assignee names rather than patent inventor names to match with ORBIS data as we lack information about employment of the patents' inventors. Finally, we retrieve the core NACE industry codes of patents' assignees (NACE Rev. 2 Core Code 4 digits) after merging of the two datasets.

However, to establish a link between NUTS 3 regions and patents, we use the addresses of the inventors, as shown in the PATSTAT database. In case a patent has been associated with several assignees representing different NACE codes and/or several inventors representing different NUTS3 regions we used fractional counts and assign patents' fractions to the respective industries and regions.

It should be noticed that we considered European patent applications, regardless of their final status- whether they were finally granted or not. This reflects the belief that even if the examination process would find the innovative step not significant enough to guarantee patent registration, technologies covered by the patent applications may be subject to spillovers.

Patent (IPC) classification

Technologies protected by patents are classified based on the type of knowledge involved. A relevant classification was established in 1971 by the Strasbourg Agreement concerning the International Patent Classification (IPC), which became effective in October 1975, providing a system of a common classification of patents and utility models. The principal objective of the IPC is the establishment of an effective search tool for patent document retrieval by patent examiners for proper evaluation of patent novelty, inventive step and non-obviousness. The IPC classification is subject of frequent modifications.

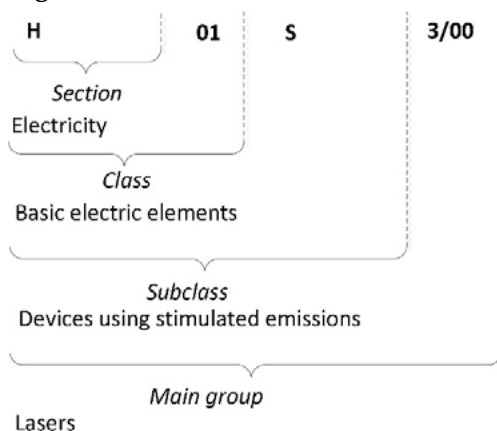
We use the IPC in chapter 4 to establish technological relatedness between industries. For this project, the IPC version of 31.12.2005 has been used.

IPC classification represents the whole body of patent technologies related knowledge and is divided into eight sections denoted by capital letters:

- A. Human necessities
- B. Performing operations; transporting
- C. Chemistry; Metallurgy
- D. Textiles
- E. Fixed constructions
- F. Mechanical engineering; Lighting; Heating; Weapons; Blasting
- G. Physics
- H. Electricity

The hierarchical structure of the IPC classification is presented in Figure 3.1

Figure 3.1 Hierarchical structure of IPC classification



3/09 ● Processes or apparatus for excitation e.g. pumping

3/091 ●● by optical pumping

3/094 ●●● by coherent light

Subgroup H01S 3/094 concerns thus "Processes or apparatus for excitation of lasers using optical pumping by coherent light"

Source: IPC guide (2014) WIPO

3.2.4 Trade marks data

A trade mark may consist of any signs, such as words, letters, numerals, colors, the shape of goods, packaging or sounds that are capable of distinguishing the goods or services of one undertaking from the other undertakings⁵. To serve as a trade mark a sign must be distinctive in relation to the goods or services to which the trade mark is applied. If a sign is too descriptive, it lacks sufficient distinctiveness and cannot be registered as a trade mark. The second common requirement for a trade mark is that it cannot have a misleading character nor violate public order or morality (WIPO 2004).

A trade mark may be protected on the basis of use or registration. Modern trade mark protection systems generally combine those two types of protection. However, the Paris Convention for the Protection of Industrial Property, adopted on March 20, 1883, imposes on contracting parties an

⁵ Directive (EU) No. 2015/2436 of the European Parliament and of the Council of 16 December 2015 to approximate the laws of the Member States relating to trade marks.

obligation to provide for a trade mark register. Only trade mark registration secures full trade mark protection (WIPO 2004). In accordance with the Directive (EU) 2015/2436 of the European Parliament and of the Council on 16 December 2015 to approximate the laws of the Member States relating to trade marks, trade marks are registered for 10 years from the date of filing of the application. Registration may be renewed for further 10-year periods subject to renewal fees. There is no upper cap of the number of renewals.

Similarly to the patent protection procedures, there are several possibilities for obtaining trade mark protection in the EU. The simplest way is by registration of the national trade mark in each country where the trade mark protection is sought. If an applicant wants to extend protection beyond one country, he may use the international procedure, foreseen by the Madrid Arrangement for the International Registration of Marks (“the Madrid Agreement”) adopted in 1891 or the Madrid Protocol adopted in 1989. Both the Madrid Agreement and Protocol systems are administered by WIPO.

Since the adoption of Council Regulation 40/94 on 20 December 1993 on Community trade mark, there is a possibility to obtain uniform protection in all countries of the European Union on the basis of a single registration procedure administered by the European Union Intellectual Property Office (EUIPO) formerly Office for Harmonization in the Internal Market (OHIM). In contrast to European patents, European Union Trade Mark (EUTM) has a unitary character and grants the same level of protection in all the countries of the European Union.

National IPR registers were the source of information on national trade marks. Data on national trade marks have been provided by the national IP offices from 12 Member States of the European Union (AT, BE, DE, DK, ES, FR, GB, HU, IT, LT, NL and PT).

To calculate trade mark stocks of individual firms and industries, we aggregated data on national trade mark registrations. We chose national rather than European trade marks as the primary specification because the scope of relevant information for both types of rights is similar. National trade marks may, however, reflect better than EUTMs the trade mark activity of smaller companies that focus on domestic markets. Moreover, since the trade mark registration procedures are relatively inexpensive and straightforward in comparison to the patent registration process, firms that are active on several national markets tend to register national trade mark at least in their home country, besides trade mark registration at EUIPO.

However, we conduct robustness checks of the main models using data on the European Union Trade Marks (EUTM).

Due to the complexity of the matching process, and in particular, regional focus of our research, we were confined to consider only trade mark registrations in the home countries of the firms. As a result, we do not control for trade mark stocks registered in the national IP offices of countries, where a company does not have its principal seat.

Trade mark (NICE) classification

A trade mark is registered for use in relation to specified products or/and services. The detailed catalogue of protected goods and/or services is defined for each individual trade mark in a trade mark register. The International Classification of Goods and Services for the Purposes of the Registration of Marks (NICE classification) divides products and services into 45 class headings, respectively 34 class headings for goods and 11 for services. The class headings are the descriptive names of the categories of goods or services for which the trade mark protection is sought. The main purpose of the NICE classification is the ease of searching and assessment of the trade mark application acceptability for registration (Griffiths 2011). NICE classification was established by international agreement concluded at the diplomatic conference in Nice, on June 15, 1957. It was further revised in 1967 and in 1977 and amended in 1979. The current version is the 2018 version of the eleventh edition of classification that became effective on January 1, 2018. It is accompanied by explanatory notes providing a detailed description of products and services covered by each heading.

Some class headings cover much broader sets of products or services than others and they are much more represented among the trade marks. Specifically, Class 9 (Electrical Apparatus; Computers), Class 35 (Advertising; Business Management) and Class 42 (Scientific & Technological Services) account for over 25% of the total class filings at the European Union Intellectual Property Office (EUIPO 2018). Therefore, linking NICE class headings with industry classifications is problematic, especially if one aims at the one-to-one concordance table. In our empirical work we use information on NICE classes only for robustness check, to link a subset of trade marks not matched by our algorithm to infer NACE industries as explained in the section 3.6.2. We count each trade mark as one, regardless of the number of class headings associated with each trade mark.

Table 3.1 Comparison of European and national patent stocks and applications

| country | Applications | | Entities with patents | | Stocks | | Mean stocks | |
|---------|--------------|----------|-----------------------|----------|----------|----------|-------------|----------|
| | European | national | European | national | European | national | European | national |
| AT | 24,230 | 15,410 | 2,025 | 2,199 | 16,535 | 9,138 | 8.17 | 4.16 |
| BE | 11,546 | 2,252 | 2,636 | 2,813 | 7,490 | 1,624 | 2.84 | 0.58 |
| DE | 249,443 | 341,629 | 18,798 | 27,149 | 161,295 | 205,880 | 8.58 | 7.58 |
| DK | 10,286 | 6,398 | 1,805 | 1,357 | 7,022 | 3,705 | 3.89 | 2.73 |
| ES | 7,750 | 13,442 | 3,090 | 6,348 | 5,448 | 8,976 | 1.76 | 1.41 |
| FR | 65,992 | 87,596 | 7,729 | 12,952 | 43,563 | 57,577 | 5.64 | 4.45 |
| GB | 39,044 | 89,990 | 8,572 | 20,623 | 24,710 | 55,828 | 2.88 | 2.71 |
| HU | 277 | 676 | 151 | 497 | 185 | 468 | 1.23 | 0.94 |
| IT | 29,662 | 33,271 | 8,580 | 16,883 | 17,975 | 21,949 | 2.09 | 1.30 |
| LT | 34 | 295 | 18 | 173 | 32 | 223 | 1.78 | 1.29 |
| NL | 51,096 | 15,294 | 5,404 | 8,381 | 30,308 | 10,089 | 5.61 | 1.20 |
| PT | 356 | 981 | 178 | 357 | 238 | 762 | 1.34 | 2.13 |

Note: stocks are calculated for year 2010. Number of applications is an aggregate number of filings between 2000 and 2010;

Source: all the calculations based on the merged database developed by author as described in section 3.4.

Table 3.2 Comparison of European and national trade mark stocks and applications

| country | Applications | | Entities with trade marks | | Stocks | | Mean stocks | |
|---------|--------------|----------|---------------------------|----------|----------|----------|-------------|----------|
| | European | national | European | national | European | national | European | national |
| AT | 7,594 | 22,544 | 3,303 | 10,617 | 9,897 | 31,034 | 3 | 2.92 |
| BE | 5,342 | 23,486 | 2,661 | 13,027 | 6,827 | 35,573 | 2.57 | 2.73 |
| DE | 70,220 | 124,126 | 23,512 | 54,622 | 88,791 | 189,086 | 3.78 | 3.46 |
| DK | 6,165 | 21,088 | 2,453 | 10,125 | 7,817 | 36,527 | 3.19 | 3.61 |
| ES | 32,771 | 272,241 | 17,822 | 148,757 | 40,465 | 444,509 | 2.27 | 2.99 |
| FR | 23,335 | 134,459 | 7,538 | 44,175 | 28,870 | 240,756 | 3.83 | 5.45 |
| GB | 39,014 | 102,964 | 15,123 | 45,673 | 49,234 | 159,893 | 3.26 | 3.50 |
| HU | 470 | 10,444 | 318 | 5,127 | 633 | 13,529 | 1.99 | 2.64 |
| IT | 30,549 | 183,318 | 13,963 | 75,134 | 37,680 | 285,353 | 2.70 | 3.80 |
| LT | 262 | 11,615 | 177 | 6,568 | 329 | 17,528 | 1.86 | 2.67 |
| NL | 16,958 | 90,528 | 8,036 | 45,506 | 21,052 | 133,360 | 2.62 | 2.93 |
| PT | 3,210 | 57,842 | 1,800 | 31,578 | 3,920 | 90,513 | 2.18 | 2.87 |

Note: stocks are calculated for year 2010. Number of applications is an aggregate number of filings between 2000 and 2010;

Source: all the calculations based on the merged database developed by author as described in section 3.4.

3.3 Previous methods to establish industry-patent links

Patent data has been a subject of research for many years. Despite several limitations already discussed, it proved to be a valuable source of data for the analysis of technological change within several strands of the literature (Basberg 1987). For many years, however, a mismatch between patent and industrial classifications constrained potentially interesting economic analyses (Lybbert & Zolas 2014). The first step in many previous efforts to analyse innovation intensity by industries, therefore, consisted of combining patent information with data on sectors where the patent applicants are active.

As discussed above, until recently, comprehensive firm-level datasets were not available to researchers. Additionally, matching firm level data with patent registers is a complex and computationally intensive exercise. Therefore, the most popular approach for building a bridge between patent and industry data consisted of developing of concordance tables linking IPC classes with industry classifications. Concordance tables provide a meso-level mapping complementing or substituting the macro- or firm-level ones (Lybbert & Zolas 2014).

The key assumption of concordance tables is that probability of assigning a patent to an industry relies uniquely on the technology field of the patent and not on other factors such as the country of applicant or the date of application.

A focus on trade marks as a valuable source of economic data is a relatively recent phenomenon. Although there were several attempts to build concordance between trade mark NICE classes and the industry classification, results of such works were not widely disseminated and are not commonly used in economic research. In this section, we will, therefore, focus on previous efforts linking patents with industries data.

There were several attempts undertaken already in 1960' to combine patent and industry classifications, even though, at first, they were limited to only some sectors of the economy (Comanor & Scherer 1969).

In 1980' Kronz & Grevink (1980) presented a set of patent statistics that included a breakdown of patent filings by NACE industries. However, no concordance table has been presented and those statistics reflected more the intuition of authors than the development of systematic linkages between patent and industrial classifications (Schmoch et al. 2003).

Several concordance tables were developed based on the patent data of Canada. Between 1978 and 1993 patent examiners of the Canadian Patent Office were required to assign Industry of Manufacture (IOM) and Sector of Use (SOU) information to each patent. For both IOM and SOU fields, examiners were supposed to use the Canadian Standard Industrial Classification (cSIC). As each patent also contained relevant technology information based on the IPC classification, Canadian patent data, has been a valuable source for developing concordance tables linking IPC classes with IOM and SOU.

A first attempt to build a concordance table based on Canadian Patent Office data has been undertaken by Kortum & Putnam (1997), who created the so called Yale Technology Concordance (YTC). The YTC is the matrix of conditional probabilities of patents being assigned to industries given IPC technology classes covered by patents. The Maximum Likelihood Estimator (MLE) is used to infer the final matrix of probabilities on the basis of the Canadian patent dataset.

The set of Canadian patents has also been the primary source on which the OECD Concordance Table (OTC) has been built (Johnson 2002). The methodology of construction of the OTC consisted of two steps: (i) translation of IPC classes to eSIC sections and then (ii) conversion of eSIC section to ISIC. The first step has been copied verbatim from the original YTC and its reprogrammed version (Johnson & Evenson 1999), taking into account IOM and SOU combinations (Johnson 2002). For the second step, no readily available previous concordance table was at hand. Instead, a group of researchers compared the definitions of each eSIC sector and decided which ISIC corresponded best. In case several ISIC sectors corresponded to one eSIC, subjective judgment about the best fit had to be used. In such cases, two researchers independently had to make such a judgment and the final result is a consensus view of the researchers (Johnson 2002).

Several significant disadvantages of the YTC have been identified in the subsequent literature. Industry codes were assigned to patents by examiners and this exercise was rather subjective. Examiners assigned industry information without detailed knowledge of the official industry class represented by the patent assignee (Schmoch et al. 2003). Moreover, the Canadian version of industrial classification could not easily and without loss of information be converted to other national and international industry classifications (Lybbert & Zolas 2014). Furthermore, since the practice of

assigning of industry codes by examiners was maintained only between 1978 and 1993, it is static and linkages between patent classes and industries cannot be dynamically updated. This critique has been partially confirmed by the analysis of Kortum & Putnam (1997) who concluded that the prediction errors differ depending on the subsets of patents and they increase for patents published after 1989. Notwithstanding those weaknesses, for many years, researchers who wanted to exploit the fine-grained relationship between patents and industries relied on the YTC and its derivations such as the OECD concordance table. There are however other, subsequently developed, alternatives which do not depend on the Canadian patent dataset.

The MERIT concordance table (Verspagen et al. 1994) links IPC classes and ISIC- rev. 2 classifications. MERIT Concordance links patent classes to 22 industrial classes, being a mix of 2- and 3-digit ISIC codes. Although the one-to-one linkage dominates, there are cases where one IPC is related to more than one ISIC class.

The so-called DG Concordance table (Schmoch et al. 2003; Van Looy et al. 2015) links IPC classes to 44 pre-defined manufacturing fields, which are associated with one or more ISIC class. The assignment of the IPC class to the industry has been done in several stages. In the initial stage, the link between technologies and industries has been established on the basis of a qualitative expert assessment. In the second stage, the link has been refined based on information on the industry of operation of the firm filing the patent application retrieved from the Dun&Bradstreet (D&B) database. More than 3000 applicant firms with a total portfolio of over 150 000 patents filed between 1997 and 1999 have been used to construct DG Concordance. The final result of DG Concordance is a one-to-one mapping of the IPC classes to one of the manufacturing fields. The DG Concordance table was revised to reflect revisions of NACE classification⁶ and the introduction of new IPC classes (Van Looy et al. 2015).

More recently Lybbert & Zolas (2014) proposed a method of “*Algorithmic Links with Probabilities*” (ALP), whereby the title and abstracts of patents, extracted from PATSTAT, are mined using keywords extracted from descriptions of industry classifications (various versions of ISIC and SITC classifications). After tabulation by IPC code, frequency matches between the industry and IPC classifications are revealed. In the next step, those frequencies are further processed to create a probabilistic mapping. While

⁶ NACE Rev. 2 in 2006

associating technologies with industries, Bayesian weights are being constructed with some implied rules allowing for the overweighting of classes which are very specific to few industries and underweighting those that are used by many industries (Lybbert & Zolas 2014). Conceptually, the whole ALP process automates and resembles the manual assignation of industry codes by patent examiners as it was done in the Canadian patent office. The ALP process is done for each individual patent. To showcase their method, Lybbert & Zolas (2014) matched 20 million patent applications, with the title and abstract available in PATSTAT, with 4-digit ISIC and SITC industry classifications. However, no linkage between IPC classes and NACE industry classification has been provided by the authors. The conversion between ISIC Rev. 4 and NACE Rev. 2 is relatively easy, using concordance tables linking those two classifications, but only on the 2-digit levels (NACE divisions-2-digit ISIC industries). Also, the ALP concordance is limited to manufacturing industries.

Recently Dorner & Harhoff (2018) developed a novel technology-industry concordance table based on German patents filed with the European Patent Office between 1999 and 2011 and matched to ORBIS data records. Dorner & Harhoff (2018) used the employer-employee database of the Institute for Employment Research (IAB) to link inventors of German patents to their employers rather than to patent assignees. Employment episode of the inventor at the moment of patent filing has been chosen as a source of NACE code associated with the patent. The actual industry-technology concordance table has been generated from the matched data on the basis of fractional counts of co-occurrences of industry codes and technology area (Dorner & Harhoff 2018).

3.4 Matching ORBIS data with patent and trade mark registers

The existing concordance tables with the highest granularity provide the link between IPC patent classes and NACE 3-digit industry classification⁷. For our research questions, however, it is essential to assign patenting activity of incumbents and entrants to industries at the highest level of granularity possible. It is also crucial that the industry information for patents and trade marks is assigned based on data aligned with the information on industry assignment of entrants. In addition, due to focus of our dissertation, which investigates joint use of patents and trade marks by incumbents, we had to be able to implement the same matching algorithm to patent and trade mark records. None of the existing methods discussed above facilitates a simultaneous match between NACE industry codes, patents and trade mark data. Therefore, we had to develop our own matching algorithm for data preparation. Given our research design, we could not use existing concordance tables, but had to create our own matching algorithms.

Linking data across datasets was the major challenge in the preparation of the final data. There is no common identifier, such as VAT number or business register's number that would make matching data straightforward. Instead, standard procedures for matching business data with IPR registers are done on the basis of the name, requiring extensive cleaning and harmonizing of firms' names before actual matching can be done. Even if the name contains exactly the same characters, two records may not be matched because of the usage of capital letters or title case, the presence of the whitespaces within the strings, or the difference of the legal form abbreviations.

Hence, we developed our own algorithms based on the KU Leuven/Eurostat methodology (Magerman et al. 2006). The major steps of data cleaning and harmonisation are presented in Figure 3.2. The goal of the pre-processing is to harmonize the way the name is represented in various datasets, or even in the same data repository. In the first step of the data cleaning process, we converted the special characters present in some of the languages into their Unicode equivalent and changed its format into the upper case.

⁷ We disregard ALP concordance which provides 4-digit industry -IPC classes concordance, since it does not use NACE industry classification. In order to get to NACE Rev. 2 classification, we would have to aggregate the data to 2-digit level.

A more substantial part of the data cleaning and harmonization consists of the replacement of the various versions of the legal forms into their standardized equivalents. For that purpose, we have prepared a dictionary of legal forms in the form of a list of regular expressions typically used by legal entities in the countries covered by our dataset. Figure 3.2 presents the algorithm used for the cleaning of the legal forms in the treated datasets. In the last stage of data pre-processing, we have cleaned the names from non-distinctive frequent words specific for the language of the focal country, such as: *the, a, UK, Britain* for the UK.

Although the possibility to use approximate string matching is suggested in the literature (Magerman et al. 2006), we applied only an *exact match* methodology. Approximate string matching methods, such as Levenshtein distance (Levenshtein 1966), allow for matching of two records which are slightly different, and thus potentially enable correction of key-in errors. However, our experience shows that this method, although effective when matching standard dictionary strings, may be very imprecise when matching firms' names, which by definition are very distinctive and abstract. Two names with a relatively small difference in two data sources may represent genuinely different companies.

When there is only one pair of matched names in two data repositories, we accept that match as correct. However, where one entity from IPR register links to several potential matches in ORBIS, we run the disambiguation algorithms.

Multiple matches may arise in the case of some most popular firm names, i.e. created from the family name of the owner, or in the case of economic groups, with several branches active in different locations. We leveraged information available in both datasets such as an address, legal form and economic linkage between firms to indicate the correct match among many candidates. The detailed algorithm we used for the disambiguation of one-to-many matches is illustrated in Figure 3.4⁸. In cases, where the disambiguation process did not allow us to indicate an unequivocal pair of records, we rejected the match and treated the IPR record as not matched to external data

⁸ For simplicity, we illustrate the process of match disambiguation in ORBIS and PATSTAT. However, exactly the same process applies to legal forms cleaning in national trade mark registers data.

from firms' register. While matching records, we link firms at the level of individual establishments.

IPRs can be assigned not only to the legal entities but also to natural persons. Since the IPRs registers we had access to, do not distinguish between different types of owners, our matching algorithms search for matches within the whole universe of the IPR owners. The matching rate among physical persons is however very low, as we are able to find the match only in the case the physical person is also registered in the business register under her name. We are not able to find a match between an IPR and the company in case a physical person, such as a majority stakeholder of the company, is registered as an assignee of the IP right. For instance, the low matching rate for the European patents applications filed by Hungarian entities is due to the fact that physical persons make a substantial share of the European patent applicants from that country.

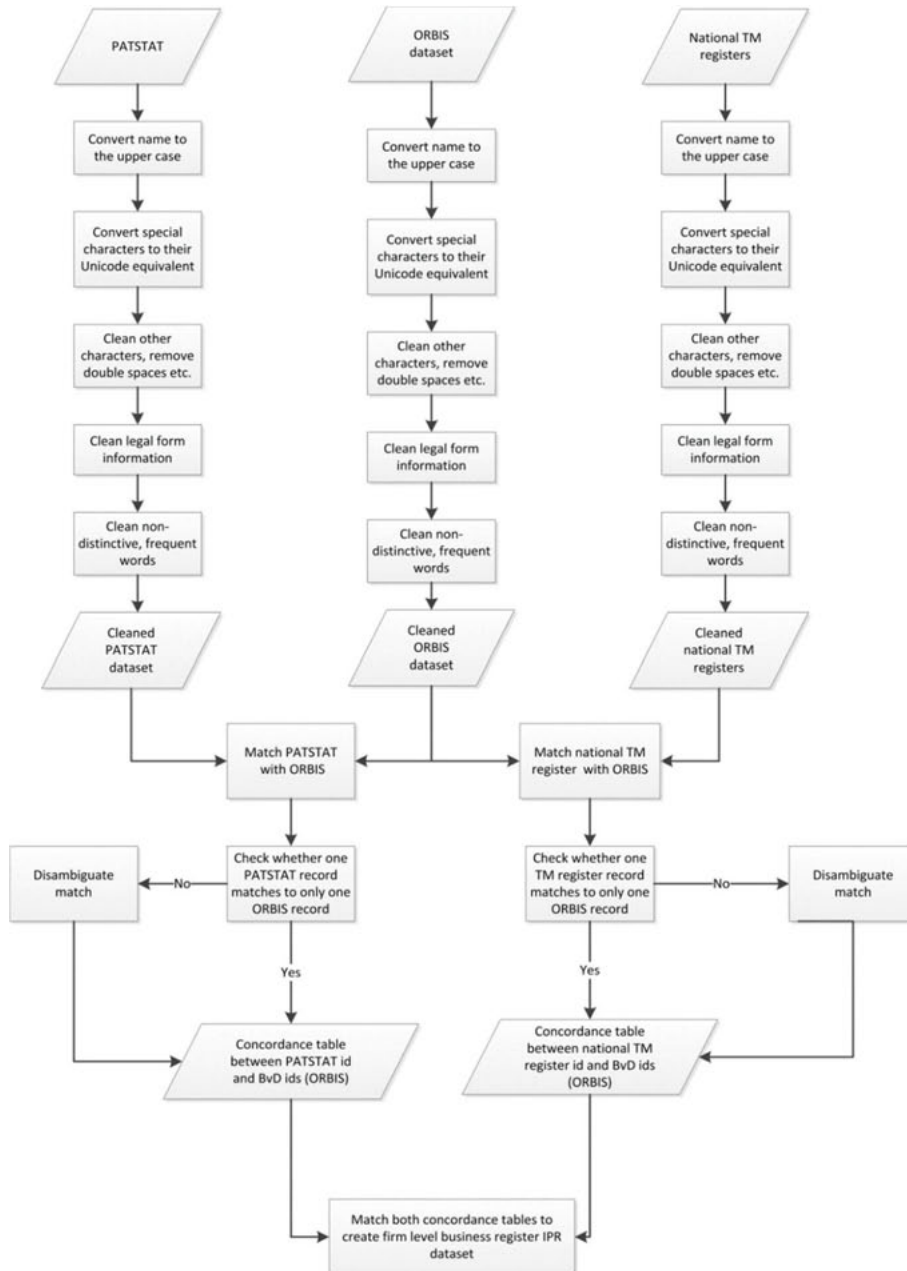
Detailed matching statistics for European patents and national trade marks are available in Table 3.3.

Table 3.3 Rate of matching of patent and trade mark applications to ORBIS data on applicants

| | Patent applications | | Trade mark applications | |
|-----------|---------------------|--------|-------------------------|---------|
| | matching rate | number | matching rate | number |
| AT | 57.82% | 22132 | 52.81% | 99433 |
| BE | 56.06% | 23988 | 62.60% | 364758 |
| DE | 63.82% | 397564 | 51.64% | 693072 |
| DK | 70.37% | 15378 | 60.72% | 178070 |
| ES | 59.37% | 14199 | 58.37% | 917630 |
| FR | 62.97% | 112780 | 34.31% | 1050577 |
| GB | 67.95% | 64780 | 64.39% | 703221 |
| HU | 22.62% | 1491 | 43.13% | 85018 |
| IT | 56.44% | 56239 | 40.32% | 1168964 |
| LT | 47.83% | 86 | 75.38% | 55017 |
| NL | 77.85% | 67889 | 70.13% | 218674 |
| PT | 41.54% | 958 | 63.89% | 302387 |

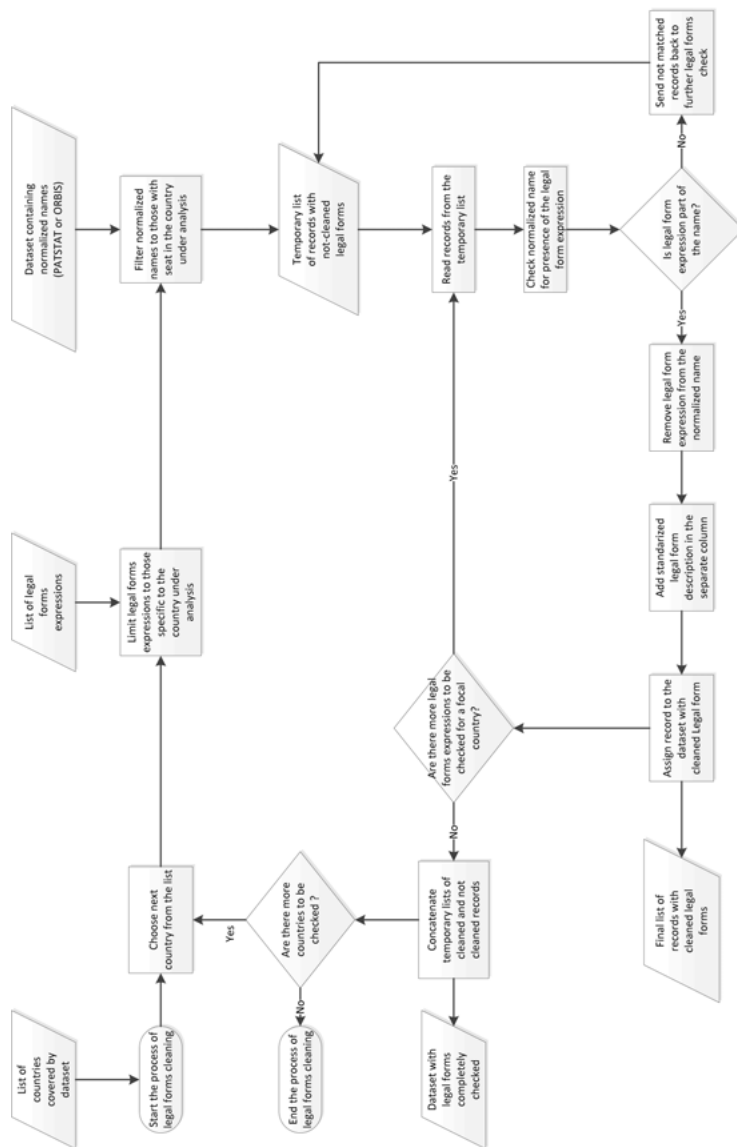
Note: matching statistics calculated on the basis of the applications filed between 2000 and 2010. Column number contains the total number of applications matched;
Source: own calculations based on the merged database developed by author as described in section 3.4.

Figure 3.2 Data cleaning and harmonization process



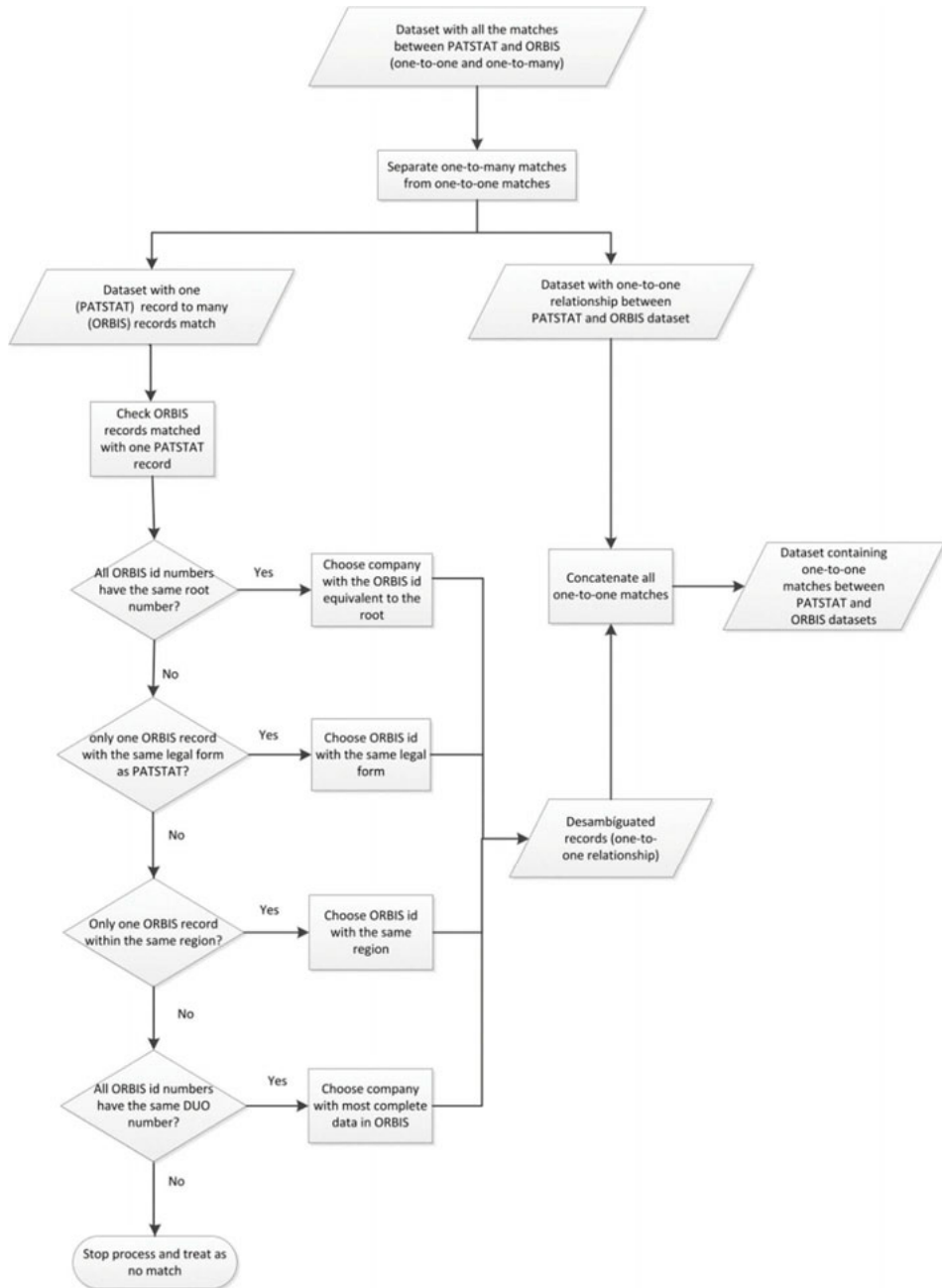
Note: adapted from EPO&OHIM (2013).

Figure 3.3 Process of legal forms cleaning



Note: adapted from EPO&OHIM (2013).

Figure 3.4 Disambiguation process



Note: adapted from EPO&OHIM (2013).

3.5 Comparison of matched dataset with patent-industry concordance tables

As discussed before, given our research focus and variety of datasets we need to link, we decided to develop our own matching algorithm. However, it is worthwhile to compare the results of our matching process with available alternatives to assess the reliability of matching procedure and better understand possible differences in the results of the empirical investigations using different approaches. In our comparative analysis, we follow the approach of Dorner & Harhoff (2018). For comparison of our matched dataset with alternative methods, we used information based on the pooled dataset of 667 569 European patent applications filed between May 1978 and September 2012, for which we were able to assign NACE industry codes. NACE codes have been assigned based on matching described in section 3.4. We compared our matching results with the two most recent concordance tables linking IPC classes with NACE industry classification: DG Concordance and weighted concordance of Dorner & Harhoff (2018). Alternative NACE codes have been assigned to the same set of patents, using concordance tables provided by researchers who developed those alternative approaches.

3.5.1 Comparison with DG Concordance

DG Concordance (Van Looy et al. 2015) links IPC and NACE classes on various levels of aggregation. Although IPC subclasses (4 digits) dominate, sometimes IPC class on the group level is linked with NACE. We compare our match with DG Concordance on the IPC subclass and NACE division (2-digits) level which is the least common denominator for both datasets.

By the nature of our matching process, which has been performed on the level of patent assignee, our matched dataset allows for one (IPC) to many (NACE) relationship. However, NACE codes are not equally distributed among IPC classes and there are some dominant NACE industries associated with each IPC class. We use this variability to assess the matching by comparing the most frequent NACE divisions in each IPC class with DG Concordance pairs.

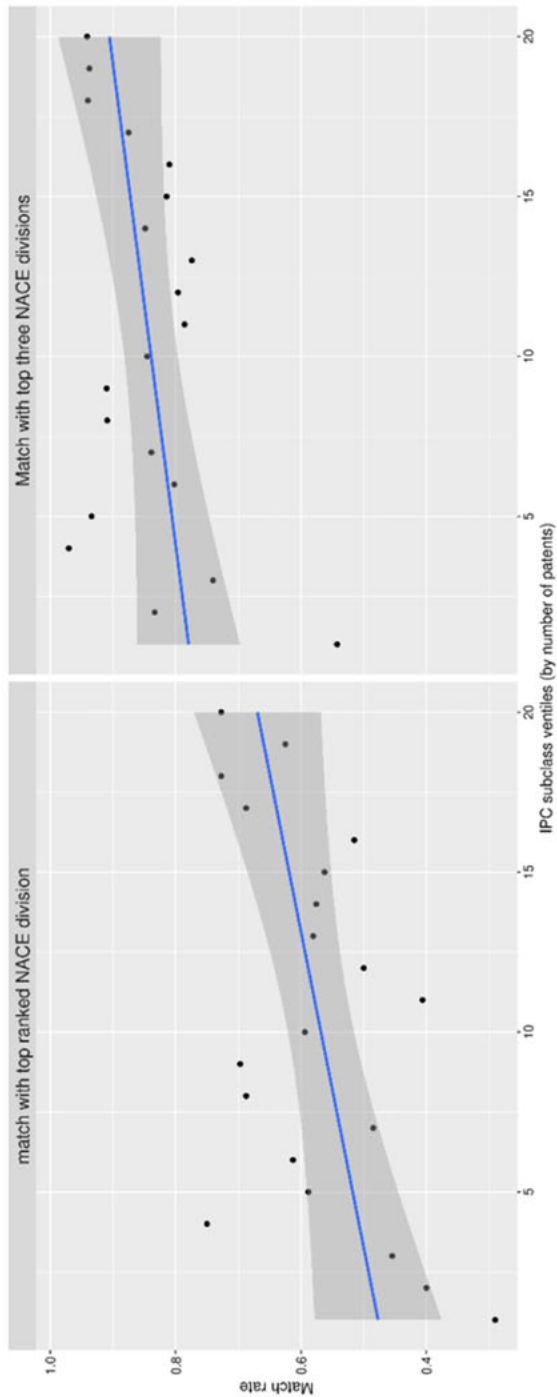
For 58% of IPC subclasses in our dataset the highest-ranking NACE division has been the same as in the case of NACE division indicated in DG Concordance table. In 85% cases, the NACE division assigned in DG Concordance was among the three top-ranked divisions in our matched data. Figure 3.5 shows the mean rate of agreement between our matched dataset and DG Concordance within 20 equally populated IPC class groups (ventiles) ordered by the popularity of IPC classes among patent applicants. The left panel shows the percentage of the cases where IPC-NACE in DG Concordance is the same as the most frequent NACE division in

our dataset. The right panel shows the percentage of cases where IPC-NACE in DG Concordance is the same as one of the top three NACE divisions associated with the same IPC class in our dataset. Analysis of Figure 3.5 confirms that the more popular IPC classes, the higher the agreement between DG Concordance and our matched dataset.

Table 3.4 presents a comparison between ten most patent-intensive divisions as calculated from our matched dataset and the similar ranking calculated from DG Concordance. Using IPC subclass information attached to each patent and DG Concordance we assign NACE division information to each patent. We calculate the number of patents by each NACE division and assign a rank to the final list. To arrive at a similar ranking based on matched data, we retrieved NACE Division information from the patent owners' data. In the next step, we aggregate patents for each NACE division and assign corresponding ranks. As DG Concordance is limited to manufacturing industries only, for this comparison, we restrict our matched dataset only to NACE divisions representing manufacturing industries.

Out of 10 first industries in our ranking, 9 are also present among the top 10 patent-intensive industries in DG Concordance. The only exception is NACE Division 30-Manufacture of other transport equipment which is classified as 10th in our ranking and 11th in the ranking based on DG Concordance. First 5 places in both rankings are exactly the same. Patents are more concentrated in the top industries in the ranking based on DG Concordance. Whereas the top 3 industries in our ranking are associated with 55% of all the patents in top 10 ranking, the corresponding number for DG Concordance based ranking is 63%.

Figure 3.5 Comparison of rate of equal IPC-NACE assignment in matched dataset and IPC-NACE assignment in DG Concordance



Note: comparison for top ranked NACE division (left) and top three NACE divisions (right) in matched dataset;
Source: own calculations based on the merged database developed by author as described in section 3.4 and data from DG Concordance available in PATSTAT, table TLS902_IPC_NACE2.

Table 3.4 Top 10 most patent intensive NACE divisions in matched dataset compared with DG Concordance

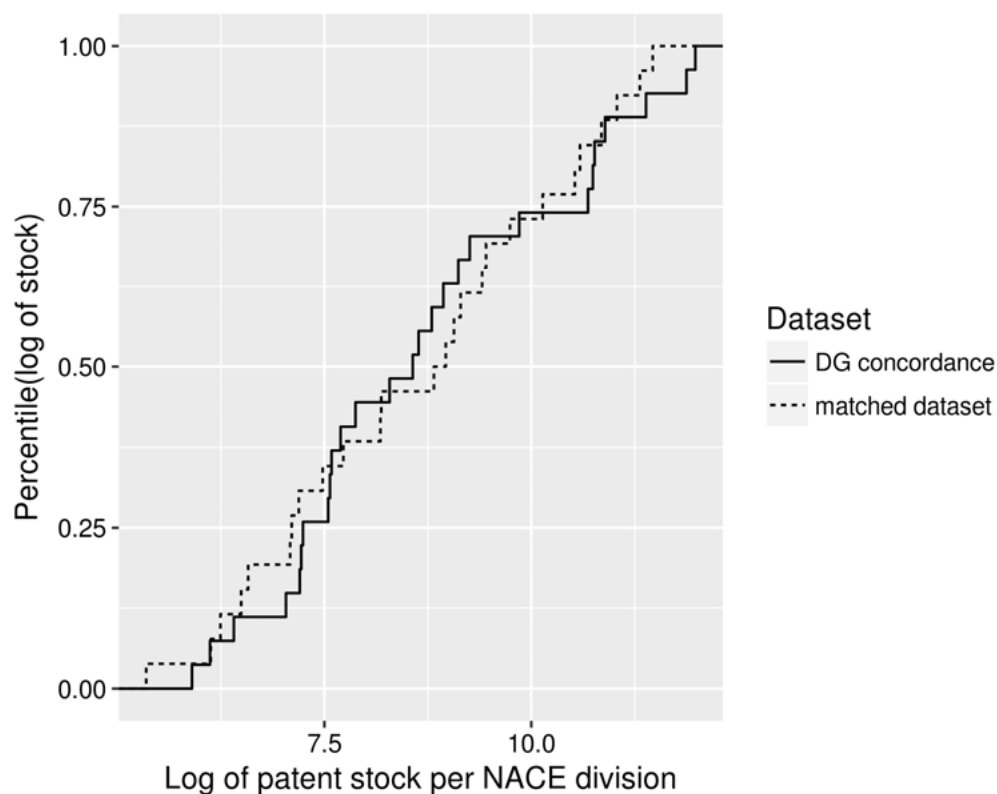
| NACE rev. 2 | Description of NACE rev. 2 division | Matched dataset | | DG Concordance | |
|----------------|------------------------------------------------------------------------------|-----------------|------|----------------|------|
| | | patents no | rank | patents no | rank |
| 26 | Manufacture of computer, electronic and optical products | 95547.37 | 1 | 159854.51 | 1 |
| 28 | Manufacture of machinery and equipment n.e.c. | 81763.92 | 2 | 143529.24 | 2 |
| 20 | Manufacture of chemicals and chemical products | 62005.08 | 3 | 88078.81 | 3 |
| 27 | Manufacture of electrical equipment | 51388.12 | 4 | 53713.82 | 4 |
| 21 | Manufacture of basic pharmaceutical products and pharmaceutical preparations | 39690.5 | 5 | 47319.6 | 5 |
| 29 | Manufacture of motor vehicles, trailers and semi-trailers | 37277.67 | 6 | 43713.23 | 7 |
| 25 | Manufacture of fabricated metal products, except machinery and equipment | 25277.08 | 7 | 19032.92 | 8 |
| 22 | Manufacture of rubber and plastic products | 17021 | 8 | 10473.23 | 9 |
| 32 | Other manufacturing | 12752.41 | 9 | 46352.27 | 6 |
| 30 | Manufacture of other transport equipment | 12159.83 | 10 | 7607.63 | 11 |

Source: own calculations based on the merged database developed by author as described in section 3.4 and data from DG Concordance available in PATSTAT, table TLS902_IPC_NACE2.

Finally, we compare the empirical cumulative distribution function (ecdf) of distribution of patents to NACE divisions calculated from the matched dataset with similar ecdf calculated on the basis of DG Concordance.

The p-value of a two-sided non-parametric Kolmogorov-Smirnov test (K-S test) we used to assess the equality of distributions is 0.8264 with D value of 0.1596. The K-S test uses the maximal absolute difference between the ecdfs, denoted D, as the test statistic. Based on the K-S test we are not able to reject the hypothesis that the two datasets come from the same distribution.

Figure 3.6 Comparison of ECDF of patent stocks' distributions by NACE divisions calculated from matched dataset and on the basis of DG concordance



Source: own calculations based on the merged database developed by author as described in section 3.4 and data from DG Concordance, available in PATSTAT, table TLS902_IPC_NACE2.

3.5.2 Comparison with weighted concordance – DH concordance (Dorner & Harhoff 2018)

The structure of our matched data and weighted concordance of Dorner & Harhoff (2018) is similar with one to many matches between IPC subclasses and NACE codes, and different intensity of patenting within focal IPC subclass of firms representing different NACE industries. Therefore, we can calculate a correlation rate between two sets of weights from both datasets, which amounts to 78%.

For 67% of IPC subclasses, the highest-ranking NACE divisions are the same in our matched dataset as in the weighted concordance. For 99% of compared cases, one among top three NACE divisions in matched dataset corresponded to the highest-ranked NACE division in Dorner & Harhoff (2018).

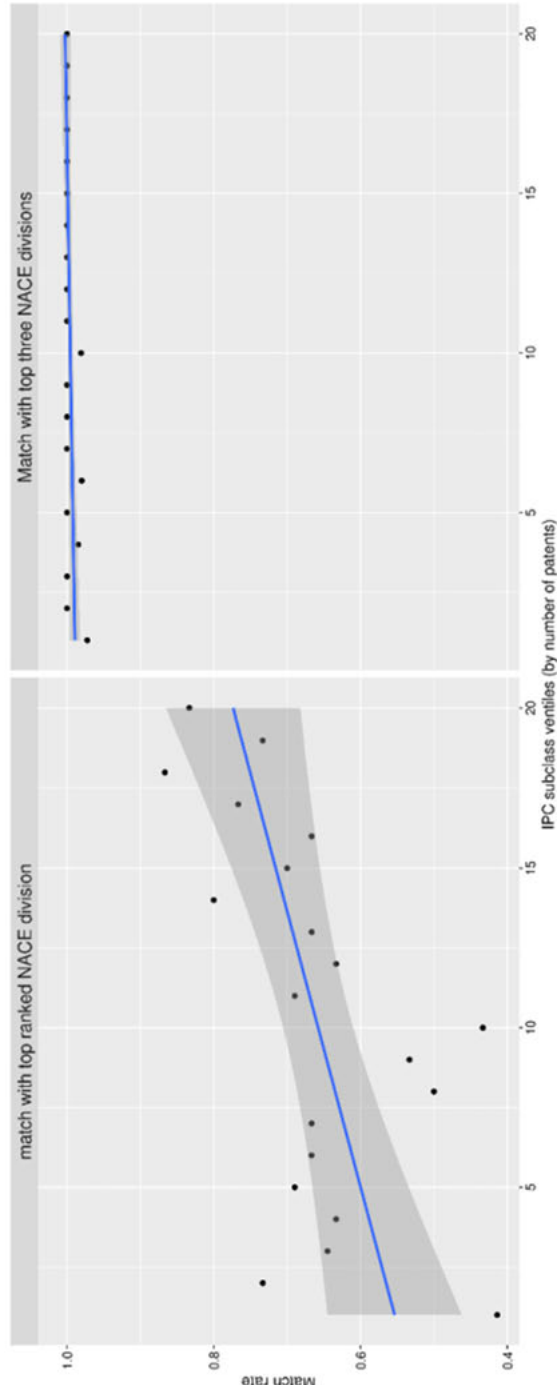
The mean number of NACE divisions assigned to each IPC subclass in Dorner & Harhoff (2018) is 25.3, with standard deviation of 13.9. In our matched dataset the same statistics amounts to 35.4 with standard deviation of 16. When the tails of the dataset are cut at 2% relative contribution of NACE to IPC, respective statistics are: mean 7.1, standard deviation 3.4 for weighted concordance and mean of 8.9, standard deviation 2.89 for our matched dataset.

On the basis of matched data, we calculated the number of patents assigned to each NACE rev. 2 division and created the rank of top 10 NACE divisions by the number of patents. In the next step, using IPC subclass information attached to each patent and weighted concordance (Dorner & Harhoff 2018), we calculated similar rankings of NACE rev. 2 divisions. Then we compared the aggregated number of patents and respective rankings across two datasets. In contrast to DG Concordance, which is limited only to manufacturing industries, DH Concordance contains information on service industries. Therefore, the present comparison is done for the whole range of NACE divisions available in both datasets.

Comparison of both rankings confirms that for some service industries, typically ignored in concordance tables, patent protection may play an important role. Both in ranking calculated based our dataset as well as calculated based on DH concordance, three service industries made it to the top 10. In our matched dataset, they are 72- Scientific research and development (ranked 6th), 46 - Wholesale Trade, except for motor vehicles and motorcycles (ranked 8th) and 61- Telecommunications (ranked 10th). In the ranking developed from DH concordance, they were 72- Scientific research and development (ranked 4th), 46- Wholesale Trade, except for motor vehicles and motorcycles (ranked 8th) and Architectural and engineering activities; technical testing and analysis (ranked 10th). Although in the present dissertation we focus on the manufacturing industries, both rankings indicate that patenting plays an important role in some

service industries. Therefore, in the calculations of related patent stocks, as explained further, we take into account also service industries.

Figure 3.7 Comparison of rate of equal IPC-NACE assignment in matched dataset and most frequent IPC-NACE pairs in DH concordance.



Note: comparison for top ranked NACE division (left) and top three NACE divisions (right) in matched dataset;
Source: own calculations based on the merged database developed by author as described in section 3.4 and data made available as data supplement to Dornier&Harhoff (2018).

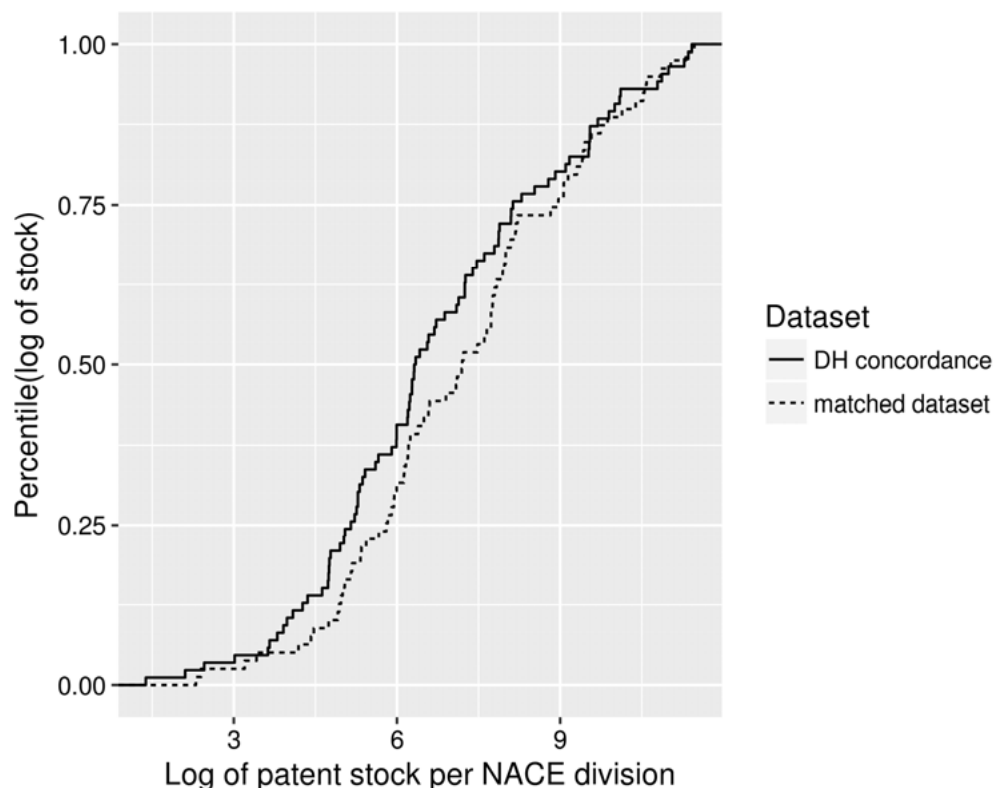
Table 3.5 Top 10 most patent intensive NACE divisions in matched dataset compared with Weighted (DH) Concordance

| NACE rev. 2 | Description of NACE rev. 2 division | Matched dataset | | Weighted concordance | |
|----------------|------------------------------------------------------------------------------|-----------------|------|----------------------|------|
| | | patents no | rank | patents no | rank |
| 26 | Manufacture of computer, electronic and optical products | 95547.37 | 1 | 91172.98 | 1 |
| 28 | Manufacture of machinery and equipment n.e.c. | 81763.92 | 2 | 85503.75 | 2 |
| 20 | Manufacture of chemicals and chemical products | 62005.08 | 3 | 79299.45 | 3 |
| 27 | Manufacture of electrical equipment | 51388.12 | 4 | 48522.87 | 6 |
| 21 | Manufacture of basic pharmaceutical products and pharmaceutical preparations | 39690.5 | 5 | 22082.56 | 9 |
| 72 | Scientific research and development | 38178 | 6 | 59420.52 | 4 |
| 29 | Manufacture of motor vehicles, trailers and semi-trailers | 37277.67 | 7 | 52556.02 | 5 |
| 46 | Wholesale trade, except of motor vehicles and motorcycles | 32465.92 | 8 | 24169.78 | 8 |
| 25 | Manufacture of fabricated metal products, except machinery and equipment | 25277.08 | 9 | 24611.14 | 7 |
| 61 | Telecommunications | 19392.53 | 10 | 2621.46 | 26 |

Source: own calculations based on the merged database developed by author as described in section 3.4 and data made available as data supplement to Dorner&Harhoff (2018).

The p-value of a K-S test for comparison of distributions of patent stocks across NACE divisions calculated on the basis of our matched dataset and of DH concordance is 0.32 with a D value of 0.1438. Based on the K-S test we conclude that there is no statistically significant difference between the two distributions.

Figure 3.8 Comparison of ECDF of patent stocks distributions by NACE divisions calculated from matched dataset and on the basis of DH concordance



Source: own calculations, based on the merged database developed by author as described in section 3.4 and data made available as data supplement to Dorner&Harhoff (2018).

3.5.3 Discussion

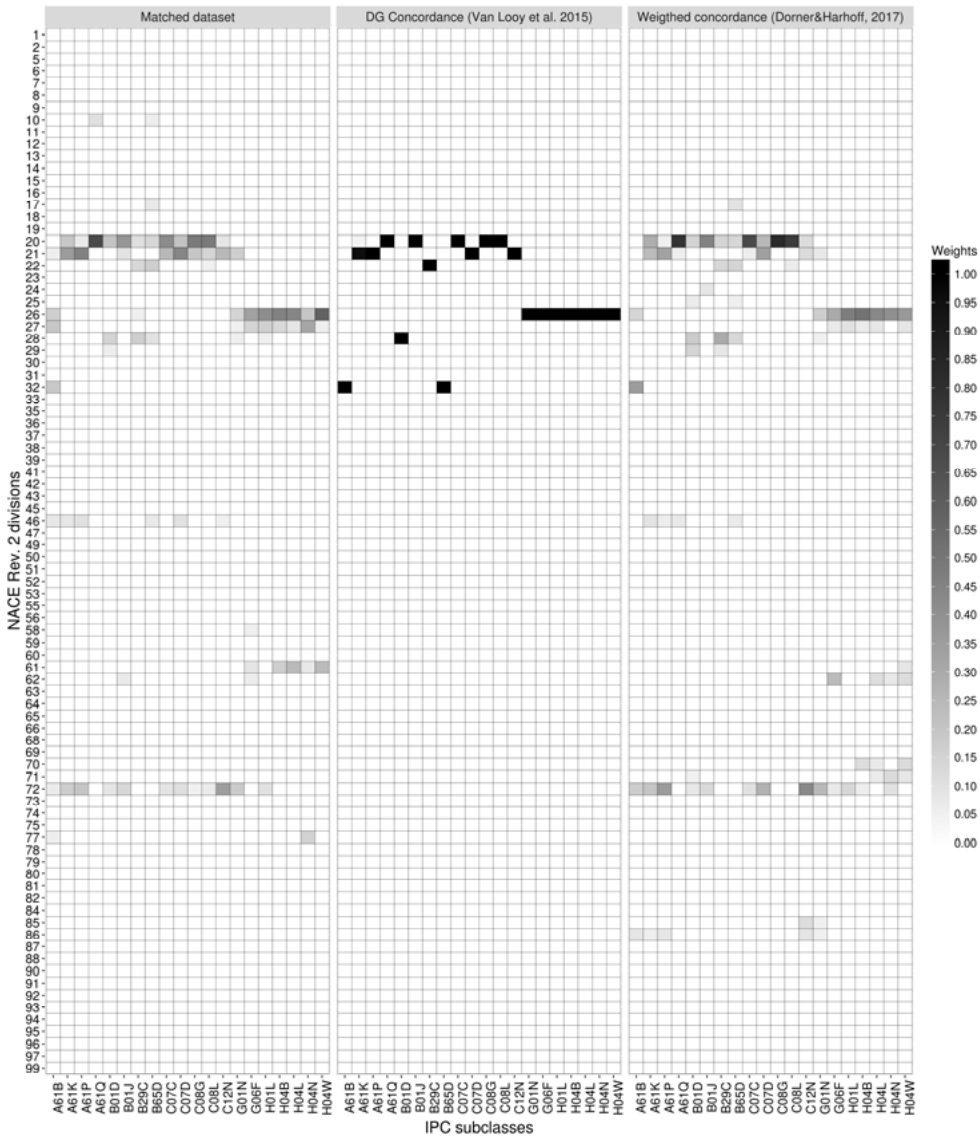
Our method of assigning of industry information to patents is the most similar to Dorner & Harhoff (2018). It is expected as for both datasets the assignment has been done on the basis of empirical data and the NACE industry codes have been retrieved from individual firms associated with patents. The empirical differences between the two stem from the different geographical scope of the underlying data (Germany vs 12 Member States of the EU) and the type of link between a firm and a patent (employer of the inventors at the time of patent filing or assignee). Inventors of most patents are either employees or otherwise contractually linked to the patent assignees. Patented technologies evolve from the technological capacities of the patent assignees as a solution to particular problems noticed and acted upon in the course of their commercial activity. In this sense, industries represented by patent assignees may be treated as industries of patent origin, similarly to the industries represented by employers of inventors. Technological innovation provides direct economic value to the patent owner. The patent owner is also making decisions as regards the commercial exploitation of patented technology. Therefore, positive or negative externalities from those technologies will affect firms active in the industries represented by assignees. It may be that inventors are employed by separate business units of the assignee working in a different industry, but the differences are not expected to be substantial. Conceptually, the method of assignment at the patent owner level is better aligned with our research focus. The limited differences are confirmed by the high degree of similarity between our concordance table and that constructed by Dorner & Harhoff (2018).

In the construction of DG Concordance some degree of subjective judgement is involved. One of the main limitations of DG Concordance is the one-to-one assignment of IPC classes to the main industry, which is unrealistic, as it assumes that the focal IPC class is used within one NACE division only. This assumption precludes any technological overlapping between different industries, which is a core requirement for the construction of technological relatedness matrix between industries as discussed in Chapter 4.

Figure 3.9 presents three heatmaps comparing the fractional distributions (matched dataset and DH concordance) and the one-to-one association of NACE divisions (based on DG Concordance) to the 20 most popular IPC subclasses. Both our matched dataset and the DH concordance associate IPC classes with much more comprehensive sets of industries, including service industries. They present a more complex and nuanced picture of usage of technology classes by various industries than the simplified DG Concordance. However, as can be seen in the figure, despite the different methods used for their construction, all three concordances largely overlap as regards the dominant industries.

Analyses conducted in the present section allow us to conclude that patent-NACE assignment based on our algorithm follows the patterns established by potential alternatives and is a reliable basis for further analyses.

Figure 3.9 Comparison of NACE rev. 2 (divisions) assignation to top 20 IPC subclasses



Note: plot presents three heatmaps calculated on the basis of three concordances between IPC classes and NACE Divisions. In DG Concordance IPC class is linked only to one industry therefore weight always equals 1. For our matched dataset and DH concordance multiple linkages between IPC class and NACE Division are possible. However, usually only one or few industries use a focal IPC more frequently than others. More intensive colour indicates higher association between IPC class and NACE Division. Weights sum to one for each column (IPC class);

Source: own calculations based on the merged database developed by author as described in section 3.4, DG Concordance, available in PATSTAT, table TLS902_IPC_NACE2 and data made available as data supplement to Dorner&Harhoff (2018).

3.6 Calculation of the patent and trade mark stocks

3.6.1 Main patent and trade mark measures

After merging the IPR and firm level data, we can calculate the patent and trade mark stocks. The final stocks of European patents have been calculated using the following formula:

$$PS_{trj} = PS_{trj-1} * 0.85 + P_{trj} \quad (3.1)$$

Where: PS_{trj} - denotes patent stock in year t in NUTS3 region r and 4-digit NACE industry j; PS_{trj-1} - denotes patent stock in year t-1; P_{trj} - stands for number of patents applied for in year t with inventors located in NUTS3 region r and assignees representing 4-digit industry j. The use of a 15% depreciation rate is common in research on patents and R&D (Hall et al. 2005; Bloom et al. 2013; Lychagin et al. 2016; Belderbos & Somers 2015). For the calculation of the European patent stocks, we have used all the applications for European patent protection filed since 1980.

Similarly, we create trade mark stock by aggregating the national trade marks that are still in force over incumbents representing 4 digit NACE industry and located in NUTS 3 regions. For each year of our analysis, we update the stock by adding new registered trade marks and subtracting all trade marks that expire that year.

The stock of national trade marks is calculated with the following formula:

$$TS_{trj} = TS_{trj-1} - T_{trje} + T_{trjn} \quad (3.2)$$

Where: TS_{trj} - denotes trade mark stock in year t in NUTS3 region r and 4-digit NACE industry j; TS_{trj-1} - denotes trade mark stock in NUTS3 region r and 4-digit NACE industry j in year t-1; TS_{trje} - stands for number of trade marks associated with NUTS3 region r and 4 digit industry j that expired⁹ in year t

⁹ For the trade marks with the last status expired, the exact expiration date was available only in the case of UK, DE and HU. In those cases the number of trade marks forming part of the relevant trade mark stock could be calculated on the basis of exact information of trade mark validity. For all other countries we assumed that trade marks with the last status expired were valid for 20 years before the expiration date, i.e. for the two 10-years protection periods.

and T_{trjn} stands for the subsequently registered trade marks applications related to NUTS3 region r and 4 digit industry j that were filed in year t .

To account for the possibility that knowledge spillovers extend beyond the borders of NUTS3 regions, we present the specification in which we consider patent and trade mark stocks of adjacent NUTS3 regions weighted by the distance to the focal NUTS3 region. Bottazzi & Peri (2003) concluded that spillovers are very localized and extend only up to 300 km and decay rapidly with distance. This assumption is confirmed by empirical paper of Geroski & Gugler (2004), who concluded that *“European industrial structure’ is that it is a patchwork of national (or possibly sub-national) industrial structures, which seem to be retaining their separate identity even as they gradually change over time”*. Therefore, we chose a radius of 200 km between the centroids of two regions as a cut-off to consider the possibility of spillovers between the regions. Indeed, we assume that the strength of impact of the knowledge stocks depends on the geographical distance between regions. In accordance with Tobler’s law, the greater the distance between the regions, the smaller interaction intensity between them (Tobler 1970).

We know little about the exact impact of the geographical distance on the strength of the knowledge spillovers and the process of its decay, although non-linear effects of distance on the knowledge flows have been confirmed in the context of patents’ citations by Criscuolo & Verspagen (2008). In cases where the information about the assumed spatial process is incomplete, the literature on spatial data analysis recommends using weights that sum up to unity for the impact of neighbours (Bivand et al. 2008)

Hence, we calculate the weights for patent and trade mark variables related to adjacent regions in two steps. In the first step we calculate weights based on the inverse of geographical distance from the centroid of focal NUTS 3 region, in accordance with the following formula:

$$w_{rp} = \begin{cases} \frac{1}{d_{rp}}, & \text{when } d_{rp} \leq 200 \text{ km} \\ 0, & \text{when } d_{rp} > 200 \text{ km} \end{cases} \quad (3.3)$$

Where w_{rp} is a geographical weight, d_{rp} is the distance in kilometres between centroids of regions r and p .

In the second step we row standardise weight matrix of adjacent regions as shown in equation (3.4) so in the transformed matrix of weights, sum of elements of each row equals 1.

$$w_{rp}^* = \frac{w_{rp}}{\sum_{i=1}^p w_{ri}} \quad (3.4)$$

Finally aggregated variables for our focal NUTS 3 regions are calculated using the following formula.

$$V_{gr} = V_r + \sum_{i=1}^p w_{rp}^* * V_p \quad (3.5)$$

Where V_{gr} is a variable calculated for focal NUTS 3 and adjacent regions located within 200 km from its centroid, V_r is a value of the variable for focal NUTS3 only, without taking into account adjacent regions, w_{rp}^* is a transformed geographical weight as explained in equations (3.3) and (3.4) and V_p is value of a variable for region p. The final patent and trade mark stocks are therefore a sum of the stocks from the focal NUTS3 region and the weighted mean of relevant patent and trade mark stocks from regions lying up to 200 km from the focal NUTS3 centroid, where weights depend on the distance from focal NUTS3.

3.6.2 Alternative measures based on European trade marks and controls for non-matched patents and trade marks

As discussed in section 3.2.4, we chose national trade marks data as the primary source for the calculation of trade mark stock variables. In general, national trade mark stocks are higher than stocks of European trade marks (EUTMs) as shown in Table 3.2. However, it is worth to compare whether results of our main models differ if we construct our trade mark stocks on the basis of EUTM rather than national trade marks.

Furthermore, with our algorithms, we were not able to match all the patent and trade mark records with information on their owners' available in the ORBIS database. As shown in Table 3.3, for some countries, the matching rate could be below 50%. Our findings may be influenced by possible systematic bias in the matching procedure, resulting in differences in the distribution of the matched and total stocks across industries and countries. There is no straightforward way to account for a fraction of non-matched patents and trade marks, since the allocation to industries crucially depends on

information on the firms that apply for them. We, therefore, decided to leverage the data from the matched records to construct concordance tables and use these for the construction of patent and trade mark stocks to examine the sensitivity of our results to this issue. We note that the recalculation of patent and trade mark stocks described below has to rely on a range of assumptions and is likely to introduce substantive noise in the measures. Therefore, we use the variables based on European trade marks and control for non-matched stock of patent and trade mark variables in the robustness checks rather than in the main models' specifications.

We define the total stock of patents in an industry i and region r using the following equation:

$$P_{tir} = P_{mir} + c_i * P_{nmr} \quad (3.6)$$

where P_{tir} is the total number of patents assigned to industry i and region r , P_{mir} is a part of patent stock in the region that we were able to match with ORBIS data, c_i is a share of all non-matched patents assigned to industry i and P_{nmr} is a pool of patents assigned to region r on the basis of inventors' addresses but not matched to ORBIS records and consequently not assigned to any industry. Factor c_i is calculated based on the IPC classes of non-matched patents and using a concordance table developed based on our matched patent dataset as described in the section 3.5.

Similarly, we constructed the variable for total stock of trade marks in industry i and region r using the following equation:

$$T_{tir} = T_{mir} + s_{ic} * T_{nmr} \quad (3.7)$$

where T_{tir} is total number of trade marks assigned to industry i and region r , T_{mir} is a part of trade mark stock in the region that we were able to match with ORBIS data, s_i is a share of non-matched trade marks assigned to industry i and T_{nmr} is a pool of trade marks assigned to region r on the basis of addresses of applicants stored in the EUIPO register but not matched to ORBIS records and consequently not assigned to any industry.

Factor s_i is calculated based on NICE classes of non-matched trade marks and using a concordance table developed based on our matched trade mark dataset. As discussed in section 3.2.4, there are only 45 NICE classes available for trade mark classification. Since trade marks in a specific class may be registered by firms active in many industries, they are rather poor instruments for the construction of the concordance table of NICE-NACE

combinations. To mitigate this problem, we construct two types of concordance tables for each country available in our dataset. For the first type of concordance we explore the fact that trade mark protection may be sought in relation to several NICE goods and services classes. In the first step we analysed the combination of NICE classes in the pool of non-matched trade marks and compared the combination of NICE classes in the subset of matched trade marks to assign the most likely industries. In case in the subset of non-matched trade marks there were new combinations of NICE classes, not present in the matched subset, we assigned the NACE industry codes on the basis of individual NICE class- NACE industry combinations. Both types of concordance tables have been developed individually for each country available in our dataset, to account for possible national specificities in NACE- NICE classes combinations. Since we had detailed information on NICE classes for European trade marks only and the inventors' address information is much more complete for European patents than for national ones, we conduct robustness checks using European IPRs only.

We present and discuss the results of robustness checks based on alternative controls for patent and trade mark variables in the relevant parts of the dissertation.

3.7 Regional patent and trade mark stocks- descriptive statistics

This section presents the descriptive statistics on the patent and trade mark stocks for manufacturing industries, which are the focus of our analysis in the present dissertation.

Table 3.6 presents the list of top ten manufacturing industries with the largest patent stocks in 2010 in our dataset.

Table 3.7 shows the similar ranking of the top 10 industries with the highest stocks of trade marks in 2010 aggregated over all the regions in our dataset.

Table 3.6 Top 10 NACE industries with the highest stocks of patents in 2010

| Stock of European patents | NACE | NACE description |
|---------------------------|------|---------------------------------------------------------------------------------|
| 18,383 | 2651 | Manufacture of instruments and appliances for measuring, testing and navigation |
| 15,871 | 2751 | Manufacture of electric domestic appliances |
| 13,064 | 2824 | Manufacture of power-driven hand tools |
| 9,546 | 2120 | Manufacture of pharmaceutical preparations |
| 8,295 | 2611 | Manufacture of electronic components |
| 6,660 | 2910 | Manufacture of motor vehicles |
| 6,571 | 2932 | Manufacture of other parts and accessories for motor vehicles |
| 5,081 | 3030 | Manufacture of air and spacecraft and related machinery |
| 4,601 | 2899 | Manufacture of other special-purpose machinery n.e.c. |
| 4,249 | 2110 | Manufacture of basic pharmaceutical products |

Note: table presents simple stocks of patents, not including information on stocks from adjacent regions. The aggregate numbers are calculated on the basis of the whole matched dataset (12 MS of the EU);

Source: own calculations based on the merged database developed by author as described in section 3.4.

Table 3.7 Top 10 NACE industries with the highest stocks of national trade marks in 2010

| Stock of national trade marks | NACE | NACE description |
|-------------------------------|------|---------------------------------------------------------------------------------|
| 32,188 | 2120 | Manufacture of pharmaceutical preparations |
| 25,950 | 1102 | Manufacture of wine from grape |
| 16,417 | 2042 | Manufacture of perfumes and toilet preparations |
| 15,495 | 1051 | Operation of dairies and cheese making |
| 11,180 | 1089 | Manufacture of other food products n.e.c. |
| 9,587 | 1013 | Production of meat and poultry meat products |
| 9,570 | 1082 | Manufacture of cocoa, chocolate and sugar confectionery |
| 9,029 | 1101 | Distilling, rectifying and blending of spirits |
| 9,008 | 2030 | Manufacture of paints, varnishes and similar coatings, printing ink and mastics |
| 8,433 | 1413 | Manufacture of other outerwear |

Note: table presents simple stocks of trade marks, not including information on stocks from adjacent regions;

Source: own calculations based on the merged database developed by author as described in section 3.4.

Table 3.8 presents the list of top 10 NUTS 3 regions with the highest stocks of European patents in 2010. Unsurprisingly German and French regions dominate this ranking. However, the inventors representing the Dutch region of Zuidoost-Noord-Brabant are associated with the highest number of patents. The main contributors to the patent stock in this region are inventors associated with Philips Electronics, NXP semiconductors and ASML.

Table 3.8 Top 10 NUTS 3 regions with the highest geographically weighted stocks of European patents (manufacturing industries)

| Stock of European patents | NUTS 3 | NUTS 3 name |
|---------------------------|--------|---------------------------|
| 6,477 | NL414 | Zuidoost-Noord-Brabant |
| 2,892 | FR101 | Paris |
| 2,784 | DE212 | München, Kreisfreie Stadt |
| 2,614 | DE115 | Ludwigsburg |
| 2,577 | FR105 | Hauts-de-Seine |
| 2,288 | FR103 | Yvelines |
| 2,216 | DE111 | Stuttgart, Stadtkreis |
| 1,890 | DE300 | Berlin |
| 1,687 | DE113 | Esslingen |
| 1,676 | FR107 | Val-de-Marne |

Note: for each NUTS3 stocks are calculated in accordance with equation (3.5) and include stocks produced in the focal region and fraction of stocks produced in adjacent regions, calculated on the basis of the distance between the focal and adjacent NUTS3 centroids;

Source: own calculations based on the merged database developed by author as described in section 3.4.

As can be seen in Table 3.9 the analysis of the regions with the highest stocks of trade marks gives an entirely different picture. The French regions of Paris and Hauts-de-Seine are the only regions represented in both rankings. No German or Dutch regions are represented among the top 10 regions with the highest trade mark stock. Instead, the ranking is dominated by Spanish and Italian regions.

Table 3.9 Top 10 NUTS 3 regions with highest geographically weighted stocks of national trade marks (manufacturing industries)

| Stock of national trade marks | NUTS 3 | NUTS 3 name |
|-------------------------------|--------|---------------------|
| 28,735 | ES511 | Barcelona |
| 21,340 | ITC4C | Milano |
| 15,376 | FR101 | Paris |
| 14,829 | ES300 | Madrid |
| 14,581 | FR105 | Hauts-de-Seine |
| 9,426 | ES523 | Valencia / València |
| 7,590 | ITC11 | Torino |
| 7,130 | ES514 | Tarragona |
| 7,021 | ES521 | Alicante / Alacant |
| 7,015 | ES512 | Girona |

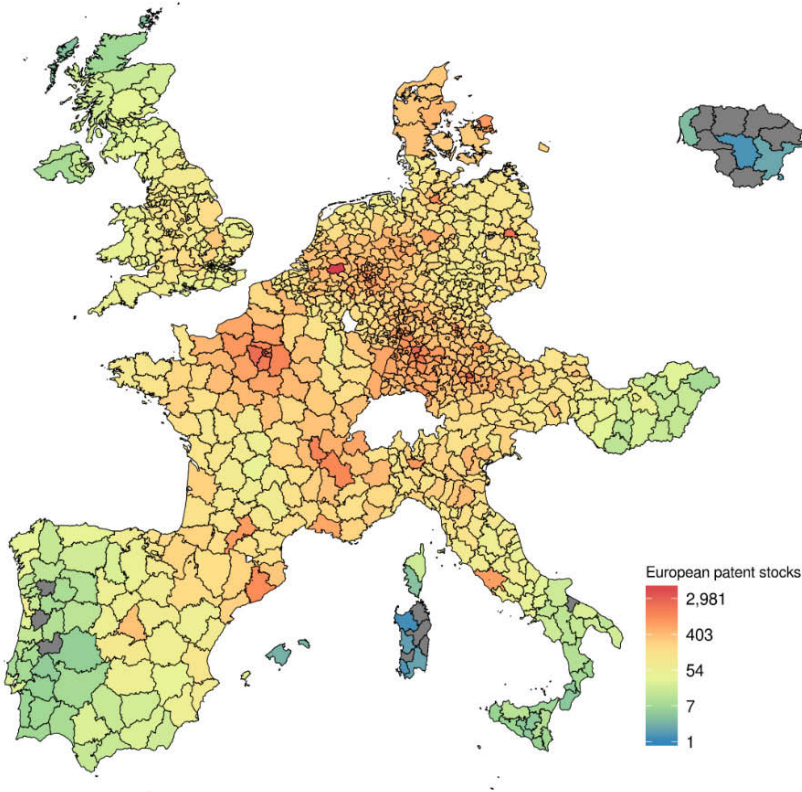
Note: stocks calculated for each NUTS3 are calculated in accordance with equation (3.5) and include stocks produced in the focal region and fraction of stocks produced in adjacent regions, with fractions calculated on the basis of the distance between the focal and adjacent NUTS3 centroids;

Source: own calculations based on the merged database developed by author as described in section 3.4.

Figure 3.10 and Figure 3.11 present the distribution of geographically weighted stocks of patents and trade marks for all the NUTS 3 regions in our dataset. As could be seen in the maps, patents stocks are especially high in Denmark regions, West part of Germany, Benelux countries, central France, northern part of Italy and South East England. Trade mark stocks tend to be more evenly distributed among the European regions with especially high presence in France, northern and central Italy, eastern part of Spain and South East England.

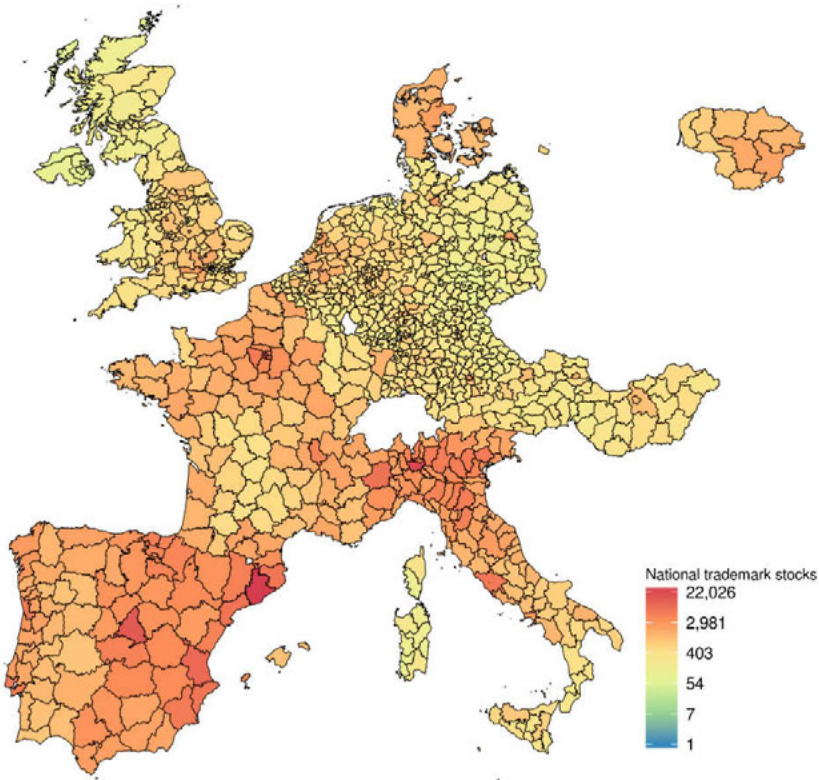
Although the analysis of aggregated stocks may be interesting, our main focus in the present dissertation is set on the impact of industry specific stocks of patents and trade marks relevant for entrants. Due to the high number of industries/regions combination, descriptive statistics for the whole dataset is not easy to present. In Figure 3.12 through 3.19, we present the distribution of patent and trade mark stocks for a number of selected industries. We made sure that the industries we chose represent various intensities of innovation and trade mark use. As can be seen from those maps, depending on the industry analysed, the distribution of stocks differs, and the most important poles of innovation are not always those regions that dominate in the aggregate statistics. Also, as already discussed, the patenting activity highly differs, and for some industries, it plays a more important role than for others.

Figure 3.10 Geographically weighted stocks of European patents aggregated for NUTS 3 regions (manufacturing industries)



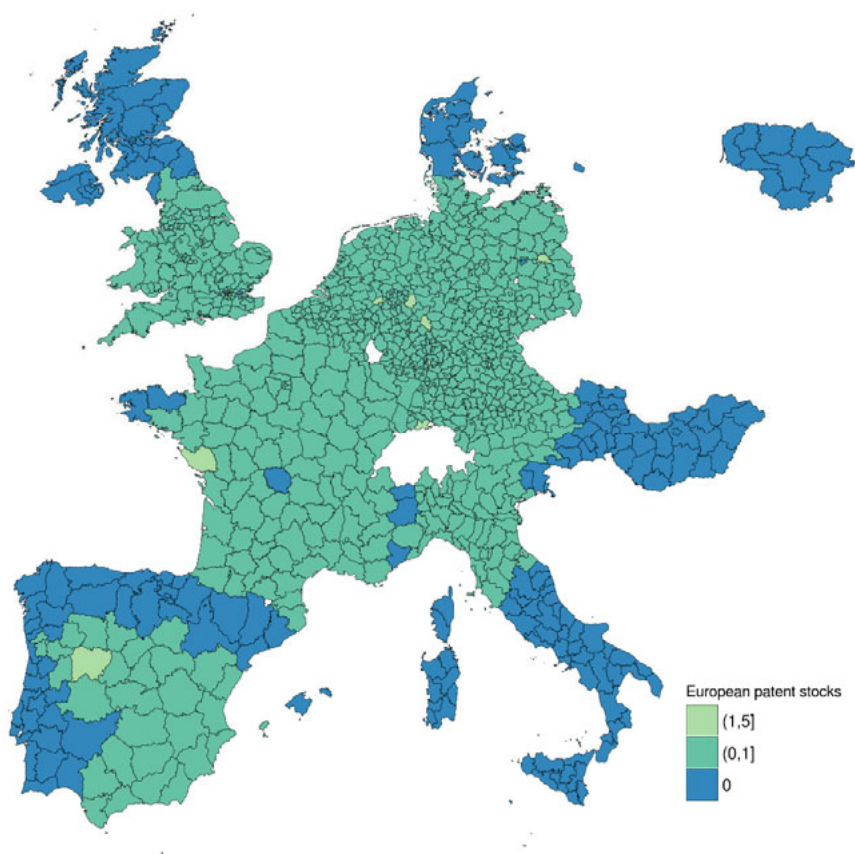
Source: own calculations based on the merged database developed by author as described in section 3.4.

Figure 3.11 Geographically weighted stocks of national trade marks aggregated for NUTS 3 regions (manufacturing industries)



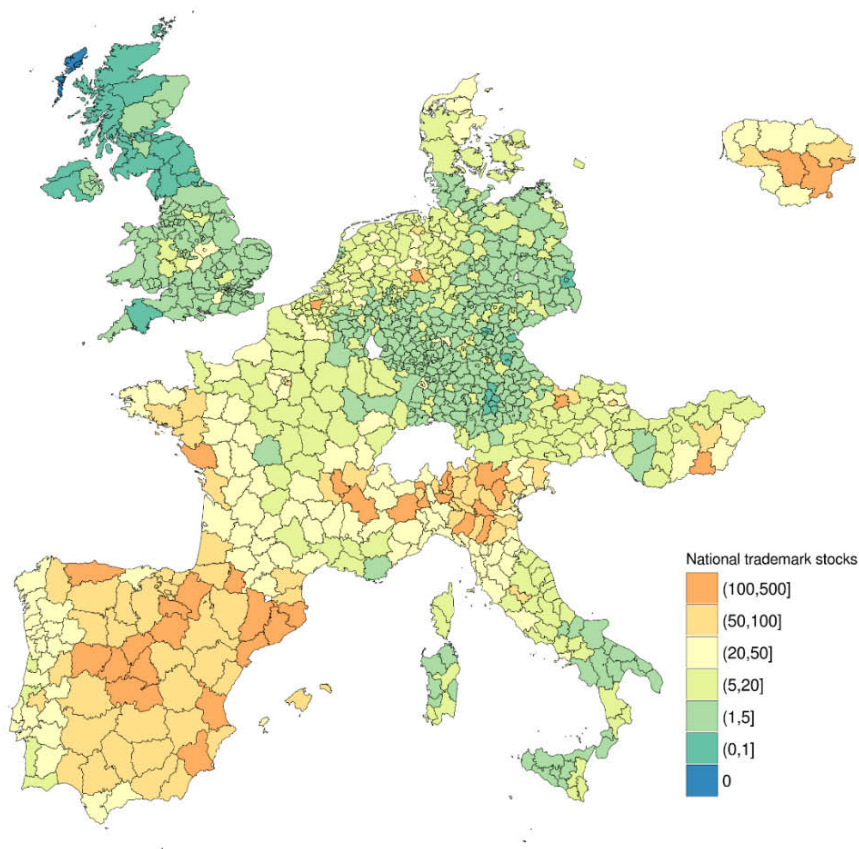
Source: own calculations based on the merged database developed by author as described in section 3.4.

**Figure 3.12 Geographically weighted European patent stocks
(NACE 10.13 Production of meat and poultry meat)**



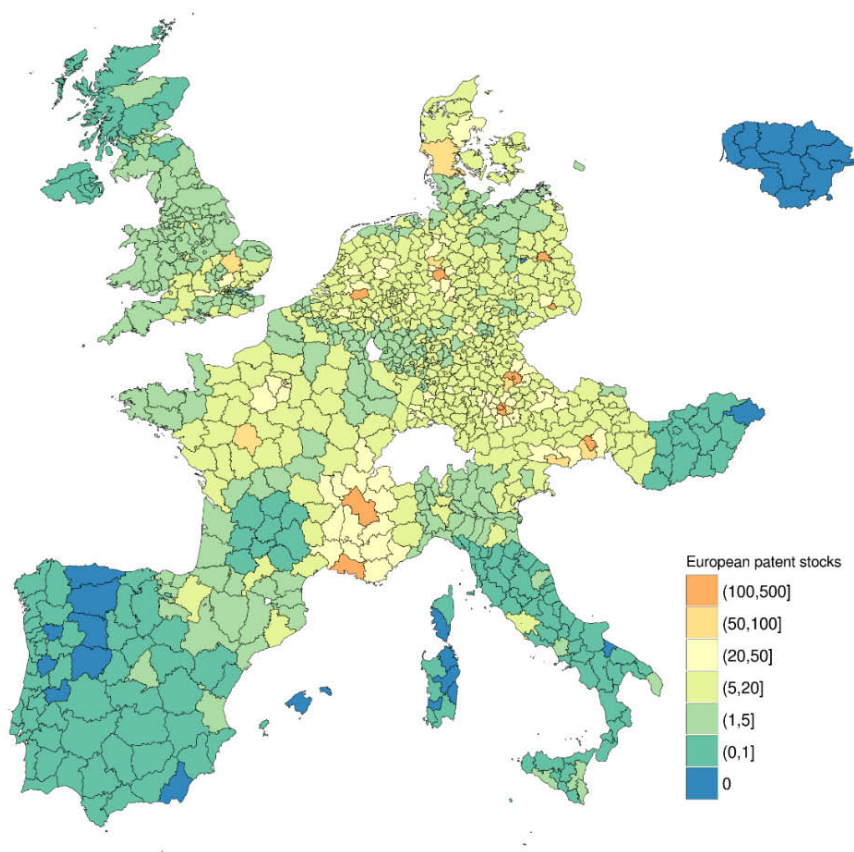
Source: own calculations based on the merged database developed by author as described in section 3.4.

**Figure 3.13 Geographically weighted national trade mark stocks
(NACE 10.13 Production of meat and poultry meat)**



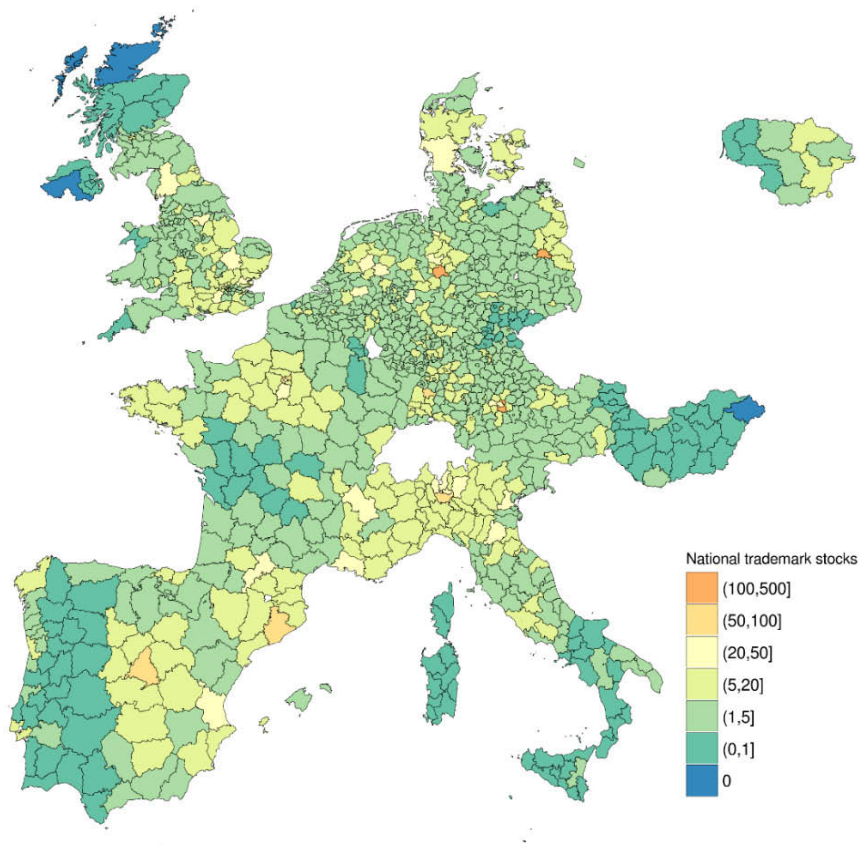
Source: own calculations based on the merged database developed by author as described in section 3.4.

Figure 3.14 Geographically weighted stocks of European patents aggregated for NUTS 3 regions (26.11 Manufacture of electronic components)



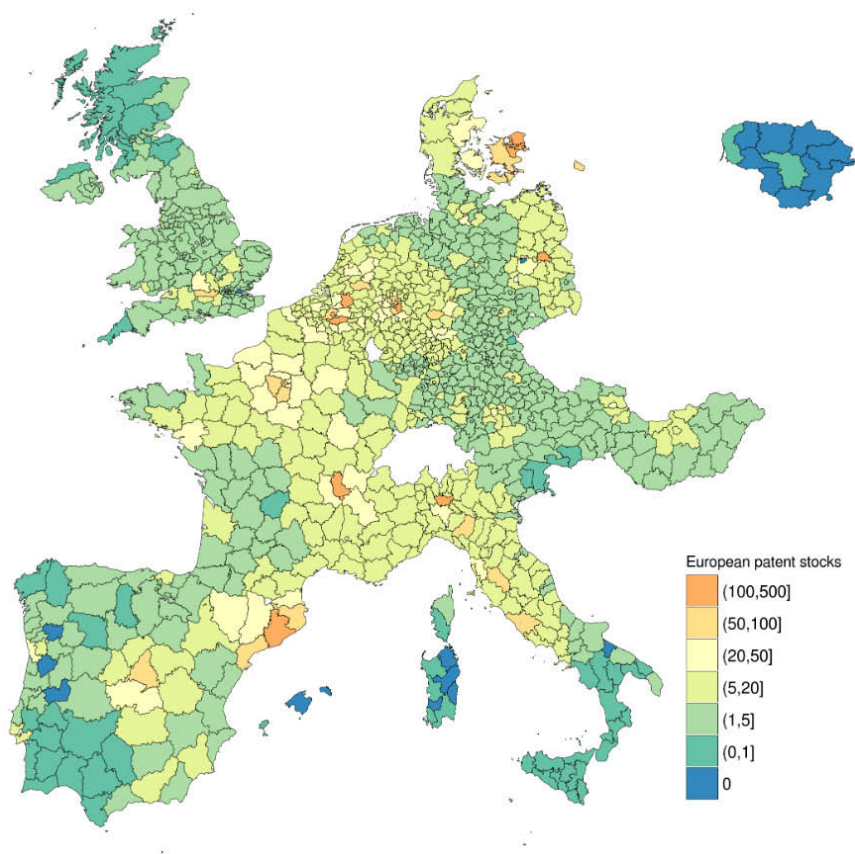
Source: own calculations based on the merged database developed by author as described in section 3.4.

**Figure 3.15 Geographically weighted national trade mark stocks
(26.11 Manufacture of electronic components)**



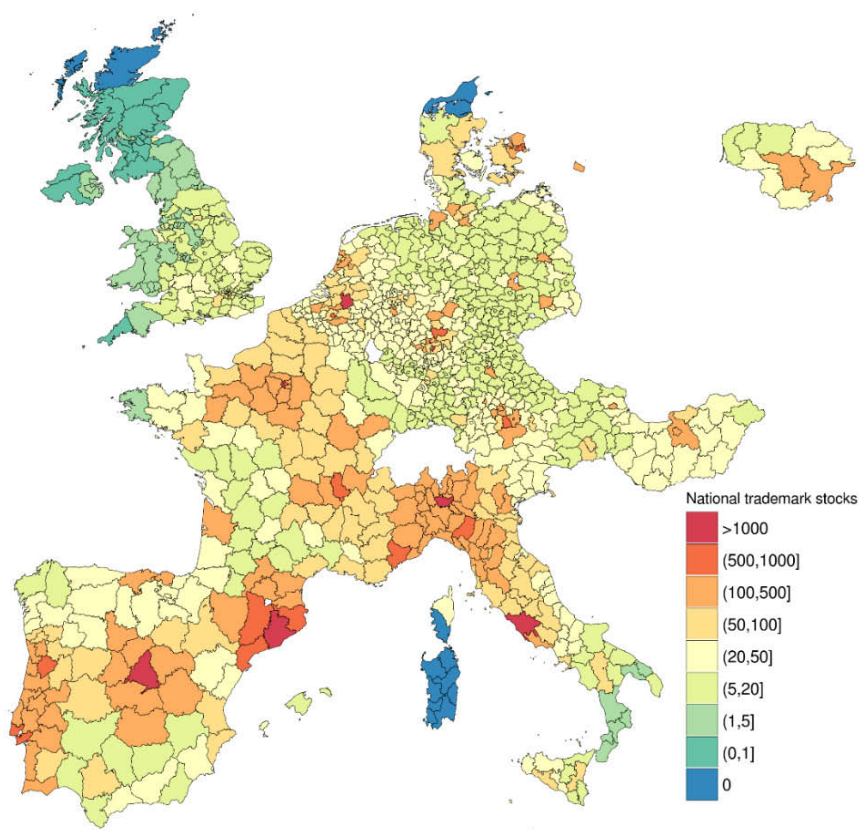
Source: own calculations based on the merged database developed by author as described in section 3.4.

**Figure 3.16 Geographically weighted European patent stocks (21.20
Manufacture of pharmaceutical preparations)**



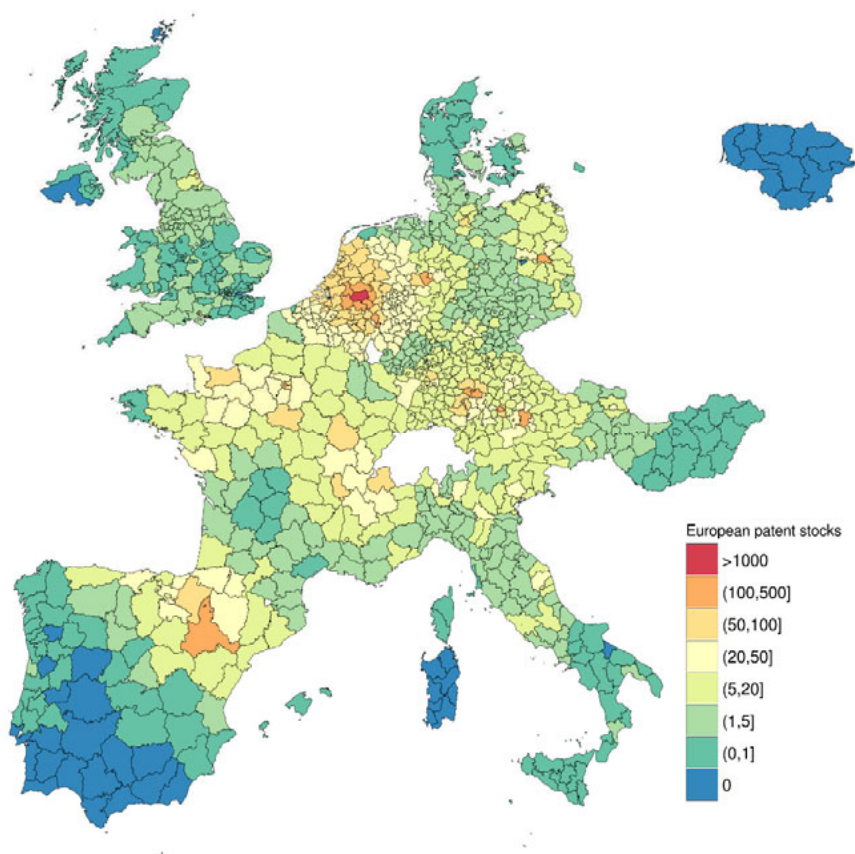
Source: own calculations based on the merged database developed by author as described in section 3.4.

**Figure 3.17 Geographically weighted national trade mark stocks
(21.20 Manufacture of pharmaceutical preparations)**



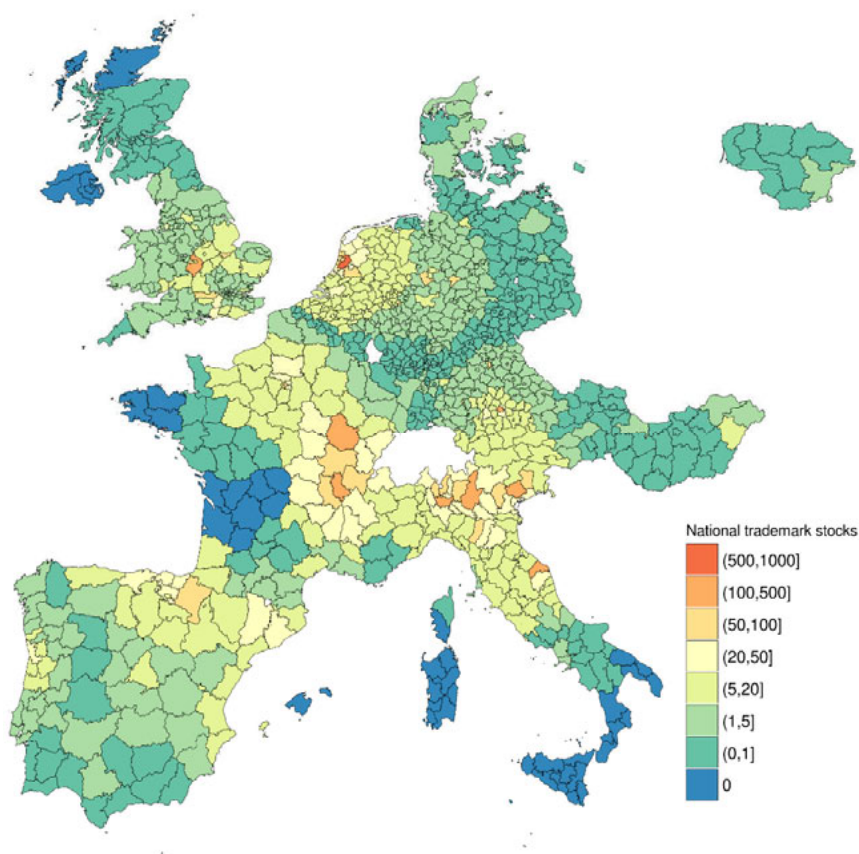
Source: own calculations based on the merged database developed by author as described in section 3.4.

**Figure 3.18 Geographically weighted European patent stocks (27.51
Manufacture of electric domestic appliances)**



Source: own calculations based on the merged database developed by author as described in section 3.4.

**Figure 3.19 Geographically weighted national trade mark stocks
(27.51 Manufacture of electric domestic appliances)**



Source: own calculations based on the merged database developed by author as described in section 3.4.

3.8 Discussion

In this chapter, we have presented the construction of the dataset we use for the empirical investigation of entry and growth of new manufacturing firms. Our data links information on industries to IPR records at the firm level, allowing for detailed analyses of industrial patterns of patenting and trade mark activity. The particular advantages of our data are its granularity (detailed information on 4-digit NACE industries). In our empirical investigation we aim to analyze the opportunity creating and competitive aspects of local knowledge stocks, the strategic use of trade marks by incumbents, and inter-industry knowledge spillovers. A high level of granularity is crucial for this research.

By drawing on information from business registries, we are able to present richer information on patent and trade mark activity by industries than those available by using alternative methods. In particular, our method allows for including service industries, which may be of particular importance for research focused on trade marks. Further, we are not constrained by the one-to-one relationship between patent or trade mark classifications and NACE industries. Comparison with previous methods of retrieving industry information for patents showed that our algorithm is a reliable basis for further analysis.

Although methods based on IPC classes for industry assignation led to interesting and valuable insights regarding patent usage by industries, methods based on goods and services descriptions of trade marks have serious limitations, mostly due to the limited set of NICE classes in trade marks. As discussed in the next chapter, avoiding the one-to-one constraint allows us to develop inter-industry technological relatedness measures based on overlapping use of the same IPC technology classes by firms active in different industries.

3.9 Data limitations

Administrative datasets, such as ORBIS, have some disadvantages in comparison to the data compiled by national statistical offices (NSOs). NSOs data collection techniques are developed on the basis of long experience and involve important quality controls designed to limit systematic errors. As a result, they meet high quality standards (Ribeiro et al. 2010). In contrast, quality controls of data compiled by business providers, such as Bureau Van Dijk, are not always well documented and probably are only cursory in comparison to the official statistics. As a result, they may contain data of poor quality, in terms of missing values, outliers and data inconsistencies. This makes it difficult to distinguish between errors and true data variability.

Due to the national provisions allowing for less strict rules of financial reporting for the micro and small firms, as well as non-compliance with disclosure obligations by some entities, availability of employment and financial data differs depending on the sector and country (Squicciarini & Dernis 2013). Notwithstanding these potential problems, ORBIS has become a standard data source for micro-data analysis at OECD (Ribeiro et al. 2010). Moreover, crucial variables used in our research such as NACE industry codes or date of incorporation have relatively better coverage in the ORBIS database for all firm types and sizes.

In the IPR registers, a substantial share of IPRs is associated with owners that are physical persons, rather than business entities. In many cases they may be also the principal owners of the firms and, therefore, IPRs are employed to protect intellectual property used by firm. Given the data limitations, we are not able to link those IPRs to a specific industry. Also, our matching algorithms are strict. In the case of doubt we prefer to reject matching than increase the risk of incorrect match.

Due to those data limitations we were not able to link all the patents and trade marks records to their owners. If the matching rates for some industries/regions are systematically lower, it may result in underestimation of local patent and trade mark activity for some regions/industries. Therefore, the findings of the present dissertation can be generalized only under the assumption that there is no systematic bias between the data we were able to match and unmatched records.

4 Technological inter-industry relatedness

4.1 Introduction

The concept of knowledge spillovers is widely recognised as being important for economic growth (Aghion & Howitt 1992; Aghion & Jaravel 2015), geographical agglomeration (Krugman 1991; Marshall 1920) or strategic entrepreneurship (Audretsch 1995a) and studied in many research areas (Agarwal et al. 2010). Therefore, it is necessary to operationalize and measure this concept to do a rigorous empirical testing of the validity of these theories. It is, however, methodologically challenging. In his seminal work, Krugman (1993) indeed acknowledged that “[k]nowledge flows (...) are invisible; they leave no paper trail by which they may be measured and tracked”.

Various scholars have developed direct and indirect measures in an attempt to capture knowledge spillovers. We follow an approach where we construct the *relevant* stock of knowledge that can potentially generate knowledge spillovers leading to entry in an industry (and region). For this, we need to take into account not only knowledge in the own (focal) industry but also knowledge stocks in related industries. Preferably, knowledge stocks from industries that are more closely located in the technological space should be considered as having more potential for knowledge spillovers, and hence should receive a higher weight in the total relevant knowledge stock.

In the present chapter, we discuss how the technological relatedness between different industries has been operationalized in the previous literature. We subsequently present our novel approach to the construction of a relatedness matrix, which is driven by our specific research focus and characterised by a higher level of granularity of the data than ever previously obtained.

One of the major obstacles for the construction of relatedness measures based on the overlap of patent classes in the past was the lack of direct information on the industries in which patent assignees are active. Since we merged patent data with demographic data of individual firms, including their NACE codes, we are now able to directly observe the overlap in the usage of patent classes by firms in different NACE industries. This enables us to construct a very detailed inter-industry relatedness matrix on the granular 4-digit level. As not only manufacturing firms are filing for patent protection, we also include relationships between manufacturing and industries representing other sectors.

Such a detailed relatedness measure is of crucial importance for our research strategy, as it facilitates construction of individual pools of relevant knowledge for each newly created firm and control better for positive and negative externalities stemming from that pool.

In this chapter, we discuss previous efforts to establish inter-industry relatedness (section 4.2), review the methodology to develop our own more granular relatedness measure (section 4.3), compare and validate it with other studies (section 4.4). Subsequently, we present summary statistics (section 4.5) and discuss the methodology and its limitations (section 4.6).

4.2 Measurement of knowledge flows in the literature

It is a standard approach in economic and strategy research to assess technology spillovers by modelling a production function, whereby relevant knowledge pools constitute a separate input to the production process. In the previous literature, spillovers were measured either directly or indirectly, by analysing their drivers (Belderbos & Mohnen 2013).

Direct measurement of spillovers is possible by eliciting information directly from firms taking part in innovation surveys (Czarnitzki & Kraft 2012) or, in the cases of patented inventions, by leveraging data on citations in the patent documentation. Indirect measures may be based on economic transactions between firms or, on some measures of similarity between firms or industries, independent from economic relations.

Operationalization of the inter-industry knowledge flows on the basis of the transaction data has been pioneered by Terleckyj (1980) who used input-output tables. Scherer (1982) used 1972 US input-output tables to build ratios of flows from the industry of origin to the industry of use. Both sets of industries have been determined based on manual examination of 15 000 US patents. Knowledge pools for potential spillovers were proxied by R&D expenditure of the industries. Other transaction data used to build such tables included transactions in capital goods, licensing and acquisition of technology or cross-employment of R&D personnel (Belderbos & Mohnen 2013).

A method of using patent citations to evaluate better the importance or value of underlying innovations has been pioneered by Trajtenberg (1990). The body of citations represents the previous state of knowledge. It helps to determine novel aspects and consequently, the legal scope of protection of a focal patent (Jaffe et al. 1993; Criscuolo & Verspagen 2008). The citation of

previous patents in subsequent patent applications confirms that, to some extent, cited patents opened the way to a wave of successful line of innovation (Trajtenberg 1990). Consequently, at least those citations that have been added by a patent applicant can be seen as a good indicator of knowledge flows. In the previous literature, there are two approaches to trace knowledge flows through patents. First, the number of citations is treated as a proxy for the actual volume of knowledge flows. Second, the intensity of patent citations between firms or industries is taken as a proxy for technological *closeness* or *relatedness* between a pair of firms or industries (Belderbos & Mohnen 2013).

Measures of proximity or closeness between industries are an alternative method that can be used to calculate knowledge similarity matrices. Initially, this method has been proposed by Jaffe (1986), who used patent classes information to compute the proximity between patent portfolios of pairs of firms. As this is our method of choice, in section 4.3, we present a more detailed description of the method proposed by Jaffe.

Jaffe similarity has been used by other researchers who calculated cosine similarity measure between various industry pairs, but they based their calculation on other variables than patent classes. Goto & Suzuki (1989) used data on 50 industries' R&D expenditure for 30 product areas. Relatedness between industries is calculated as a cosine of the angle between vectors of R&D assigned to each of 30 product areas.

Los (2000) presented another derivation built on Jaffe. His measure was designed to capture inter-industry technological relatedness based on input-output tables. Standard measures of knowledge relatedness based on IO tables directly proxy technological relationship between two industries i and j with IO coefficient, which reflect the share of the output of industry j used as input in the production of industry i . In contrast, Los (2000) derived the relatedness between industries i and j from the similarity of their input structure as described by vectors of IO coefficients. Similarity coefficient is calculated as the cosine between a pair of vectors of input coefficients, respectively for industry i and j and all other industries contributing to their production. This method is based on the assumption that input coefficients reflect production technology of a given industry and allow capturing pure technological spillovers rather than supplier-buyer relationship.

Patent based matrices of inter-industry technological relatedness

As a standard indicator of innovation, patent data could be a potentially very useful source of information to track inter-industry knowledge flows. For many years, however, incompatibility of patent and industrial classifications, discussed in chapter 3, was the biggest challenge for constructing comprehensive inter-industry knowledge matrices. Once concordance tables became available, they were used to build such matrices.

First analyses of inter-industry knowledge relatedness have been naturally built on the Canadian patent dataset since it contained information on the industry of manufacturing (IOM) and sector of use (SOU) of patents. Johnson & Evenson (1999) used IOM and SOU relationship, established by OTC to explain agricultural total factor productivity by spillover effects from domestic and foreign R&D done in other sectors.

As emphasized by Verspagen (1997b), matrices based on market transaction data, such as IO tables, may overlook important aspects of technology spillovers. Technological breakthroughs developed in one industry may benefit inventors working on similar technological problems in many other sectors, not necessarily involved in producer-user transactions.

To capture pure technological spillovers, Verspagen (1997b) created three technology flow matrices based on the MERIT concordance table (Verspagen et al. 1994). Two of them were based on relatedness between patent classes. Matrix A used the distinction between main and supplementary classes in the patent documentation. Matrix B used the main class and supplementary classes of unclaimable knowledge¹⁰. A third matrix (US matrix) was based on the lists of citations to other patents included in the US patent data. Relatedness between industrial sectors in the US matrix has been established on the basis of the intensity of patent citations between them. Matrices weights have been constructed, however, not as cosines between industry vectors as proposed by Jaffe (1986) but by dividing the number of patents in each cell by its row total.

Since the pioneering effort of Verspagen (1997b), patent citations have been used to build several matrices of inter-industry knowledge flows (Maurseth

¹⁰To account for claimable and unclaimable knowledge, Verspagen (1997c) used the distinction in the patent documentation between two forms of classifications: invention information and additional information. The latter is not claimed and does not form part of invention but may be useful to the examiner.

& Verspagen 2002; Verspagen 1997c). Most recently Belderbos et al. (2013) used patent citations to develop a knowledge flows matrix between 22 Japanese industrial sectors. Subsequently, this matrix has been used to assess R&D spillovers on total factor productivity of Japanese manufacturing plants.

Breschi et al. (2003) constructed the relatedness measure for 30 broad technological fields. Those fields have been defined based on IPC classes aggregation. They did not distinguish between primary or secondary IPC classes based on position of the IPC class in the patent documentation, but instead took the whole spectrum of technologies indicated in the patent documents as valid for relatedness calculations. Subsequently, they constructed the matrix of a number of co-occurrences of various technological fields in the same patent. The final relatedness is calculated as a cosine index. Breschi et al. (2003) did not link patents with industries but developed the final relatedness measure between technological fields, based only on broad IPC classes.

Arts et al. (2018) recently presented an interesting contribution to the literature on the inter-industry technological relatedness, which does not rely on IPC classes nor patents' citations. Their relatedness measure is based on the text-mining techniques and analysis of common keywords within two patents or two patents' portfolios. The similarity is represented by a Jaccard index calculated by dividing the number of unique keywords in the intersection of the two patents by the number of unique keywords in the union. Thus the Jaccard similarity represents a continuous measure between zero and one.

4.3 Construction of inter-industry relatedness matrix

In the simplest empirical setting, relevant knowledge stocks may be created using a symmetric approach, where the knowledge stock of every industry in a given region is treated equally, and all intangible assets' investments made by all industries located within given region (or territory more generally) are aggregated with equal weights. However, those simple approaches do not take into account the fact that the similarity of knowledge stocks may be higher between some industry pairs than between others. As shown in Figure 3.9 same technologies (proxied by IPC subclasses) are used by different industries. More nuanced approaches, taking into account those complex relations, require the construction of an inter-industry technology relatedness matrix whereby every pair of industries is treated separately and

the relevant stock of spillovers for the i^{th} industry is constructed using some distance measure relating i^{th} industry with all other industries.

This approach can be described by the equation:

$$K_a = \sum_{j=1}^n w_{ij} K_j \quad (4.1)$$

where K_a is a knowledge pool available for a firm a active in industry i , w_{ij} is a weighting matrix representing a fraction of knowledge entering a production function of industry i borrowed from industry j and K_j is a knowledge pool produced by incumbents active in industry j . Weighting factors should become smaller as the technological *distance* between i^{th} industry and j^{th} industry increases (Griliches 1991).

We use our matched dataset described in chapter 3 to calculate inter-industry relatedness between NACE rev. 2 classes (4-digit level). For that purpose, we adapt the original Jaffe method and calculate similarity between industries based on co-occurrence of patent subclasses in patent portfolios of firms representing those industries, as follows:

$$TECH_{ij}^J = \frac{F_i F_j'}{(F_i F_i')^{1/2} (F_j F_j')^{1/2}} \quad (4.2)$$

Where $TECH_{ij}^J$ is the technological relatedness between industries i and j , F_i and F_j are the vectors of patent classes of industry i and j respectively. For our calculations, we aggregated patent portfolios on NACE class (4-digit) level instead of data on individual firms.

Let us explain the intuition behind the equation (4.2) for the multi-industry data with the following example. Suppose we have four industries k , l , m and n and five technology (IPC) subclasses p_1 , p_2 , p_3 , p_4 and p_5 . As illustrated in Figure 3.1 patent subclasses represent the third level of the patent IPC classification. Table 4.1 presents the matrix $F = [F_k, F_l, F_m, F_n]$ in which each column vector stores individual industry's patent counts in each IPC subclass. In our example matrix F has a dimension of 5×4 .

Table 4.1 Matrix of hypothetical industries' patent counts distributed into patent subclasses

| | F_k | F_l | F_m | F_n |
|-----------|--------|--------|-------|-------|
| p_1 | 100 | 0 | 0 | 15 |
| p_2 | 0 | 0 | 0 | 85 |
| p_3 | 50 | 30 | 200 | 0 |
| p_4 | 100 | 0 | 0 | 0 |
| p_5 | 250 | 20 | 0 | 0 |
| $\ p_n\ $ | 291.55 | 36.055 | 200 | 86.31 |

Source: own calculations based on hypothetical data.

The last row of the table is a Euclidean length (Euclidean norm) of the industries' n-dimensional Euclidean space R^n of patent classes and is calculated in the following way:

$$\|p_{nk}\| = \sqrt{\sum_{i=1}^n p_{ik}^2} \quad (4.3)$$

Equation (4.3) in the matrix algebra notation can be represented as the square root of the dot product of a vector with itself.

$$\|p_{nk}\| = \sqrt{F_k F'_k} = (F_k F'_k)^{1/2} \quad (4.4)$$

Next, matrix \hat{F} is calculated. In that matrix, each column from the matrix F is normalized by the Euclidian norm of the respective industry' patent classes vector.

$$\hat{F} = [F'_k / (F_k F'_k)^{1/2}, F'_l / (F_l F'_l)^{1/2}, \dots, F'_n / (F_n F'_n)^{1/2}] \quad (4.5)$$

The Jaffe measure between all the industries is calculated by multiplying the matrix \hat{F} by its inverse (Bloom et al. 2013)

$$TECH = \hat{F}' \hat{F} \quad (4.6)$$

The result of the Jaffe similarity calculation in our hypothetical example are shown in Table 4.2.

Table 4.2 Similarity indices for hypothetical industries

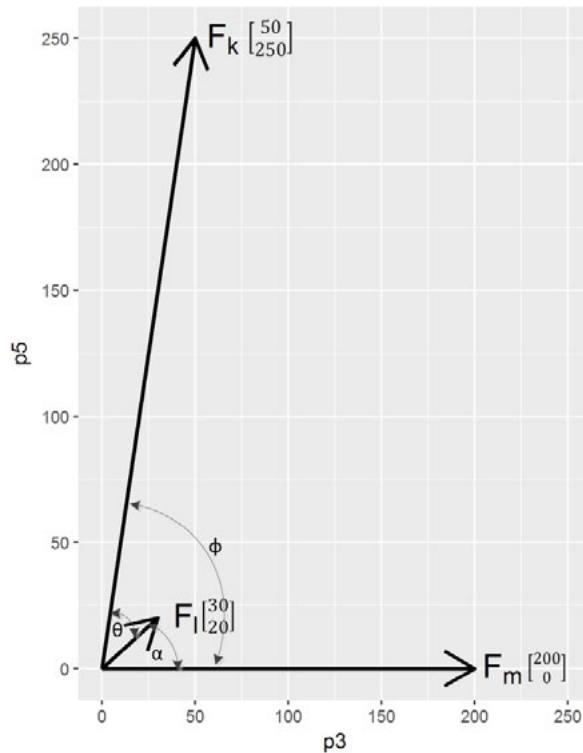
| | k | l | m | n |
|----------|----------|----------|----------|----------|
| k | 1 | 0.17 | 0.62 | 0.06 |
| l | 0.17 | 1 | 0.83 | 0 |
| m | 0.62 | 0.83 | 1 | 0 |
| n | 0.06 | 0 | 0 | 1 |

Source: own calculations based on hypothetical data.

The Jaffe similarity index is bounded between 0 and 1, with value of 1 for firms' pairs that are characterized by exactly the same patenting pattern and 0 for firms' pairs whose vectors are orthogonal.

Figure 4.1 illustrates the calculation of the similarity between industries k, l and m for a space of patent classes limited only to two dimensions: p_3 and p_5 . The Jaffe similarity measure is equal to the cosine of the angle between the vector classes of the industries and is also called the *angular separation of vectors* (Jaffe 1989). In our example, similarity between industries k and l would be calculated as a cosine of the angle θ , between industries k and m as a cosine of the angle ϕ and between industries l and m as a cosine of the angle α . The similarity is not sensitive to the length but only to the direction of patent classes' vectors (Xia et al. 2015). It is also not sensitive to zeros (Leydesdorff 2005).

Figure 4.1 Illustration of similarity calculation in two-dimensional patent classes' space for hypothetical industries



Source: own calculations based on hypothetical data.

Intuitively, the relatedness between two industries stems in our matrix from the overlap between technology classes in the patent portfolios of firms active within those industries. Our matrix assumes that the more similar the pattern of IPC classes applied for by firms in two industries, the more likely it is that the firms in those industries may learn from technological inventions developed by firms from the other industry.

Los (2000) argues that theoretical background for the Jaffe measure can be derived from two different schools of thought: neoclassical and evolutionary. Neoclassical theories, mainly *induced innovation* theories, show that optimizing firms direct their R&D efforts to the activities with lower use of inputs associated with higher costs. As a result, firms (or industries) with similar input structures will engage in similar R&D activities, creating room for spillovers.

Under the evolutionary theory, satisficing firms will look for alternatives to existing routines only if the predetermined, aspiration rate of return on capital cannot be maintained. In the search for more profitable routines firms are more likely to look to technologies which are closer to the existing competencies than more distant ones.

In his analysis of the performance of various measures of potential pools of knowledge spillove, Kaiser (2002) concluded that an uncentered correlation approach appears to replicate knowledge spillovers better in comparison with other alternatives. Jaffe method of calculating similarity based on co-occurrence of patent classes meets many of the desired properties for evaluating proximity defined by Bloom et al. (2013) and complies with many of the stylized facts developed by Belderbos & Mohnen (2013).

For the construction of the inter-industry relatedness matrix we used information based on the dataset of 667 569 European patent applications filed between May 1978 and September 2012, for which we were able to assign NACE industry codes. NACE codes have been assigned on the basis of matching described in section 3.4.

For the calculation of the inter-industry relatedness, we used all the subclasses associated with patents (see section 3.2.3 for the structure of the IPC). Similarly to Breschi et al. (2003) we did not distinguish between primary and secondary IPC classes, as according to the PATSTAT manual, the position of the class symbol in the sequence of classes in the European patent documentation is not meaningful¹¹. It is contrary to popular practice of research using US PTO patent data, where often only the first class listed on the patent document, or *Original Classification* is used for the technological similarity calculations. However, the calculations based on the first class may not characterize the technological scope of the patent accurately and result in discarding useful information (Benner & Waldfogel 2008). Patents technological classes are not an ideal measure of relatedness; however, in our view, this approach is more appropriate than other alternatives. Citation of prior art is discretionary and may be used strategically by applicants to over or underreport (Nelson 2009) possible relatedness to previous patents. Moreover, it was never designed as a taxonomy (Aharonson & Schilling 2016). New approaches based on text mining of patent documents may be

¹¹As explained in PATSTAT data catalogue
[http://documents.epo.org/projects/babylon/eponot.nsf/0/75BDD8F5C4C66C33C125826700432260/\\$File/data_catalog_global_5_11_en.pdf](http://documents.epo.org/projects/babylon/eponot.nsf/0/75BDD8F5C4C66C33C125826700432260/$File/data_catalog_global_5_11_en.pdf) (accessed on 29/9/2018).

potentially useful; however, they require the development of keywords and their synonyms, typical for particular technological fields. Therefore, they were so far implemented mainly in narrow technological domains (Aharonson & Schilling 2016) rather than across the whole spectrum of manufacturing technologies we are interested in.

4.4 Comparison of inter-industry relatedness measure with Belderbos et al. (2013) matrix

There is no natural way of testing of the superiority of different knowledge flows matrices (Kaiser 2002). We can, however, compare our inter-industry technological relatedness matrix to some previous research approaches. Unfortunately, many of the matrices discussed above used old industry classifications that cannot be precisely converted to the NACE Rev. 2 which we use for the construction of our inter-industry relatedness matrix.

There is only one recent inter-industry relatedness measure developed on the basis of patent data by Belderbos et al. (2013) that we can use for the comparison with our results. Belderbos et al. (2013) calculated their inter-industry relatedness weights based on Leten et al. (2007). Leten et al. (2007) measured coherence between broadly defined technological fields based on the citations of patents classified in one technology field in the prior art of patents classified in other technologies. Those technological fields have been subsequently associated by Belderbos et al. (2013) with 21 industries on 2 or 3 digit level from Japan Standard Industrial Classification (JSIC)¹². In spite of differences between industrial classifications, we were able to translate JSIC industries to corresponding NACE Rev. 2 industries thanks to the correspondence table made available by Eurostat¹³. In the next step, we aggregated our baseline dataset on patent information to the same 21 industries as used in the paper of Belderbos et al. (2013).

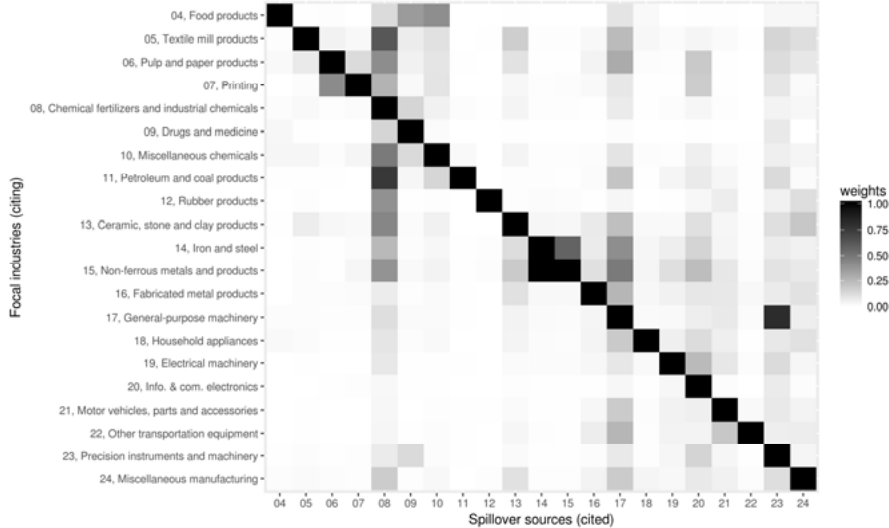
As the relatedness matrix of Belderbos et al. (2013) is developed on patent citation data, it is not symmetrical. The relatedness value between sector *i* as knowledge recipient and sector *j* as knowledge source may be different from a relatedness measure calculated for sector *j* as knowledge recipient and sector *i* as a knowledge source.

¹² http://www.soumu.go.jp/english/dgpp_ss/seido/sangyo/san07-3.htm.

¹³ http://ec.europa.eu/eurostat/ramon/other_documents/NACE_Rev2-JSIC_12/NACE_Rev2-JSIC_12.xls.

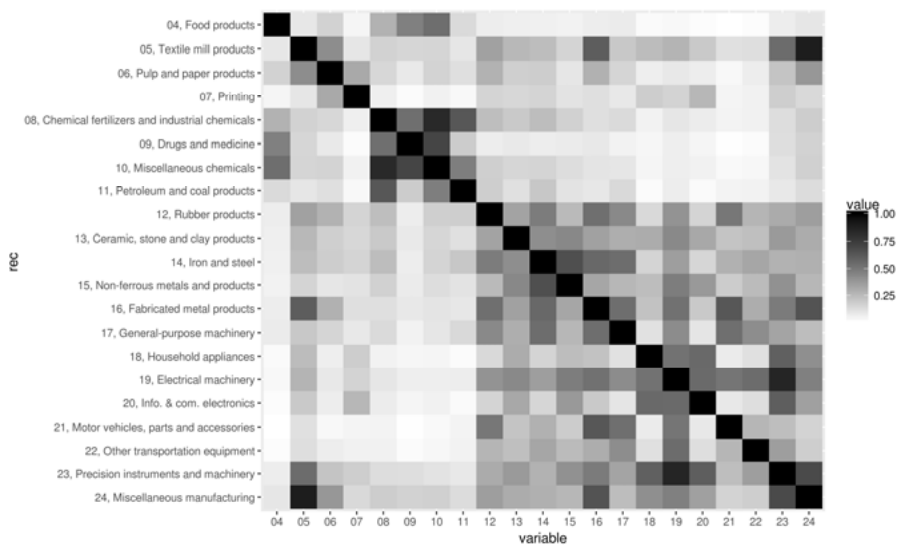
The correlation of weights between our and Belderbos et al. (2013) matrices yields a value of 0.69. We consider this value to be high, given that the compared matrices were calculated on the basis of different relatedness measures (IPC classes versus citations) and the latter measure is not symmetrical. As far as rank correlation is concerned, a Spearman rank correlation calculation yields a value of 0.50 for comparison of our matrix to the Japanese instrument for ranks calculated by rows (most important spillover sources by recipient industries) and the value of 0.61 for ranks calculated by columns (most important recipient industries by spillover source industries).

Figure 4.2 Heatmap of the inter-industry relatedness weights as computed by Belderbos et al. (2013)



Source: own calculations based on inter-industry relatedness matrix of Belderbos et al. (2013).

Figure 4.3 Heatmap of the inter-industry relatedness weights as computed from EPO patents using Jaffe proximity and aggregation aligned with Belderbos et al. (2013)



Source: own calculations based on inter-industry relatedness measure calculated by author as described in section 4.3.

4.5 Descriptive statistics

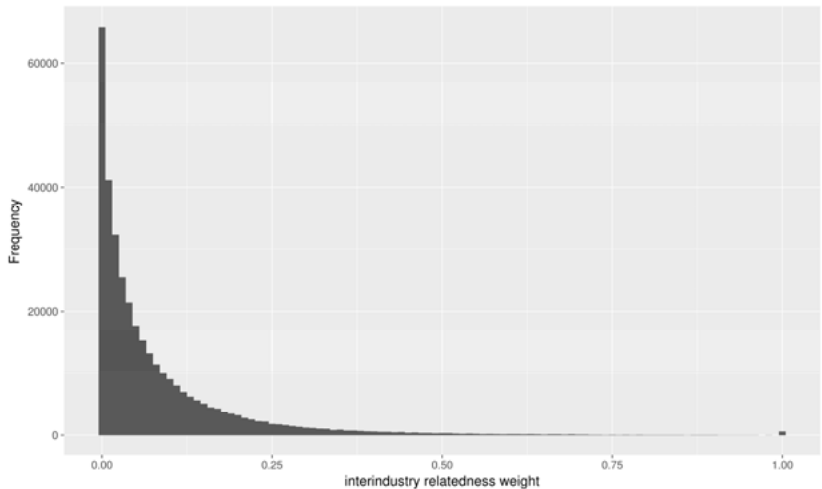
Table 4.3 presents summary statistics for inter-industry relatedness weights and table 4.4 presents the distribution of inter-industry relatedness weights. In general, the distribution of weights is highly skewed to the right. Low weights predominate. On average, for each NACE industry class, there are other 8 NACE classes with similarity weight equal to or higher than 0.5.

Table 4.3 Summary statistics for Jaffe similarity measure

| Statistic | N | Mean | Pctl(25) | Median | Pctl(75) | St. Dev. | Min | Max |
|-----------|------------|------|----------|--------|----------|----------|-----|-----|
| value | 350 464 | 0.08 | 0.01 | 0.04 | 0.1 | 0.12 | 0 | 1 |

Source: own calculations based on inter-industry relatedness measure calculated by author as described in section 4.3.

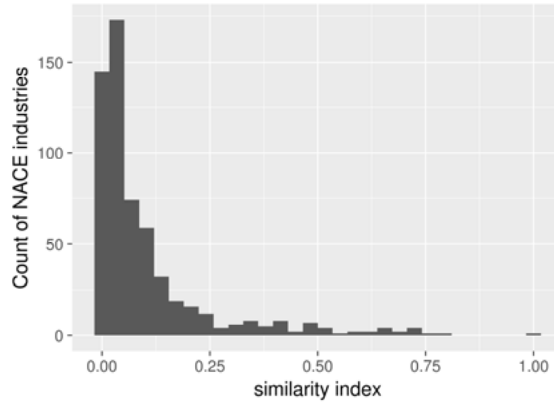
Figure 4.4 Distribution of inter-industry relatedness weights



Source: own calculations based on inter-industry relatedness measure calculated by author as described in section 4.3.

Figure 4.5 to Figure 4.8 and Table 4.4 to Table 4.7 present the distribution of weights and ranking of the 10 most similar NACE classes for four selected NACE industries: 10.13 Production of meat and poultry meat, 26.11 Manufacture of electronic components, 21.20 Manufacture of pharmaceutical preparations and 27.51 Manufacture of electric domestic appliances.

**Figure 4.5 Distribution of similarity weights for industry 10.13
Production of meat and poultry meat**



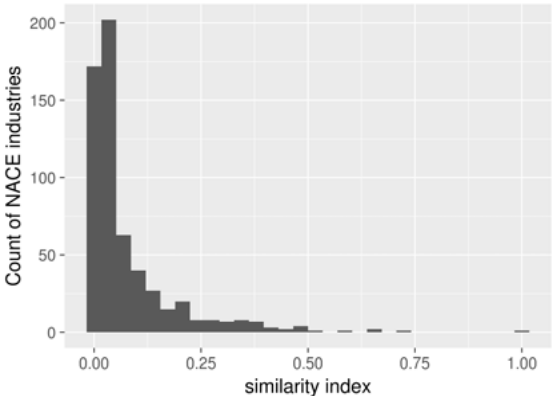
Source: own calculations based on inter-industry relatedness measure calculated by author as described in section 4.3.

**Table 4.4 10 industries with the highest similarities to industry
10.13 Production of meat and poultry meat**

| NACE | NACE description | Similarity index | Number of applications |
|------|-----------------------------------------------------------------------------------|------------------|------------------------|
| 1013 | Production of meat and poultry meat products | 1.00 | 82 |
| 1011 | Processing and preserving of meat | 0.81 | 21 |
| 1085 | Manufacture of prepared meals and dishes | 0.74 | 13 |
| 1039 | Other processing and preserving of fruit and vegetables | 0.74 | 68 |
| 1042 | Manufacture of margarine and similar edible fats | 0.73 | 14 |
| 1107 | Manufacture of soft drinks; production of mineral waters and other bottled waters | 0.73 | 45 |
| 1084 | Manufacture of condiments and seasonings | 0.73 | 35 |
| 1032 | Manufacture of fruit and vegetable juice | 0.68 | 13 |
| 1020 | Processing and preserving of fish, crustaceans and molluscs | 0.68 | 22 |
| 8730 | Residential care activities for the elderly and disabled | 0.67 | 4 |
| 1073 | Manufacture of macaroni, noodles, couscous and similar farinaceous products | 0.66 | 97 |

Source: own calculations based on inter-industry relatedness measure calculated by author as described in section 4.3.

Figure 4.6 Distribution of similarity weights for industry 26.11 Manufacture of electronic components



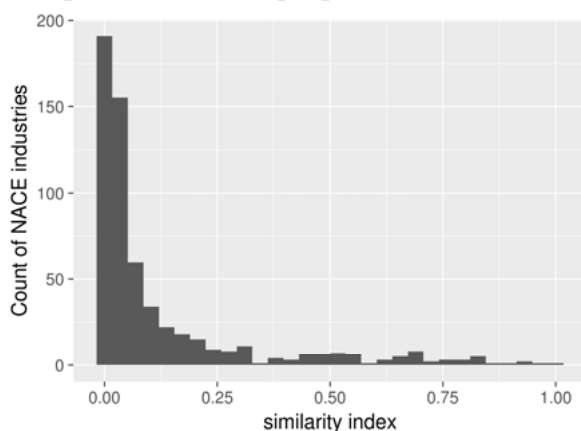
Source: own calculations based on inter-industry relatedness measure calculated by author as described in section 4.3.

Table 4.5 10 industries with the highest similarities to industry 26.11 Manufacture of electronic components

| NACE | NACE description | Similarity index | Number of applications |
|-------------|---------------------------------------------------------------------------------|------------------|------------------------|
| 2611 | Manufacture of electronic components | 1.00 | 15574 |
| 6311 | Data processing, hosting and related activities | 0.71 | 2750 |
| 6611 | Administration of financial markets | 0.67 | 97 |
| 1813 | Pre-press and pre-media services | 0.66 | 172 |
| 2651 | Manufacture of instruments and appliances for measuring, testing and navigation | 0.57 | 45886 |
| 2790 | Manufacture of other electrical equipment | 0.52 | 5680 |
| 8411 | General public administration activities | 0.50 | 124 |
| 8020 | Security systems service activities | 0.49 | 671 |
| 2751 | Manufacture of electric domestic appliances | 0.48 | 36353 |
| 2445 | Other non-ferrous metal production | 0.48 | 1099 |
| 7021 | Public relations and communication activities | 0.46 | 261 |

Source: own calculations based on inter-industry relatedness measure calculated by author as described in section 4.3.

**Figure 4.7 Distribution of similarity weights for industry 21.20
Manufacture of pharmaceutical preparations**



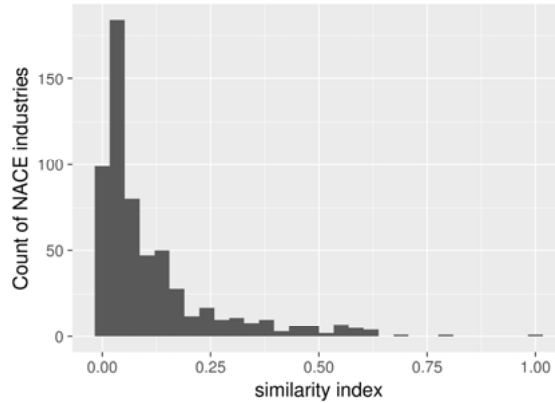
Source: own calculations based on inter-industry relatedness measure calculated by author as described in section 4.3.

**Table 4.6 10 industries with the highest similarities to industry
21.20 Manufacture of pharmaceutical preparations**

| NACE | NACE description | Similarity index | Number of applications |
|------|---------------------------------------------------------------------------------|------------------|------------------------|
| 2120 | Manufacture of pharmaceutical preparations | 1.00 | 31361 |
| 2110 | Manufacture of basic pharmaceutical products | 0.96 | 8208 |
| 4646 | Wholesale of pharmaceutical goods | 0.93 | 7319 |
| 7219 | Other research and experimental development on natural sciences and engineering | 0.91 | 26640 |
| 8690 | Other human health activities | 0.88 | 1928 |
| 8622 | Specialist medical practice activities | 0.86 | 60 |
| 8532 | Technical and vocational secondary education | 0.83 | 55 |
| 4762 | Retail sale of newspapers and stationery in specialised stores | 0.83 | 77 |
| 8542 | Tertiary education | 0.82 | 1761 |
| 4645 | Wholesale of perfume and cosmetics | 0.82 | 255 |
| 7490 | Other professional, scientific and technical activities n.e.c. | 0.82 | 12746 |

Source: own calculations based on inter-industry relatedness measure calculated by author as described in section 4.3.

**Figure 4.8 Distribution of similarity weights for industry 27.51
Manufacture of electric domestic appliances**



Source: own calculations based on inter-industry relatedness measure calculated by author as described in section 4.3.

**Table 4.7 10 industries with the highest similarities to industry
27.51 Manufacture of electric domestic appliances**

| NACE | NACE description | Similarity index | Number of applications |
|------|---------------------------------------------------------------------------------|------------------|------------------------|
| 2751 | Manufacture of electric domestic appliances | 1.00 | 36353 |
| 7740 | Leasing of intellectual property and similar products, except copyrighted works | 0.81 | 12587 |
| 6311 | Data processing, hosting and related activities | 0.70 | 2750 |
| 5911 | Motion picture, video and television programme production activities | 0.63 | 74 |
| 4651 | Wholesale of computers, computer peripheral equipment and software | 0.63 | 541 |
| 7112 | Engineering activities and related technical consultancy | 0.62 | 13161 |
| 7021 | Public relations and communication activities | 0.62 | 261 |
| 2651 | Manufacture of instruments and appliances for measuring, testing and navigation | 0.60 | 45886 |
| 1820 | Reproduction of recorded media | 0.60 | 105 |
| 6020 | Television programming and broadcasting activities | 0.60 | 94 |
| 6130 | Satellite telecommunications activities | 0.60 | 179 |

Source: own calculations based on inter-industry relatedness measure calculated by author as described in section 4.3.

4.6 Discussion and limitations

Inter-industry relatedness matrices have been used in the past to shed light on many important features of knowledge spillovers. Many matrices based on patent data used concordance tables developed on the basis of expert assessments of the relationship between patent classes and industry codes of patent assignees or potential users of patented technologies. So far, one of the major constraints for constructing inter-industry relatedness matrix based on co-occurrence of IPC classes was that IPC classes have been used to determine industries. In DG Concordance, IPC subclass is related to only one NACE industry and therefore there is no overlap between the vectors of subclasses in patent portfolios of firms representing different NACE industries. As we were able to assign NACE industries to patents directly, through the matching of PATSTAT with ORBIS, we are not constrained by this limitation. Although some alternatives based on the direct match between patents and firms' registers exist, to our knowledge, they were never used in the past for the construction of the inter-industry relatedness matrices. Therefore, our approach based on the direct match between patents and detailed 4-digit NACE industries, based on patent assignee names and firm names, can be an useful addition to the literature on knowledge spillovers.

The first advantage is that our matrix is not limited only to the manufacturing industries. To the extent that service firms are also involved in the development of patent-related innovation, technological similarities of service industries to manufacturing industries will also be captured in our method.

A further strength of our inter-industry relatedness measure is its granularity. Previous technology-based matrices described inter-industry relationships on a fairly aggregate level. The most fine-grained tables offered the possibility to analyse up to 30 industries. However, for some research questions, a more fine-grained level may be necessary. As suggested by Belderbos & Mohnen (2013) and as discussed in section 2.4, spillovers may be weak or even negative between firms with highly overlapping knowledge bases and between direct market competitors, as they have little to learn from each other. Similarly, Bloom et al. (2013) suggested that besides positive externalities from third parties' investment in knowledge, also some negative effects may appear due to the market stealing effects. Those complex relationships between knowledge externalities and market rivalry may be better controlled for by more detailed tables.

Finally, our inter-industry relatedness measure allows us to control for a more comprehensive pool of related knowledge. In empirical research, knowledge relatedness is often equated with knowledge similarity, while knowledge complementarity is ignored as a separate source of externalities (Makri et al., 2010). In this context, our measure of knowledge in the focal industry could be seen as a similar knowledge, while knowledge stocks contributed by related industries can be interpreted as complementary knowledge pools.

Recently, the need for better measurement of technological relatedness is revived within the concept of smart specialisation in the regional policy of the European Union. Regional economies benefit from the development of complex technologies that are highly specific and may not be easily emulated. Such competences should be built along related trajectories upon existing strengths of regions (Balland et al. 2018). Practical tools based on the relatedness concepts can potentially help regional decision makers to identify unused regional potentials and target public interventions into the related, promising activities (Boschma & Gianelle 2013). However, regional decision makers lack the theoretically grounded methodologies for identifying prospective industries and technologies they should be endorsing (Iacobucci & Guzzini 2016). Detailed analysis of technological relatedness between industries based on our empirical data may be a timely addition to the regional authorities' toolbox.

Some limitations of our approach should also be acknowledged. As documented in the present chapter, there exists an abundance of possible approaches to construct weights of knowledge flows between industries. This abundance is a reflection of the variety of possible channels through which knowledge flows may be transmitted (Mohnen 1997), so ideally spillover matrices should be sufficiently broad to capture correlated effects of different channels (Belderbos & Mohnen 2013). However, matrices, like ours, that consider only one aspect of relatedness between industries, even if more granular in comparison to previous research, are not likely to capture the whole richness of the technological relatedness.

Also, we built our inter-industry relatedness matrix on the fine-grained 4-digit industry classification using principal economic activity of the firm as reported in the business register. This method of industry assignation is aligned with the approach used to aggregate industry data by the statistical offices. However, firms may be active on several markets. In fact, the whole

research area, which focuses on the firms' diversification strategies, assumes that many firms do not limit their activity only to the principal sector they are associated with in the companies' registers. To some extent, possible biases stemming from our approach are reduced by matching individual establishments instead of the economic groups. Also, if there is some misalignment between industry codes and real activities of firms in our dataset, it will likely be reflected in higher technological relatedness weights between industries that are related not only by technologies but also market proximities.

5 Incumbents' innovation and entry¹⁴

5.1 Introduction

Entrepreneurship and creation of new firms are increasingly linked with economic growth. New firms have been recognized as important contributors to the evolution of the regional economic structures (Geroski 1991). High levels of entry are seen as a sign of economic vitality of regions (Lee et al. 2004). Support for new firm formation is put high in the priorities' lists of national and regional governments. Therefore, it is important to understand the factors that drive regional differences between the rates of new firm formation. Increasing attention is given to the impact of knowledge and innovation intensity of incumbents on new firm formation in close vicinity. Although regional innovation by incumbents is seen as an important source of entrepreneurial opportunities, to date empirical results to corroborate this view have been mixed (Knoben et al. 2011; Jofre-Monseny et al. 2011; Tsvetkova 2015). Those mixed results may be due to the lack of recognition of several important factors moderating impact of incumbents' knowledge stocks on entry. In the current study, we address these issues by distinguishing between local knowledge stocks in the focal industry and knowledge stocks in technologically related industries, by taking into account trade mark stocks of incumbents in the focal industry and by investigating subsets of entering firms and industries.

On the one hand, uncertainty, information asymmetries, and high transaction costs inherent to knowledge induce divergent views as regards its value, which may create new business opportunities for third parties (Malerba 2007; Christensen 2012; Acs et al. 2009; Acs et al. 2009). On the other hand, incumbent firms will aim to shield knowledge from direct rivals and potential entrants in order to increase appropriation (Belderbos & Somers 2015) and to improve their competitive position towards existing or potential competitors (Bloom et al. 2013). Knowledge externalities may occur in the *same* or closely *related* industries (Glaeser et al. (1992) - following the notion of agglomeration due to Marshall (1920), Arrow (1971) and Romer (1986)- or

¹⁴ This chapter is partially based on the paper Patents, Trademarks and New Firm Formation in European Regions by Michał Kazimierczak, René Belderbos and Micheline Goedhuys, submitted to a Special Issue on trade marks for possible publication in *Regional Studies*.

they may occur due to knowledge diversity across industries (Jacobs (1970), with so far little conclusive evidence on the most salient spillover mechanism (Beaudry & Schifffauerova 2009; Qian 2018).

This chapter contributes with an analysis of new firm formation across regions and industries in Europe to shed new light on these issues. We examine the differential impact of knowledge produced locally on new firms' formation depending on technological relatedness between industries and the appropriation strategies and market rivalry between incumbents and new firms. We also explore differences in the relationship between local knowledge conditions and entry depending on the R&D intensity of industries and type of entry.

This chapter is structured as follows. In section 5.2 we review the literature on firm entry, emphasizing literature linking local knowledge stocks with entry. In that section, we identify some important research gaps, that might blur the association between knowledge and entry in empirical research, discuss how they can be addressed and, based on that discussion, develop research questions. In section 5.3, we present our dataset and measurements. In section 5.4, we discuss the econometric methods we employ to answer our research questions and in section 5.5, we present robustness checks designed to corroborate our results with different specifications. We summarize our findings and discuss the contribution of our research in section 5.6, whereas in section 5.7, we highlight the main limitations of our data and identify research opportunities for the future.

5.2 Related literature and research questions

Given the vital role of new firm creation for economic development and its prominent role in the industrial policy, it has been a significant subject of economic investigation since at least the seminal contribution of Marshall (1920). In this section, we review the literature and motivate our research questions. In section 5.2.1, we present the extant economic theories on the antecedents of entry and new firm formation. Section 5.2.2 discusses the literature linking entry with innovation and knowledge spillovers. In section 5.2.3, we focus on the literature analysing the relative importance of spillovers from the same or related industries for entry. In section 5.2.4, we focus on those aspects of knowledge stocks and incumbents' strategic behaviour that may lead knowledge stocks in the form of patents to reduce rather than encourage entry. Finally, in section 5.2.5, we emphasize that knowledge stocks may have a different impact on entry depending on the

role of technological innovation in the industry and the type of entry (innovative vs non-innovative entrants).

5.2.1 Drivers of entry and location of business activity

Understanding the determinants of new firm startups has been at the core of Industrial Organisation literature. In a traditional view, entry is the result of a level of profitability in excess of the long-run equilibrium (Geroski 1991). New entrepreneurs enter the market to produce more of already existing homogenous goods, thereby restoring price and profit equilibria (Marshall 1920). A conventional theoretical approach to industrial geography based on neoclassical reasoning focuses on factors that allow for reducing the costs of manufacturing, such as costs of transportation (Hayter 1997). In this perspective, location matters because different locations offer different cost structures. Marshall (1920) argued that labour market pooling and input sharing contribute to the geographical concentration of industries. Labour market pooling (high density of employees with specific technical knowledge) facilitates the flow of the workers between firms by strengthening employer-employee matches. Relatively close distances from suppliers of raw materials reduce transportation costs. Krugman (1991) argued that due to increasing returns to scale, production in the manufacturing industries tends to be located in a limited number of regions. To save on transportation costs, *ceteris paribus*, producers will choose the sites associated with the highest demand for the final products. Neoclassical perspective renders the characteristics of individual firms as irrelevant as the most efficient location is selected by the competitive process (Hayter 1997).

Existence of favourable environments for a particular economic activity can be explained either by the natural advantages of some regions or historical chance (Arthur 1990). Shipyards are naturally concentrated close to the water bodies and mines are located near raw deposits. However, many clusters started from small historical events that triggered the path-dependent process of evolution creating an economic configuration favourable for certain economic activities.

While empirical studies found that entry rates are indeed relatively high in fast-growing and profitable industries and relatively low in industries where incumbents have absolute cost advantages or with high capital requirements (Lipczynski et al. 2005), entry is associated with much larger variation than profits, and entry rates are hard to explain by usual measures of profitability and entry barriers (Geroski 1995).

Alternative behavioural perspectives seek to incorporate individual factors, such as limited or uncertain information into the models of industrial location (Hayter 1997). The behavioural perspective acknowledges bounded rationality of decision makers. Their locational choices are made on the basis of information collected from the environment they are active in. In such perspectives, exogenous factors, including agglomeration economies, may be more important for the small businesses and new entrants who are more sensitive to the different types of externalities than for large incumbents who rely on internal networks that may operate over the larger distances (Glaeser & Kerr 2009).

5.2.2 Entry and knowledge spillovers

Increasingly agglomeration economies are linked to the benefits generated by knowledge spillovers. Knowledge spillovers have been recognized as an important factor spurring entry already by Marshall (1920). However, only after innovation and knowledge creation has grown to prominence in the modern theories of economic growth, scholars started to look into existing knowledge pools as one of the major factors facilitating new firm creation. In the KSTE theory knowledge spillovers from incumbents play a central role for the emergence of entrepreneurial opportunities (Acs et al. 2009) and creation of new firms is directly linked to knowledge created but not commercially exploited by incumbents (Acs et al. 2013). Given uncertain prospects of novel technologies and limited resources, even large incumbents will leave open some business opportunities related to knowledge for exploration and exploitation by other economic agents, thereby fostering entry of new firms.

Our analysis starts from the notion that knowledge spillovers occur and constitute an important source of new entrepreneurial ideas. We examine this by focusing on local knowledge stocks (patents) as an important determinant of new firm formation, explaining entry patterns across regions and industries. Our first research question is therefore:

Research question 1

Is entry positively related to higher levels of knowledge stocks in focal industries?

However, so far, the results of empirical research on the role of local knowledge stocks for firm entry has been mixed. The impact of regional knowledge stock on new firm formation was found either to be of minor importance or not confirmed at all (Knoben et al. 2011; Jofre-Monseny et al.

2011; Tsvetkova 2015). We posit that those mixed results might have been due to research gaps that may have blurred the association between knowledge and entry. In particular, we focus on three aspects that prior research has not sufficiently taken into account.

First, not all the knowledge is equally relevant for entrants. Knowledge produced by incumbents in other industries using different technologies will have no impact on entrepreneurs' decision to start a new firm. On the other hand, spillovers may cross-industrial boundaries, hence taking into account knowledge stocks from related industries, in addition to knowledge stocks from focal industry, is essential to study the association between knowledge and entry.

Second, innovating incumbents, creating the local knowledge stocks, may at the same time use strategies to increase appropriation of the returns from their own innovation and limit spillovers from their knowledge. This may discourage entry in the same industry and thus moderate the knowledge-entry relationship.

Third, local knowledge stocks may be relevant only for subsets of entrants. Indeed, the entrepreneurship literature distinguishes between *opportunity* and *necessity* entrepreneurship. While necessity entrepreneur enters the market out of necessity, due to a lack of other viable alternatives in the labour market and driven by adverse economic conditions (Fairlie & Fossen 2017), *opportunity* entrepreneur concept is akin to the *Schumpeterian entrepreneur* who enters the market with innovative products and services. Knowledge stocks may arguably be more important for the latter type of entrepreneurship. Hence the knowledge-entry relationship may be stronger for particular types of entries, such as for innovative entries, or for entry in industries with high importance of innovation or R&D.

5.2.3 Importance of technological relatedness of knowledge for entry

As discussed in section 2.4.2, not all the regional knowledge stocks are equally crucial for the potential recipients. Although geographical proximity is often taken into account in empirical research, cognitive proximity between knowledge available locally and entrants' activity is not easy to control for. Cognitive relatedness is, however, crucial for knowledge spillovers to occur, as it facilitates search, understating, processing and implementing new information (Boschma 2005). Knowledge spillovers are not limited to firms

active in the same product market. Extant research distinguishes between intra- and inter-industry knowledge spillovers and so far there is little evidence which types of spillovers are more critical for new firm formation.

On the one hand, Marshall (1920), Arrow (1971) and Romer (1986) hypothesize that the concentration of an industry enhances knowledge spillovers and promotes innovation in a region. In accordance with the Marshall-Arrow-Romer model formalized by Glaeser et al. (1992), knowledge externalities and spillovers occur mainly between firms active in the same or very similar industries. The arguments regarding the intra-industry strength of knowledge spillovers are shared by Porter (1990).

On the other hand, Jacobs (1970) claims that knowledge spillovers often occur between distinct industries and that they are more important to economic growth than intra-industry knowledge externalities. She argues that economic expansion occurs when novel features are added to the particular chunks of work within old technology. A diverse economic structure on a given territory fosters the exchange of knowledge between seemingly different industries, which share and recombine each other's ideas.

Our next research question is therefore:

Research question 2

Is entry positively related to higher levels of knowledge stocks in related industries?

5.2.4 Innovation, market rivalry and appropriation

Many agglomeration theories predict that the presence of a local pool of incumbents active in a certain industry is a factor that favours new entry in the same industry. However, empirical papers nuance these straightforward predictions. Innovating incumbents may fear of spillovers to competitors and engage in strategies signalling their determination to increase appropriation from their innovation and fencing-off potential leakage of knowledge. This may deter entry. In the presence of strong incumbents aggressively defending their market position, potential entrants may choose alternative economic activities. Avoiding direct competition with strong incumbents, they may prefer an employee status in existing organisations or setting up firms active in other markets or regions. The moderating impact of appropriation strategies on knowledge spillovers has been difficult to test empirically within the KSTE framework. However extant research suggests that it is an important factor that has to be controlled for.

Rosenthal & Strange (2003) indicate that employment in the same industry encourages entrepreneurs to start up, but the strength of this relationship is moderated by the regional corporate organization and industrial structure. Employment in small firms has a more positive impact on entry than employment in medium and large companies, which are better at appropriating their knowledge and use strategic tools to discourage entry and limit spillovers.

Given the high cost and importance of knowledge and innovation for competitiveness, incumbent firms will indeed aim to shield their knowledge and increase appropriation, to deter direct rivals and potential entrants (Belderbos & Somers 2015; Bloom et al. 2013). Belderbos & Somers (2015) confirm that potential technological spillovers may be conditional on the incumbent strategic behaviour. They showed that a high concentration of technology activities among regional incumbent firms and a strong degree of technology development internalization, including cross-border internalization, may discourage foreign R&D investors from setting up subsidiaries in the region. Faberman & Freedman (2016) found that relocating firms move rather to lower density metropolitan areas than regions with a higher density of firms in the same industry. Dumais et al. (2002) also conclude that entry acts as a factor reducing geographic concentration.

Trade marks may be strategically used by incumbents to increase entry costs for new firms and act as entry deterrent. There are strong theoretical arguments that trade marks complement and enhance patent protection (Rujas 1999; Thoma 2015; Llerena & Millot 2013). Trade marks are increasingly used as a proxy revealing companies' strategies and capabilities at commercialization activities (Castaldi 2018). Trade mark based variables, especially in conjunction with patents, are potentially good proxies for the incumbents' commercialization efficiency.

High intensity of trade marking in an industry is likely to raise additional barriers for entrants, reducing the attractiveness of knowledge. Intensive use of trade marks may thus act as an additional knowledge filter, limiting the benefits from the incumbent's knowledge stocks in the region. While trade marks, as an indicator of new products, may have a positive impact on the new firm formation, if employed by patenting incumbents aiming to enhance appropriation, they may reduce entrants' opportunities to exploit knowledge spillovers. This suggests a moderating impact of trade mark registration on

the relationship between focal industry patenting and new firm formation. Our next research question is therefore:

Research question 3

To what extent does trade mark activity by incumbents moderate the relationship between incumbent innovation (patenting activity) and new firm formation in the incumbents' industries?

While innovation and spillovers are likely to create entrepreneurial opportunities for new entrants, patented inventions and the associated intellectual property rights are also part of firms' appropriation strategy that may limit the exploitation of technological opportunities by entrants (Leten et al. 2016). We may expect that incumbents will be more active in appropriating the benefits of innovation in their core industries, and aim to limit spillovers and use their patent positions to challenge entry in these industries. This conduct will be less evident in the case of entry in related industries, as it does not directly affect the market position of incumbents. Hence, our next research question:

Research question 4

Are knowledge stocks in related industries stronger than knowledge stocks in the focal industry, as positive determinants of new firm formation?

5.2.5 Industry characteristics and type of entry

In our view, the KSTE has not given due attention to the fact that innovation and knowledge play a different role in different industries. In mature industries, with relatively low innovation activity, the competition between firms focuses mainly on cost of production. In such mature industries, incumbents have an advantage over potential entrants due to their experience and size. By contrast, knowledge may be more critical for entry in industries with relatively high innovation and R&D activity, where firms compete to introduce new products or new features to the existing products. Relatively higher knowledge stocks and innovation activity may contribute to higher uncertainty, helping young entrepreneurs to find their own niche in the industry (Bhide 2003). Higher knowledge stocks may be thus more related to entry in the context of high-tech than low-tech industries. Hence our next research question:

Research question 5

Are relevant knowledge stocks more important for entry in industries with high R&D intensity than in industries with low R&D intensity?

Similarly, the distinction between *necessity* and *opportunity* entrepreneurship is not well recognized within KSTE paradigm. Entry in the regions and industries with relatively higher knowledge stocks may be more attractive for innovative entrepreneurs than for those that focus mainly on producing standardized products already offered by incumbents. As predicted by KSTE, innovative entrepreneurs may be lured to enter the market by the possibility to build on and commercialize knowledge underutilized by incumbents, whereas *necessity* entrepreneurs may avoid regions and industries where strong, innovative incumbents are present. Therefore, models explaining general entry may not be able to give due attention to the importance of knowledge for innovative entry. Hence:

Research question 6

Are relevant knowledge stocks more important for entry of innovative entrepreneurs than for the entry more generally?

We will address these questions empirically in the following sections.

5.3 Measures and methods

In this section, we discuss how we operationalise and measure the main concepts of our analysis.

5.3.1 Dependent variable: New firm formation

The main outcome of interest and the dependent variable in our models is the number of newly established firms in any particular year t in a NUTS 3-region and 4-digit NACE industry. New entrants are identified on the basis of the date of incorporation, or establishment date, available at ORBIS. Firms with an establishment date between 01/01/2001 and 31/12/2009 have been assigned a *start-up* status for our analysis.

We account for the possibility that also necessity entrepreneurs are counted among the starters. We run separate models on entry of firms that subsequently file for patent, utility model and/or trade mark protection. For that purpose, we checked whether an entrant had filed the IPR application for patent, utility model or trade mark protection at national or European office until 2012. This enables us to distinguish between general and

innovative entry. We also reduce the likelihood of confounding opportunity with necessity entrepreneurship by limiting our sample to the manufacturing industries, which are characterized by higher capital requirements.

In the basic setup we do not distinguish between de novo entrepreneurs and spin offs from incumbents, however we introduce such a control in the models we run for robustness check of our results.

Our dependent variable is measuring gross entry in industry. Due to the limitations of the ORBIS database, we are not able to control precisely for the exit of firms from an industry and region. Even so, as a result of the granularity of our data (4 digit NACE industry and NUTS3 region), as seen in Table 5.1, the number of firms entering in a narrowly defined industry and region is relatively low and in many cases there is no entry activity at all. This is even more evident in the case of innovative entry.

5.3.2 Main variables of interest

Knowledge stocks

Our key variable of interest to explain entry is the presence of local knowledge stocks. As explained in chapter 3, we proxy local knowledge stocks by stocks of European patent applications, calculated for each NACE4/NUTS3 combination in our dataset. We associate patents with NUTS3 regions based on the address of inventors as reported in PATSTAT. We retrieve NACE industry codes from the ORBIS dataset after matching IPR and firm records on the basis of the patent assignee and company name strings (see chapter 3).

We distinguish between patent stocks of firms active in the same or *focal industry* of the entering firms and patent stocks of firms active in *related industries*. For the calculation of the stocks of related industries we use the inter-industry relatedness matrix described in chapter 4 using the following formula:

$$K_i = \sum_{j=1}^n w_{ij} K_j \quad (5.1)$$

where w_{ij} is an index of similarity between industries i and j and K_j represents the geographically weighted patent stock produced by incumbents active in industry j and located within focal NUTS 3 and neighbouring regions with centroid lying up to 200 km from the centroid of focal NUTS 3.

Trade mark activity of incumbents

Our trade mark stock variable is calculated in accordance with equation (3.2) based on the national trade mark data. In section 5.5.2, we present the robustness checks of our findings based on data on EUTMs.

Independently from being an innovation indicator, trade mark stocks may moderate the effects of technological knowledge stocks on entry. To empirically check the role of combining patents with trade marks' registration we construct an interaction term between the two (Jaccard & Turrisi 2003; Jaccard & Jacoby 2010).

5.3.3 Control variables related to technological regime

Contribution of young firms to the knowledge stock

As discussed by Winter (1984), technological regimes may have an important influence on the propensity to start new firms. Technological regimes have traditionally been analysed at the level of industry. However, Audretsch & Fritsch (2002) have shown that different innovative regimes exist at the level of industry/region. As discussed in section 2.4.1, the concept of innovative regime is a very broad one and it is hard to control for in our empirical setting. To control for some aspects of the type of the innovative regime predominant in a focal NACE/NUTS we created a variable measuring the contribution of young firms to the patent stock in year t . It is calculated in accordance with the following equation

$$i_{rit} = \frac{\sum_{c=1}^y p_i}{\sum_{c=1}^n p_i} \quad (5.2)$$

where i_{rit} is the contribution of young firms to the formation of knowledge stock in region r and industry i until year t ; y stands for a subset of patent applications filed by young firms, and n stands for all the patent applications; p_i is a patent filed by the applicant active in an industry i .

We define a firm as young when in year t it is 5 years old or younger, based on the information on its establishment date in the ORBIS database.

Contribution of universities to the knowledge stock

Similarly, a more significant contribution of universities to regional knowledge stocks may be beneficial for entrants. Supposedly, those

institutions are not so determined to fence-off their knowledge as firms. On the other hand, patents applied for by the universities may be further away from the commercialisation phase and therefore their knowledge stocks may be less relevant for entrants looking for the opportunities of spillovers. To control for this aspect, we created an additional variable for the contribution of universities to the regional knowledge stock. It is calculated as follows:

$$s_{rt} = \frac{\sum_{c=1}^u p}{\sum_{c=1}^n p} \quad (5.3)$$

Where s_{rt} is a contribution of universities¹⁵ to the knowledge stock available in region r and time t , u stands for a subset of patent applications filed by universities and n stands for all the patent applications. Variable p stands for an individual patent.

Overall industry growth

Entrepreneurs may be induced to entry by super-normal profits and enter predominantly into fast-growing industries. To control for that aspect we include in our models an output growth variable calculated from national accounts data available in Eurostat, mainly on the level of NACE divisions (2-digits).¹⁶

5.3.4 Controls for agglomeration economies

As explained in the literature section, agglomeration economies are one of the most critical factors determining firm locations. Omission of proxies for agglomeration may lead to an overestimation of the strength of the regional knowledge base (Knoben et al. 2011). We follow a comprehensive review of variables used in location choice models by Arauzo-Carod et al. (2010) to select variables that can account for agglomeration economies, other than knowledge spillovers. These are:

¹⁵ We determined the type of patent applicant based on the PSN_SECTOR field of PATSTAT. For calculation of this variable we took into account patents associated with category: *university*.

¹⁶ Output measured in current prices sourced from national accounts aggregates by industry (up to NACE A*64) table- nama_10_a64.

Number of incumbents

The logarithm of the number of incumbent firms (establishment year prior to year t or no establishment year available) active in focal NACE4d industry - NUTS 3 region, as retrieved from ORBIS.

Buyers' and suppliers' fit

As discussed in section 5.2.1, some locations may be characterised by an economic structure particularly suited for the given economic activity. The presence of supplier and buyer industries in the local vicinity may additionally spur entry as they may reduce the costs of manufacturing firms, such as transportation costs. Therefore, models explaining entry should also control for this aspect of the regional economies.

We use national input-output table available in Eurostat¹⁷ to construct both control measures. Input-output tables are prepared on a higher level of granularity than our data (on 2 digit NACE level with some industries grouped into broader industry classifications). Therefore, each 4 digit industry in our set has been assigned to the industry group corresponding to the higher aggregation level of the input-output table.

We also use industry employment data sourced from national accounts' employment data also available at Eurostat¹⁸. It has the same sectoral aggregation scheme as the input-output table, however industrial employment data is available only on the national level. We have distributed national industry employment across regions (NUTS 3) in accordance with the proportion of incumbents in those regions¹⁹, with the following formula.

$$E_{irt} = E_{int} * \frac{N_{irt}}{N_{int}} \quad (5.4)$$

¹⁷ Symmetric input-output table at basic prices (industry by industry)- table naio_10_cp1750. For our purposes we use input-output table computed for Italy in 2010 as it is the most detailed one and has the lowest number of missing values.

¹⁸ National accounts employment data by industry (up to NACE A*64)- table nama_10_a64_e.

¹⁹ For compatibility with our measure of knowledge stocks we have calculated employment for the broader focal NUTS3+ regions located within 200 km from focal NUTS3 region centroid using the same weight based on geographical distance. Wherever we refer to a region in our description of the customers' and suppliers' fit measures we mean those broader NUTS3+200km regions.

Where E_{irt} and E_{int} are employment in the industry i at time t in the NUTS3 region r and in the entire country n respectively and N_{irt} and N_{int} stand for a number of firms in an industry i and year t respectively in the NUTS3 region r and in the entire country n .

Following Dumais et al. (2002) we define product customer fit using the following formula

$$Output_{rit} = \sum_{j \neq i} O_{ji} * \frac{E_{jrt}}{E_{rt}} \quad (5.5)$$

Where O_{ji} is the share of industry i 's outputs that are purchased by industry j . E_{jrt} is employment of industry j in region r in year t and E_{rt} is total employment in the region r .

Similarly we calculate suppliers' fit as follows

$$Input_{rit} = \sum_{j \neq i} I_{ji} * \frac{E_{jrt}}{E_{rt}} \quad (5.6)$$

Where I_{ji} is the share of industry i 's inputs that are sold by industry j . E_{jrt} is employment of industry j in region r in year t and E_{rt} is total employment in the region r .

Population density

As a measure of urbanization, we use *Population density by NUTS 3 regions (inhabitants per square km)*²⁰. A positive effect of this variable on new firm formation would indicate that more urbanized regions are more attractive for entrants.

Share of population with secondary and tertiary education

The variable presents the highest level of education completed by the individuals of a given population. When determining the highest level, both general and vocational education is taken into consideration. The variable used in the models is *ED3-8- Upper secondary, post-secondary non-tertiary and*

²⁰ retrieved from Eurostat table *demo_r_d3dens*. Table contains some missing data for some regions in some years. We have imputed missing data based on the NUTS 3 area and population data available in Eurostat.

tertiary education, corresponding to the levels 3-8 of the International Standard Classification of Education (ISCED) 2011²¹.

5.3.5 Other control variables

Unemployment

Unemployment data is available from Eurostat²² and based on the EU Labour Force Survey (EU-LFS). The unemployment rate shows unemployed persons as a percentage of the economically active population.

GDP per capita- and growth of GDP per capita

We use this as a broad economic indicator of living standards and changes therein. The data are taken from Eurostat and expressed in purchasing power standards (PPS) to eliminate differences in price levels between countries²³. We constructed the variable of growth of GDP per capita from Eurostat data taking the log-differences between values of GDP per capita in year t-1 and year t.

²¹ Educational attainment data are available from Eurostat table edat_lfse_04 – “Population aged 25-64 by educational attainment level, sex and NUTS 2 regions (%)”. The availability of data for educational attainment varies depending on country. For example educational attainment data is not available for Danish regions before 2007. Until then only the aggregated country data was delivered to Eurostat by Danish authorities.

²² table lfst_r_lfu3rt- “Unemployment rates by sex, age and NUTS 2 regions (%)”.

²³ table nama_r_e3gdp “Gross domestic product (GDP) at current market prices by NUTS 3 regions”. Since the first year available in Eurostat for this variable was 2000, calculation of the GDP growth variable was possible only starting from 2001. Ideally, we could have used a lagged value of both variables, but it would limit further the number of annual observations in our models. We ran additional robustness check on our main model and the differences for our main variables of interest were minimal. Therefore, we report the results with unlagged variables controlling for GDP per capita and GDP per capita growth.

Table 5.1: Descriptive statistics for variables used in the models

| Statistic | N | Mean | St. Dev. | Min | Max |
|-----------------------------------------------------------|-----------|-------|-------------|--------|--------|
| Number of startups in NACE4 and NUTS3 | 1,937,800 | 0.19 | 1.272 | 0 | 307 |
| Number of innovative startups in NACE4 and NUTS3 | 1,937,800 | 0.014 | 0.143 | 0 | 17 |
| Number of independent startups in NACE4 and NUTS3 | 1,937,800 | 0.174 | 1.231 | 0 | 306 |
| Log of incumbents' number in NACE4 and NUTS3 (lag 1) | 1,937,800 | 0.765 | 1.012 | 0 | 8.285 |
| Log of patent stock in focal industry (lag 1) | 1,937,800 | 0.248 | 0.549 | 0 | 8.746 |
| Log of patent stock in related industries (lag 1) | 1,937,800 | 2.742 | 1.17 | 0 | 8.38 |
| Log of trade mark stocks in focal industry (lag 1) | 1,937,800 | 0.645 | 0.878 | 0 | 8.392 |
| Contribution of young firms to knowledge stock (lag 1) | 1,937,800 | 0.032 | 0.163 | 0 | 1 |
| Contribution of universities to knowledge stock (lag 1) | 1,937,800 | 0.053 | 0.112 | 0 | 1 |
| Buyers' fit (lag 1) | 1,937,800 | 0.002 | 0.99 | -1.934 | 7.296 |
| Suppliers' fit (lag 1) | 1,937,800 | 0.001 | 0.942 | -2.206 | 17.498 |
| Industry growth (NACE2, lag 1) | 1,937,800 | 0.029 | 0.073 | -0.331 | 0.857 |
| Unemployment level | 1,937,800 | 0.077 | 0.041 | 0.012 | 0.26 |
| Log of GDP per capita in the region (PPS) | 1,937,800 | 9.992 | 0.329 | 8.455 | 11.316 |
| Growth of GDP per capita in the region (PPS) | 1,937,800 | 0.019 | 0.05 | -0.315 | 0.343 |
| Share of population with secondary and tertiary education | 1,937,800 | 0.718 | 0.149 | 0.16 | 0.97 |
| Log of population density | 1,937,800 | 5.391 | 1.265 | 1.932 | 9.964 |

Source: own calculations based on the dataset compiled by author as explained in section 5.3.

Table 5.2: Correlation matrix for variables used in the models

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 |
|--------------------------------------------------------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|------|
| 1.Number of startups (NUTS3/NACE4) | | | | | | | | | | | | | | | | |
| 2.Number of innovative startups (NUTS3/NACE4) | 0.41 | | | | | | | | | | | | | | | |
| 3.Number of independent startups (NUTS3/NACE4) | 0.99 | 0.39 | | | | | | | | | | | | | | |
| 4. Log of incumbents' number in NACE4 and NUTS3 (lag 1) | 0.38 | 0.21 | 0.37 | | | | | | | | | | | | | |
| 5.Log of patent stock in focal industry (lag 1) | 0.07 | 0.08 | 0.06 | 0.27 | | | | | | | | | | | | |
| 6.Log of patent stock in related industries (lag 1) | 0.05 | 0.03 | 0.04 | 0.20 | 0.39 | | | | | | | | | | | |
| 7.Log of trade mark stocks in focal industry (lag 1) | 0.23 | 0.20 | 0.22 | 0.55 | 0.39 | 0.19 | | | | | | | | | | |
| 8.Contribution of young firms to knowledge stock (lag 1) | 0.07 | 0.05 | 0.06 | 0.18 | 0.29 | 0.17 | 0.14 | | | | | | | | | |
| 9.Contribution of universities to knowledge stock (lag 1) | 0.01 | 0.00 | 0.01 | 0.00 | -0.09 | -0.29 | -0.02 | -0.04 | | | | | | | | |
| 10.Buyers' fit (lag 1) | 0.00 | 0.01 | 0.00 | 0.01 | -0.01 | -0.09 | 0.01 | -0.01 | 0.03 | | | | | | | |
| 11.Suppliers' fit (lag 1) | -0.01 | 0.04 | -0.01 | 0.03 | 0.13 | 0.01 | 0.22 | 0.04 | -0.03 | 0.20 | | | | | | |
| 12.Industry growth (NACE2, lag 1) | 0.00 | 0.01 | 0.00 | -0.01 | 0.03 | -0.03 | 0.00 | 0.01 | 0.01 | 0.08 | 0.08 | | | | | |
| 13.Unemployment level | -0.01 | 0.00 | -0.01 | -0.06 | -0.06 | -0.25 | -0.06 | -0.03 | 0.14 | 0.04 | -0.03 | 0.01 | | | | |
| 14.Log of GDP per capita in the region (PPS) | 0.03 | 0.03 | 0.03 | 0.11 | 0.13 | 0.45 | 0.12 | 0.07 | -0.17 | -0.07 | -0.05 | -0.05 | -0.37 | | | |
| 15.Growth of GDP per capita in the region (PPS) | 0.01 | 0.01 | 0.01 | -0.02 | -0.03 | -0.09 | -0.03 | -0.01 | 0.01 | 0.00 | 0.01 | 0.15 | 0.04 | -0.03 | | |
| 16.Share of population with secondary and tertiary education | -0.08 | -0.07 | -0.08 | -0.13 | 0.09 | 0.35 | -0.20 | 0.04 | -0.17 | -0.14 | -0.13 | -0.03 | -0.05 | 0.09 | 0.00 | |
| 17.Log of population density | 0.04 | 0.02 | 0.04 | 0.11 | 0.08 | 0.29 | 0.02 | 0.07 | -0.09 | -0.10 | -0.08 | -0.10 | -0.14 | 0.50 | -0.05 | 0.16 |

Source: own calculations based on the dataset compiled by author as explained in section 5.3.

5.4 Main model estimation

5.4.1 Econometric specification

The dependent variable (number of firms entering the market in NACE4 industry, NUTS3 region in year t) is a count variable that takes only non-negative integer values. In cases of modelling such data, linear regression modelling is inadequate (Cameron & Trivedi 2005; Kennedy 2008; Wooldridge 2010). The proper modelling approach for count variables is based on a Poisson distribution, which is parametrized in terms of a single parameter (μ) and all moments of function y are a function of only this parameter (Cameron & Trivedi 2005). The Poisson distribution assumes equidispersion- equality of mean and variance.

However, our data is characterised by a large overdispersion. Whereas the mean number of start-ups in NACE4 industry, NACE3 region in year t is 0.19, its variance amounts to 1.62. The consequences of overdispersion, in this case, are comparable to the failure of the assumption of homoscedasticity in the linear regression model (Cameron & Trivedi 2005). Whereas the coefficients of the model are consistent, standard errors are grossly deflated. As a result, t -statistics are inflated and may lead to false statistical significance conclusions. Similarly, an underestimation of the frequency of zeros results in estimates that are inconsistent. Overdispersion and an excess of zero observations are the result of unobserved heterogeneity in the conditional mean parameter (Mullahy 1997).

In many empirical applications focused on the location of new firms, the equidispersion assumption is too restrictive (Arauzo-Carod et al. 2010). The adequate strategy in such circumstances is to account for the bias in the standard errors by using robust or clustered standard errors. We apply robust variance adjustment to the data to reflect the fact that observations are not independent. Modified variance estimators allow for inference that is robust to within regions (NUTS3) correlation. Poisson regression with empirical standard errors is often used adjustment for overdispersion, or any other type of excess correlation within data (Hilbe 2014). In order to check whether the main model is not overdispersed, after estimating the main model with clustered standard errors, we calculated the Pearson test statistics (Hilbe 2014). In the case of our main model, the Pearson dispersion statistics amounts to 1.047. Based on this test, we conclude that by applying clustered standard errors overdispersion has been eliminated from our model.

A fixed effect specification is a very interesting option for econometric modelling of panel data as it allows controlling for unobserved variables that are fixed over the analysed period. The basic unit of observation of our dependent variable is the NUTS 3 region- NACE 4-digit industry. However, for many such combinations, we observe zero entries with no existing incumbents. We also may observe entries into new industries, not previously present in the region. Therefore, using the unconditional fixed effects specification for our models is not adequate. Instead, following Glaeser&Kerr (2009), we control for NUTS 3 region, NACE 4 digit industry and years fixed effects by using dummy variables, conditioning the fixed effects out of our models (Allison 2009).

5.4.2 Results

Main model

Table 5.3 presents the results of the basic estimations of entry into manufacturing industries. The first column shows a model with focal variables for patent stocks, in own and related industries (model 1). To that model, are added: the trade mark stocks in the own industry (model 2) and the interaction of patent and trade mark stocks in the own industry (model 3).

The first model suggests that mainly patent stocks in related industries have a positive effect on entry. The coefficient of patent stocks in related industries implies that a 10% increase in related patent stocks results in a 0.9% increase in the number of entrants. The relationship between entry and patent stocks in the focal industry is much weaker and statistically significant only at the 90% confidence level.

Table 5.3 Results of the Poisson regression models

| <i>Dependent variable: number of new firms NACE4d/NUTS3</i> | | | |
|--------------------------------------------------------------------|--------------------------------|-----------------------------------------|--------------------------------|
| | (1) | (2) | (3) |
| Log of patent stock in focal industry (lag 1) | 0.019 [†] (0.010) | 0.016 (0.011) | 0.081*** (0.016) |
| Log of patent stock in related industries (lag 1) | 0.087*** (0.020) | 0.086*** (0.019) | 0.079*** (0.019) |
| Log of trade mark stocks in focal industry (lag 1) | | 0.007 (0.008) | 0.017 [†] (0.010) |
| Interaction between patent and trade mark stocks in focal industry | | | -0.019*** (0.004) |
| Contribution of young firms to knowledge stock (lag 1) | 0.073*** (0.022) | 0.073*** (0.022) | 0.064*** (0.022) |
| Contribution of universities to knowledge stock (lag 1) | 0.056 (0.077) | 0.056 (0.077) | 0.055 (0.078) |
| Log of incumbents' number (lag 1) | 0.925*** (0.007) | 0.921*** (0.009) | 0.920*** (0.009) |
| Buyers' fit (lag 1) | 0.006 (0.011) | 0.006 (0.011) | 0.005 (0.011) |
| Suppliers' fit (lag 1) | 0.017 [†] (0.009) | 0.017 [†] (0.009) | 0.015 (0.009) |
| Industry growth (NACE2, lag 1) | 0.467*** (0.056) | 0.467*** (0.056) | 0.459*** (0.056) |
| Log of GDP per capita in the region (PPS) | -0.087 (0.089) | -0.088 (0.089) | -0.088 (0.089) |
| GDP per capita growth in the region (PPS) | 1.082*** (0.109) | 1.080*** (0.109) | 1.083*** (0.109) |
| Unemployment level | -0.164 (0.324) | -0.160 (0.323) | -0.144 (0.322) |
| Share of population with secondary and tertiary education | -0.610** (0.289) | -0.612** (0.290) | -0.572** (0.290) |
| Log of population density | -0.361** (0.164) | -0.364** (0.165) | -0.339** (0.161) |
| Constant | -2.024 [†] (1.190) | -1.993 [†] (1.197) | -2.115 [†] (1.192) |
| Regional (NUTS 3) fixed effects | Yes | Yes | Yes |
| Industry (NACE 4) fixed effects | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes |
| Observations | 1,937,800 | 1,937,800 | 1,937,800 |
| McFadden pseudo R2 | 0.592 | 0.5920 | 0.5921 |
| Akaike Inf. Crit. | 1,143,014 | 1,143,009 | 1,142,847 |
| <i>Note:</i> | | [†] p<0.1; **p<0.05; ***p<0.01 | |

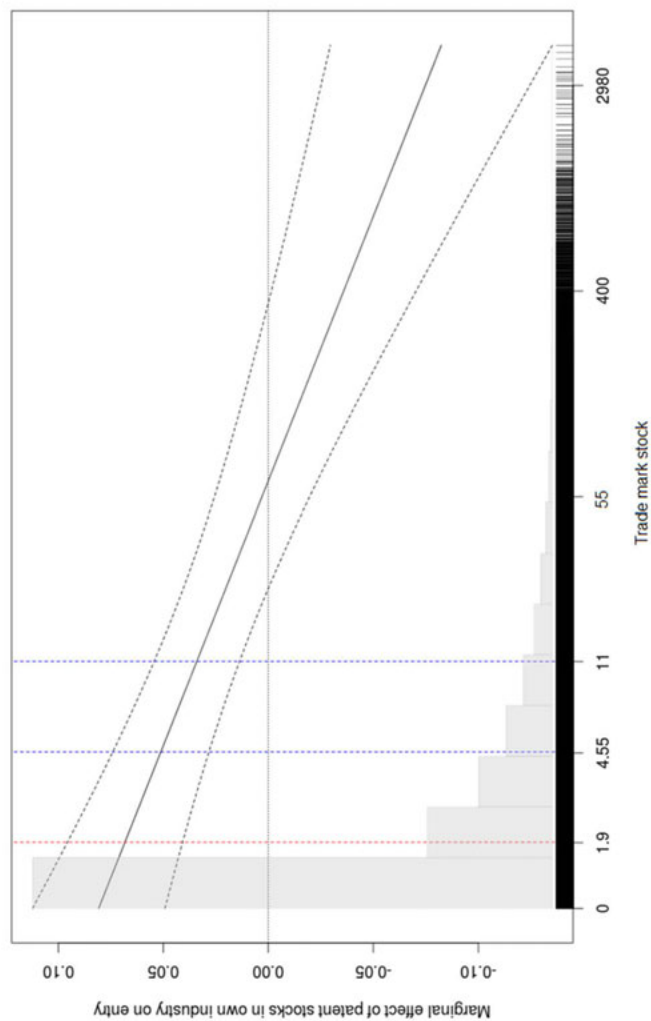
Adding trade mark stocks in focal industry variable in model 2 does not radically change the picture. The coefficient of the knowledge stocks in related industries remains positive and statistically significant and its magnitude is the same as in the first model. The coefficient of the knowledge stocks in the own industry remains non-significant and its magnitude barely differs from model 1. Interestingly the coefficient for trade mark stocks in the own industry is not statistically significant.

Model 3 reveals that appropriation strategies of incumbents are crucial for the strength of knowledge spillovers as a trigger for entry. When the interaction variable between patents and trade marks is added to the model, the difference between the coefficients of own and related knowledge stocks disappears: patent stock in the focal industry contribute significantly when trade mark stocks are at zero. The results of the model imply that when trade mark stocks of incumbents are kept at zero, a 10 percent increase of the patent stock of own industry results in a 0.8 percent higher entry at each level of other variables included in the model. The main effects of incumbents' trade mark stocks are positive, but the coefficient of trade mark stocks is much lower in comparison with patent stocks. It is also statistically significant at 90% confidence level only. Results of these estimations allow us to answer positively to our research question 1, which concerned the relationship between entry and knowledge stocks in the focal industry. Entry rates are positively related to higher levels of knowledge stocks in the focal industry at relatively lower levels of trade mark activity of incumbents.

Our research question 2 focuses on the association between knowledge stocks in related industries and entry. Our results indicate that knowledge stocks accumulated by incumbents active in related industries are also positively associated with entry. When examining entry in manufacturing industries with the trade mark stocks of incumbents active in the focal industry held at zero, the influence of focal and related knowledge stocks on entry is almost equal.

The coefficient of the interaction variable confirms that trade mark stocks of incumbents negatively moderate the impact of patent stocks on entry. As shown in Figure 5.1, on average, when the stock of incumbents' trade marks reaches approximately 70 trade marks, the relationship between additional patent applications and entry becomes negative.

Figure 5.1 Relationship between patent stocks and entry for different levels of trade mark stocks



Note: red dashed line corresponds to mean value of log transformed stock of trade marks, blue lines correspond to mean+ standard deviation and mean - 2 x standard deviation value of log transformed stock of trade marks;
Source: own calculations based on model 3 in Table 5.3.

In research question 3 we were inquiring about the possibility of incumbents' trade mark stocks to negatively moderate the positive relationship between incumbents' knowledge stocks in the focal industry and entry. The results presented in Table 5.3 indicate that higher intensity of trade marking reduces the positive impact of knowledge stocks in focal industry on entry and, with intensive trade mark activity of incumbents, it may turn negative. So, the potential benefits of locating close to the innovating incumbents are reduced by their more intensive strategic efforts to appropriate knowledge stocks and protect them from potential spillovers.

Our research question 4 concerned the relative importance of knowledge stocks in focal and related industries for entry. As already discussed above, we were able to confirm that incumbents in the focal industry may use trade marks to restrict the positive externalities from knowledge, such that knowledge stocks in related industries may, in general, be more important for entry than knowledge stocks in the focal industry. Models 1 and 2 of Table 5.3, where the moderating effect of incumbents' trade mark stocks is not controlled for, suggest that knowledge stocks in a focal industry is not related with entry. However, as shown in model 3 of the Table 5.3 it is mainly higher appropriation of those knowledge stocks by incumbents, as proxied by the simultaneous use of trade mark stocks, that makes focal industry knowledge stocks less important than related knowledge stocks.

An analysis of the control variables related to technological regime indicates that, as expected, the higher the share of young firms in the patenting activity in a region and industry, the higher is the entry activity. On the other hand, a higher contribution of universities to the relevant patent stocks in the region does not translate into higher entry activity.

Agglomeration economies are critical for entry. The number of incumbents within the focal NACE4d industry- NUTS3 region has a strong positive effect on the number of firms entering the market. The coefficient of this variable is positive, with elasticity just under 1. Surprisingly, other factors often associated with localization advantages, such as population density and the level of education, are negatively related to firm formation and the relevant coefficients are statistically significant. In their comprehensive review of empirical studies of industrial location, Arauzo-Carod et al. (2010) noticed that in empirical studies the relationship between population density and education attainment of a region on the one hand, and entry, on the other hand, is mixed. Especially in studies analysing entry into manufacturing

industries, the coefficient of population density in some previous studies was negative. Conversely, the coefficient of the population density tended to be positive in empirical studies focused on entry into high technological sectors. As explained by Frenken et al. (2007) population density may be interpreted as a measure both of agglomeration economies and diseconomies such as cost of land, labour and negative externalities from congestion. Those negative externalities may be especially crucial for entry of firms in the low-tech and mature industries where firms compete mainly by prices. On the other hand, positive externalities of urbanization may be more important for entry of innovative firms and firms in the high-tech industries.

For educational attainment, an explanation for a negative association with entry may be that it is correlated with higher knowledge stocks, which are already controlled for in our models by other variables directly measuring available knowledge pools. Additionally, in our models, we do not control for salaries. Hence, the negative sign of the educational attainment variable may reflect possible negative effects of higher wages in the region that are correlated with the level of education (Bartik 1985, Arauzo Carod 2005) ²⁴

As could be expected, cyclical factors have a statistically significant impact on entry. Both, increases in GDP per capita in the region and industry growth are positively related to entry, although the magnitude of both coefficients is lower than the magnitude of coefficients for patent variables. The coefficient of growth of GDP per capita is twice as high as the coefficient of industry growth.

Models on entry into high tech versus low tech manufacturing industries

Incumbent innovations may be an important source of entrepreneurial opportunities in the industries with high levels of innovation, whereas they do not play such an important role in more traditional industries, where the level of innovation is low. In addition, some innovations are not patentable at all and, in some circumstances, it is more profitable for firms to protect their innovations with other, often informal means. The nature of innovation

²⁴ Both population density and the educational attainment are measured at the level of the region (NUTS3 or NUTS2) with little annual variation. Since we control for region fixed effects, the influence of these variables may be difficult to identify correctly. We note that the significant effect of educational attainment is not robust, and disappears in models in which the GDP variables are lagged.

in some industries makes intellectual assets more prone to be protected by patents than in other industries.

To account for the possible differential impact knowledge stocks may have for entry, depending on the industry, we estimate separate models in two different sets of industries, grouped by the R&D intensity²⁵.

Table 5.4 presents models of entry estimated on two separate datasets. The first model shows the results of the estimations on data limited to high tech industries while the second model presents the results of low tech industries. Industries grouped by Eurostat into two medium technology groups: medium-high technology and medium-low technology have been disregarded in this model.

As shown in Table 5.4, entry into high-tech industries is more strongly related with patent stocks in the focal industry in comparison with the main model estimated for all manufacturing industries, and in particular, comparing to entry in low-tech industries. However, the relationship between patent stocks in related industries and entry is non-significant in high-tech industries.

On the other hand, in low-tech industries, patent stocks in the focal industry are not significant for entry. Knowledge stocks accumulated by incumbents active in related industries are positively related to entry. Neither knowledge stocks in the own industry, trade mark stocks nor the interaction of both are related to entry. The coefficients of those variables are not statistically significant.

²⁵ Respective groups of industries are defined by Eurostat according to technological intensity. For our estimation we used Eurostat definitions on 3-digit level as explained on the webpage https://ec.europa.eu/eurostat/statistics-explained/index.php/Glossary:High-tech_classification_of_manufacturing_industrie (accessed on 10/06/2019).

Table 5.4 Results of the Poisson regression models- estimation for sectors grouped on the basis of R&D intensity of industries

| <i>Dependent variable: number of new firms NACE4d/NUTS3</i> | | |
|--------------------------------------------------------------------|-----------------------------|----------------------|
| | High-tech (1) | Low-tech (2) |
| Log of patent stock in focal industry (lag 1) | 0.222*** (0.024) | -0.048 (0.051) |
| Log of patent stock in related industries (lag 1) | -0.062 (0.046) | 0.088*** (0.031) |
| Log of trade mark stocks in focal industry (lag 1) | 0.119*** (0.019) | 0.007 (0.013) |
| Interaction between patent and trade mark stocks in focal industry | -0.044*** (0.007) | 0.005 (0.015) |
| Contribution of young firms to knowledge stock (lag 1) | 0.153*** (0.033) | 0.117** (0.047) |
| Contribution of universities to knowledge stock (lag 1) | 0.029 (0.260) | 0.106 (0.107) |
| Log of incumbents' number (lag 1) | 0.661*** (0.025) | 0.951*** (0.012) |
| Buyers' fit (lag 1) | 0.045 (0.065) | -0.111*** (0.020) |
| Suppliers' fit (lag 1) | -0.091 (0.087) | 0.013 (0.010) |
| Industry growth (NACE2, lag 1) | 0.144 (0.132) | 0.751*** (0.105) |
| Log of GDP per capita in the region (PPS) | 0.659** (0.274) | -0.217** (0.109) |
| GDP per capita growth in the region (PPS) | 0.484 (0.382) | 1.165*** (0.155) |
| Unemployment level | 0.440 (0.637) | 0.688* (0.409) |
| Share of population with secondary and tertiary education | -0.320 (0.763) | -0.776* (0.406) |
| Log of population density | 1.159** (0.485) | -0.200 (0.160) |
| Constant | -28.534*** (3.715) | -2.111 (1.357) |
| Regional (NUTS 3) fixed effects | Yes | Yes |
| Industry (NACE 4) fixed effects | Yes | Yes |
| Year fixed effects | Yes | Yes |
| Observations | 109,538 | 699,358 |
| Mcfadden pseudo R2 | 0.40337 | 0.6525 |
| Akaike Inf. Crit. | 75,098.98 | 439,453.3 |
| Note: | †p<0.1; **p<0.05; ***p<0.01 | |

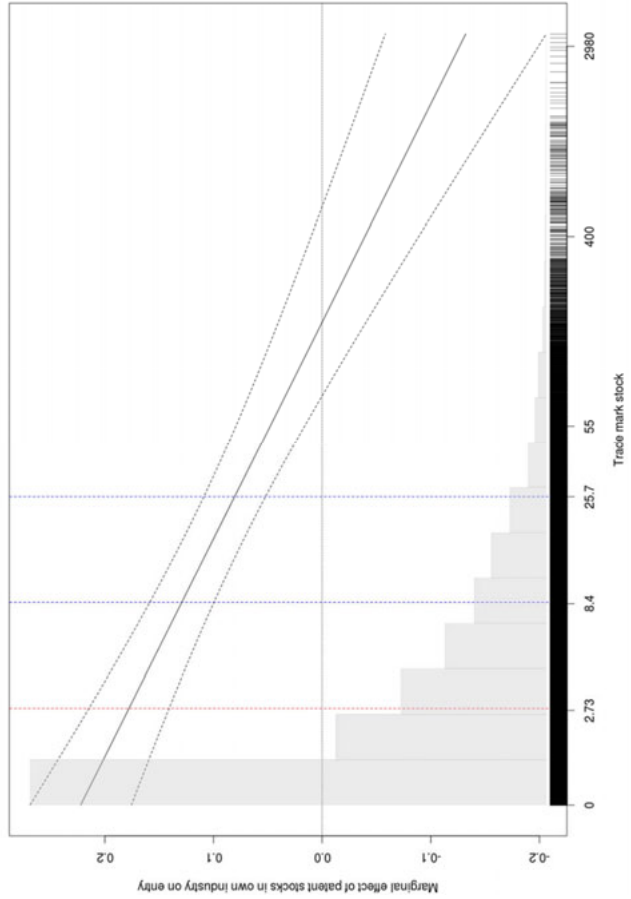
Our research question 5 concerned differences in the strength of association between knowledge stocks and entry, depending on the technology intensity of the industry. We have shown that the sector of entry is an important correlate of the influence of knowledge stocks. The association between focal and related knowledge stocks and entry plays out differently depending on the technological profile of industry. We confirmed that knowledge stocks in the *focal* industry are important to trigger entry into high-tech industries, but they do not play a role for entry in low-tech sectors. On the other hand, knowledge stocks accumulated by incumbents active in *related* industries play a more important role for entry in low-tech sectors than for entry into high-tech sectors.

It is worth noting that the coefficient of incumbents' trade mark stocks is positive in high-tech industries. With no patenting activity in the NUTS3/NACE4, a 10% increase in the incumbents' trade mark stocks is related to almost 1,2% higher entry. It confirms the conjectures of the literature that trade marks may be a complementary indicator of innovation. This innovation, similar to knowledge protected by patents, may be a source of positive spillovers.

Similar to the main model, in high-tech industries, incumbents may discourage entry by combining patent and trade mark protection. However, as illustrated in Figure 5.2, additional patents trigger negative effects for entry at relatively higher levels of trade mark stocks (approximately 155).

Estimations on entry in high-tech and low-tech industries separately further show that the relationship between variables describing general economic cycles and entry is much less pronounced for entry into high-tech industries than entry into low-tech industries or manufacturing industries in general.

Figure 5.2 Relationship between patent stocks and entry for different levels of trade mark stocks (high tech industries)



Note: red dashed line corresponds to mean value of log transformed stock of trade marks, blue lines correspond to mean+ standard deviation and mean - 2 x standard deviation value of log transformed stock of trade marks;
Source: own calculations based on model 1 in Table 5.4.

Models of innovative entry

Table 5.5 presents the results of estimations of entry of innovative firms. As discussed in section 5.3 we proxy innovative entry with entry of firms for which we have records of their subsequent application for patent, utility model or trade mark protection. Our results show that innovative entrants are much more sensitive to the presence of relevant knowledge stocks than imitative entrepreneurs.

The coefficients of the main variables of interest are much higher in the models estimating innovative entry than in the basic model estimating general entry into manufacturing industries. Patent stocks in the focal industry are positively related to entry of innovative firms in manufacturing industries irrespective of sector of activity. The positive impact of knowledge stocks on innovative entry has been confirmed in the model comprising all the manufacturing industries (model 1) as well as in models estimated on subsets of high-tech (model 2) and low-tech industries (model 3). Although the magnitude of the coefficient is similar in all three models, it is the highest for high-tech industries and suggests that 10% increase in the patent stocks in the own industry triggers almost 3% increase in entry in the same industry, with incumbents trade mark stocks held at zero. For the entire sample of manufacturing industries and the subsample of low-tech industries this association is slightly lower and implies that 10% increase in the knowledge stocks in the own industry translates into a 2.5% increase in entry. Table 5.5 also shows that knowledge stocks in related industries are positively associated with entry of innovative firms in the model comprising all the manufacturing industries and in the low-tech industries, but the coefficient is statistically insignificant in the model estimated for entry in high-tech industries.

The coefficient of the trade mark stock in focal industry is positively related to entry. As could be expected, it is relatively higher in the models estimated on the entire dataset and on data limited to low-tech, than in the model limited to high-tech industries. The coefficient of the interaction variable is negative and statistically significant in all three models.

Hence, Table 5.5 indicates that the availability of knowledge stocks is much more important for innovative entry than for other types of entry. Innovative

entrants prefer NUTS3/NACE4 with relatively higher knowledge stocks, irrespective of whether they enter in high-tech or low-tech industries, although the role of knowledge stocks in related industries differs.

Our research question 6 concerned possible differences in the impact of knowledge stocks on entry when looking at innovative entries (versus all entries). The results of our models confirm that knowledge stocks play a much more important role for entry of innovative firms than for general entry, irrespective of the R&D intensity of the industry. With relatively low levels of trade mark activity of incumbents, knowledge stocks in the *focal* industry are positively associated with innovative entry in high-tech as well as in low-tech sectors. A positive relationship between knowledge stocks in *related* industries with innovative entry was not confirmed for innovative entry in high-tech industries.

Our additional analyses of entry into different types of industries and entry of innovative firms provide a further refinement to the findings regarding questions 1,2 and 4. Our answers to these questions are contingent on type and sector of entry. With incumbents' trade mark stocks held at zero, focal knowledge stocks are positively associated with entry in high-tech sectors and entry of innovative firms but not with general entry in low-tech industries. Related knowledge stocks are positively related with general entry and entry in low-tech sectors (including innovative entry) but not with entry (both general and innovative) in high-tech sectors.

The influence of incumbents' trade mark strategies on discouraging entry and hence our answer to research question 3 is also dependent on the type and sector of entry. Incumbents limit the positive influence of their knowledge stocks on general and innovative entry by higher use of trade marks in all sectors. Innovative entrants are however much more sensitive to incumbents' strategies increasing their rate of appropriation from the knowledge they create. In the model estimated for all industries, when the stock of incumbents' trade marks reaches approximately 47 trade marks, the relationship between additional patents and innovative entry becomes negative. Effectiveness of trade mark stocks in reducing positive externalities from incumbents knowledge is especially high in low tech industries, where the relationship between patent stock and innovative entry turns negative at trade mark stock of 20. In the case of innovative entry in high-tech industries negative relationship appears at a relatively higher level of trade mark stocks

of 285 trade marks. Also, as we have shown in the previous section, in high-tech sectors trade mark activity of incumbents lead to a negative relationship between knowledge stocks and general entry at a much higher level of trademarks than for entry in all manufacturing industries.

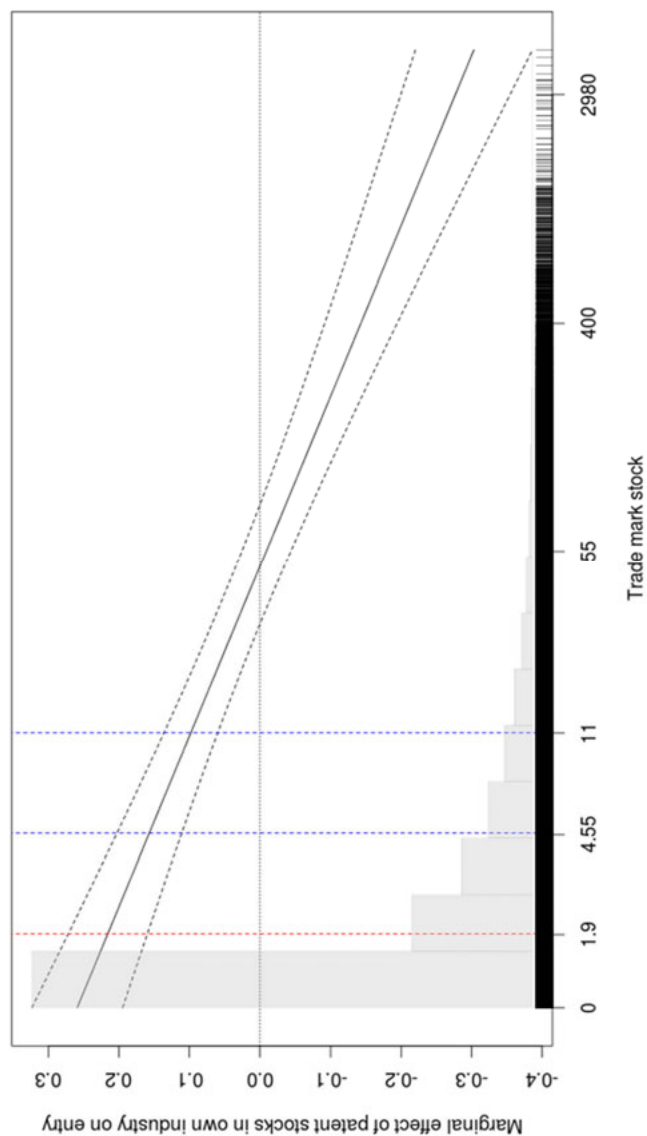
The presence of incumbents active in the same industry is the variable most related to entry of innovative firms. Its magnitude is however lower than in the case of general entry. In all three models suppliers' industries presence in the region seems to be important for entry, especially in high-tech industries.

Variables describing the general economic situation are more weakly related to entry of innovative firms than to general entry. This observation is even more evident in high-tech industries, as neither industry growth nor GDP per capita growth in the region are statistically significant.

Table 5.5 Results of the Poisson models- entry of innovative firms

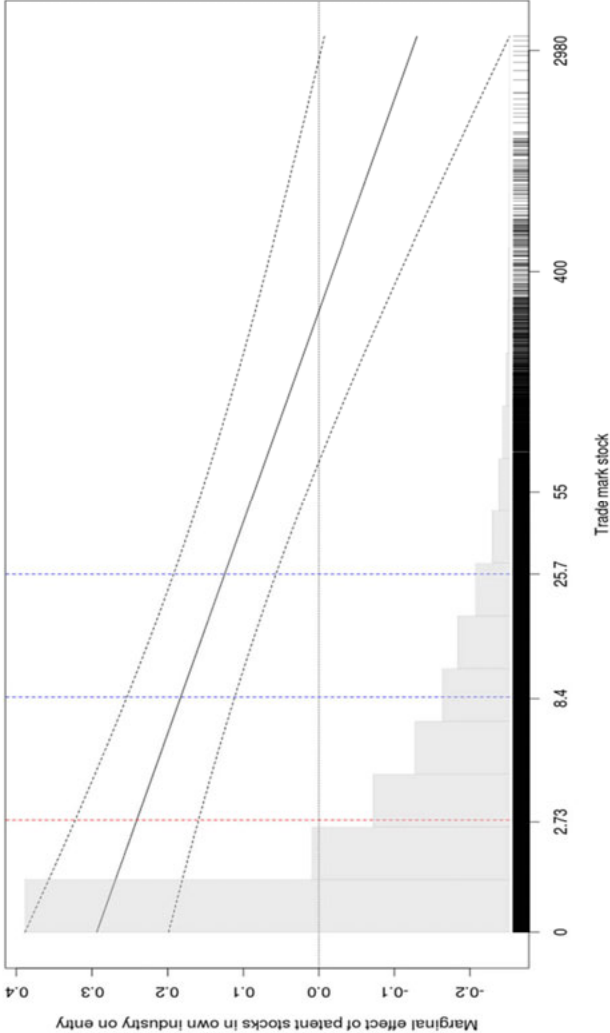
| <i>Dependent variable: number of new innovative firms NACE4d/NUTS3</i> | | | |
|------------------------------------------------------------------------|-----------------------|----------------------|--------------------------------|
| | All industries (1) | High-tech (2) | Low-tech (3) |
| Log of patent stock in focal industry (lag 1) | 0.259** (0.033) | 0.294** (0.048) | 0.256** (0.08) |
| Log of patent stock in related industries (lag 1) | 0.156** (0.035) | 0.038 (0.079) | 0.123** (0.06) |
| Log of trade mark stocks in focal industry (lag 1) | 0.350** (0.015) | 0.286** (0.038) | 0.331** (0.02) |
| Interaction between patent and trade mark stocks in focal industry | -0.067** (0.008) | -0.052** (0.011) | -0.082** (0.023) |
| Contribution of young firms to knowledge stock (lag 1) | 0.243** (0.031) | 0.280** (0.067) | 0.157** (0.055) |
| Contribution of universities to knowledge stock (lag 1) | 0.096 (0.168) | 0.159 (1.142) | 0.042 (0.239) |
| Log of incumbents' number (lag 1) | 0.626** (0.013) | 0.443** (0.042) | 0.658** (0.017) |
| Buyers' fit (lag 1) | 0.095** (0.021) | 0.106 (0.108) | 0.069 ⁺ (0.036) |
| Suppliers' fit (lag 1) | 0.085** (0.013) | 0.475** (0.165) | 0.077** (0.02) |
| Industry growth (NACE2, lag 1) | 0.471** (0.145) | 0.186 (0.287) | 0.718** (0.265) |
| Log of GDP per capita in the region (PPS) | -0.946** (0.196) | 0.029 (0.545) | -1.008** (0.284) |
| GDP per capita growth in the region (PPS) | 0.566** (0.250) | -0.416 (0.764) | 0.733 ⁺ (0.389) |
| Unemployment level | 0.279 (0.572) | 1.835 (1.562) | 0.445 (0.743) |
| Share of population with secondary and tertiary education | -0.460 (0.494) | -0.298 (1.525) | -2.653** (0.739) |
| Log of population density | -1.337** (0.385) | -0.684 (0.709) | -1.038 ⁺ (0.537) |
| Constant | -5.354** (2.493) | -20.334** (6.156) | -5.634 (3.643) |
| Regional (NUTS 3) fixed effects | Yes | Yes | Yes |
| Industry (NACE 4) fixed effects | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes |
| Observations | 1,937,800 | 109,538 | 699,358 |
| McFadden pseudo R2 | 0.3889 | 0.3577 | 0.4535 |
| Akaike Inf. Crit. | 201,928.3 | 19,352.4 | 78,753.2 |
| <i>Note: ⁺p<0.1; **p<0.05; ***p<0.01</i> | | | |

Figure 5.3 Relationship between patent stocks and innovative entry for different levels of trade mark stocks (all sectors)



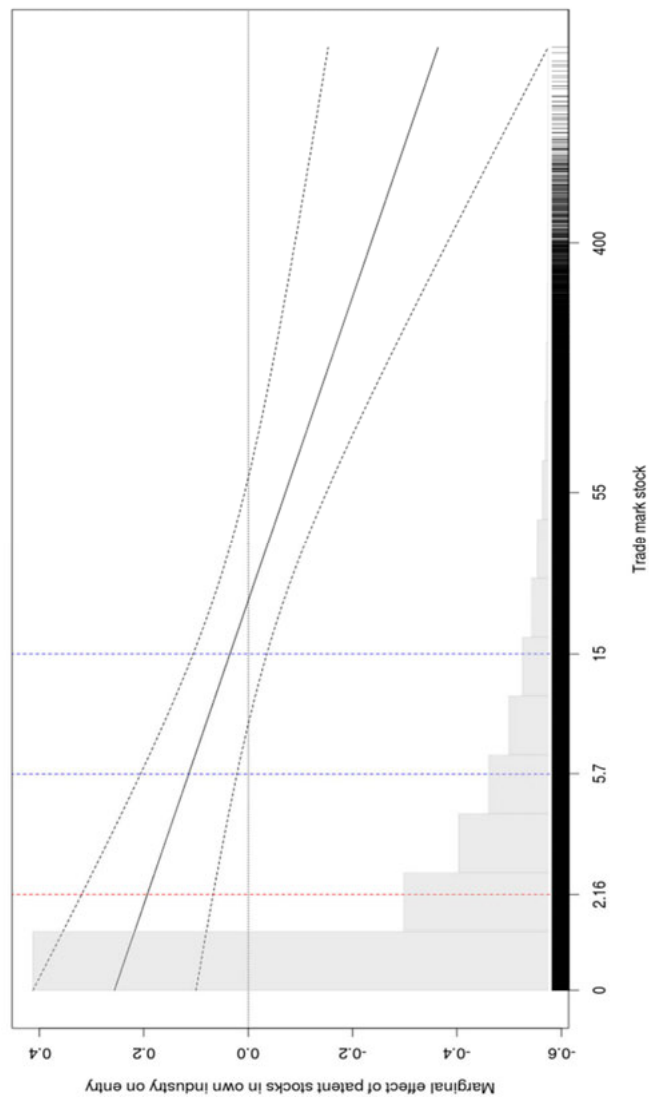
Note: red dashed line corresponds to mean value of log transformed stock of trade marks, blue lines correspond to mean+ standard deviation and mean + 2 x standard deviation value of log transformed stock of trade marks
Source: own calculations based on model 1 in Table 5.5.

Figure 5.4 Relationship between patent stocks and innovative entry for different levels of trade mark stocks (high tech industries)



Note: red dashed line corresponds to mean value of log transformed stock of trade marks, blue lines correspond to mean+ standard deviation and mean - 2 x standard deviation value of log transformed stock of trade marks
Source: own calculations based on model 2 in Table 5.5.

Figure 5.5 Relationship between patent stocks and innovative entry for different levels of trade mark stocks (low tech industries)



Note: red dashed line corresponds to mean value of log transformed stock of trade marks, blue lines correspond to mean+ standard deviation and mean - 2 x standard deviation value of log transformed stock of trade marks
Source: own calculations based on model 3 in Table 5.5.

5.5 Robustness checks

5.5.1 Entry in regions with direct neighbours in the dataset and *de novo* entrants

In our models, we assume that the knowledge spillovers are not limited to the administrative borders of NUTS3 regions but may extend beyond them. However, our results may be distorted by the fact that for some NUTS3 regions located on country borders, we may miss information on patent and trade mark activity in adjacent regions located across the border. Therefore, we check whether our findings hold for the models run on a narrower data base, where we dropped those focal NUTS 3 regions where at least one bordering NUTS3 was missing in our initial dataset. Based on the information available from Eurostat we have identified 87 such border regions. The second column of Table 5.6 presents the results of the estimation of the model, based on the limited dataset.

Including spillovers from incumbents' innovations may be more important for *de novo* entrepreneurs not linked to larger economic groups. Spin-offs from larger incumbents may rely on the direct knowledge spillovers from their parent company, not necessarily limited to the region of entry and its neighbouring regions. To distinguish between the impact of knowledge spillovers on *de novo* entrants and entrants belonging to larger economic groups, we created an alternative dependent variable, aggregating only *de novo* entrants²⁶ for which there is no information available in ORBIS on:

- Domestic Ultimate Owner;
- Global Ultimate Owner;
- Immediate Shareholder;

The results of the estimation of the model with a dependent variable consisting of *de novo* entrants are presented in column 3 of Table 5.6.

²⁶ In accordance with the ORBIS manual, to define an Ultimate Owner BvD analyses the shareholding structure of a firm, in case the firm is associated with BvD Independence Indicator different from A+, A or A-, i.e. an entity independent by itself (such as individuals and families; public authorities or state; employees, managers or directors) or an entity with no single shareholder with more than 25% of shares.

Table 5.6 Results of robustness check models

| <i>Dependent variable: number of new firms NACE4d/NUTS3</i> | | | |
|--------------------------------------------------------------------|-----------------------------------------|------------------------------------------|-------------------------------|
| | Main model (1) | Regions with all neighbours (2) | De novo entrants (3) |
| Log of patent stock in focal industry (lag 1) | 0.081*** (0.016) | 0.079*** (0.016) | 0.057*** (0.016) |
| Log of patent stock in related industries (lag 1) | 0.079*** (0.019) | 0.068*** (0.020) | 0.067*** (0.021) |
| Log of trade mark stocks in focal industry (lag 1) | 0.017 [†] (0.010) | 0.018 [†] (0.010) | -0.003 (0.010) |
| Interaction between patent and trade mark stocks in focal industry | -0.019*** (0.004) | -0.019*** (0.005) | -0.016*** (0.005) |
| Contribution of young firms to knowledge stock (lag 1) | 0.064*** (0.022) | 0.055** (0.022) | 0.056** (0.025) |
| Contribution of universities to knowledge stock (lag 1) | 0.055 (0.078) | 0.005 (0.089) | 0.058 (0.083) |
| Log of incumbents' number (lag 1) | 0.920*** (0.009) | 0.919*** (0.010) | 0.935*** (0.010) |
| Buyers' fit (lag 1) | 0.005 (0.011) | 0.007 (0.011) | 0.005 (0.011) |
| Suppliers' fit (lag 1) | 0.015 (0.009) | 0.020 [†] (0.011) | 0.016 [†] (0.010) |
| Industry growth (NACE2, lag 1) | 0.459*** (0.056) | 0.481*** (0.059) | 0.430*** (0.057) |
| Log of GDP per capita in the region (PPS) | -0.088 (0.089) | -0.099 (0.097) | -0.027 (0.092) |
| GDP per capita growth in the region (PPS) | 1.083*** (0.109) | 1.105*** (0.122) | 1.063*** (0.115) |
| Unemployment level | -0.144 (0.322) | -0.240 (0.343) | -0.084 (0.329) |
| Share of population with secondary and tertiary education | -0.572** (0.290) | -0.586 [†] (0.301) | -0.640** (0.292) |
| Log of population density | -0.339** (0.161) | -0.237 (0.150) | -0.304** (0.148) |
| Constant | -2.115 [†] (1.192) | -2.407** (1.207) | -2.847** (1.182) |
| Regional (NUTS 3) fixed effects | Yes | Yes | Yes |
| Industry (NACE 4) fixed effects | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes |
| Observations | 1,937,800 | 1,764,276 | 1,937,800 |
| McFadden pseudo R2 | 0.6617 | 0.5984 | 0.5965 |
| Akaike Inf. Crit. | 1,142,847 | 1,053,483 | 1,062,795 |
| Note: | [†] p<0.1; **p<0.05; ***p<0.01 | | |

5.5.2 Poisson regression with European trade marks and control for non-matched IPR

In this section, we provide additional robustness checks based on models with control for the European trade marks and control for stocks augmented with non-matched part of regional IPR stock. In section 3.6.2, we presented the detailed description of data preparation for this additional robustness checks. Column 1 of Table 5.7 presents the results of our main model for general entry with control for national trade mark stocks and knowledge and trade mark stock variables constructed only on matched data. Column 2 shows the results of the model estimated on the dataset with trade mark stock based on EUTM rather than national trade marks. In this model coefficient of stock of patents in the own industry becomes smaller than in the base model. Both the coefficient of trade mark stocks and coefficient of the interaction between patent and trade mark stocks become non-significant. The coefficient of patent stocks in related industries is the only coefficient out of all the main variables of interest in the model 2 which is statistically significant on 99% confidence level and with similar magnitude to the result of the base model. The magnitude and direction of other control variables in the model 2 are similar to the base model. In column 3, we present results of a model with stocks augmented with non-matched stocks. All the main coefficients, except the coefficient for the patent stocks in related industries, become non-significant. The coefficient of related patent stock is significant on 99% confidence level and its magnitude is higher than in the two remaining models. The higher coefficient for the variable of patent stocks in related industries may be, however, an artefact of the way we control for non-matched patent stocks. Instead of assigning a patent to one industry of the main activity of patent's assignee, for a non-matched fraction of patents, we assign them proportionally to multiple industries based on the IPC classes of relevant patents. As we measure the inter-industry relatedness also based on co-occurrence of the patents taken by firms representing different industries, our procedure for controlling of a non-matched fraction of patent stocks results in inflating the stocks in related industries and diminishing stocks in own industry of entrants.

As can be seen in Table 5.8, the results of models using alternative specifications are much more similar when the focus is on estimating innovative entry. The coefficients of patent stocks in own and related industries are positive and of similar magnitude in all three models, with the coefficient of related stock of patents only slightly lower in the model 2, with

control for EUTM trade mark stocks. Incumbents' trade mark stock is a variable with the highest difference of coefficient magnitude among three models. Value of this coefficient is over twice as high in the main model in comparison with models 2 and 3. The lower value of trade mark stocks coefficients in those two models may be due to the fact that in both models we take into account only EUTMs rights, whereas in the main model we control only for national trade marks. EUTM is probably used by stronger incumbents with view of international commercialization of their innovations, more efficient in protecting their innovations against potential spillovers.

Table 5.7 Comparison of results of Poisson estimation of entry, with national (1), European (2) trade marks and augmented stocks (3)

| <i>Dependent variable: number of new firms NACE4d/NUTS3</i> | | | |
|--------------------------------------------------------------------|--------------------------------|--------------------------------|-------------------------------|
| | Main model | EUTMs | augmented stocks (3) |
| | (1) | (2) | |
| Log of patent stock in focal industry (lag 1) | 0.081*** (0.016) | 0.031** (0.013) | 0.004 (0.014) |
| Log of patent stock in related industries (lag 1) | 0.079*** (0.019) | 0.086*** (0.020) | 0.111*** (0.025) |
| Log of trade mark stocks in focal industry (lag 1) | 0.017 ⁺ (0.010) | 0.001 (0.012) | -0.0005 (0.012) |
| Interaction between patent and trade mark stocks in focal industry | -0.019*** (0.004) | -0.007 (0.005) | -0.003 (0.005) |
| Contribution of young firms to knowledge stock (lag 1) | 0.064*** (0.022) | 0.069*** (0.022) | 0.077*** (0.022) |
| Contribution of universities to knowledge stock (lag 1) | 0.055 (0.078) | 0.056 (0.077) | 0.049 (0.078) |
| Log of incumbents' number (lag 1) | 0.920*** (0.009) | 0.925*** (0.007) | 0.927*** (0.007) |
| Buyers' fit (lag 1) | 0.005 (0.011) | 0.006 (0.011) | 0.007 (0.011) |
| Suppliers' fit (lag 1) | 0.015 (0.009) | 0.017 ⁺ (0.009) | 0.017 ⁺ (0.009) |
| Industry growth (NACE2, lag 1) | 0.459*** (0.056) | 0.464*** (0.055) | 0.472*** (0.056) |
| Log of GDP per capita in the region (PPS) | -0.088 (0.089) | -0.084 (0.088) | -0.122 (0.090) |
| GDP per capita growth in the region (PPS) | 1.083*** (0.109) | 1.081*** (0.108) | 1.103*** (0.108) |
| Unemployment level | -0.144 (0.322) | -0.160 (0.324) | -0.156 (0.324) |
| Share of population with secondary and tertiary education | -0.572** (0.290) | -0.614** (0.291) | -0.659** (0.290) |
| Log of population density | -0.339** (0.161) | -0.350** (0.162) | -0.337** (0.160) |
| Constant | -2.115 ⁺ (1.192) | -2.090 ⁺ (1.182) | -1.858 (1.186) |
| Regional (NUTS 3) fixed effects | Yes | Yes | Yes |
| Industry (NACE 4) fixed effects | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes |
| Observations | 1,937,800 | 1,937,800 | 1,937,800 |
| McFadden pseudo R2 | 0.6617 | 0.591 | 0.592 |
| Akaike Inf. Crit. | 1,142,847 | 1,142,999 | 1,143,066 |
| <i>Note:</i> | | †p<0.1; **p<0.05; ***p<0.01 | |

Table 5.8 Comparison of results of Poisson estimation of entry of innovative firms, with national (1), European (2) trade marks, and augmented stocks (3)

| <i>Dependent variable: number of new firms NACE4d/NUTS3</i> | | | |
|--------------------------------------------------------------------|----------------------|----------------------|----------------------------|
| | Main model (1) | EUTMs (2) | augmented stocks (3) |
| Log of patent stock in focal industry (lag 1) | 0.259** (0.033) | 0.198*** (0.021) | 0.252*** (0.027) |
| Log of patent stock in related industries (lag 1) | 0.156*** (0.035) | 0.186*** (0.035) | 0.182*** (0.049) |
| Log of trade mark stocks in focal industry (lag 1) | 0.350*** (0.015) | 0.141*** (0.020) | 0.163*** (0.021) |
| Interaction between patent and trade mark stocks in focal industry | -0.067*** (0.008) | -0.052*** (0.010) | -0.054*** (0.009) |
| Contribution of young firms to knowledge stock (lag 1) | 0.243*** (0.031) | 0.259*** (0.031) | 0.255*** (0.031) |
| Contribution of universities to knowledge stock (lag 1) | 0.096 (0.168) | 0.106 (0.162) | 0.091 (0.165) |
| Log of incumbents' number (lag 1) | 0.626*** (0.013) | 0.786*** (0.014) | 0.781*** (0.014) |
| Buyers' fit (lag 1) | 0.095*** (0.021) | 0.098*** (0.022) | 0.092*** (0.022) |
| Suppliers' fit (lag 1) | 0.085*** (0.013) | 0.100*** (0.013) | 0.093*** (0.013) |
| Industry growth (NACE2, lag 1) | 0.471*** (0.145) | 0.554*** (0.143) | 0.570*** (0.145) |
| Log of GDP per capita in the region (PPS) | -0.946*** (0.196) | -0.961*** (0.192) | -1.027*** (0.196) |
| GDP per capita growth in the region (PPS) | 0.566** (0.250) | 0.663*** (0.250) | 0.707*** (0.250) |
| Unemployment level | 0.279 (0.572) | 0.073 (0.568) | 0.103 (0.571) |
| Share of population with secondary and tertiary education | -0.460 (0.494) | -0.480 (0.488) | -0.584 (0.482) |
| Log of population density | -1.337*** (0.385) | -1.434*** (0.386) | -1.394*** (0.382) |
| Constant | -5.354** (2.493) | -4.807† (2.481) | -4.336† (2.493) |
| Regional (NUTS 3) fixed effects | Yes | Yes | Yes |
| Industry (NACE 4) fixed effects | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes |
| Observations | 1,937,800 | 1,937,800 | 1,937,800 |
| McFadden pseudo R2 | 0.3889 | 0.3850 | 0.3851 |
| Akaike Inf. Crit. | 201,928.3 | 203,224.3 | 203,184 |
| <i>Note: †p<0.1; **p<0.05; ***p<0.01</i> | | | |

5.6 Discussion and concluding remarks

This chapter expands literature focusing on the relationship between regional knowledge stocks and entry. We add new insights by distinguishing knowledge stocks in the industry of entry from knowledge stocks in related industries. We also contribute with the analysis of the impact of combined use of trade marks and patents on the strength and direction of this relationship.

Our analysis suggests that not only knowledge creation but also knowledge appropriation by incumbent firms determine entry. Knowledge stocks of incumbents in the focal industry have less impact on entry than knowledge stocks in the related industries, contributed by incumbents not competing directly on the same market. Those incumbents have fewer incentives to shield their knowledge from entrepreneurs not directly challenging their market position. Although the possibility that strategic behaviour of incumbents may affect the likelihood of knowledge spillovers has been recognized in the KSTE literature (Audretsch et al. 2006; Plummer & Acs 2014) it has not received sufficient attention and has not been subject to empirical testing. The absence of this consideration in prior work is a possible explanation why prior findings on the role of regional knowledge stocks in spurring new firm formation have been mixed (Knoben et al., 2011; Jofre-Monseny et al., 2011; Tsvetkova, 2015). In case incumbents combine patenting with more intensive trade mark activity and more aggressive appropriation strategies, the relationship between knowledge stocks and entry becomes much weaker and eventually higher knowledge stocks may rather discourage than encourage entry.

Our research also contributes to the nascent literature on the role of trade marks in industrial dynamics and regional innovation systems. Our analysis confirms that trade marks may serve as a complementary indicator of innovation (Mendonca et al. 2004; Millot 2009; Flikkema et al. 2014; Castaldi 2018) that may also be subject to positive externalities. There is however important qualification to such a function of trade marks: this effect only occurs in the absence of substantial patent activity of incumbent firms. In the context of higher patent stocks, a relatively higher stocks of trade marks may be treated as an indicator of more intensive commercialization and more aggressive strategy of protection of knowledge assets by incumbents. Overall, our findings are more in line with the notion in the Industrial Organization literature (Tirole 1988; Lipczynski et al. 2005; Belleflamme &

Peitz 2010), that trade marks may be used strategically by incumbents and serve as an indicator of their commitment to defend their knowledge and raise entry barriers. As a consequence, if combined with patent stocks, trade marking reduces the positive externalities of knowledge stocks and has an overall negative effect on entry. Faced with such strategies, potential entrants may prefer other, related industries or regions with similar knowledge endowments but with a relatively lower determination of incumbents to protect their knowledge. Our findings suggest that new firms may avoid head on competition with aggressive incumbents but rather benefit from incumbents' innovation activities in exploring opportunities stemming from technologically related innovation.

Results of our research reveal that there are important differences in the strength of the relationship between local knowledge stocks and entry depending on industry and type of entry. Whereas in general entrants seem to benefit more from related knowledge stocks than from the knowledge stocks contributed by incumbents active in the focal industry, the pattern of entry is somewhat different in the case of entry into high-tech industries. Entrants in high-tech industries do benefit mainly from the knowledge stocks accumulated by incumbents active in the focal industry and related knowledge stocks have no impact on their decision to set up a new firm. Also more intensive trade marking by incumbents is less effective for discouraging entry of innovative firms into high-tech industries and negative effects of higher patent stocks are triggered at relatively higher level of trade mark stocks.

Our findings confirm that knowledge spillovers seem to be affected by the nature of technological regimes in the focal region. As suggested in the extant literature (Winter 1984; Audretsch & Fritsch 2002) a more active role played by young firms in local knowledge creation encourages entrepreneurs to set up a business. It is especially evident for entry of the most innovative firms, which subsequently filed an application for IPR protection. The nature of the regional technological regime seems to be also particularly important for entry in high-tech industries. Young firms, focused on innovation and struggling to expand rapidly their market share, are less concerned about shielding their knowledge from prospective entrants. A higher share of young firms in patenting may also indicate that search for a dominant design is not yet concluded and new firms may still succeed with new products or services. It supports the observation of Bhide (2003) that higher uncertainty,

stemming for instance from technological changes, helps entrepreneurs with limited endowments to start their business.

5.7 Limitations

The present study has a number of limitations. Our dependent variable reflects gross entry in the industry and region. Some of the entering firms replace exiting incumbents. Due to the limitations of our data sources, we are not able to adequately control for exiting firms to calculate net entry. Also, although the ORBIS database is constructed on commercial data registers, data of some of the newly established firms may be missing. Other sources of data on entry, e.g. Eurostat, do not contain information at a similar granularity and therefore it is difficult to assess the possible bias of the ORBIS data. Future studies, based on more detailed census data may verify our main findings and differences in the association between knowledge stocks, the strategic use of trade marks by incumbents and net and gross entry.

Our interaction variable (product of knowledge and trade marks stock) is based on the data aggregated to the NACE4d/NUTS3 level of industries and regions. We are not observing an actual bundling of patents and trade marks on the level of the individual innovation or even the individual firm. It would be interesting to verify our findings with the more granular data on such bundling strategy.

Although we assembled data on the very granular NACE 4 digits level, some industries may be broad enough as to include firms not competing directly. Even within 4 digit NACE industries there may exist some separate niches. So, although in the present chapter we assumed that firms entering the specific industry compete head to head with stronger, innovating incumbents in specific cases this assumption may be false.

We control for ratio of contribution of universities to the knowledge stocks on the regional level. However we do not have as good proxy for assessing relatedness of knowledge contributed by universities with industry of entrant, as we have for variable of contribution of young firms. Lack of confirmation of association between entry and contribution of universities to knowledge stocks may be due to these caveats. Future research, having better data allowing for more precise assesment of relatedness of university patenting with industries, may verify our findings in this regard.

Finally, spatial data samples, such as ours, require proper handling of the spatial dependence between the observations. There are alternative

estimation procedures to deal with this problem developed under the classical spatial econometrics literature, however they are not suited for count data (LeSage 1999). We partially dealt with spatial dependence by weighting and aggregating knowledge and trade marks stocks for the regions lying within the 200 km radius from the focal NUTS 3 centroids. However, it is likely that some spatial correlation still remains in the standard errors of our models. There are several alternative estimation techniques considered for count data that could be used in the future to deal with spatial correlation, with most promising approaches based on Bayesian setting (Simões & Natário 2016).

6 Own innovation, innovation by incumbents', and new entrants' growth

6.1 Introduction

This chapter investigates the association between technological innovation, trade marks, and the growth of new entrants. The post-entry growth of newly established firms is a complementary analysis to the entry analysis in Chapter 5 and is important from the perspective of industry dynamics, innovation and entrepreneurship. Indeed, as noticed by Penrose (1959) "*[g]rowth is not for long, if ever, simply a question of producing more of the same product on a larger scale; it involves innovation, changing techniques of distribution, and changing organization of production and management*". New entrepreneurial firms play an important role in bringing innovation to markets (Schumpeter 1934; Venkataraman 1997; Spulber 2014). Entrepreneurs who successfully develop innovations achieve higher growth rates but also start a process of industrial mutation which many times sets the stage for new industrial trajectories.

While empirical evidence has been found that young small and innovative firms tend to grow faster, detailed evidence on the role of localised stocks of knowledge is still missing. Some locations may offer entrepreneurs easier access to technological knowledge not fully utilized by incumbents, which may serve as a source of new entrepreneurial opportunities (Acs et al. 2013) and as a potential external enabler of growth. On the other hand, greater localized competition stemming from higher investment in new knowledge by incumbents may harm the prospects of new entrepreneurial firms (Plummer & Acs 2014).

Current chapter analyses the growth performance of firms, established in 2000, from 2003 through 2009. Our data enables analysis at the fine-grained NUTS3 locational level and NACE 4 industrial level. We apply novel panel quantile regression models and control for selection bias related to sample attrition (exits).

Similarly to chapter 5, we look at the innovation of incumbents active in close geographical vicinity to examine the growth prospects of newly created firms. A new aspect that we introduce in the current chapter is the analysis of the role of entrants' own innovation efforts for their growth prospects. In addition, we examine the role of entrants' trade marks, which may help

young firms overcome some aspects of the *liability of newness* (Block et al. 2017; Coad 2017), but which may also be used strategically by incumbents to raise barriers for entrants. Similar to the analysis presented in chapter 5, we distinguish between knowledge produced by firms in the industry of the focal firm and technologically related knowledge stocks of other industries at the local level.

This chapter is structured as follows. In section 6.2, we present a review of previous research focused on firms' growth, emphasizing findings on the impact of innovation on growth and the specific strengths and weaknesses of newly established firms. Based on the research gaps identified in the literature review, we also derive our specific research questions. Section 6.3 describes our dataset, and in section 6.4, we discuss econometric methods best suited to answer our research questions, given the data at hand. We employ panel quantile regression model to allow the relationships between knowledge stocks, trade marks, and growth to differ across the growth distribution. In section 6.6, we describe additional robustness checks to verify whether the main findings stand up to scrutiny with alternative specifications. We summarize our findings and discuss the contribution of our research in section 6.7. In section 6.8 we examine the main limitations of our data and analysis and propose avenues for future research.

6.2 Related literature and research questions

In this section we review the relevant literature motivating our research questions. We start with the description of Gibrat's law which over many years dominated views on firm growth. In the subsequent sections, we present the theoretical and empirical works indicating some correlates of higher growth, emphasizing those which are important for our research focus such as age, size and innovation. In section 6.2.5 we review the literature on trade marks and discuss to what extent trade marking may help newly established firms reduce the negative effects of *liability of newness*. In section 6.2.6, we point to research gaps related to local incumbents' innovation and trade marking activity and positing that these factors may also be related with growth prospects of newly created manufacturing firms.

6.2.1 Gibrat's Law

The traditional view within the Industrial Organization literature is that growth is purely stochastic, i.e. normally distributed and occurring randomly. The random growth hypothesis is represented by the Law of Proportionate Effect (LPE), also known as Gibrat's law.

$$size_{it} = (1 + \epsilon_t) * size_{it-1} \quad (6.1)$$

Its three main propositions as formulated by Kumar (1985) are as follows:

- i) Firms representing different size classes have on average the same proportionate growth;
- ii) The dispersion of growth rates around the mean is the same for firms representing different size classes;
- iii) There is no serial correlation in growth rates.

Gibrat's law does not preclude the possibility to attribute strong growth performance to some systematic factors *ex-post*; rather it implies that it is impossible to predict strong growth *ex-ante* using firms' observable characteristics (Lipczynski et al. 2005).

As shown in reviews by Sutton (1997) and Caves (1998), early empirical studies, based mainly on limited samples of larger enterprises, provided support for the LPE. However, as early as in 1960', Mansfield (1962) observed that contrary to Gibrat's law, smaller firms tend to have higher growth rates and that their growth is more variable. He concluded that "*[a]lthough Gibrat's law is very convenient from an analytical point of view, it does not seem to hold up very well empirically. It seems to be a rather unreliable base on which to rest theories of the size distribution of firms*".

6.2.2 Growth, size, and age

Partly as a response to those empirical findings, Jovanovic (1982), in his "*noisy selection*" theory, modelled a firm's growth as a learning process in which firms learn their efficiency against competitors. Younger firms, with less knowledge about their efficiency on a given market, may set a suboptimal level of output, which may be adjusted as they learn from their past performance. Small size at the start may be a rational strategy of entrants to limit their commitments and sunk investments while learning about their unknown capabilities (Caves 1998). One of the outcomes of the Jovanovic model is higher growth rates and higher variability among the young (and smaller) firms, controlling for the selection bias associated with their higher exit rates. Growth of larger firms that have survived for a longer time is less variable and converges to a constant value. Higher growth rates of the smaller firms, beyond Jovanovic (1982) arguments, can also be explained by the fact that young firms entering the market at a sub-optimal level are facing decreasing average costs and therefore grow more rapidly (Jensen et al. 2001;

Lotti et al. 2003). Another theoretical argument associates higher growth rates of younger and smaller firms with efforts to reach a minimum efficient scale (MES), as newly created firms may have a suboptimal size (Audretsch 1995a; Almus 2000) and therefore their high growth rate is necessary for long term survival.

Consistent with Jovanovic's theoretical model, papers that used more comprehensive datasets, including data on medium and small enterprises found that, on average, small firms grow faster than large firms (Mansfield 1962; Kumar 1985; Hall 1987; Evans 1987a; Goedhuys & Sleuwaegen 2010) with the variance of growth rates being also larger for smaller firms (Hall 1987; Evans 1987b). An inverse relationship between size and growth has also been confirmed for larger firms, although in this group the differences are more attenuated (Mansfield 1962; Hall 1987; Evans 1987a; Lotti et al. 2003), leading to the conclusion that "[t]he departures from Gibrat's Law decrease as firm size increases" to the point that "Gibrat's Law is not an unreasonable assumption for the very large firms which do, at any point in time contribute most industrial output" (Evans 1987b). Lotti et al. (2003) noted that "convergence towards a Gibrat-like pattern of growth occurs with the passage of time". Some recent papers showed that growth patterns are more persistent for young firms than for older firms. Growth of young firms is characterized by a positive autocorrelation in the first years after entry but turns negative and remains so as firms get older (Coad et al. 2018).

The broadening of the empirical samples resulted in more findings contrasting with Gibrat's law (Audretsch 2012), as they brought in some, mainly internal, firm characteristics associated with higher growth rates besides the traditional size and age. The current state of the economic literature has been aptly summarized by Coad (2009) who concluded that "[A]lthough the random element is indeed prevalent, it is nonetheless possible to find ways of identifying new regularities".

6.2.3 Innovation and firms' growth

Schumpeter (1934) was the first scholar noting a decisive role of innovation for economic and social change but also for starting the process of *creative destruction* whereby firms employing new methods of production and offering new superior products undermine the market position of incumbents.

In the active learning model of Ericson & Pakes (1995) a firm's entry decision and subsequent growth is a result of active exploration of its economic

environment, including investment in the development of new products. By doing this, the firm is able to improve its efficiency and ultimately to increase its survival chances (Cefis & Marsili 2006). The impact of innovation on the growth prospects of firms is one of the main features of the evolutionary theory of economic change (Nelson & Winter 1974; Nelson & Winter 1982; Dosi & Nelson 1994). Evolutionary economics sees market processes as a complex system facilitating a continuous search for variety and selection of the most viable ideas. Some ideas are successfully implemented and are propagated by decisions of individuals, firms and institutions, and are embodied in new firms, new organisational forms and technologies. Those constitute the basis for further variety development.

Successful innovation introduces changes in payoffs. *“It leads to both higher profit for the innovator and to profitable investment opportunities. Thus, profitable firms grow. In so doing they cut away the market for the noninnovators and reduce their profitability”* (Nelson & Winter 1982). Those firms that are able to adapt to the new situation and are using profitable routines expand and those which are not able to adapt contract. *“Through the joint action of search and selection, the firms evolve over time, with the condition of the industry on each day bearing the seeds of its condition on the day following”* (Nelson & Winter 1974).

Many ideas developed in this evolutionary process prove not to be viable. Due to the limited information available to economic agents and the limited capacity of their processing, human decision making is boundedly rational (Simon 1959; Kahneman 2003). Those limitations are especially pronounced in the case of novel solutions and products. R&D and innovation are thus related to significant uncertainty (Arrow 1962) and often lead to market failures. Most innovation activity yields only modest returns. Only relatively few innovations bring high returns (Scherer & Harhoff 2000). Most issued patents have little or no commercial value and many applicants, uncertain of the value of the underlying innovation, treat their patent applications in fact as lottery tickets that may pay-off if they are lucky (Lemley & Shapiro 2005).

Innovating firms are, therefore assuming more risks than imitating entrepreneurs, increasing their odds for both exceptional performance and bankruptcy (Buddelmeyer et al. 2010). This view is consistent with the standard risk-return trade-off view in finance (Hyytinen et al. 2015).

Empirically, Mansfield (1962) was one of the first scholars confirming a link between successful innovation and firms' growth. Scherer (1965) noted that inventive output has a positive impact on profits, but the main driver of this

phenomenon appeared to be an increase in sales rather than higher margins as could be expected from the temporary monopolies associated with patents. After regressing firms' growth rates on a range of 16 independent variables describing internal characteristics of firms, Geroski & Toker (1996) concluded that high levels of advertising and high innovation activity play a significant role in helping top-ranked UK firms to preserve their initial position.

Geroski & Machin (2013) argue that there are at least two ways that innovative activity can affect the performance of firms. It does so not only via the commercialization of the innovation, which gives rise to new sales and enables a firm to achieve higher margins, but also by a transformation of the firm via a process of learning. Engagement in innovation transforms a firm by increasing its internal capabilities, making it more flexible and more adaptable. The first effect can be observed shortly after introducing innovation on the market and is associated with a short and sharp increase in sales, while the second effect is visible in the longer term and manifests itself in the pattern of growth which is less cyclically sensitive than the growth of non-innovators. While the innovating firms perform much better in the period of recession than their non-innovating counterparts, this difference almost disappears during periods of boom. Results of this research confirm theoretical predictions that, beyond more direct benefits, firms engaged in innovation activity improve their overall performance by enhancing their absorptive capacity (Cohen & Levinthal 1990) and developing dynamic capabilities (Teece et al. 1997; Teece 2007).

Although the empirical literature provides mostly arguments supporting a link between the innovative activity of firms and their subsequent growth prospects and survival probability (Cefis & Marsili 2005; Cefis & Marsili 2006), consistent with the theoretical notions regarding the uncertainty of innovation activities, there are also studies with more ambiguous results. As noted by Audretsch (1995a) those firms that experimented with innovation but failed are more likely to perform worse than those firms that did not make any attempt to innovate. Bottazzi et al. (2001), analyzing data for the world's top 150 pharmaceutical companies, did not find an impact of innovative output on comparative growth performance. They observed that while innovation drives the evolution of each sub-market of the pharmaceutical sector, imitations and analogue developments are fast enough to minimize any long-term advantage of innovating firms. Innovation has also been shown, using quantile regression techniques, to have a strong positive impact on growth in the upper quantiles of the growth distribution, while having no

or even a negative impact on the lower quantiles of the conditional growth distribution (Coad & Rao 2008; Goedhuys & Sleuwaegen 2010; Colombelli et al. 2013).

These findings indicate that beyond a simple dichotomy of innovating and non-innovating firms there exist a more significant distinction of firms between those that *tried and succeeded*, *tried and failed* and *did not try* (Freel 2000) with *tried and succeeded* category being crucial for growth.

6.2.4 Innovation and growth of new entrants

Previous literature suggests that firms' age may impact both the innovation behaviour of a firm, as well as strength of association between innovation and firms' growth.

Prospects of newly created firms are generally worse than prospects of their older and more experienced rivals. As noted by Jensen et al. (2008) "*new firms are more sensitive than incumbent firms on a number of fronts (...), they are more susceptible to variations in economic conditions*". Older firms benefit from a longer period of learning and can draw on more tangible and intangible resources that they accumulated during their existence. The reputation a firm builds up during its existence is also an essential part of its competitive advantage. The primary source of credibility and reputation of a firm is its past performance, information which is by definition scarce or non-existent for a newly created firm (Pellegrino 2018). The absence of reputation for younger firms directly translates into higher borrowing constraints (Diamond 1989) which has been empirically confirmed for young firms in various contexts (Hyytinen & Väänänen 2006; Ylhäinen 2017; Sakai et al. 2010). Therefore, it is very difficult for new firms to outcompete incumbents in mature, stable markets. On such markets, many factors play in favour of existing players (Bhide 2003).

Conversely, newly established firms may perform better on turbulent markets. Technological uncertainty shapes the opportunities for entrants and smaller technologically oriented companies (Glynn 1996). One of the most critical factors bringing about such structural change and transformation is innovation which plays a central role as "*a primary source of differential behaviour of firms*" (Metcalf 1998). Technological innovation may undermine incumbents' advantages by changing some crucial characteristics of the industries (Christensen 2012). Existing routines of incumbents are not always easily adaptable to the new market conditions (Nelson & Winter 1982) and are limiting the search space of firms (Leten et al. 2016). Existing firms may

suffer from the inertia that reduces their ability to notice the need for innovation and implement it, especially if it may undermine their current profit base (Spulber 2014). Industrial settings of constant technological changes are more likely to generate new challenges to the incumbents and provide entrepreneurial opportunities for emerging firms (Eckhardt & Shane 2011). As argued by Glynn (1996) *“the reason that small companies continue to exist in advanced displays is that, with few exceptions, there is little agreement regarding which technologies are likely to dominate which applications”*

The absence of formal structures, deeply-rooted routines and rigid decision-making processes facilitates adaptation to new challenges and creates opportunities for new firms. They may succeed by exploring new niches enabled by new technologies or by new regulations. Uncertainty associated with innovation and market turbulence introduces *“a skew into the distribution of profits and creates a small chance that the entrepreneur will earn a large return”* (Bhide 2003). Therefore new firms tend to perform better when exploiting opportunities emerging on new markets, where demand is hardly predictable (Shane 2004). Research of Bos & Stam (2014) confirmed that young rapidly growing firms (gazelles) seem to be *“early movers with respect to the recognition and realization of industry-specific growth opportunities”*. By offering differentiated products, young firms may avoid price competition (Porter 1980) and may create new demand from those clients whose needs have not been entirely satisfied with the existing offering.

Specific weaknesses and strengths of young firms have consequences for both the intensity and quality of young firms' innovation as compared to older firms. Sørensen & Stuart (2000) found that younger firms are less likely to innovate, but that their innovation is more radical than the innovation of older firms. The more radical character of young firms' innovation and the higher quality of innovations has been confirmed in other empirical research (Coad et al. 2016; Balasubramanian & Lee 2008). Criscuolo et al. (2012) also found that although the share of product innovators is about the same among the newly established and older firms in the manufacturing industries in the UK, the share of innovative products in the overall turnover within a group of new firms is significantly higher than within the group of their more mature counterparts.

New entrants are, however, particularly vulnerable to the risks involved in innovation activity. Innovation requires substantial resource commitment and it may ultimately exceed the possibilities of new and small firms

(Rosenbusch et al. 2011). Due to resource constraints, innovative entrants may focus on the narrow technological scope and may become locked-in to their particular product design (Bayus & Agarwal 2007) which increases their vulnerabilities, as *“the surest path to extinction is to over-invest in a single solution”* (Eagleman & Brandt 2017). Failure of the particular innovation project may, therefore, pose existential risks to the young firm’s survival. Higher risks associated with the innovation of newly established firms may also be related to the adverse selection as *“inventors with less risky projects are able to transfer their technologies to existing firms, and inventors with more risky projects choose to become innovative entrepreneurs”* (Spulber 2014). Coad et al. (2016) hypothesize that older firms are engaged in more incremental innovation along with their usual R&D routines and, thanks to their long experience, are able to quickly notice that the particular innovation project is likely to fail. Usually, they also have a larger portfolio of R&D projects which, on average, is less uncertain than a one-off project of the young firms.

Empirical results reflect the dual fate of young innovating firms. Meta-analysis of the relationship between innovation and performance in SMEs conducted by Rosenbusch et al. (2011) on the basis of 42 empirical studies in the field of management concluded that new ventures benefit more from innovation than mature SMEs. Empirical research on Dutch firms conducted by Cefis & Marsili (2012; 2011; 2006) documented an *innovation premium* for small and young innovating firms that have a higher chance of surviving than those that do not innovate. This premium is however more significant in low-tech industries and disappears in high-tech industries.

Analysis of Helmers & Rogers (2010), conducted on a large sample of UK companies incorporated in Britain in 2001, showed that young firms with at least one patent have an almost 14 percent lower probability of exit, and that young firms with at least one trade mark have a 15.5 percent lower probability of exit than firms without IPRs. In an analysis of a similar sample of firms founded between 2000 and 2005, Helmers & Rogers (2011) showed that patenting contributes positively to the growth of the small firms’ assets.

However, there is also quite extensive empirical evidence that innovation activities may increase the risk of failure among newly established firms. Analysis conducted on a broad sample of Australian firms by Buddelmeyer et al. (2010) showed that innovation investments, proxied by patent applications, increase the probability of de-registration. Boyer & Blazy (2014) found that innovative status increases the risk of failure of French micro-start-

ups by about 10%. Analyses conducted by Hyytinen et al. (2015) on a sample of Finnish companies showed that the mean survival rate of innovating start-ups was 7-8 percentage points lower than the mean survival rate of start-ups not engaged in innovation. Coad et al. (2016) found that although higher R&D intensity of young firms in Spain is associated with higher sales in the upper quantiles, it has negative consequences for firms' in lower quantiles.

We conclude that extant literature suggest that technological innovation increases the chances of both exceptional performance and failure of young entrepreneurial firms. Applying for patents is related to relatively radical and novel innovative activity with substantial risks regarding commercialization. Patenting is also related to higher costs in comparison to other forms of protection of intellectual assets such as secrecy. When successful, patenting increases the odds for exceptional performance. However, if patented innovation is not successfully marketed it can be a drain on vital resources of young firms, compromising their future growth potential. Our first research question concerns the new feature we introduce in this chapter: the association between technological innovation performed by newly established firms and their growth prospects:

Research question 1

What is the relationship between technological innovation as proxied by patenting activity by newly created firms and their sales growth? Is patenting associated with higher growth for the entire population of newly established firms, or is this a feature only of firms in the top of the growth distribution?

6.2.5 Trade marks and growth of new entrants

Newly established firms can hardly compete with large incumbents on price, due to their relatively small size and the advantages of incumbents as regards economies of scale. Niche strategies that are potentially more attractive for entrants require product or service differentiation. The development of new brands associated with the new product varieties introduced by the new firm may be crucial for this strategy to be effective. Trade marks provide the most important legal anchor for brands (Griffiths 2015).

As already discussed, newly established firms suffer from a *newness liability*, which can seriously impact their possibilities to compete with more experienced firms. Investment in brand development may be an especially effective strategy for entrants as it has the potential to reduce the information asymmetry between newly established firms and their business partners and

customers. Brands can help firms build a reputation and overcome some of the weaknesses associated with the *liability of newness*. Therefore, brands, serving as a quality signal, may be instrumental in strengthening the market position of newly established firms.

Trade marking is a relatively inexpensive legal instrument which often may be the unique intellectual property right accessible for resource constrained new firms, especially if their new product is not radical enough to warrant patent protection. Usage of trade marks or brands may facilitate the appropriation of innovation and helps to associate innovations with the original innovating firm. Trade mark registration may, therefore, have a crucial appropriation function for new entrants and smaller firms (Block et al. 2015).

Research of Block et al. (2015) on SMEs motivations for registering trade marks revealed that protection of products and service offerings from imitation was the most commonly indicated motive for a trade mark registration. This was followed by supporting marketing efforts and image. On the other hand, SMEs that filed trade mark applications for specific reasons always considered marketing motives as well, leading to the conclusion that *‘the marketing motive is a cornerstone of each SME trade marking strategy, whereas exchange and protection are enriching and complementary motives’* (Block et al. 2015). Nevertheless, marketing aspects are often neglected in empirical research, which results in the implied assumption that commercial success is determined mainly by the technological features of innovation (Crass 2014).

In the research of Buddelmeyer et al. (2010) conducted on a sample of Australian firms, both trade mark applications and trade mark stocks, treated by the authors as proxies for incremental innovation, were found to be associated with a longer median life of a firm. Bosworth & Rogers (2001) found a positive effect of trade mark stocks on the market value of firms in non-manufacturing industries. Greenhalgh & Rogers (2006) found that higher R&D, patenting and UK trade marks all tended to increase market value. While controlling for R&D and patents, Sandner & Block (2011) found that investors assign higher valuation to the firms with a more significant portfolio of trade marks and that the number of oppositions filed by trade mark owner against the registration of similar trade marks was also positively related to firm value. These findings confirm that investors value

firms that actively defend their marketing assets and underscore the importance of trade marks as an appropriation strategy.

Similarly, Crass (2014) has shown that the use of established brands to promote innovation is associated with a 35% higher sales of innovative products. This relationship was not confirmed, however, for the use of new brands. A study conducted by Office of Harmonization on Internal Market (OHIM 2015) showed that expected revenue per employee of trade mark owning firms was almost 30% higher than the revenue of firms not registering trade marks, and that this difference was especially pronounced in the case of SMEs.

The development of branded, niche products helps young firms to escape the fierce price competition with better-endowed incumbents. The application process for trade mark protection is relatively less demanding and cheap in comparison to other registered IPRs, in particular patents. Trade marking may thus be an effective way of protecting a broader range of new products, including incremental and marketing innovations. Usually, innovations protected by trade mark applications are not radical and are not excessively compromising vital financial resources of newly created firms. Trade marks may be the only means of protection accessible to financially stricken firms. Therefore, innovations protected by trade marks may contribute to higher growth of firms across the entire population of newly established firms, with different innovation capabilities and resource endowments. Our second research question also concerns the new aspect of innovation introduced in the current chapter: the influence of own innovations protected by trade marks on growth prospects of newly established firms:

Research question 2

Are trade marks held by newly established firms associated with higher turnover growth? Are benefits related with differentiation and innovation as proxied by trade marks more evenly distributed between firms located at different levels of growth distribution in comparison with benefits related to innovations protected by patents?

6.2.6 Local incumbents' innovation, trade marks and growth of new entrants

Our first two questions concerned the new aspects introduced in the present chapter: benefits associated with own innovation performed by newly established firms. Academic literature indicates however that not only internal features of the company but also environmental characteristics of the region they are active in are important for subsequent performance of entrants (Sarkar et al. 2006; Leten et al. 2016). As we argue in the present dissertation, a focus on external conditions beneficial for discovery and exploitation of entrepreneurial opportunities may be an important part of the entrepreneurial field of research (Shane & Venkataraman 2000). If innovation constitutes one of the critical aspects of firms' growth, external factors such as the industry environment and the location of the business may play important roles, as the "*innovation process is not solely an internal process*" (Rogers 2004). In their search for more profitable routines, firms draw on knowledge from other firms engaged in the similar activity and, more generally, from their external environment (Winter 1984). Leten et al. (2016) emphasize a need for an integrative framework linking firms' internal resources with external characteristics of the environment the firms are active in. They showed, in the context of firms' entries into new technology domain that the technology environment that firms face influences both the entry decision and the direction of firms' technologies exploration.

Innovation is a salient impetus for firms' growth but also for the dynamics and evolution of entire industries (Malerba 2007). Industry structure, intensity and scope of innovation and the nature of collaboration between firms differ depending on the industry (Pavitt 1984; Bogliacino & Pianta 2016). Those differences stem mainly from existing knowledge bases and learning processes related to innovation (Malerba 2002). In some industries, characterized by *routinized technological regimes*, knowledge is routine and innovation comes mainly from incumbent organisations. Other industries, with more *entrepreneurial technological regimes*, favour entrepreneurial entry and offer better growth prospects to young and innovative companies (Winter 1984).

Differences in the level of technological intensities and technological opportunities may be important for competitive dynamics (Klevorick et al. 1995), impacting both growth and survival prospects of newly founded firms (Sarkar et al. 2006). There is a higher probability of high growth firms (HGFs) emergence within industries that are highly innovative than in industries

with low or moderate innovation activity (Audretsch 1995a). Eckhardt & Shane (2011) found that changes in the application of technology by industries over time are associated with the differential importance of HGFs in industries. They interpret this finding as the existence of a link between technological innovation and the prevalence of entrepreneurial opportunities with high-growth prospects.

In one of the first attempts to link innovation regime and industry innovation intensity with firm growth and survival, Audretsch (1995b) found that both the total innovation rate and the small-firm innovation rate within an industry have positive impacts on short-term (two years) growth of entrants, but a negative impact on short-term survival within this group. Conversely, Jensen et al. (2008) found that new firm survival rates are higher in the industries with intensive competition through innovation, as proxied by a composite measure based on R&D expenditures, R&D employment, labour productivity, patents, trade marks, and design applications and a survey measure of organisational change. They explain their findings by the fact that industries characterised by rapid change in technological conditions provide new firms with more possibilities to find a market niche. Kim & Lee (2016), investigating a sample of newly founded Korean manufacturing firms, note that the type of technological regime moderates the effects of other factors influencing firm survival, including firms' R&D efforts. High technological opportunities are necessary for the positive effect of own R&D intensity on firm survival, which implies that *"the condition of high technological opportunity allows firms investing in innovative activities to better utilize abundant promising opportunities for radical and disruptive innovations"* (Kim & Lee 2016).

Newly established firms cannot devote substantial financial resources to R&D and innovation so they may depend to a greater extent on external sources of R&D to sustain their innovation activity (Audretsch & Vivarelli 1994; Rogers 2004; Cassia et al. 2009). Glynn (1996), in a series of case studies conducted on a sample of small companies in six industries in the US, documented how access to the leading-edge research conducted at universities and larger companies is critical for young and small companies. *"[L]arger companies have been very important for early innovation in advanced display technologies as well as for spinning off new companies. Similarly, large-scale corporate research programs have been extremely important in developing new computer and software technologies that enable these technology-intensive sectors of the economy, even though the larger companies themselves may not have exploited these technologies"* (Glynn 1996).

Until recently, consistent with the view of random growth of firms, the literature on the growth of new firms has lacked a strong focus on the locational characteristics favourable for the growth of firms. Scholars shared the idea that high growth firms can be found in all the regions and are not necessarily concentrated in specific locations (Giner et al. 2017). On the other hand, there is a widely held view that firms located within geographical clusters exhibit higher innovation, rates of growth and improved survival chances.

This ignorance of the geographic dimension has been identified by Audretsch (2012) as “*a remarkable hole in the research in the literature that begs for analysis*”. This is striking given extensive literature on agglomeration economies and research linking locational characteristics to entry rates. Not only firms’ emergence but also newly established firms’ growth prospects may depend on environmental factors associated with the characteristics of the regions they are active in. Within recently reconceptualised construct of entrepreneurial opportunity (Davidsson 2015), uncommercialized innovations developed by incumbents may act as *External Enablers* facilitating new firms emergence and influencing their growth prospects.

So far empirical investigations on the relationship between locational characteristics and growth prospects of young firms concentrated mainly on variables describing regional university and public research endowments, with relatively less focus on local incumbents’ innovation. Extant empirical research has generally confirmed a positive impact of public research and innovation on firms’ performance (Cassia et al. 2009; Audretsch et al. 2006; Helmers & Rogers 2010).

The impact of incumbents’ innovation on the performance of newly established firms is not that obvious. The presence of the innovating incumbents is not only a source of possible business opportunities for prospective entrepreneurs and young companies, but it may also be a source of strong competitive pressures impacting their business prospects. Intense localized competition may reduce the performance of local firms, especially if they are young and inexperienced. Due to the *product market rivalry effect* incumbent innovation may reduce the prospect of new competitors in the vicinity (Bloom et al. 2013). The successful introduction of new production processes or new products may exert downward pressure on prices or help incumbents increase their market share by offering new differentiated products or services *stealing* market from their competitors. Incumbents may

also be better positioned than young companies to compete for the best human capital.

On the other hand, Gilbert et al. (2008) argue that local competition within the cluster boosts the performance of individual firms, as they are obliged to innovate in order to maintain their competitiveness. Local rivals having access to similar endowments, e.g. labour pool, factor costs, and markets, have to compete on product and process design. Therefore, intense local competition may be seen as a local asset rather than a liability (Gilbert et al. 2008). Notwithstanding these arguments, Gilbert et al. (2008) were not able to confirm a positive relationship between knowledge spillovers and sales growth of new ventures located in clusters. Similarly, Kukalis (2010) investigating the financial performance of 194 firms active in semiconductor and pharmaceutical industries over 31 years, was not able to confirm any significant differences between clustered and non-clustered firms in the early stages of the industry life cycle.

The lack of confirmation of a positive relationship between clusters and the performance of firms and new entrants in the extant literature may be due to the focus only on average effects in most studies – related to the reliance on OLS regression. This average effect may conceal differentiated effects across the distribution of growth of newly established firms. Market stealing may be the prevailing effect in the case of the weakest young firms, whereas positive spillovers may dominate for the most dynamic and apt ones. Our third research question is therefore:

Research question 3

What is the association between knowledge stocks (patents) accumulated by incumbents in the region and the growth of newly created firms active in the same industry? Are there differences in the direction and strength of this relationship depending on the position of the newly established firm in the growth distribution?

Whereas innovation by incumbents in the same industry results both in the emergence of new entrepreneurial opportunities and an increase in the competitive pressure on newly established firms, innovation by firms active in other but similar industries not competing on the same market with new entrants may play a less ambiguous role. Incumbents not competing directly on the same market with young firms may be less concerned by the newly established firm reutilizing their ideas in new contexts. Innovation by firms active in similar industries may be a significant source of novelty and useful

ideas that are often overlooked by mature firms (Ahuja & Morris Lampert 2001). Such novelty may be necessary for creating a new customer base and new niches, giving young firm opportunities to grow. Innovation by incumbents active in technologically related industries may, therefore, be more critical for the growth of young firms than innovation from incumbents competing in the same industry.

While innovation of incumbents active in the focal industry of a young firm, apart from potentially positive externalities, may result in market stealing, those possible negative consequences are of less concern in the case of incumbents' innovation in the related industries. Some innovations developed in the related sectors may be adapted and applied in industries that are technologically related but do not compete on the same markets. Young firms, which are looking for the profitable routines, may be inspired by innovations developed by incumbents active in other sectors but in close geographical vicinity. They may be more willing to experiment with some novel concepts, as they have more flexible routines than their older rivals and are not so much bounded by their past experiences. Hence our next research question is:

Research question 4

What is the association between accumulated knowledge stocks (patents) in technologically related industries in the region and the growth of newly established firms? Is there a difference with the role of regional knowledge stocks of incumbent in the same industry?

In the extant literature, trade marks are treated as a signal of product and service differentiation and may complement patents as an indicator of broader innovative activities (Mendonca et al. 2004; Castaldi 2018; Stoneman & Bakhshi 2009; Millot 2009). Trade marks of incumbents may measure innovation activity with potential positive externalities benefiting new entrants active in the vicinity of incumbents. On the other hand, trade marks may be used strategically by incumbents to shield them from effective price competition, as strong brands and reputation make it more difficult for entrants to build their market position (Spulber 2006; Aaker 2007). This strategic use of trade marks by incumbents may be more effective against weaker entrants building their strategy on imitation and price competition, than stronger firms entering with differentiated products looking for unexploited niches on the market.

The combined use of patents and trade marks by incumbents may be a signal of a strong commercialization focus and higher determination to defend their market position. A strategy based on bundling of patent and trade mark protection by incumbents may reduce effective positive externalities accruing to new entrants and may increase competitive pressures. Trade marks may, therefore, negatively moderate the relationship between incumbent patent stocks and growth of newly established firms. Hence our last research question is:

Research question 5

What is the association between trade mark stocks accumulated by incumbents in the region and the growth of newly created firms active in the same industry? Are there differences in the direction and strength of this relationship depending on the position of the newly established firm in the growth distribution? Are trade mark stocks negatively moderating the relationship between growth of newly established firms and incumbents patent stocks?

6.3 Measures and methods

To address the research questions presented above, this section develops the empirical approach and explains how the core concepts and variables are measured.

Turnover growth of young firms

Our sample of firms is extracted from ORBIS and registers of intellectual property data. From this data we have selected a subsample of firms established in 2000 that contains information on annual growth rates of turnover for the years 2003 to 2009. We start to measure growth in the third year of activity to allow for the observation of patent and trade mark applications. In our econometric specifications we focus on turnover growth as our dependent variable. Turnover growth is more directly linked in the previous literature with successful innovation, while the impact of innovation, especially process innovation, on employment growth has not been clear (Delmar et al. 2003; Coad 2009; Piva & Vivarelli 2017).

Annual growth is measured by taking log-differences of size, the most common approach in the literature (Evans 1987b; Stanley et al. 1996; Coad 2009).

$$G_{it} = \log(S_{it}) - \log(S_{i,t-1}) \quad (6.2)$$

Where G_{it} is the growth rate of firm i in year t , S_{it} is its size in year t and $S_{i,t-1}$ is its size in year $t-1$. Our data has a panel structure, as we observe a firm i for up to 7 years. As illustrated in Table 6.2, we observe growth rates of 22 218 manufacturing firms created in 2000 in one of the 12 Member States of the European Union²⁷. The maximum number of annual growth rate observations is 7. However, for many firms, there are breaks in the series; on average, there are 4.23 annual growth observations per firm. Table 6.1 presents information on the distribution of the number of annual growth rates per firm observed in the dataset. Another challenge related to our dependent variable is that our sample suffers from attrition. At least to some extent, missing observations for firms are related to their exit. Out of 22 218 firms in our dataset, only for 13 687 we are able to calculate a growth rate for the year 2009. In case the probability of exit is correlated with our dependent variable, our main findings may be biased (Kennedy 2008). Therefore, in addition to the main panel quantile model, we also estimate models taking into account selection bias, as discussed in section 6.6.

Table 6.1 Distribution of number of observed growth rates of newly established firms

| Number of observations per firm | Number of firms |
|---------------------------------|-----------------|
| 1 | 3729 |
| 2 | 2615 |
| 3 | 2730 |
| 4 | 2243 |
| 5 | 3617 |
| 6 | 1241 |
| 7 | 6043 |

Source: own calculations based on the dataset compiled by author as explained in section 6.3

Our main relationship of interest is the link between newly established firms' innovation as proxied by patenting and trade marking behaviour and their growth in heterogeneous local competitive and innovation environments (knowledge and trade mark stocks of incumbents). To calculate knowledge

²⁷ AT, BE, DE, DK, ES, FR, GB, HU, IT, LT, NL and PT.

and trade mark stocks, we use the same methodology as described in chapter 5.

Patent and trade marking activity of newly established firms

Based on European and national patent data available in PATSTAT and national and European trade mark registers, we created a set of binary variables indicating whether a newly created firm has filed for patent or trade mark protection in years $t-3$ up to $t-1$. This specification assumes that innovation protected by patents or trade mark has its primary impact on growth in the short term, after which turnover stabilises at a higher level and new, or follow-up innovations are required for additional growth. This leads to a classification of a firm in year t into one of the following exclusive categories:

- Firms that have no patent or trade mark applications (firms for which we were not able to find any trade mark or patent records during the time window referred to above);
- Firms with trade mark applications only;
- Firms with patent applications only;
- Firms with both patent and trade mark applications.

Each observation in our dataset is classified into one of those categories and the categories are orthogonal to each other. In the present dissertation, we are not interested in the impact of the IPR protection on turnover growth but rather treat patent and trade mark applications as proxies for innovative activity of newly created firms.

Knowledge stocks and trade mark activity of incumbents

Knowledge stocks of incumbents are calculated as patent application stocks for each NACE4/NUTS3 combination in our dataset, as explained in section 3.6 and in accordance with equations (3.1), (3.3) and (3.5). Similar to chapter 5, we distinguish between patent stocks of firms active in the focal industry of the newly established firms and patent stocks of firms active in related industries, calculated in accordance with equation (4.1).

Trade mark activity of incumbents is calculated as incumbents' trade mark stock, as described in chapter 3.6 and in accordance with equations (3.2), (3.3) and (3.5). To empirically analyze the role of combining patents with trade marks, we construct an interaction term between the two (Jaccard & Turrisi 2003; Jaccard & Jacoby 2010).

Control variables

As already discussed above, the first covariates of growth discovered in economic research were the firm's age and its size. In our econometric specifications, we include these respective variables. We define *age* as a number of years since establishment, using establishment date available in ORBIS. We control for *size* using a logarithm of turnover at year t-1.

To control for the strength of local competition, we include a variable *log of firms in the industry (NACE4d/NUTS3)* calculated as a logarithm of the total number of incumbent firms in the focal NUTS3 region and NACE4 industry at year t-1. In addition, we include the *log of startups in industry (NACE4d/NUTS3)* calculated as the logarithm of the total number of newly established firms in the focal industry in year t-1.

To account for potential benefits stemming from agglomeration economies we control for buyer and supplier fit, using measures proposed by Dumais et al. (2002) as explained in section 5.3 and equations (5.5) and (5.6)

Individual firm growth may be simply the reflection of the overall growth of sales in the industry. To control for this aspect, we include in our models an industry-country output growth variable calculated from national accounts data available in Eurostat. Growth prospects of firms may also depend, to a large extent, on the overall economic situation of the region. To control for that aspect, we use two variables extracted from Eurostat. We use *log of GDP per capita* to control for the level of economic development of the region and *GDP per capita change* to control for economic growth.

Similar to the models described in chapter 5, we include a variable indicating the contribution of the young firms to the overall knowledge stock available in the NUTS3/NACE4 and calculated in accordance with equation (5.2). In the estimations, we also include a variable denoting the contribution of universities to the overall knowledge stock in the NUTS3 region, calculated in accordance with equation (5.3).

Finally, we control for a set of local socio-economic variables:

Population density – operationalized with Eurostat variable *Population density by NUTS 3 regions (inhabitants per square km)*.

Unemployment – available from Eurostat and based on the EU Labour Force Survey (EU-LFS). The unemployment rate shows unemployed persons as a percentage of the economically active population.

Educational attainment level- operationalized with a variable *Upper secondary, post-secondary non-tertiary and tertiary education*, corresponding to the levels 3-8 of the International Standard Classification of Education (ISCED) 2011²⁸.

Table 6.2 presents the descriptive statistics and Table 6.3 the correlation matrix for the variables included in the growth model.

²⁸ Description of the sources of variables retrieved from Eurostat is available in chapter 5.

Table 6.2 Descriptive statistics for the main variables in the turnover growth model

| Variable | | Mean | Std. Dev. | Min | Max |
|-------------------------------------------------------------------------|---------|-------|-----------|--------|-------|
| Growth of turnover | overall | 0.00 | 0.58 | -8.91 | 10.97 |
| | between | | 0.49 | -7.92 | 6.62 |
| | within | | 0.75 | -8.90 | 11.44 |
| No patent or trademark | overall | 0.94 | 0.24 | 0.00 | 1.00 |
| | between | | 0.19 | 0.00 | 1.00 |
| | within | | 0.31 | -0.06 | 1.94 |
| Only patent applications | overall | 0.01 | 0.11 | 0.00 | 1.00 |
| | between | | 0.10 | 0.00 | 1.00 |
| | within | | 0.15 | -0.99 | 1.01 |
| Only tm applications | overall | 0.04 | 0.20 | 0.00 | 1.00 |
| | between | | 0.15 | 0.00 | 1.00 |
| | within | | 0.25 | -0.96 | 1.04 |
| Patent and trade mark | overall | 0.01 | 0.08 | 0.00 | 1.00 |
| | between | | 0.07 | 0.00 | 1.00 |
| | within | | 0.10 | -0.99 | 1.01 |
| Log of patent stock in focal industry (lag 1) | overall | 0.58 | 0.84 | 0.00 | 6.63 |
| | between | | 0.84 | 0.00 | 6.58 |
| | within | | 1.19 | -5.99 | 7.22 |
| Log of patent stock in related industries (lag 1) | overall | 3.18 | 1.39 | 0.00 | 7.65 |
| | between | | 1.41 | 0.00 | 7.57 |
| | within | | 1.99 | -3.24 | 10.35 |
| Log of tm stock in focal industry (lag 1) | overall | 2.45 | 1.61 | 0.00 | 8.39 |
| | between | | 1.60 | 0.00 | 8.23 |
| | within | | 2.32 | -5.61 | 10.78 |
| Size (lag 1) | overall | 6.42 | 1.73 | 0.00 | 17.59 |
| | between | | 1.79 | 0.00 | 17.38 |
| | within | | 2.53 | -7.40 | 23.06 |
| Age | overall | 6.08 | 1.94 | 3.00 | 9.00 |
| | between | | 1.39 | 3.00 | 9.00 |
| | within | | 2.40 | 0.08 | 12.08 |
| Contr. of young firms to knowledge stock (lag 1) | overall | 0.11 | 0.27 | 0.00 | 1.00 |
| | between | | 0.26 | 0.00 | 1.00 |
| | within | | 0.37 | -0.89 | 1.11 |
| Contr. of univ. to knowledge stock (lag 1) | overall | 0.06 | 0.12 | 0.00 | 1.00 |
| | between | | 0.12 | 0.00 | 1.00 |
| | within | | 0.17 | -0.94 | 1.06 |
| Log of incumbents (lag 1) | overall | 3.68 | 1.60 | 0.69 | 8.28 |
| | between | | 1.61 | 0.69 | 8.28 |
| | within | | 2.33 | -3.92 | 11.27 |
| Log of startups (lag 1) | overall | 1.21 | 1.21 | 0.00 | 5.73 |
| | between | | 1.16 | 0.00 | 5.34 |
| | within | | 1.72 | -4.13 | 6.55 |
| Buyers' fit (lag 1) | overall | 0.14 | 1.09 | -1.91 | 6.59 |
| | between | | 1.06 | -1.91 | 6.52 |
| | within | | 1.54 | -7.75 | 8.10 |
| Suppliers' fit (lag 1) | overall | 0.05 | 1.09 | -1.91 | 12.39 |
| | between | | 1.09 | -1.91 | 11.84 |
| | within | | 1.54 | -12.45 | 13.39 |
| Industry growth (NACE 2, lag 1) | overall | 0.03 | 0.06 | -0.33 | 0.86 |
| | between | | 0.05 | -0.33 | 0.50 |
| | within | | 0.08 | -0.59 | 0.82 |
| Log of GDP per capita in the region | overall | 10.07 | 0.31 | 8.59 | 11.32 |
| | between | | 0.34 | 8.78 | 11.32 |
| | within | | 0.47 | 8.19 | 12.03 |
| GDP per capita growth in the region | overall | 0.02 | 0.05 | -0.31 | 0.34 |
| | between | | 0.03 | -0.22 | 0.20 |
| | within | | 0.06 | -0.33 | 0.35 |
| Unemployment level | overall | 0.08 | 0.04 | 0.02 | 0.26 |
| | between | | 0.04 | 0.02 | 0.26 |
| | within | | 0.05 | -0.15 | 0.30 |
| Share of population with secondary and tertiary education in the region | overall | 0.60 | 0.14 | 0.17 | 0.97 |
| | between | | 0.15 | 0.17 | 0.97 |
| | within | | 0.23 | -0.09 | 1.20 |
| Log of population density | overall | 5.49 | 1.27 | 1.96 | 9.96 |
| | between | | 1.29 | 1.96 | 9.96 |
| | within | | 1.79 | -1.97 | 13.16 |

Unbalanced Panel: N=93953, n=22218, T=1-7, T-bar=4.23

Table 6.3: Correlation matrix for variables used in the models

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 |
|-------------------------------------------------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|------|
| 1. Growth rate | | | | | | | | | | | | | | | | | | | | | |
| 2. No patent or trade mark | -0.03 | | | | | | | | | | | | | | | | | | | | |
| 3. Only patent applications | 0.01 | -0.46 | | | | | | | | | | | | | | | | | | | |
| 4. Only tm applications | 0.03 | -0.81 | -0.02 | | | | | | | | | | | | | | | | | | |
| 5. Patent and trade mark | 0.01 | -0.32 | -0.01 | -0.02 | | | | | | | | | | | | | | | | | |
| 6. Log of patent stock in own industry (lag1) | 0.00 | -0.07 | 0.11 | -0.02 | 0.11 | | | | | | | | | | | | | | | | |
| 7. Log of patent stock in related industries (lag 1) | 0.00 | 0.00 | 0.05 | -0.04 | 0.04 | 0.51 | | | | | | | | | | | | | | | |
| 8. Log of trade mark stock in own industry (lag 1) | -0.02 | -0.12 | -0.01 | 0.14 | 0.03 | 0.32 | 0.17 | | | | | | | | | | | | | | |
| 9. Size (lag 1) | -0.08 | -0.21 | 0.13 | 0.12 | 0.14 | 0.15 | 0.09 | 0.01 | | | | | | | | | | | | | |
| 10. Age | -0.13 | 0.00 | 0.02 | -0.01 | 0.02 | 0.08 | 0.10 | 0.02 | 0.09 | | | | | | | | | | | | |
| 11. Contr. of young firms to knowledge stock (lag 1) | 0.00 | -0.04 | 0.07 | -0.02 | 0.06 | 0.29 | 0.27 | 0.14 | 0.06 | 0.00 | | | | | | | | | | | |
| 12. Contr. of universities to knowledge stock (lag 1) | 0.00 | 0.00 | -0.03 | 0.03 | -0.02 | -0.20 | -0.44 | 0.00 | -0.08 | 0.02 | -0.12 | | | | | | | | | | |
| 13. Log of incumbents (lag 1) | -0.03 | 0.06 | -0.06 | -0.02 | -0.04 | 0.20 | 0.21 | 0.67 | -0.15 | -0.01 | 0.17 | 0.00 | | | | | | | | | |
| 14. Log of startups (lag 1) | -0.02 | 0.06 | -0.05 | -0.03 | -0.04 | 0.14 | 0.16 | 0.57 | -0.16 | -0.06 | 0.16 | 0.01 | 0.88 | | | | | | | | |
| 15. Buyers' fit (lag 1) | 0.01 | -0.01 | -0.01 | 0.02 | -0.01 | -0.07 | -0.15 | -0.05 | 0.00 | 0.03 | -0.06 | 0.16 | -0.07 | -0.08 | | | | | | | |
| 16. Suppliers' fit (lag 1) | 0.01 | -0.11 | 0.03 | 0.11 | 0.02 | 0.05 | -0.05 | 0.19 | 0.06 | 0.01 | 0.00 | 0.03 | -0.07 | -0.09 | 0.26 | | | | | | |
| 17. Industry growth (NACE 2, lag 1) | 0.06 | -0.01 | 0.00 | 0.02 | 0.00 | -0.03 | -0.09 | 0.03 | 0.00 | 0.07 | -0.03 | 0.08 | 0.04 | 0.05 | 0.22 | 0.07 | | | | | |
| 18. Log of GDP per capita in the region | -0.02 | -0.04 | 0.04 | 0.01 | 0.04 | 0.31 | 0.58 | 0.31 | 0.13 | 0.12 | 0.19 | -0.27 | 0.23 | 0.16 | -0.11 | -0.04 | -0.03 | | | | |
| 19. GDP per capita growth in the region | 0.12 | -0.01 | -0.01 | 0.02 | -0.01 | -0.06 | -0.12 | 0.01 | -0.05 | -0.39 | -0.02 | 0.08 | 0.03 | 0.05 | 0.02 | -0.01 | 0.30 | 0.01 | | | |
| 20. Unemployment level | -0.03 | 0.01 | -0.05 | 0.03 | -0.03 | -0.18 | -0.30 | -0.01 | -0.12 | 0.01 | -0.10 | 0.29 | 0.04 | 0.06 | 0.14 | -0.02 | -0.06 | -0.43 | -0.13 | | |
| 21. Share of pop. with secondary, and tertiary, edu. | 0.00 | 0.02 | 0.06 | -0.07 | 0.04 | 0.14 | 0.38 | -0.33 | 0.06 | 0.19 | 0.08 | -0.31 | -0.19 | -0.19 | -0.21 | -0.13 | -0.06 | 0.12 | -0.08 | -0.28 | |
| 22. Log of population density | -0.02 | 0.00 | 0.03 | -0.03 | 0.03 | 0.27 | 0.46 | 0.21 | 0.06 | 0.02 | 0.18 | -0.22 | 0.28 | 0.24 | -0.21 | -0.13 | -0.10 | 0.58 | -0.01 | -0.17 | 0.17 |

Source: for Table 6.2 and Table 6.3 own calculations based on the dataset compiled by author as explained in section 6.3.

6.4 Empirical Methods

6.4.1 Empirical model

Traditional OLS regression only examines the means of the distribution of the dependent variable, which has its limitations. It gives an incomplete picture of the relationship of interest in non-central locations of the distribution of the dependent variable, which may be of particular interest of the researcher. Besides, it requires that the conditional distribution meets the requirements of normality and homoscedasticity. Our research questions in section 6.2 suggest to investigate whether the impact of own and incumbents' innovation and trade marking may be different for firms located in the higher quantile of growth than for firms in lower quantiles. Conditional quantile estimation is the most adequate model for answering our research questions.

Quantile regression replaces least-squares estimation with the minimization of the sum of absolute residuals (Koenker & Bassett Jr 1978). Quantile regression assumes the possibility of differential effect of covariates on various quantiles and thus is able to capture the effect of explanatory variables on the location, scale and shape of the distribution of the dependent variable (Hao et al. 2007). In this way, it is more suited to deal with heteroscedasticity than traditional conditional mean regression and may be better suited to deal with data with non-Gaussian errors (Koenker & Bassett Jr 1978). Estimation of the median regression is able to achieve the same effect as OLS. Moreover, in the case of a highly skewed distribution, median regression remains more informative than conditional mean models. Outliers do not have as significant influence on the fitted regression line as in the case of the linear regression model. An additional advantage of the quantile regression is the possibility to model associations in multiple quantiles, which facilitates a more complete understanding of the response variable change as a function of predictor variables (Hao et al. 2007). In recent years quantile regression is being increasingly used for studies focusing on firms growth, particularly in the context of innovation and R&D (Coad et al. 2016; Goedhuys & Sleuwaegen 2010; Coad & Rao 2008).

The quantile regression model corresponding to the standard conditional mean regression can be expressed by the following equation

$$y_i = \beta_0^{(\tau)} + \beta_1^{(\tau)} X_i + \varepsilon_i^{(\tau)} \quad (6.3)$$

Where $0 < \tau < 1$ indicates the proportion of the population with scores below the quantile at τ .

The conditional τ^{th} quantile is determined by the parameters $\beta_0^{(\tau)}$ and $\beta_1^{(\tau)}$, specific to the quantile and value of X_i . Estimation of those parameters is based on the weighted data of the full sample, and not only on a subset of the sample located at the given quantile (Hao et al. 2007). Estimations follow from the solution to the following minimization problem:

$$\min \left[\sum_{y_i \geq \beta_0^{(\tau)} + \beta_1^{(\tau)} X_i} \tau |y_i - \beta_0^{(\tau)} + \beta_1^{(\tau)} X_i| + \sum_{y_i < \beta_0^{(\tau)} + \beta_1^{(\tau)} X_i} (1 - \tau) |y_i - \beta_0^{(\tau)} + \beta_1^{(\tau)} X_i| \right] \quad (6.4)$$

Thus, unlike OLS which minimizes squared residuals, quantile regression minimizes absolute deviations from the given quantile, assigning different weights to positive and negative residuals.

Our dataset consists of firms with yearly growth observations. It has a longitudinal structure, as shown in the equation below:

$$y_{it} = \mu_t + \beta X_{it} + \alpha_i + \varepsilon_{it} \quad (6.5)$$

Where y_{it} is a turnover growth of firm i in year t , μ_t is an intercept that may vary in each period, β is a vector of coefficients for a set of variables that vary over time (X_{it}). Distinctive to panel data models are two error terms: the standard idiosyncratic disturbances ε_{it} and individual heterogeneity α_i , which varies only across individual firms. While ε_{it} represents purely random variation at each point in time, α_i represents the combined effect of all unobserved variables that stay constant for a firm over time.

Firms are heterogeneous. They differ from one another in fundamental ways. There is a plethora of unmeasured variables that affect behaviour and fates of firms. Omission of such variables may cause bias in estimation (Kennedy 2008). Having longitudinal data creates an opportunity to control for unobserved subject characteristics that do not change over time, thus reducing the risk of bias from important omitted variables which may affect firms' growth. The vector of firm-specific effects α_i is, therefore, crucial (Allison 2009). The answer to the key question of how to incorporate

unobserved characteristics - random effects versus fixed effects – depends on whether or not these are correlated with the observed explanatory variables X_{it} (Wooldridge 2010). The random effect framework assumes no correlation between the observed explanatory variables and unobserved effects. The fixed effects framework allows for arbitrary dependence between the unobserved effect α_i and the observed explanatory variables X_{it} . Under the fixed effects framework all stable characteristics of firms are controlled for, and only within- firms variation is used to estimate the regression parameters (Allison 2009).

Quantile regression methods for panel data have the potential to combine controls for individual heterogeneity with quantile regression's strength of analysis of the covariates' differential impact over the distribution. However, in a quantile regression setting, there is no general transformation that could eliminate individual effects (Kato et al. 2012). Koenker (2004) noticed that introduction of a large number of *fixed effects* might significantly increase the variability of estimates of other coefficients of interest and increases the risk of incidental parameters problem (Galvao & Montes-Rojas 2010). The risk of incidental parameter problem is especially acute in settings with large numbers of individuals and a fixed number of time periods (Arellano & Bonhomme 2009).

A solution for the estimation of quantile panel regression has been proposed for the first time by Koenker (2004). In his specification, α_i captures some individual specific source of unobserved heterogeneity that is not adequately controlled for by other variables in the model. Since in most applications the number of observations on each individual is relatively small, Koenker (2004) admits that it is quite unrealistic to estimate a quantile dependent distributional shift for each individual. Instead, he focuses on methods allowing to estimate individual-specific shift effects. Quantile regression with fixed effect proposed by Koenker (2004) has the following structure:

$$Q_{y_{ij}}(\tau|x_{ij}) = \alpha_i + x_{ij}^T \beta(\tau) \quad j = 1, \dots, m_i, i = 1, \dots, n \quad (6.6)$$

Within this structure, the effects of covariates x_{ij} depend upon the quantile, however, fixed effects α_i remain the same over all the quantiles.

To deal with a large number of fixed effects, Koenker (2004) considers L1-lasso regularization (Tibshirani 1996) by adding a factor comprising the sum of the absolute value of coefficients in the optimization objective in the form of the *shrinkage penalty term*:

$$\lambda \sum_{i=1}^n |\alpha_i| \quad (6.7)$$

Lambda (λ) is a tuning parameter that controls for the relative impact of firm fixed effects (α_i) on the estimation of the regression variables. When $\lambda \rightarrow \infty$ and $\hat{\alpha} \rightarrow 0$ fixed effects are purged for all i (Koenker 2004). As λ gets larger, estimates of the key variables of interest become less sensitive to the differences between firms.

Therefore, in the quantile regression with fixed effects estimators solve for

$$\min (\alpha, \beta) \sum_{k=1}^q \sum_{j=1}^n \sum_{i=1}^{m_i} \omega_k \rho_{\tau_k} (y_{ij} - \alpha_i - x_{ij} \beta(\tau_k)) + \lambda \sum_{i=1}^n |\alpha_i| \quad (6.8)$$

The weights ω_k control for the relative influence of the τ quantiles on the estimation of α_i parameters.

In the fixed effect quantile regression model as proposed by Koenker (2004), the choice of lambda only directly influence the estimation of a particular set of coefficients to be penalized, i.e. fixed-effect firms coefficients, and has only an indirect impact on the estimation of focal variables of our interest. The choice of tuning parameter lambda is determined exogenously. There is no obvious way of choosing the tuning parameter and several methods have been proposed in the literature for panel quantile regression (Koenker 2005; Lamarche 2010).

We compute an estimate of the tuning parameter $\hat{\lambda}$ following Koenker (2005) by the equation:

$$\hat{\lambda} = \hat{\sigma}_\varepsilon / \hat{\sigma}_\alpha \quad (6.9)$$

where $\widehat{\sigma}_\varepsilon^2$ is the variance of the error term and $\widehat{\sigma}_\alpha^2$ is a variance of the individual effect. The method recommended by Koenker (2005) indicates that in the context of our data, a value for lambda of 0.1 would be preferred. However, for transparency, in Table 6.5, we report results of our key variables estimated using various penalty terms.

The method proposed by Koenker (2004) is based on the extensive literature emphasizing risks of overfitting in traditional fixed effects regression and this approach is natural to the Bayesian paradigm. This risk is especially present in unbalanced panels, where for some firms there are only few data points available. For such observations, the margin of error is high and traditional

fixed effect model may exaggerate actual differences between firms (Gelman & Hill 2006).

As suggested by Koenker & Machado (1999), we assess the Goodness of Fit of the quantiles models by comparing the weighted sum of the absolute value of residuals calculated for the median quantile of the focal model with a model restricted to only the intercept.

6.5 Results

Table 6.4 presents our results of fixed effects quantile regression for the quantiles 0.05, 0.25, 0.50, 0.75 and 0.95. The coefficients show the marginal change in the dependent variable at the given quantile associated with a marginal change in the regressors. Table 6.5 shows the sensitivity of results with respect to the choice of lambda.

Our first research question aimed to uncover the relationship between patenting activity by newly created firms and their sales growth, differentiating firms by their position in the growth distribution. As can be seen in Table 6.4 and Figure 6.1, the coefficient of a patent application is not statistically significant at 95% confidence level in the lowest quantiles of firms' growth. However, the strength of the relationship increases in the higher quantiles, and technological innovation proxied by patenting is positively related with turnover growth of new firms in the upper quantiles of growth distribution (from 0.25 onwards). The coefficient reaches a value of 0.14 in the 0.95 quantile of firms' growth. This suggests that technological innovation proxied by application for a patent is related with an increase of the growth rate among the highest growing entrants by 14 percent points. Technological innovation is, therefore, an important factor that contributes to the superior performance of new manufacturing firms.

Table 6.4 Fixed effects panel quantile regression estimates for sales growth

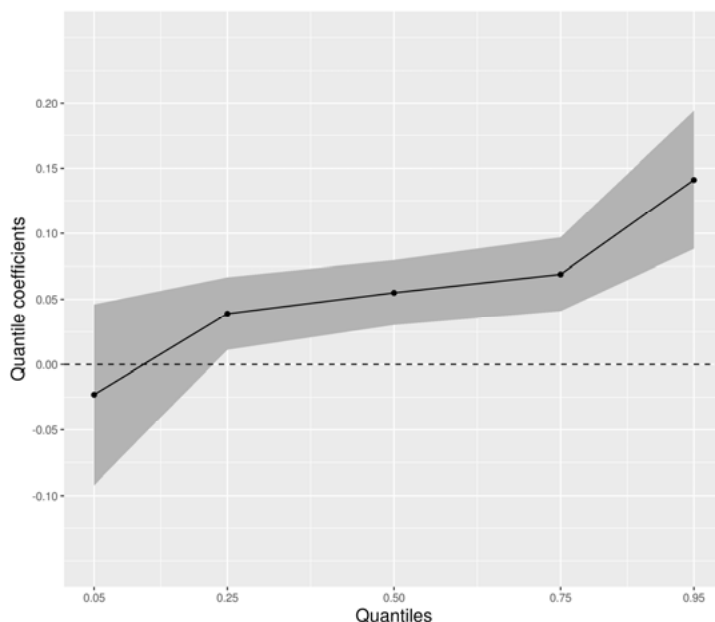
| | 0.05 | 0.25 | 0.5 | 0.75 | 0.95 |
|--------------------------------------------------------------------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|
| Only patent app | -0.023 (0.035) | 0.039 *** (0.014) | 0.055 *** (0.013) | 0.069 *** (0.014) | 0.141 *** (0.027) |
| Only trade mark app | 0.023 (0.022) | 0.032 *** (0.008) | 0.02 *** (0.006) | 0.029 *** (0.007) | 0.062 *** (0.02) |
| Patent and trade mark | -0.035 (0.054) | 0.024 (0.021) | 0.031 + (0.018) | 0.052 *** (0.019) | 0.096 + (0.053) |
| Log of patent stock in focal industry (lag 1) | 0.043 *** (0.016) | 0.069 *** (0.011) | 0.077 *** (0.011) | 0.083 *** (0.011) | 0.124 *** (0.016) |
| Log of patent stock in related industries (lag 1) | 0.071 *** (0.006) | 0.052 *** (0.004) | 0.048 *** (0.004) | 0.043 *** (0.004) | 0.02 *** (0.005) |
| Log of trade mark stock in focal industry (lag 1) | 0.016 ** (0.006) | 0.033 *** (0.004) | 0.036 *** (0.004) | 0.038 *** (0.004) | 0.046 *** (0.005) |
| Interaction between patent and trade mark stocks in focal industry | -0.009 ** (0.004) | -0.011 *** (0.003) | -0.012 *** (0.003) | -0.011 *** (0.003) | -0.013 *** (0.004) |
| Size (lag 1) | -0.282 *** (0.008) | -0.323 *** (0.008) | -0.325 *** (0.008) | -0.336 *** (0.008) | -0.386 *** (0.008) |
| Age | -0.055 *** (0.003) | -0.02 *** (0.001) | -0.012 *** (0.001) | -0.012 *** (0.001) | -0.029 *** (0.003) |
| Contribution of young firms to knowledge stock (lag 1) | -0.012 (0.02) | -0.019 + (0.01) | -0.014 (0.01) | -0.012 (0.011) | -0.001 (0.016) |
| Contribution of universities to knowledge stock (lag 1) | -0.039 (0.057) | -0.061 + (0.033) | -0.057 + (0.029) | -0.033 (0.031) | -0.027 (0.046) |
| Log of incumbents' number (lag 1) | -0.088 *** (0.007) | -0.099 *** (0.004) | -0.102 *** (0.004) | -0.104 *** (0.004) | -0.127 *** (0.006) |
| Log of startups (lag 1) | 0.012 (0.008) | 0.006 ** (0.003) | 0.008 *** (0.003) | 0.006 ** (0.003) | 0.011 + (0.007) |
| Buyers' fit (lag 1) | 0.052 *** (0.006) | 0.035 *** (0.004) | 0.039 *** (0.003) | 0.04 *** (0.003) | 0.031 *** (0.005) |
| Suppliers' fit (lag 1) | -0.052 *** (0.006) | -0.037 *** (0.004) | -0.043 *** (0.003) | -0.048 *** (0.004) | -0.033 *** (0.005) |
| Industry growth (NACE2, lag 1) | 0.763 *** (0.076) | 0.51 *** (0.028) | 0.345 *** (0.024) | 0.284 *** (0.026) | 0.361 *** (0.063) |
| Log of GDP per capita in the region (PPS) | 0.192 *** (0.026) | 0.131 *** (0.018) | 0.126 *** (0.018) | 0.119 *** (0.018) | 0.12 *** (0.026) |
| GDP per capita growth in the region (PPS) | 1.274 *** (0.12) | 0.718 *** (0.036) | 0.449 *** (0.025) | 0.399 *** (0.032) | 0.128 (0.096) |
| Unemployment level | -1.55 *** (0.159) | -1.417 *** (0.072) | -1.307 *** (0.061) | -1.369 *** (0.06) | -1.346 *** (0.13) |
| Share of population with secondary and tertiary education | 0.007 (0.051) | -0.144 *** (0.031) | -0.31 *** (0.03) | -0.417 *** (0.031) | -0.431 *** (0.046) |
| Log of population density | -0.046 *** (0.005) | -0.012 *** (0.003) | -0.01 *** (0.003) | -0.006 ** (0.003) | 0.016 *** (0.004) |
| Constant | -0.009 ** (0.004) | -0.011 *** (0.003) | -0.012 *** (0.003) | -0.011 *** (0.003) | -0.013 *** (0.004) |

Model estimated on the unbalanced panel of 22 218 firms created in 2000, T=1-7, N=93 953, $\Lambda=0.1$

Note: *p<0.1; **p<0.05; ***p<0.01

R1 0.86 calculated by comparing residuals of fixed effects quantile model with pooled quantile regression with only intercept for median quantile

Figure 6.1 Asymptotic 95% confidence interval of quantile-regression estimate of the association of individual patenting with new firms' annual growth rate of turnover

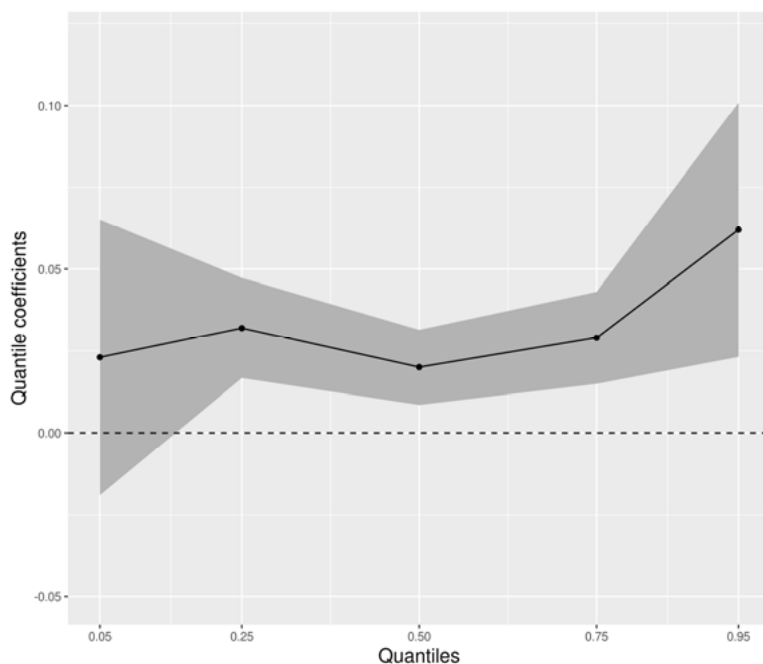


Note: dots present the point estimates of the focal coefficient for a given quantile of new firms' growth distribution. A band around the line presents the 95% confidence interval calculated for each estimate;

Source: own calculations based on the results of model presented in Table 6.4.

Analysis of Figure 6.1 suggests that the technological innovations proxied by individual patenting increase the spread in the distribution of sales' growth rates, increasing differences between firms in the lower and upper tails of the growth distribution.

Figure 6.2 Asymptotic 95% confidence interval of quantile-regression estimates of the association of individual trade marking with new firms' annual growth rate of turnover

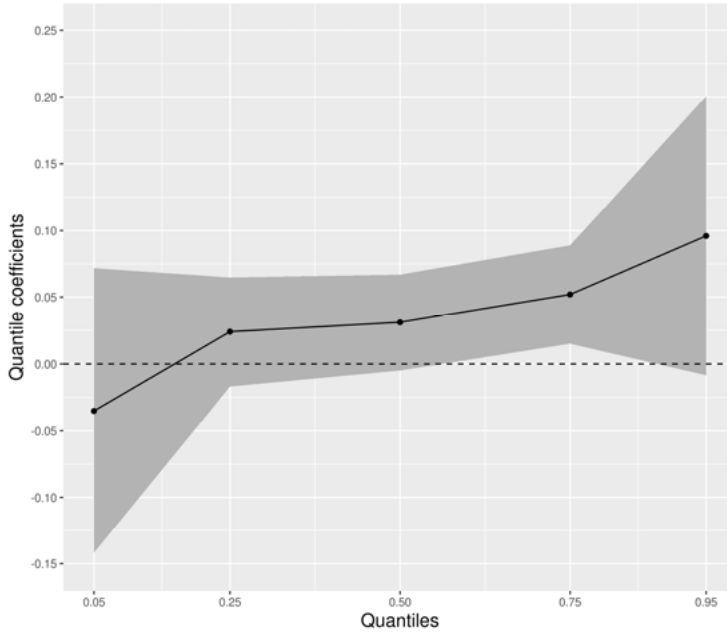


Note: dots present the point estimates of the focal coefficient for a given quantile of new firms' growth distribution. A band around the line presents the 95% confidence interval calculated for each estimate;

Source: own calculations based on the results of model presented in Table 6.4.

Our second research question concerned the relationship between innovations proxied by trade marks and turnover growth of newly created firms. As illustrated in Table 6.4 and Figure 6.2, similar to the case of new firm patenting, innovations proxied by application for trade marks is positively related with new firms' growth starting from the 0.25 quantile. For the lowest quantiles it is positive, but not statistically significant. Results of the estimation indicate that innovations proxied by application for a trade mark is associated with a 3.2 percent point higher growth of firms in the 0.25 and 6.2 percent point higher growth of firms in the highest quantile. Hence, innovations proxied by trade marking activity have a more moderate impact in terms of increasing asymmetry in the distribution of growth rates of newly established manufacturing firms than those related with patenting activity.

Figure 6.3 Asymptotic 95% confidence interval of quantile-regression estimates of the association of patent and trade mark application with new firms' annual growth rate of turnover

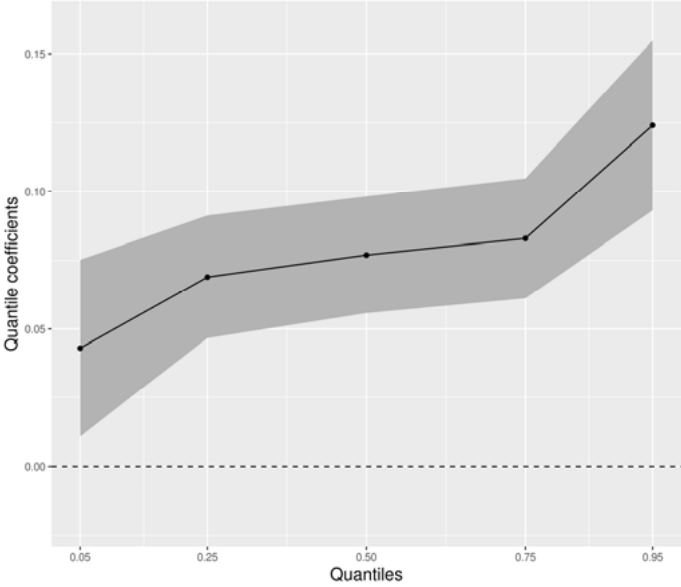


Note: dots present the point estimates of the focal coefficient for a given quantile of new firms' growth distribution. A band around the line presents the 95% confidence interval calculated for each estimate;

Source: own calculations based on the results of model presented in Table 6.4.

As regards the relationship between innovations proxied by the combined use of trade mark and patent application and growth, our model confirms the positive association only for the 0.75 quantile at 95% confidence level and for the 0.5 and 0.95 quantiles at 90% confidence. In absolute terms, the coefficient of the patent and trade mark bundle for firms located in the 0.75 quantile of growth indicates that bundling patent and trade mark increases turnover growth by 5.2 percentage points. As can be seen in Table 6.5, the coefficient of the bundle is the most sensitive one to the choice of the lambda parameter. In the models with the value of the tuning parameter equal to 0.5 and above, the results of this coefficient become statistically significant for all the firms with above-median growth. Additionally, the absolute value of the bundling coefficient becomes the highest among the dummies describing IP activity of a firm.

Figure 6.4 Asymptotic 95% confidence interval of quantile-regression estimates of the association of incumbents’ patent stocks (same NACE industry) with new firms’ annual growth rate of turnover



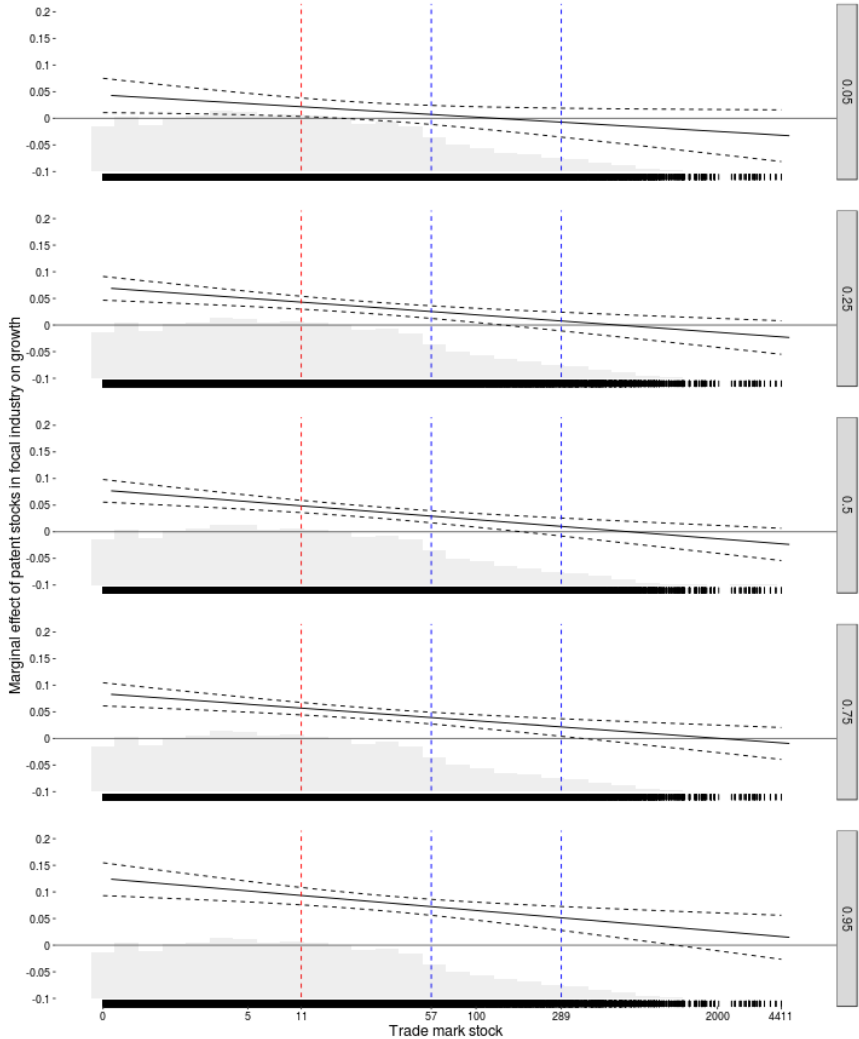
Note: dots present the point estimates of the focal coefficient for a given quantile of new firms’ growth distribution. A band around the line presents the 95% confidence interval calculated for each estimate;

Source: own calculations based on the results of model presented in Table 6.4.

Research question 3 concerns the relationship between incumbents’ patent stocks and the growth of newly created firms. As could be seen from Table 6.4 and Figure 6.4, with incumbents trade mark stocks held at 0, patent stocks in the focal industry are positively associated with the growth of newly created firms over the entire distribution of the growth rates. However, the higher the growth quantile the stronger is this relationship. Our results indicate that 10% higher patent stocks are related with 0.4 percent point higher growth of newly established firms in the 0.05 quantile of growth and with 1.24 percent point in the 0.95 quantile of growth.

However, as illustrated in Table 6.4 and Figure 6.5, this relationship is moderated by the incumbents’ trade mark stocks.

Figure 6.5 Asymptotic 95% confidence interval for quantile regression estimates of association between patent stocks and new firm growth for different levels of trade mark stocks



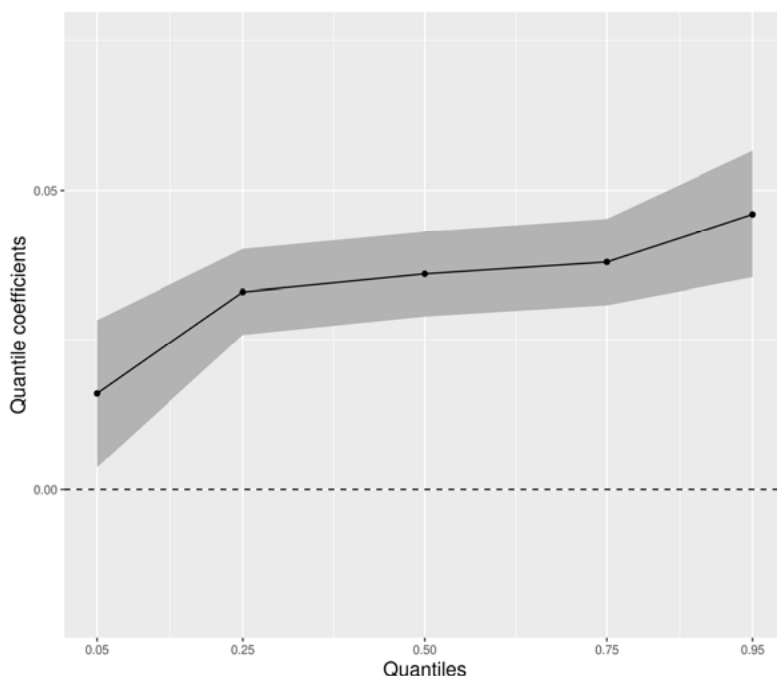
Note: red dashed line corresponds to mean value of log transformed stock of trade marks, blue lines correspond to mean +sd and mean+2*sd value of log transformed stock of trade marks. Grey histogram presents distribution of log transformed stock of trade marks in the dataset. Black lines in the bottom of the plot represent individual observations of log transformed trade mark stock in the dataset;
Source: own calculation based on the results of the model presented in Table 6.4.

The coefficients of the interaction variable between incumbents' patent and trade mark stock are negative, implying that the positive relationship between incumbent's patent stock and growth becomes weaker in regions with relatively higher incumbents' trade mark stocks. As could be seen in Figure 6.5 the relationship between incumbents' patent stock and growth rates becomes statistically insignificant for firms located in the 0.05 quantile of growth already when the trade mark stock reaches its mean value (of approximately 11 trade marks). Patent stocks relationship with the growth of newly created firms located in the lowest quantile of growth turns negative at the trade mark stock of 120. For the 0.25 and 0.5 quantile of firms' growth, this relationship becomes statistically insignificant approximately at a trade mark stock of 100 (which corresponds to 90 percentile of trade mark stock distribution). For the newly created firms located in the highest quantile of growth (0.95), the relationship between incumbents' patent stock and growth becomes statistically insignificant only at a trade mark stock of 1325 (which corresponds to over 99 percentile of trade mark stock distribution) and stays positive even at the highest levels of trade mark stocks.

This analysis allows us to answer our research question 5 which dealt with the possible moderating effect of incumbents' trade mark stocks on the relationship between incumbents' patent stocks and the growth rate of newly created firms. Our results confirm the existence of such a negative moderating effect. This effect is, however, much stronger for newly created firms located in the lowest quantiles of growth than for firms located on the high end of the growth rates distribution. Incumbents can limit the positive impact of their knowledge stocks on the growth of the newly created firms located in the lowest quantiles of growth with relatively less intensive trade mark activity. However, this is much more difficult in the case of the most dynamic entrants, located in the highest quantile of growth. For them the positive effects of incumbents' knowledge stocks on growth fades away only in the case of very intensive trade marking activity of incumbents located in the region.

Extant literature implied that incumbents' trade mark stock may play a role not only as a moderator for patent stocks but may also proxy for broader innovative activities, not captured by patents, which may also be subject to positive externalities enhancing growth opportunities. This conjecture is confirmed by the results shown in Table 6.4 and Figure 6.6.

Figure 6.6 Asymptotic 95% confidence interval of quantile-regression estimate of incumbents' trade marks stock (same NACE industry) impact on firms' annual growth rate of sales



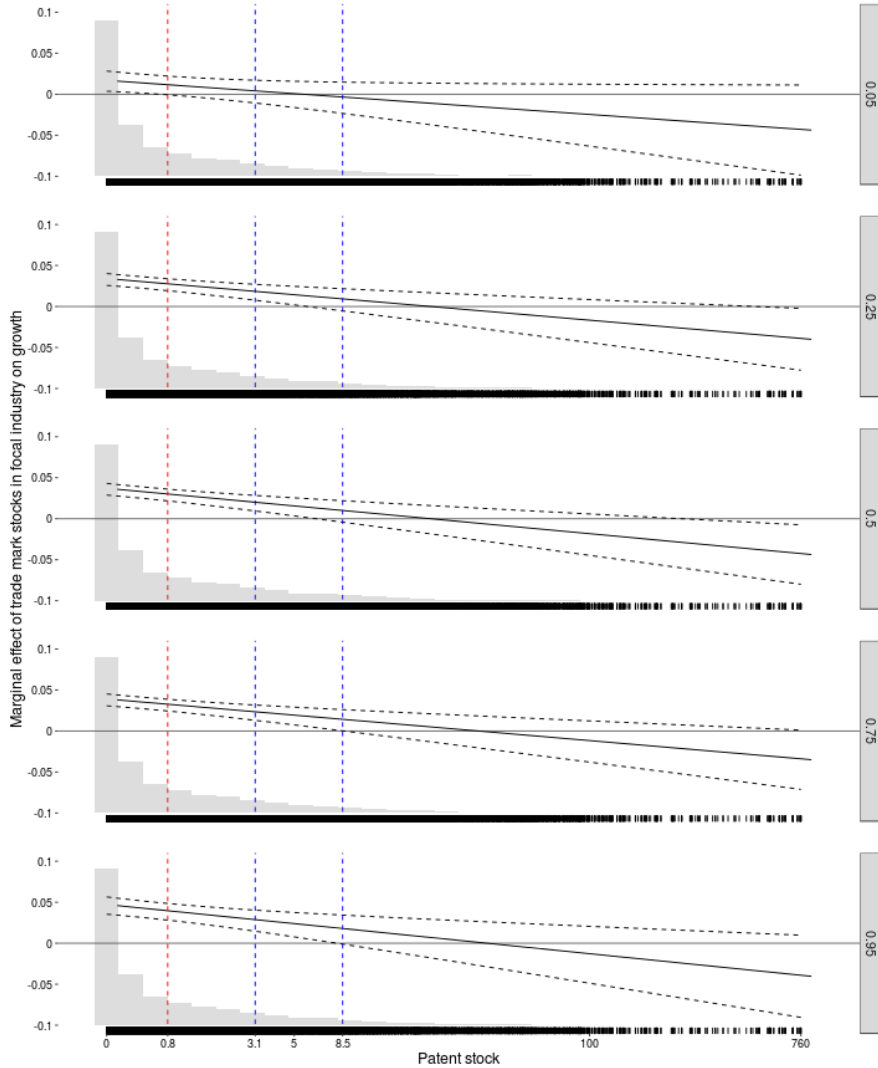
Note: dots present the point estimates of the focal coefficient for a given quantile of new firms' growth distribution. A band around the line presents the 95% confidence interval calculated for each estimate;

Source: own calculations based on the results of model presented in Table 6.4.

With patent stocks held at 0, trade mark stocks of incumbents active in the same NACE industry and same region are always positively associated with the growth rates of newly established firms. The pattern of this relationship is similar to the association between patent stocks in the focal industry and growth. The results imply that for firms located in the lowest quantiles of growth (0.05) a 10% increase in the trade mark stock is associated with a 0.16 percentage point higher growth rate. For firms located in the highest quantiles of growth (0.95) this increase in trade mark stock is associated with 0.46 percentage point higher growth rate. Overall, increases in trade mark stocks of incumbents active in the same industry, similarly to increases in patent stocks, raise the spread of the distribution of newly created firms' sales growth.

Moderation effect of trade mark and patent stocks is however symmetrical and as illustrated in Figure 6.7 relationship between trade mark stock of incumbents and newly created firms' growth is less beneficial in industries and regions with relatively more intensive patent activity of incumbents. This relationship becomes insignificant at the relatively low level of patent stocks of 8 patents, even for firms located in the highest percentile of growth. It becomes even negative in settings characterised by higher patent stocks.

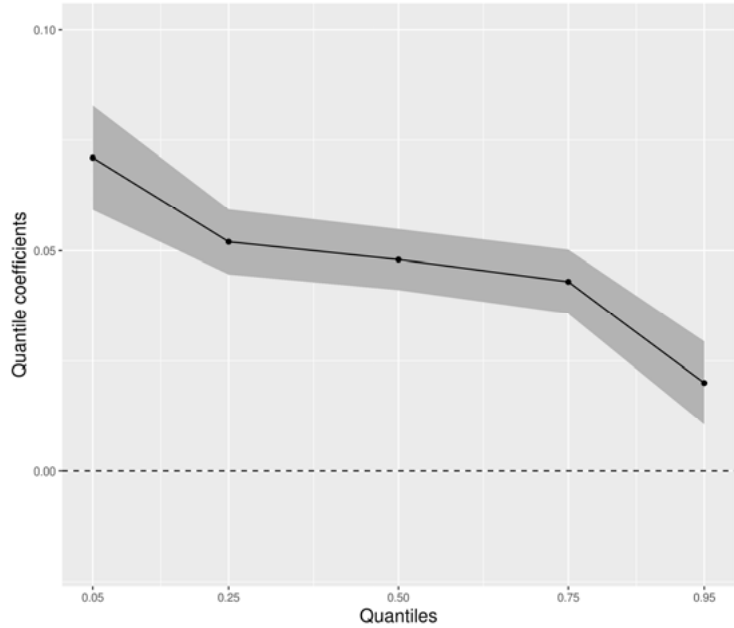
Figure 6.7 Asymptotic 95% confidence interval for quantile regression estimates of association between trade mark stocks and new firm growth for different levels of patent stocks



Note: red dashed line corresponds to mean value of log transformed stock of patents, blue lines correspond to mean +sd and mean+2*sd value of log transformed stock of trade marks. Grey histogram presents distribution of log transformed stock of patents in the dataset. Black lines in the bottom of the plot represent individual observations of log transformed patent stock in the dataset;

Source: own calculation based on the results of the model presented in Table 6.4.

Figure 6.8 Asymptotic 95% confidence interval of quantile-regression estimate of incumbents’ patents stock (related industries) impact on firms’ annual growth rate of sales



Note: dots present the point estimates of the focal coefficient for a given quantile of new firms’ growth distribution. A band around the line presents the 95% confidence interval calculated for each estimate;

Source: own calculations based on the results of model presented in Table 6.4.

Finally, research question 4 focused on the difference between the effects of focal industry knowledge stocks and knowledge stocks in related industries. The results indicate that relationship between growth rates of newly established firms and patent stocks in related industries is positive over the entire distribution of growth rates. However, contrary to patent stocks in the same NACE industry, this relationship is the strongest for newly created firms located in the lowest quantiles of growth. Whereas, for new firms in the 0.25 quantile, a 10% higher patent stock in related industries is associated with a 0.71 percentage point higher growth rate, for firms located in the 0.95 quantile, such an increase translates into a 0.2 percentage point higher growth. Therefore, patenting by incumbents active in related industries decreases the spread of the distribution of sales growth of firms. This result suggests that weaker firms in particular are better off in areas where the

knowledge stocks of incumbents active in the related industries are higher relatively to knowledge stocks in the focal industry.

Apart from the results directly related to our research questions, we discuss below the results of the significant control variables. Firms in the lower quantiles of sales growth are more sensitive to the business cycle in the broader defined industry and shifts in the GDP per capita than firms located in the upper quantiles of growth. Our results suggest, however, that the per capita GDP growth in the region has a stronger relationship with growth in the lowest quantiles than industry growth. Growth of industry output and GDP per capita both reduce the spread of the sales growth rates, while a decline in industrial output and GDP per capita increases this spread.

Results of other control variables are generally as expected. Size and age are negatively related to growth in all quantiles as is the number of incumbents active in the same NACE industry and NUTS 3 region. On the other hand, startup activity in the industry/region is positively related with the growth of newly created firms, at least around the middle of the firms' growth distribution, although the strength of this relationship is relatively low. GDP per capita is positively related to the growth of sales of young firms over all the quantiles of growth, while unemployment in the region is negatively related with newly established firms' growth prospects. Surprisingly, *ceteris paribus* the higher education rate in the region, the lower the growth of newly established manufacturing firms. This result is similar to the findings in chapter 5. As discussed in chapter 5, the main theoretical argument for the positive relationship between education in the region and entry or growth is the impact it may have on the innovation capacity in the region. This is however already controlled for in our models by the variables of the knowledge stocks in the focal and related industry. Our education variable may, therefore, capture the higher costs of salaries of a highly educated workforce, which may lead to the higher costs of manufacturing and lower sales prospects.

6.6 Robustness checks

6.6.1 Choice of lambda in fixed effects quantile regression

As already discussed in section 6.4, the results of our model may be sensitive to the lambda tuning parameter weighing the penalty. For our main model we chose a lambda parameter of 0.1, computed as suggested by Koenker (2005). In Table 6.5, we present the comparison of the coefficients of interest estimated with models using alternative penalty terms. As discussed in section 6.4, with higher penalty terms, the estimates of the key variables of interest become less sensitive to the differences between individual firms.

As shown in Table 6.5, the general pattern of relationship between our key variables of interest and newly created firms' growth is preserved with different values of lambda. The main differences concern incumbents patent and trade mark stocks. With higher values of lambda, of 1 and above, the relationship between these stocks and newly created firms' growth becomes negative (for the 0.05 quantile) or statistically non-significant (for the 0.25 quantile) in the lowest quantiles of growth distribution. Also, the absolute values of the respective coefficients in the highest quantiles of growth are smaller in comparison with estimations based on models with a lambda of 0.1. As far as patent stocks in related industries are concerned, models estimated with higher values of lambda show that this relationship turns negative for newly created firms located in the 0.75 and 0.95 quantile of growth. Finally, with higher values of lambda the coefficients of the dummy variables of own patent and trade mark activity of newly created firms become more pronounced, especially for firms located in the highest quantiles of growth distribution in comparison with the results estimated with models using lower values of lambda.

Table 6.5 Comparison of main coefficients of interest in models with different penalty terms (lambda)

| | | Quantiles | | | | |
|---------------------------------------------------|-----------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|
| | λ | 0.05 | 0.25 | 0.5 | 0.75 | 0.95 |
| Only patent app | 0.1 | -0.023 (0.035) | 0.039 *** (0.014) | 0.055 *** (0.013) | 0.069 *** (0.014) | 0.141 *** (0.027) |
| | 0.5 | 0 (0.032) | 0.035 *** (0.013) | 0.072 *** (0.009) | 0.1 *** (0.011) | 0.194 *** (0.03) |
| | 1 | -0.003 (0.039) | 0.008 (0.011) | 0.05 *** (0.008) | 0.09 *** (0.009) | 0.172 *** (0.033) |
| | 3 | 0.002 (0.034) | -0.003 (0.01) | 0.028 *** (0.008) | 0.076 *** (0.01) | 0.177 *** (0.038) |
| Only trade mark app | 0.1 | 0.023 (0.022) | 0.032 *** (0.008) | 0.02 *** (0.006) | 0.029 *** (0.007) | 0.062 *** (0.02) |
| | 0.5 | 0.082 *** (0.025) | 0.045 *** (0.007) | 0.04 *** (0.006) | 0.052 *** (0.007) | 0.118 *** (0.02) |
| | 1 | 0.09 *** (0.024) | 0.043 *** (0.005) | 0.044 *** (0.005) | 0.055 *** (0.006) | 0.143 *** (0.022) |
| | 3 | 0.083 *** (0.025) | 0.036 *** (0.006) | 0.043 *** (0.005) | 0.057 *** (0.006) | 0.142 *** (0.02) |
| Patent and trade mark | 0.1 | -0.035 (0.054) | 0.024 (0.021) | 0.031 + (0.018) | 0.052 *** (0.019) | 0.096 + (0.053) |
| | 0.5 | -0.003 (0.066) | 0.064 *** (0.017) | 0.083 *** (0.015) | 0.109 *** (0.019) | 0.209 *** (0.034) |
| | 1 | -0.008 (0.074) | 0.05 *** (0.015) | 0.073 *** (0.012) | 0.109 *** (0.016) | 0.258 *** (0.046) |
| | 3 | -0.004 (0.052) | 0.02 + (0.012) | 0.055 *** (0.01) | 0.097 *** (0.01) | 0.28 *** (0.062) |
| Log of patent stock in focal industry (lag 1) | 0.1 | 0.043 *** (0.016) | 0.069 *** (0.011) | 0.077 *** (0.011) | 0.083 *** (0.011) | 0.124 *** (0.016) |
| | 0.5 | 0.022 (0.015) | 0.024 *** (0.004) | 0.029 *** (0.003) | 0.043 *** (0.005) | 0.093 *** (0.014) |
| | 1 | -0.032 ** (0.014) | 0.004 (0.003) | 0.014 *** (0.002) | 0.034 *** (0.004) | 0.074 *** (0.014) |
| | 3 | -0.044 *** (0.016) | -0.003 (0.003) | 0.007 *** (0.002) | 0.026 *** (0.004) | 0.072 *** (0.014) |
| Log of patent stock in related industries (lag 1) | 0.1 | 0.071 *** (0.006) | 0.052 *** (0.004) | 0.048 *** (0.004) | 0.043 *** (0.004) | 0.02 *** (0.005) |
| | 0.5 | 0.035 *** (0.005) | 0.022 *** (0.001) | 0.011 *** (0.001) | 0.001 (0.002) | -0.02 *** (0.005) |
| | 1 | 0.061 *** (0.005) | 0.022 *** (0.001) | 0.007 *** (0.001) | -0.005 *** (0.001) | -0.026 *** (0.004) |
| | 3 | 0.064 *** (0.006) | 0.022 *** (0.001) | 0.006 *** (0.001) | -0.006 *** (0.001) | -0.03 *** (0.004) |
| Log of trade mark stock in focal industry (lag 1) | 0.1 | 0.016 ** (0.006) | 0.033 *** (0.004) | 0.036 *** (0.004) | 0.038 *** (0.004) | 0.046 *** (0.005) |
| | 0.5 | 0.035 *** (0.005) | 0.022 *** (0.001) | 0.011 *** (0.001) | 0.001 (0.002) | -0.02 *** (0.005) |
| | 1 | -0.014 ** (0.006) | 0 (0.001) | 0.002 ** (0.001) | 0.006 *** (0.001) | 0.021 *** (0.004) |
| | 3 | -0.019 *** (0.007) | -0.002 (0.001) | 0.001 (0.001) | 0.006 *** (0.001) | 0.019 *** (0.005) |
| Interaction between patent and trade mark stocks | 0.1 | -0.009 ** (0.004) | -0.011 *** (0.003) | -0.012 *** (0.003) | -0.011 *** (0.003) | -0.013 *** (0.004) |
| | 0.5 | -0.01 ** (0.004) | -0.006 *** (0.001) | -0.005 *** (0.001) | -0.005 *** (0.001) | -0.006 + (0.004) |
| | 1 | 0 (0.004) | -0.003 *** (0.001) | -0.002 *** (0.001) | -0.003 *** (0.001) | 0 (0.004) |
| | 3 | 0.001 (0.004) | -0.002 + (0.001) | -0.002 ** (0.001) | -0.002 ** (0.001) | -0.002 (0.003) |

6.6.2 Control for the attrition bias

As discussed in section 6.3, our dataset suffers from sample attrition. We can observe turnover growth rates for only a subset of manufacturing firms that started in 2000. For some firms, we observe growth rates for the first years of our time frame only, as they stop to report turnover at some point. Clearly, sample attrition may bias our estimations.

Standard methods dealing with sample selection are developed for additive models like OLS. Progress in development of non-additive selection corrections has been slower. In linear quantile models, quantile curves on the selected sample are generally not linear (Arellano & Bonhomme 2017b; Arellano & Bonhomme 2017a). Arellano & Bonhomme (2017a) recently proposed a solution based on shifting the quantile levels as a function of the degree of selection. In their method, a selection is modelled by a copula, the cumulative distribution function of the errors in the outcome and selection equations. Copulas are used to describe the dependence between random variables. Corrections applied to quantile levels depend on the strength of the selection and are observation-specific (Arellano & Bonhomme 2017a). The estimation algorithm proposed by Arellano & Bonhomme (2017a) consists of three steps: estimation of propensity scores of exit, estimation of the copula model and estimation of the quantile parameters. For the model estimation, we use the algorithm based on Arellano & Bonhomme (2017a) and implemented in R by Koenker (2019).

Fixed effect quantile regression models with control for attrition bias are currently not available, so we can only run sample selection models for quantile regressions not involving fixed effects. Hence, in order to assess the impact of sample attrition on our estimation results, as a first step, we run a pooled quantile regression model with control for NUTS2/NACE2²⁹ fixed effects instead. The results of this estimation are shown in Table 6.6. As could be expected, results of the regression estimated on the pooled observations are in general similar to the fixed effects quantile regression models estimated with the higher value of the lambda penalty parameter discussed in section 6.6.1.

²⁹ We control for fixed effects for higher level of aggregation of regions and industries due to the computational complexity of estimation of quantile regression models with many dummy variables.

Table 6.6 Quantile regression estimates for sales growth (pooled observations)

| | 0.05 | 0.25 | 0.5 | 0.75 | 0.95 |
|--------------------------------------------------------------------|----------------------|----------------------|----------------------|----------------------|-----------------------|
| Only patent app | -0.008 (0.031) | 0.002 (0.009) | 0.027 *** (0.008) | 0.07 *** (0.011) | 0.165 *** (0.037) |
| Only trade mark app | 0.053 ** (0.026) | 0.035 *** (0.005) | 0.039 *** (0.005) | 0.054 *** (0.007) | 0.131 *** (0.019) |
| Patent and trade mark | -0.035 (0.04) | 0.014 (0.015) | 0.049 *** (0.01) | 0.097 *** (0.012) | 0.267 *** (0.064) |
| Log of patent stock in focal industry (lag 1) | 0.01 (0.017) | 0.006 + (0.003) | 0.008 *** (0.003) | 0.01 ** (0.004) | 0.026 + (0.015) |
| Log of patent stock in related industries (lag 1) | -0.018 + (0.009) | -0.003 (0.002) | 0 (0.002) | 0.001 (0.002) | 0.004 (0.007) |
| Log of trade mark stock in focal industry (lag 1) | -0.026 (0.007) | -0.001 (0.001) | 0.005 *** (0.001) | 0.013 *** (0.002) | 0.032 *** (0.005) |
| Interaction between patent and trade mark stocks in focal industry | -0.001 (0.004) | -0.001 (0.001) | -0.002 ** (0.001) | -0.001 (0.001) | 0.001 (0.004) |
| Size (lag 1) | 0.054 *** (0.003) | 0.007 *** (0.001) | -0.005 (0.001) | -0.025 (0.001) | -0.105 *** (0.002) |
| Age | -0.028 (0.005) | -0.017 (0.001) | -0.015 (0.001) | -0.021 (0.001) | -0.032 *** (0.004) |
| Contribution of young firms to knowledge | -0.029 (0.022) | -0.002 (0.004) | -0.001 (0.003) | 0.004 (0.005) | 0.004 (0.015) |
| Contribution of universities to knowledge stock (lag 1) | -0.169 ** (0.08) | -0.026 (0.022) | -0.001 (0.013) | 0.012 (0.019) | -0.009 (0.053) |
| Log of incumbents' number (lag 1) | 0.027 *** (0.008) | -0.002 (0.002) | -0.007 (0.001) | -0.014 (0.002) | -0.043 *** (0.006) |
| Log of startups (lag 1) | -0.007 (0.009) | -0.002 (0.002) | 0 (0.001) | -0.002 (0.002) | -0.005 (0.007) |
| Buyers' fit (lag 1) | 0.004 (0.013) | 0.002 (0.003) | 0.003 (0.002) | -0.001 (0.003) | -0.019 ** (0.008) |
| Suppliers' fit (lag 1) | -0.023 ** (0.011) | -0.001 (0.002) | -0.002 (0.001) | 0 (0.002) | 0.014 (0.009) |
| Industry growth (NACE2, lag 1) | 1.019 *** (0.154) | 0.479 *** (0.032) | 0.269 *** (0.023) | 0.269 *** (0.028) | 0.381 *** (0.088) |
| Log of GDP per capita in the region (PPS) | -0.043 (0.039) | -0.006 (0.006) | 0.004 (0.005) | -0.003 (0.008) | 0.006 (0.032) |
| GDP per capita growth in the region (PPS) | 1.057 *** (0.136) | 0.744 *** (0.031) | 0.51 ** (0.023) | 0.456 *** (0.03) | 0.378 *** (0.101) |
| Unemployment level | -2.576 (0.389) | -1.729 (0.089) | -1.51 *** (0.063) | -1.071 (0.07) | -0.704 *** (0.233) |
| Share of population with secondary and | -0.44 (0.41) | -0.382 (0.078) | -0.344 (0.073) | -0.237 ** (0.109) | -0.624 ** (0.289) |
| Log of population density | -0.02 ** (0.009) | -0.001 (0.002) | -0.001 (0.001) | 0.004 (0.002) | 0.021 *** (0.008) |
| Constant | 0.34 (0.458) | 0.53 *** (0.162) | 0.607 *** (0.138) | 0.948 *** (0.182) | 2.126 *** (0.409) |
| NUTS2 dummies | Yes | Yes | Yes | Yes | Yes |
| NACE2 dummies | Yes | Yes | Yes | Yes | Yes |
| R1 | 0.0866 | | | | |

Model estimated on the dataset of 93 953 annual observations of 22 218 firms created in 2000

Note:

+p<0.1; **p<0.05; ***p<0.01

To account for selection, we created a binary variable D , which takes the value of 0 in case the firm stopped to report turnover before 2009. For some of those firms, there is information available in ORBIS that they did not survive to 2009. However, for others, we do not have information about the reason for not reporting turnover data.

As in the standard additive sample selection correction, excluded variables that affect exit but not turnover growth are required for credible identification. Based on the extant literature on firm exit, we propose two such variables. Minimum efficient scale (MES) is defined as the median size (measured by turnover) of the firms representing 50% of overall sales in NACE 4-digit industry in 12 Member States covered by our sample (Audretsch 1995b). The likelihood of survival should be negatively correlated with the greater importance of scale economies in the industry. In industries with higher MES smaller firms experience more disadvantages in comparison with larger incumbents. Second, subsidiary status is a binary variable taking the value of 1 in case a firm has economic links with other firms. Newly established firms that are subsidiaries of other larger firms do not suffer equally from the *liability of newness* as independent firms and may have easier access to financial resources to improve their survival chances.

In Table 6.7, we present the results of the estimation of the first stage selection equation and in Table 6.8 the main quantile selection model.

Table 6.7 Results of first stage selection model

| <i>Dependent variable: participation</i> | |
|--------------------------------------------------------------------|-----------------------------------------|
| Only patent app | 0.142*** (0.048) |
| Only trade mark app | 0.240*** (0.028) |
| Patent and trade mark | 0.206*** (0.075) |
| Log of patent stock in focal industry (lag 1) | 0.009 (0.017) |
| Log of patent stock in related industries (lag 1)) | -0.051*** (0.010) |
| Log of trade mark stock in focal industry (lag 1) | -0.007 (0.007) |
| Interaction between patent and trade mark stocks in focal industry | -0.0001 (0.004) |
| Size (lag 1) | 0.101*** (0.003) |
| Age | 0.313*** (0.006) |
| Contribution of young firms to knowledge stock (lag 1) | 0.035 [†] (0.020) |
| Contribution of universities to knowledge stock (lag 1) | 0.091 (0.059) |
| Log of incumbents' number (lag 1) | 0.002 (0.009) |
| Log of startups (lag 1) | -0.007 (0.009) |
| Buyers' fit (lag 1) | 0.017 (0.012) |
| Suppliers' fit (lag 1) | -0.022*** (0.009) |
| Industry growth (NACE2, lag 1) | -0.909*** (0.117) |
| Log of GDP per capita in the region (PPS) | -0.191*** (0.036) |
| GDP per capita growth in the region (PPS) | -3.460*** (0.144) |
| Unemployment level | 3.833*** (0.384) |
| Share of population with secondary and tertiary education | -3.922*** (0.378) |
| Log of population density | 0.002 (0.009) |
| Subsidiary status | 0.542*** (0.020) |
| Log MES in industry | -0.008** (0.004) |
| Constant | 1.911*** (0.553) |
| NUTS2 dummies? | Yes |
| NACE2 dummies? | Yes |
| Observations | 93,953 |
| Akaike Inf. Crit. | 88,635.94 |
| Note: | [†] p<0.1; **p<0.05; ***p<0.01 |

Table 6.8 Quantile regression estimates for sales growth (pooled observations, control for sample selection)

| | 0.05 | 0.25 | 0.5 | 0.75 | 0.95 |
|--------------------------------------------------------------------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|
| Only patent app | 0.038 (0.027) | 0.017 (0.01) | 0.037 *** (0.01) | 0.07 *** (0.011) | 0.155 *** (0.04) |
| Only trade mark app | 0.039 + (0.022) | 0.031 *** (0.006) | 0.035 *** (0.005) | 0.044 *** (0.006) | 0.144 *** (0.023) |
| Patent and trade mark | -0.072 ** (0.034) | 0.02 (0.015) | 0.048 *** (0.011) | 0.089 *** (0.013) | 0.262 *** (0.065) |
| Log of patent stock in focal industry (lag 1) | 0.019 (0.016) | 0.008 ** (0.004) | 0.013 *** (0.004) | 0.013 *** (0.005) | 0.041 *** (0.015) |
| Log of patent stock in related industries (lag 1) | -0.021 ** (0.009) | -0.003 (0.002) | 0.001 (0.002) | 0.002 (0.003) | -0.003 (0.008) |
| Log of trade mark stock in focal industry (lag 1) | -0.015 *** (0.005) | 0.001 (0.002) | 0.007 *** (0.001) | 0.012 *** (0.002) | 0.027 *** (0.006) |
| Interaction between patent and trade mark stocks in focal industry | -0.004 (0.004) | -0.002 + (0.001) | -0.002 ** (0.001) | -0.001 (0.001) | 0.001 (0.004) |
| Size (lag 1) | 0.026 *** (0.003) | -0.001 (0.001) | -0.011 *** (0.001) | -0.029 *** (0.001) | -0.108 *** (0.003) |
| Age | -0.049 *** (0.004) | -0.026 *** (0.001) | -0.023 *** (0.001) | -0.028 *** (0.002) | -0.037 *** (0.005) |
| Contribution of young firms to knowledge stock (lag 1) | -0.011 (0.016) | -0.001 (0.005) | -0.001 (0.004) | 0.003 (0.005) | 0.02 (0.017) |
| Contribution of universities to knowledge stock (lag 1) | -0.105 (0.071) | -0.029 (0.022) | 0.001 (0.013) | 0.008 (0.02) | -0.053 (0.059) |
| Log of incumbents' number (lag 1) | 0.01 (0.007) | -0.006 *** (0.002) | -0.01 *** (0.002) | -0.014 *** (0.002) | -0.047 *** (0.007) |
| Log of startups (lag 1) | 0.003 (0.007) | 0.001 (0.002) | 0.001 (0.002) | -0.004 (0.002) | -0.001 (0.008) |
| Buyers' fit (lag 1) | -0.003 (0.01) | 0.002 (0.003) | 0.001 (0.002) | -0.003 (0.003) | -0.013 (0.011) |
| Suppliers' fit (lag 1) | -0.019 ** (0.008) | -0.001 (0.002) | -0.001 (0.002) | 0.001 (0.002) | 0.017 + (0.009) |
| Industry growth (NACE2, lag 1) | 0.967 *** (0.111) | 0.522 *** (0.033) | 0.342 *** (0.028) | 0.345 *** (0.031) | 0.339 *** (0.094) |
| Log of GDP per capita in the region | 0.011 (0.032) | -0.001 (0.008) | 0.003 (0.007) | -0.004 (0.008) | 0.006 (0.037) |
| GDP per capita growth in the region | 1.454 *** (0.109) | 0.785 *** (0.031) | 0.534 *** (0.028) | 0.509 *** (0.034) | 0.463 *** (0.114) |
| Unemployment level | -3.473 *** (0.358) | -1.941 *** (0.102) | -1.504 *** (0.075) | -1.105 *** (0.076) | -0.71 *** (0.246) |
| Share of population with secondary and tertiary education | -0.486 + (0.294) | -0.188 ** (0.093) | -0.171 ** (0.078) | -0.08 (0.129) | -0.51 (0.323) |
| Log of population density | -0.01 (0.008) | 0 (0.002) | -0.001 (0.002) | 0.003 (0.002) | 0.025 *** (0.008) |
| Constant | 0.289 (0.459) | 0.438 (0.331) | 0.485 *** (0.18) | 0.68 *** (0.153) | 1.576 *** (0.427) |
| NUTS2 dummies | Yes | Yes | Yes | Yes | Yes |
| NACE2 dummies | Yes | Yes | Yes | Yes | Yes |
| R1 | 0.50 | | | | |

Selection model estimated on the dataset of 93 953 observations of annual growth rates of 22 218 firms created in 2000

Growth model estimated on the dataset of firms, with growth data available for 2009, N=69813

Note: *p<0.1; **p<0.05; ***p<0.01

R1 calculated by comparing residuals of sample selection quantile model with pooled quantile regression with only intercept for median quantile and estimated on dataset of firms, with growth data available for 2009

As shown in Table 6.8, the main coefficients of interest remain similar in the model controlling for sample selection as in the quantile regression estimated on the pooled dataset as reported in Table 6.6. The magnitudes of coefficients and the direction of the relationship between the core variables and growth remain the same. The results of the robustness check performed on the same dataset in a pooled quantile regression setting give us some assurance that results are not significantly biased by sample attrition. This finding is consistent with previous research on firms' growth rates that controlled for attrition bias (Hall 1987).

6.6.3 Fixed effects quantile regression analysis with European trade marks and control for not matched IPR

Finally, we provide additional robustness checks based on models that substitute European trade mark stocks for national trade mark stocks, and that control for patent and trade marks that could not be matched to firms. Data preparation for those models has been explained in section 3.6.2. As can be seen in Table 6.9 and Table 6.10, the estimated effects of trade mark stock of incumbents show most differences compared to the main model. In our main model, the values of this coefficient are positive for all quantiles of growth, implying a positive association of incumbents' trade mark stocks with growth of newly created firms if the patent stock is held at 0. In the alternative model with European trade mark stocks (Table 6.9) the coefficients are negative for the lowest quantile of growth and non-significant for other quantiles except for the 0.95 quantile. In the model controlling for non-matched patents and trade marks (Table 6.10) the pattern is similar, but with the coefficient for the 0.95 quantile statistically significant only at the 90% confidence level. The much less pronounced effect of trade mark stocks in these models may be related to the measurement of a more limited set of European trade marks, which may pick up only trade marks by larger and stronger incumbents aiming for pan-European commercialization and having more instruments for appropriation at their disposal.

Table 6.9 Fixed effects quantile regression estimates for sales growth (European trade marks)

| | 0.05 | 0.25 | 0.5 | 0.75 | 0.95 |
|--------------------------------------------------------------------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|
| Only patent app | -0.027 (0.034) | 0.042 *** (0.015) | 0.056 *** (0.013) | 0.067 *** (0.014) | 0.134 *** (0.028) |
| Only trade mark app | 0.033 (0.023) | 0.036 *** (0.008) | 0.023 *** (0.007) | 0.033 *** (0.008) | 0.063 *** (0.018) |
| Patent and trade mark | -0.072 (0.059) | 0.027 (0.021) | 0.035 + (0.018) | 0.055 *** (0.019) | 0.107 *** (0.041) |
| Log of patent stock in focal industry (lag 1) | 0.002 (0.011) | 0.038 *** (0.007) | 0.052 *** (0.007) | 0.063 *** (0.007) | 0.109 *** (0.009) |
| Log of patent stock in related industries (lag 1) | 0.078 *** (0.006) | 0.054 *** (0.004) | 0.049 *** (0.004) | 0.044 *** (0.004) | 0.02 *** (0.005) |
| Log of trade mark stock in focal industry (lag 1) | -0.032 *** (0.008) | -0.009 (0.005) | -0.001 (0.005) | 0.004 (0.005) | 0.016 ** (0.007) |
| Interaction between patent and trade mark stocks in focal industry | 0.006 (0.005) | -0.003 (0.003) | -0.006 ** (0.003) | -0.009 *** (0.003) | -0.015 *** (0.004) |
| Size (lag 1) | -0.281 *** (0.008) | -0.322 *** (0.008) | -0.324 *** (0.008) | -0.335 *** (0.008) | -0.384 *** (0.008) |
| Age | -0.054 *** (0.003) | -0.018 *** (0.001) | -0.011 *** (0.001) | -0.011 *** (0.001) | -0.029 *** (0.003) |
| Contribution of young firms to knowledge stock (lag 1) | -0.008 (0.019) | -0.017 + (0.01) | -0.014 (0.009) | -0.013 (0.01) | -0.005 (0.016) |
| Contribution of universities to knowledge stock (lag 1) | -0.03 (0.058) | -0.056 ** (0.028) | -0.055 ** (0.025) | -0.031 (0.026) | -0.032 (0.047) |
| Log of incumbents' number (lag 1) | -0.074 *** (0.007) | -0.08 *** (0.003) | -0.081 *** (0.003) | -0.083 *** (0.003) | -0.103 *** (0.006) |
| Log of startups (lag 1) | 0.011 (0.008) | 0.006 ** (0.003) | 0.007 *** (0.002) | 0.005 + (0.003) | 0.008 (0.006) |
| Buyers' fit (lag 1) | 0.05 *** (0.006) | 0.033 *** (0.003) | 0.037 *** (0.003) | 0.038 *** (0.003) | 0.029 *** (0.004) |
| Suppliers' fit (lag 1) | -0.05 *** (0.006) | -0.033 *** (0.003) | -0.038 *** (0.003) | -0.043 *** (0.003) | -0.027 *** (0.005) |
| Industry growth (NACE2, lag 1) | 0.78 *** (0.084) | 0.515 *** (0.028) | 0.348 *** (0.023) | 0.286 *** (0.027) | 0.341 *** (0.061) |
| Log of GDP per capita in the region (PPS) | 0.192 *** (0.029) | 0.146 *** (0.02) | 0.142 *** (0.019) | 0.135 *** (0.021) | 0.141 *** (0.024) |
| GDP per capita growth in the region (PPS) | 1.275 *** (0.112) | 0.71 *** (0.033) | 0.447 *** (0.026) | 0.383 *** (0.035) | 0.097 (0.101) |
| Unemployment level | -1.531 *** (0.153) | -1.406 *** (0.072) | -1.308 *** (0.065) | -1.385 *** (0.067) | -1.376 *** (0.122) |
| Share of population with secondary and tertiary education | -0.009 (0.051) | -0.201 *** (0.027) | -0.369 *** (0.027) | -0.481 *** (0.029) | -0.505 *** (0.041) |
| Log of population density | -0.046 *** (0.005) | -0.012 *** (0.003) | -0.01 *** (0.003) | -0.006 ** (0.003) | 0.016 *** (0.004) |
| Constant | -0.008 (0.27) | 0.915 *** (0.176) | 1.122 *** (0.175) | 1.442 *** (0.186) | 2.155 *** (0.226) |

Model estimated on the unbalanced panel of 22 218 firms created in 2000, T=1-7, N=93 953, $\Lambda=0.1$

Note: +p<0.1; **p<0.05; ***p<0.01

R1 **0.86** calculated by comparing residuals of fixed effects quantile model with pooled quantile regression with only intercept for median quantile

Table 6.10 Fixed effects quantile regression estimates for sales growth with augmented stocks

| | 0.05 | 0.25 | 0.5 | 0.75 | 0.95 |
|--------------------------------------------------------------------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|
| Only patent app | -0.029 (0.037) | 0.043 *** (0.013) | 0.058 *** (0.013) | 0.069 *** (0.013) | 0.134 *** (0.031) |
| Only trade mark app | 0.024 (0.018) | 0.036 *** (0.007) | 0.024 *** (0.006) | 0.034 *** (0.007) | 0.073 *** (0.018) |
| Patent and trade mark | -0.075 (0.068) | 0.023 (0.02) | 0.035 + (0.018) | 0.055 *** (0.019) | 0.103 + (0.053) |
| Log of patent stock in focal industry (lag 1) | 0.014 (0.011) | 0.055 *** (0.006) | 0.071 *** (0.006) | 0.083 *** (0.007) | 0.126 *** (0.01) |
| Log of patent stock in related industries (lag 1) | 0.051 *** (0.006) | 0.024 *** (0.004) | 0.02 *** (0.004) | 0.013 *** (0.004) | -0.016 *** (0.005) |
| Log of trade mark stock in focal industry (lag 1) | -0.021 ** (0.009) | -0.003 (0.005) | 0.002 (0.005) | 0.006 (0.005) | 0.013 + (0.007) |
| Interaction between patent and trade mark stocks in focal industry | 0.004 (0.005) | -0.004 (0.003) | -0.008 *** (0.003) | -0.01 *** (0.003) | -0.014 *** (0.003) |
| Size (lag 1) | -0.28 *** (0.008) | -0.321 *** (0.007) | -0.323 *** (0.007) | -0.335 *** (0.007) | -0.384 *** (0.008) |
| Age | -0.052 *** (0.003) | -0.017 *** (0.001) | -0.01 *** (0.001) | -0.009 *** (0.001) | -0.026 *** (0.003) |
| Contribution of young firms to knowledge stock (lag 1) | -0.003 (0.017) | -0.015 (0.011) | -0.014 (0.01) | -0.014 (0.011) | -0.006 (0.016) |
| Contribution of universities to knowledge stock (lag 1) | -0.045 (0.056) | -0.077 ** (0.032) | -0.069 ** (0.03) | -0.045 (0.031) | -0.042 (0.05) |
| Log of incumbents' number (lag 1) | -0.072 *** (0.007) | -0.078 *** (0.003) | -0.08 *** (0.003) | -0.081 *** (0.003) | -0.101 *** (0.005) |
| Log of startups (lag 1) | 0.008 (0.009) | 0.005 + (0.003) | 0.007 *** (0.002) | 0.006 ** (0.003) | 0.011 + (0.006) |
| Buyers' fit (lag 1) | 0.049 *** (0.006) | 0.032 *** (0.003) | 0.036 *** (0.003) | 0.038 *** (0.003) | 0.028 *** (0.005) |
| Suppliers' fit (lag 1) | -0.05 *** (0.006) | -0.032 *** (0.004) | -0.038 *** (0.004) | -0.043 *** (0.004) | -0.026 *** (0.005) |
| Industry growth (NACE2, lag 1) | 0.771 *** (0.08) | 0.514 *** (0.028) | 0.348 *** (0.022) | 0.289 *** (0.027) | 0.339 *** (0.066) |
| Log of GDP per capita in the region (PPS) | 0.223 *** (0.029) | 0.171 *** (0.019) | 0.165 *** (0.018) | 0.16 *** (0.018) | 0.162 *** (0.024) |
| GDP per capita growth in the region (PPS) | 1.228 *** (0.104) | 0.705 *** (0.034) | 0.44 *** (0.027) | 0.374 *** (0.034) | 0.12 (0.099) |
| Unemployment level | -1.519 *** (0.174) | -1.39 *** (0.065) | -1.298 *** (0.061) | -1.366 *** (0.065) | -1.366 *** (0.128) |
| Share of population with secondary and tertiary education | 0.035 (0.051) | -0.158 *** (0.03) | -0.326 *** (0.028) | -0.439 *** (0.031) | -0.46 *** (0.045) |
| Log of population density | -0.045 *** (0.005) | -0.009 *** (0.003) | -0.007 *** (0.003) | -0.004 (0.003) | 0.018 *** (0.004) |
| Constant | -0.335 (0.273) | 0.65 *** (0.17) | 0.883 *** (0.158) | 1.192 *** (0.165) | 1.951 *** (0.23) |

Model estimated on the unbalanced panel of 22 218 firms created in 2000, T=1-7, N=93 953, $\Lambda=0.1$

Note: +p<0.1; **p<0.05; ***p<0.01

R1 0.86 calculated by comparing residuals of fixed effects quantile model with pooled quantile regression with only intercept for median quantile

6.7 Discussion and concluding remarks

The purpose of the present analysis was to examine the relationship between technological innovation and brand building initiatives undertaken by newly created firms and their sales growth. We also investigated the association between local knowledge stocks developed by incumbents, their appropriation strategies and growth of new firms.

We conducted our analysis using a novel and rich dataset on a cohort of newly established manufacturing firms, incorporated in 2000 in one of the 12 Member States of the European Union. We included a wide range of other control variables, at the fine-grained level of NACE 4-digit industries and a NUTS3 regions, that may contribute to the growth of newly established firms.

Our analysis confirms the findings from previous research that technological innovations increase chances for exceptional performance (Mansfield 1962; F. M. Scherer 1965; Geroski & Machin 1992; Geroski & Machin 2013) and may be especially crucial for the rapid growth of newly established and young firms (Helmers & Rogers 2011; Coad et al. 2016). However, as it is associated with significant uncertainties, it does not guarantee market success of all firms engaged in technological innovation. Our results showing that in the lowest quantiles patent applications by a firm are not associated with higher growth is in line with results of previous research using quantile regressions to investigate this relationship (Coad & Rao 2008; Goedhuys & Sleuwaegen 2010; Colombelli et al. 2013; Coad et al. 2016).

A more novel contribution of our research is the analysis of the role of trade marking activity and the combination of trade marks and patents. The relationship between trade marks and firm growth has not been analysed extensively in the previous literature, with only a few exceptions (Crass 2014; Greenhalgh & Rogers 2012). This scarce literature provided some arguments for a positive association of trade marking activity and firm growth. We focused on turnover growth of manufacturing firms in the first years after their establishment and conduct quantile analysis extending the focus beyond effects on average growth. Using quantile regression, we have shown that the relationship between trade mark activity of new firms and their subsequent growth is positive, except for the lowest quantiles of the growth distribution. Overall, results confirm that investment in own brands may be an attractive strategy for young firms. Product differentiation supports new entrants' strategies based on finding profitable niches not yet exploited by

incumbents. This often is the most viable option for young firms in competition against larger and more experienced incumbents.

Another contribution of our analysis is its focus on the relationship between regional industry features related to patents and trade marks and growth of newly established firms. By explicitly focusing on the relationship between relevant regional knowledge stocks, potential strategic behaviour of incumbents and growth of newly established firms we address a significant gap in the literature on knowledge-based entrepreneurship as identified by Audretsch (2012). Prior work has not been able to confirm a positive association of local knowledge stocks (location in clusters) and firms growth rates (Gilbert et al. 2008). In the case of high growth firms, our results confirm that the MAR (Marshall 1920; Arrow 1971; Romer 1986) and Porter (1990) hypothesis that the most beneficial spillovers stem from firms active in the same or very similar industries. In contrast, more diverse stocks of knowledge seem to benefit only firms located in the lower quantiles of growth. Location in cluster offers many advantages in perceiving new technological opportunities. Newly created firms located closer to innovating incumbents may benefit from insights regarding the evolution of technology and a better understanding of sophisticated buyer needs or new marketing concepts, in particular, if firms are high performing. It appears that, even within narrowly defined NACE industries, there may still be niches that could be successfully discovered and exploited by new firms. Discovery of such niches is easier for an able firm in the areas with a strong presence of incumbents innovating in the technologies most relevant for the focal market. Our findings confirm therefore the intuitions of Duranton&Puga (2001) who saw cities as nurseries of innovation, where newly created firms have to experiment to grow.

On the other hand, firms in the lower quantiles of growth benefit from locating in the areas where knowledge stocks in related industries are relatively higher and knowledge stocks in focal industry relatively lower. Hence, our results indicate that regions with innovating incumbents with higher knowledge stocks in the focal industry promote stronger selection in the industry, triggering more significant differences in growth rates between firms.

Our findings also show an important role of strategic knowledge appropriation oriented behaviour of incumbents reducing the (benefits of) knowledge spillovers to new firms. The KSTE literature already discussed the

possibility that knowledge spillovers may be moderated by the strength and strategic behaviour of incumbents (Plummer & Acs 2014), but this has not been investigated in detail. In the present analysis, we measure appropriation behaviour by incumbents' trade mark stocks. Our results indicate that trade mark stocks negatively moderate the relationship between knowledge stocks and growth of new firms. This effect is most pronounced in the lower growth quartiles, while it is weaker for the more dynamic high growth newly established firms. Through the more intensive use of trade marks, incumbents can fence-off their knowledge stocks from new entrants and reduce the benefits of knowledge spillovers by raising the barriers to use of this knowledge in their focal markets. These findings complement earlier studies suggesting that the organization of innovation, e.g. in terms of internal linkages across R&D units of incumbents, may be designed to reduce knowledge spillovers (Belderbos and Somers, 2015).

We close by emphasizing that innovation and trade marking activities of newly established firms and incumbents active in geographic vicinity is an interesting topic for further investigation in the domains of strategy and entrepreneurship. Our analysis highlights that patent and trade mark strategies are interlinked and have differential effects on firm performance across the growth distribution. However, the most popular methods of empirical analysis used by researchers are based on the estimation of the average effect, which limits the identification of such outcomes (Alcácer et al. 2018). Quantile research methods are an ideal tool to analyse heterogeneous consequences for different categories of firms.

6.8 Limitations

Although our analysis has been conducted on a large dataset comprising over 22 000 young manufacturing firms from 12 Member States of the EU, it suffers from a number of limitations. We have accounted for sample attrition by adjusting estimates of the quantile regression, taking into account firms that stopped reporting sales data. However, as several countries covered by our dataset allow for reduced reporting for smaller firms, we miss any data on turnover growth for a much broader set of firms. As a consequence, for some countries the number of observations in our dataset is much lower than suggested by data available in official statistics. Additional bias may stem from the fact that we start to measure growth only after three years from the establishment year. This may introduce bias into our analysis and may limit the possibility to generalize our findings onto the entire population of young manufacturing firms. Future researchers that have access to other sources of

data, such as tax or census information, may be able to verify our findings on a more representative sample of firms.

Our data on the growth of new firms are also likely to be influenced by self-selection. We observe only firms established by those entrepreneurs that decided to enter the specific industry and region. There is a possibility that more risk-averse and less skilled entrepreneurs avoid setting up firms in industries/regions populated by strong and innovating incumbents. Such industries/regions may instead be more attractive for the most apt individuals with higher risk tolerance. Results of our investigation in chapter 5 confirm that relevant knowledge stocks are much more critical for entry of innovative startups than for other firms. Our findings regarding the positive relationship between knowledge stocks of incumbents active in the focal industry and growth rates of young firms may, therefore, be subject to bias. Part of the relationship between knowledge stocks and young firms' growth may be explained by different qualities of entrepreneurs for which we do not control, to the extent that this is not reflected in patents or trade marks. Future research may aim to augment models with information on the personal qualities of entrepreneurs, to verify whether such bias exists and to what extent may qualify our findings.

Our indicators of innovation by newly established firms are based on patent data. There are alternative measures of innovativeness based on R&D expenditure or survey data. Those alternatives may better measure innovation by newly established firms, as we know from previous research that young and small firms may prefer alternatives to the formal IP rights for the protection of their intellectual assets.

In the dissertation, we argue that newly established firms may perform better on turbulent markets. We proxy technological turbulence with higher knowledge stocks and higher contribution of young firms to those stocks. Future studies may use however better indicators of technological turbulence and related technological opportunities promoting new firms' growth. It would also be interesting to check whether innovation premium for newly created innovating firms is higher in more turbulent markets or more mature ones, with a relatively lower level of innovation.

In our econometric specification, we control for the business cycle proxied by the industry growth variable. Ideally, this variable is calculated at the level corresponding to the granularity of our data on firms main line of business and the measurement of patent and trade mark stocks, i.e. NUTS3/NACE4.

Such data is however not available in Eurostat. As the NACE industries have been redefined in December 2006, detailed Eurostat Structural Business Statistics on NACE rev. 2 manufacturing industries are available only from 2008. There is no straightforward way to transform NACE rev. 1 definitions to NACE rev. 2. One possible alternative would be to use ORBIS aggregates for NUTS3/NACE4, however due to the scale of the missing data in ORBIS such aggregates vary a lot from year to year for some regions and industries. Our variable of choice has been calculated therefore based on National Accounts data from Eurostat. National Accounts data is available in longer time series, comprising the full period covered by our analysis. This data is available; however, only at the NACE2/country level. Hence, to the extent that incumbents' innovation activity and trade mark use at the granular level is correlated with industry growth, our estimates may be biased. Future studies may verify whether our findings are confirmed when a more fine-grained variable for industry growth is used.

7 Conclusions

7.1 Summary of the findings

The main objective of the present dissertation was the analysis of the role of regional stocks of useful technological knowledge for entry and performance of newly created firms.

We conducted this analysis based on the tailor-made comprehensive dataset, comprising manufacturing firms from 12 Member States of the European Union. We were able to link demographic and financial information on firms with information on patent and trade mark applications. This comprehensive dataset enabled us to construct better and more granular measurements than those present in the extant literature for the crucial research concepts, such as relevant knowledge pools and strategic behaviour of incumbents as regards shielding their knowledge from competitors and entrants.

Knowledge stocks

In chapter 5, we analyzed the relationship between incumbents' knowledge stocks in focal and related industries and entry of firms in narrowly defined geographical regions. Our analysis indicates that despite potential negative consequences of locating in the vicinity of innovating incumbents, such as market stealing or increased competition, entrepreneurs prefer regions with abundant knowledge. The strength of this relationship depends on industry characteristics and the type of entry. The availability of abundant knowledge stocks is more important for entrants in industries where R&D and innovation play an important role than in low-tech contexts. Knowledge stocks produced by incumbents active in the focal industry spur entry regardless of the industry type, if it concerns innovative entrants with their own patent, utility model or trade mark applications. Knowledge stocks available in related industries may be attractive especially for entry in low-tech industries, where the innovation activity of incumbents active in the focal industry is relatively limited.

The presence of abundant technological knowledge does not only encourage entry, but it also spurs growth rates of those entrants that are in the upper tail of the growth rate distribution. Ambitious entrepreneurs benefit from locating close to the innovating incumbents. Those local incumbents may be a source of positive spillovers, encouraging young firms to experiment, differentiate and innovate. Although higher innovation activity in a focal

industry can result in higher uncertainty, it may also give impetus to the development of niche strategies. Those strategies can be used by entrants to compete with their better endowed and more experienced competitors. This conjecture was supported by our analysis in chapter 6, where we focused on growth rates of a cohort of newly created manufacturing firms. We showed that, although own technological innovation does not guarantee market success, it is crucial in increasing the chances of exceptional growth performance.

Trade mark stocks

Our analysis in chapter 6 showed that developing own brands may be a viable strategy for overcoming the *liability of newness* for new manufacturing firms. With a differentiated offer, focusing on market niches, young firms may be able to escape fierce price competition from incumbents, at which they are at a substantial disadvantage. As shown in our analysis, newly created firms applying for trade marks achieve higher growth rates practically over the entire distribution of growth. Investing in their own brands is likely to be more accessible and less risky for new firms than technological innovation.

Our analysis indicated a complex role of incumbents' trade mark stock. In particular in regions and industries with relatively lower technological innovation activity, trade mark stocks of incumbents represent knowledge spillover potential. This potential may stem from marketing innovations or product innovations with relatively smaller innovative steps (not warranting patent protection). Such innovations may also be a valuable source of entrepreneurial ideas exploited by entrants.

Strategic use of trade marks by patenting incumbents

However, the combination of patent stocks with trade marking by incumbents shows more intensive commercialization efforts for incumbents' knowledge and a higher determination to protect their technological knowledge against potential spillovers. Our results suggest that the combination of trade mark and patent stocks held by incumbents has an entry deterring effect and also hamper the growth potential of new entrants. Entrepreneurs prefer, or find it easier, to enter the regions and industries with similar endowments in technological knowledge but with incumbents less determined to protect their knowledge.

7.2 Contributions

The present dissertation makes various contributions to several streams of academic literature. The first set of contributions is empirical. We developed a new matching algorithm to link demographic information about firms with data on their technological innovation and trade marking activity. Our algorithm can be replicated and used by other researchers interested in innovation at the firm level, which is an advantage compared to proprietary undisclosed matching algorithms such as those used by ORBIS.

We also make an empirical contribution to the spillover literature by creating a new patent-to-industry concordance (Chapter 3) and a new inter-industry relatedness matrix (Chapter 4), both based on the matched dataset. As the concordance and matrix are based on actual firm activities with detailed industry identification and the patents they apply for, we were able to overcome constraints in prior concordances (Schmoch et al. 2003; Van Looy et al. 2015; Dorner & Harhoff 2018; Verspagen 1997c; Kortum & Putnam 1997; Johnson 2002; Lybbert & Zolas 2014). To our knowledge, our concordance at the NACE 4 digit level and inter-industry relatedness are the most detailed so far. It opens the possibilities to better control for cognitive proximities between knowledge recipients and potential knowledge sources, as this is an important aspect to bear in mind when analyzing the strength and direction of knowledge externalities (Jaffe 1989; Boschma 2005; Belderbos & Mohnen 2013). As knowledge stocks, beyond potential spillovers, are also a source of competitive advantage for incumbents, more granular data on inter-industry technological relatedness is crucial for analyzing the impact of incumbents' knowledge stock.

With these novel empirical approaches, we were able to analyze the roles of knowledge and trade mark stocks in entry and growth of new firms using the broadest scope of analysis and detail of data so far. We were able to control for very narrowly defined industries and small geographic areas. At the same time, we were able to develop our analysis for the broad scope of manufacturing industries and geographic areas with various levels of strengths and a variety of industrial settings.

In terms of insights to the literature, while our analysis confirmed the central claim of the KSTE literature that incumbents are a vital source of knowledge spillovers (Acs et al. 2013; Acs et al. 2009), we added important qualifications to this thesis. Our analysis suggests that three critical factors determine the strength and direction of the relationship between knowledge spillovers and

entrepreneurship: relatedness of knowledge, strategic behaviour of incumbents and type of entry.

First, as not all knowledge is equally essential for new firm entry in an industry, it is necessary to control for the relevance of the knowledge base, and differentiate within the knowledge pool available locally. This knowledge may be developed by incumbents active in the focal industry of entry, but also by incumbents active in other industries, but working on similar technological problems. Those related knowledge pools may be a complementary source of entrepreneurial ideas, especially when the knowledge pools in the focal industry are small or when the incumbents active in the focal industry are determined to appropriate higher share of the benefits stemming from their knowledge.

Second, our findings add to the debate on the relative importance of the specialization versus diversity of the local knowledge pools for fostering entrepreneurship (Jacobs 1970; Beaudry and Schiffauerova 2009; Frenken et al. 2007; Van Oort 2015; Boschma 2017; Kogler 2017). Our results point to the knowledge appropriation strategies of incumbents as an important mechanism that limits knowledge spillovers and entry in industries. Strategic behaviour of incumbents is thus an important aspect qualifying the role of Marshallian type of knowledge externalities in distinct industries and regions. Our analysis highlighted that the strategic behaviour of incumbents is an additional *filter* limiting the exploration of entrepreneurial opportunities stemming from regional knowledge stocks. Although this possibility has been discussed by some scholars (Audretsch et al. 2006; Plummer & Acs 2014) the concept was difficult to operationalize in the empirical research so far.

Third, we add qualification to the KSTE by showing that the relationships between knowledge pools, appropriability strategies of incumbents and entry are much stronger for innovative entrants than for other types of entrants. It is also stronger in industries with a more critical role of R&D and innovation than in industries with a low-tech profile. Therefore, both the type of entry and the industry of entry have to be taken into account when investigating the validity of KSTE in future empirical studies.

Our analysis shows that local knowledge pools are not only related to entry but also influence the growth prospects of new firms. Firms locating in regions with abundant knowledge pools and innovating incumbents experiment and actively search for market niches to compete on the market. This experimentation increases their chances for exceptional performance.

Interestingly, with relatively low levels of trade mark stocks of incumbents, this positive relationship between incumbents' knowledge pools and growth is not limited to firms in the highest quantiles of the growth distribution but extends to the whole population of newly created firms. Therefore, our work confirms that the geographic dimension of knowledge is not only crucial for entry but also for the growth of new firms and cannot be ignored in future research looking into the determinants of the new firms' market successes.

Finally, we also contributed to the relatively new but growing stream of literature on trade marks. In our research we were able to capture various facets of trade marks. We confirmed that in industries characterized by the absence of substantial patent activity trade marks may serve as a complementary indicator of product, process or marketing innovations that may be a source of knowledge spillovers (Mendonca et al. 2004; Millot 2009; Flikkema et al. 2014; Castaldi 2018). On the other hand, as suggested in the Industrial Organization literature (Tirole 1988; Lipczynski et al. 2005; Belleflamme & Peitz 2010), trade marks may be used strategically by incumbents and serve as an indicator of their commitment to defend their knowledge and raise entry barriers. As a consequence, if combined with patent stocks, trade marking reduces the positive externalities of knowledge stocks.

7.3 Policy implications

The European Union has recognized that boosting entrepreneurship is a key factor for meeting its Europe 2020 strategy of smart, sustainable and inclusive growth. The *Research and Innovation Strategies for Smart Specialisation (RIS3)* programme launched in the EU in 2014 combines focus on regional development, innovation and entrepreneurship. Strategies for Smart Specialisation (S3) respond to the difficult task of choosing regional priorities by pointing to the *entrepreneurial process of discovery* (Foray et al. 2012). However, many concepts of smart specialization strategy implemented by the EU are novel and they are not sufficiently grounded in the economic theory and empirical evidence. Even strong supporters of smart innovation concept find this as "*a perfect example of 'policy running ahead of theory'*" (Foray et al. 2011). Our results can inform the implementation of RIS3 policies on the regional level by pointing to the important links between local knowledge pools, incumbents' strategies and entrepreneurial discovery of business opportunities. Below we highlight two most salient implications.

Our analysis shows that innovative companies prefer to locate in the regions with higher knowledge stocks they could use as a source of entrepreneurial ideas. Location of innovative firms close to the existing sources of knowledge increases the comparative advantage of regions already abundant in knowledge. For reasons discussed in the present dissertation, a growing role of knowledge in the economy did not contribute to an equal distribution of creative and innovative industries but rather to their growing concentration. Abundant knowledge pools are therefore vital for entrepreneurship and especially for innovative entrepreneurship. As innovative companies are growing more rapidly, are more productive and pay higher salaries, a growing geographical concentration of innovative industries contributes to economic inequalities and social tensions. Regions with low innovation activity lose the competition not only for R&D activities with innovative regions in the developed world but also risk losing more routine manufacturing jobs to regions characterised by cheaper production factors in developing countries. The loss of manufacturing firms compromises future innovation capacities of the regions with a low level of innovation activity, further weakening their economic prospects. Innovation and technological progress contribute therefore to the widening of inter-regional disparities (Frey 2019). Inclusive and sustainable growth requires development of policies helping declining regions identify and strengthen their comparative advantages, preferably in the economic activities where they already show relatively high innovation potential. As shown by Van Atmael & Bakker (2016) the revival of former rustbelts in the developed world is possible but only when the regional focus switches from cheap to smart manufacturing. Maintaining manufacturing capacities within regions should be a priority, as R&D and innovation can hardly be decoupled from production processes (Pisano & Shih 2012).

Our analysis confirmed that newly established firms achieve higher growth rates when located in industries and regions with relatively higher knowledge stocks. Those benefits may be limited by the strategic behaviour of incumbents fencing off their knowledge from potential competitors. However, as discussed in the present dissertation, incumbents are not always best positioned to commercialize ideas stemming from knowledge stocks - even if they contributed to their creation. Due to uncertainty related to knowledge, the commercial potential of innovation is very difficult to assess ex-ante. The more ideas are actually tested on the market, the higher the chances of discovery of the commercial potential of existing knowledge pools and the better economic prospects of regions. Policymakers may, therefore,

consider undertaking efforts strengthening more intensive collaboration and knowledge exchange between regional agents to stimulate more intensive market experimentation. A more open attitude towards sharing knowledge may also be beneficial for incumbents, as a more dynamic regional start-up environment may help them discover new uses of regional knowledge pools they were not aware of. A more collaborative attitude of regional agents may be beneficial to the economic development of the entire region as shown by Saxenian (1996) in her seminal comparison of Silicon Valley and Route 128 entrepreneurial cultures.

Our findings also have implications for trade mark protection legislation and policy. In the present dissertation, we have shown that trade marks may be important indicators signalling more intensive commercialization of the knowledge stocks by incumbents. A higher trade mark intensity within narrowly defined industries and regions may be interpreted by prospective entrepreneurs as a sign of lower spillover potential and may influence their decision of not starting a new business venture. Potentially abusive usage of trade marks such as an excessively broad range of goods and services covered by trade mark applications, a lack of use of registered trade marks or abuses of the opposition procedures against new trade mark applications may have negative consequences on the level of entrepreneurial activity in the region. Although use requirement is a standard feature of international trade mark provisions, it is not controlled with the same stringency all over the world (von Graevenitz et al. 2012). Specifically, use requirement is controlled to a much lesser degree in the European Union than in the USA. Currently, in the EU proof of use is not controlled *ex officio* and is demanded mostly within opposition or cancellation proceedings only. 41% of agents and 29% of the trade mark owners surveyed by Allensbach Institute in 2011 declared that in their opinion there were too many non-used trade marks in the OHIM register (Knaar et al. 2012). In this respect, recent changes introduced in the EU trade mark reform legislative package in 2015 and the new EUTM regulation should be welcomed. Recent legislative changes³⁰ require from trade mark applicants more precision in defining goods and services being subject of protection and limit the number of trade mark classes covered by the basic trade mark fee. In our view, those changes are going into right direction as the previous provisions encouraged applicants to apply for a broader scope of trade mark protection than needed (Johnson 2018). More

³⁰ Regulation (EU) 2017/1001 of the European Parliament and of the Council of 14 June 2017 on the European Union trade mark

empirical work is necessary to determine whether those changes sufficiently reduce the risk of trade mark cluttering. If the problem of trade mark register cluttering persists in the future, EU legislators, similarly to other jurisdictions, may consider registering trade marks only if a trade mark application is accompanied by statement of use or, in case trade mark protection is sought upon intent of use, if statement of use is delivered after a grace period. However, as such changes create additional burdens on trade mark applicants, their eventual introduction should be preceded by careful cost-benefit analyses.

7.4 Limitations and directions for future research

In the present dissertation, we identify incumbent innovation activity with codified knowledge as proxied by patent applications. However, formal knowledge is not the only source of innovation. There is considerable variety of differentiated knowledge sources such as *analytical* (science based), *synthetic* (engineering based) and *symbolic* (artistic based) that may be equally important for the emergence and discovery of entrepreneurial opportunities at the local level (Asheim et al. 2011). Depending on the nature of industrial sectors, traditional science and technology indicators may poorly capture underlying innovation activities (Laestadius 1998). Patent statistics may be relatively good indicators of *analytical* and *synthetic* knowledge, but they poorly reflect *symbolic* and more tacit types of knowledge.

The same limitations apply to our analysis of innovation in newly created firms. We proxy entrants' own innovation by their applications for patent or trade mark protection. However, there are not the only available instruments of protection of firm assets. As suggested in previous research (Cohen et al. 2000), young and small firms may use a range of informal protection measures as well. In addition, our matching algorithm cannot match all applicants with corresponding ORBIS records on firms. As a consequence, we may be classifying some entrants as not innovating, whereas in reality they do innovate.

In our work, we interpret the increasing use of trade marks in combination with patent stocks as an indicator of possible incumbents' strategy to increase the appropriability from their innovation and limit spillovers accruing to their local rivals. Ideally, we have data on patents and trade marks on the level of individual innovations to test this relationship in detail, but we could only calculate the interaction between patent and trade mark stocks at the regional and industry level.

In our empirical work, we identify the links between firms and industries on the basis of the main NACE code available in ORBIS. However, the activity of some firms spans more than one industry and with time firms may diversify their activity into other markets. This leads to a degree of imprecision. On the other hand, even though in our specification industries are defined by detailed 4 digit NACE codes, the scope of activity of some industries at this level is still so broad that it encompasses many submarkets and firms that do not compete directly with one another. Future research may use different conceptualizations of the relevant industry or market, taking into account richer information about the actual activities of firms.

Our measurement of knowledge and trade mark stocks takes into account only the number of relevant applications. Previous research has, however shown that the distribution of quality of technological knowledge and its value across patents is much skewed. Some patents protect technologies with little commercial value, whereas other patented technologies are crucial not only for individual firms but to the industry as a whole. The same will apply to brands protected by trade marks. Due to the volume of our data and problems in assessing the value of individual technologies and brands, we were unable to control for this aspect in our research. Future research, possibly limited to selected industries and/or regions, may take into account not only the volume but also the quality of knowledge and strategic instruments of their protection.

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Addendum on valorisation to the dissertation

The promotion of entrepreneurship has been one of the most important economic objectives of the European Union since the adoption of the Lisbon Strategy in March 2000. This strategic document set a goal to make the EU *“the most competitive and dynamic knowledge-based economy in the world”*. The European Council urged the Member States and the EU institutions to create an environment that is friendly to the start-up of innovative businesses, among others by adopting a regulatory framework conducive to investment, innovation and entrepreneurship and by redirecting EIB and EIF financial instruments towards supporting business start-ups, high-tech firms and micro-enterprises. The European Union has recognized that boosting entrepreneurship is a key factor for meeting its Europe 2020 strategy of smart, sustainable and inclusive growth. The Entrepreneurship 2020 Action Plan *Reigniting the entrepreneurial spirit in Europe* recognizes entrepreneurship as a powerful driver of long-term economic growth and job creation. The recent policy focus within the new EU initiative *Europe’s next leaders: the Start-up and Scale-up Initiative* is on supporting those start-ups that *“combine fast growth, high reliance on innovation for product, processes and financing, utmost attention to new technological developments and extensive use of innovative business models”* (Commission 2016b).

Our research may, therefore, be a timely addition to the growing body of research focusing on the emergence and growth prospects of new manufacturing firms in Europe. We emphasize that, beyond standard agglomeration factors, local knowledge conditions play an important role in boosting firm entry and especially innovative entry, which is the main policy focus of European initiatives. There appear to be important differences in knowledge endowments between regions, even within the same country. Therefore, any scheme of entrepreneurship support, and especially support for innovative entrepreneurship, has to take into account diverse regional knowledge endowments and should be based on a bottom-up rather than a top-down approach.

Policy practitioners may find our empirical research to be useful for designing policies to support regional entrepreneurship. We show that regional knowledge is an important factor driving entry, but that not all knowledge is equally important for the discovery of entrepreneurial opportunities and hence firm entry and growth. A key aspect here is technological relatedness between the regional knowledge base and the

knowledge required for entrepreneurial entry. Hence, practitioners should understand this relationship and assess knowledge relatedness, for which the methodologies developed in chapter 3 and 4, linking technological innovation to specific industries may be particularly helpful.

Our research confirms that innovation increases the chances of exceptional performance by newly established firms but does not guarantee it. Therefore, regional support schemes aimed at boosting regional innovative entrepreneurship has to assume that part of the resources will be allocated to projects that eventually may not succeed and may not achieve the expected results. However, this should not keep policy makers from supporting entrepreneurial search and experimentation.

We further show that the strategic behaviour of incumbent firms should be taken into account while designing regional entrepreneurship and innovation policies. While abundant knowledge stocks may be indeed available in the region, incumbents may implement aggressive strategies to appropriate the returns of their R&D efforts, and this may reduce knowledge spillovers and benefits to newly established firms.

In recent years regional policies of the European Union have been reformed and the *Research and Innovation Strategies for Smart Specialisation (RIS3)* programme has been launched in 2014. The goal of these strategies is to select the regional priorities for public research and investments in order to facilitate the process of economic modernization of European regions. Smart specialization strategies aim at converting knowledge domain strength of each region into marketable goods and services, taking into account market niches. The objective of this strategy is to create a critical mass of R&D support into few but highly promising domains, where this support may be the most effective for growth. Consequently, structural funds are increasingly seen as an instrument of support for regional innovation policy.

Our research shows that policy makers, when setting priorities for R&D, should prioritize support to schemes based on an open innovation paradigm, involving entrepreneurial firms and R&D collaboration to exploit local knowledge. In contrast, support funnelled to incumbents with a strong strategic focus on fencing off their knowledge from other market players may result in missed opportunities and may be detrimental to regional growth. Such support may be therefore less effective than assistance directed to projects foreseeing more open access to the outcomes of R&D initiatives.

Results of the present dissertation have already been disseminated in the academic and policy communities. The data on patenting by region has been used for the analysis of patterns of IPR intensity of industries in Europe and resulted in several publications of the European Union Intellectual Property Office such as *Intellectual property rights intensive industries and economic performance in the European Union* (2013; 2016) and *High-growth firms and Intellectual Property Rights. IPR profile of high-potential SMEs in Europe* (2019). A paper based on chapter 5 has been presented at several academic and policy conferences: the conference on *Cities and regions in a changing Europe: challenges and prospects* held in Athens in July 2017, the conference on *IP Statistics for Decision Makers (IPSDM)* held in Mexico City in October 2017 and *European Policy for Intellectual Property (EPIP)* conference held in Berlin in September 2018. The paper has been also submitted for publication in the special issue of *Regional Studies* on the topic of “Regions and Trademarks”. We plan to disseminate the results of other chapters of the dissertation, especially Chapter 6, at future academic and policy conferences and to publish results in international scholarly journals.

Curriculum Vitae

Michał Kazimierczak was born on 9 June 1976 in Warsaw, Poland. He graduated in International Relations from Warsaw University in 2000 and from National School of Public Administration in Warsaw in 2002. During his studies at National School of Public Administration, he completed two internships: at the Permanent Representation of Poland to the European Union in Brussels and at the Chancellery of the President of Poland. In 2003 he graduated from Polish-Dutch Postgraduate European Studies Program co-organised by Maastricht University and University of Warsaw.

He started his professional career at the Foreign Investors' Chamber of Commerce in Warsaw in 2000. Between 2002 and 2006 he served as a Head of Unit in the Department of International Relations and European Affairs in Polish Ministry of Infrastructure. In 2006 he joined Deloitte Advisory as a senior consultant responsible for coordination of Deloitte projects for public sector institutions.

In 2009 he started work for the European Union Intellectual Property Office (formerly Office for Harmonization in the Internal Market) in Alicante, Spain. From 2012 he has been working as an economist at EUIPO. He has been involved in several research projects focusing on IP contribution to the European economy, impact of IP on the performance of European companies and joint projects with OECD on analysis of scale and trends of counterfeiting in the world trade.

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