An Economic Investigation of the Use and Impact of Patents and Trade Marks in Germany

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Preface

Stimulating innovation is high up on most countries' agenda. The "Innovation Union" is one of seven flagship initiatives of the European Union's (EU) ten-year growth and jobs strategy "EU 2020." Innovation is an engine to create job opportunities, to make countries more competitive in the global market place, to increase food and resource security and to fight global warming.[1] President Obama's "Strategy for American Innovation" builds on the premise that "innovation-based economic growth will bring greater income, higher quality jobs, and improved health and quality of life to all U.S. citizens."[2] And China's 12th five-year plan includes concrete innovation targets to sustain high economic growth and to create millions of new jobs.[3]

Innovation involves a "new or significantly improved product (goods or services), or process, a new marketing method, or a new organizational method in business practice, workplace organization or external relations (OECD and Eurostat, 2005, p. 46)." At least since Schumpeter (1934; 1950) we know that innovation is an important driver of economic growth, and policy makers all over the world associate economic growth with increasing living standards. Opportunities to maintain and increase economic growth therefore attract attention by academics and policy makers alike.

To create jobs and increase international competitiveness through innovation policies, decision makers need to understand the economics of innovation - what affects innovation and what is affected by it. Innovation data is a central element of the economics of innovation. For over three decades, many economic studies of innovation and intellectual property have focused on the analysis of research and development (R&D) and patents. However, these activities are mainly observed in manufacturing industries (Griliches,

[1] http://ec.europa.eu/research/innovation-union/index_en.cfm, last accessed 10.12.2014
[2] http://www.whitehouse.gov/innovation/strategy, last accessed 10.12.2014
[3] http://www.china-botschaft.de/det/zgyw/t804125.htm, last accessed 12.10.2014

1981, 1990; Hall and Harhoff, 2012). Less attention has been paid to trade marks, even though these intellectual property rights (IPRs) are more widely used by firms of all types across the whole economy. This trend is changing.

In the second chapter, I summarise the existing empirical economic literature to inform the reader about what has been established to date and to identify what is needed from future research. This growing literature explores the expanding use of trade marks. The rising interest in the economics of trade marks is partly due to the large amount of trade mark data that have become available, but mainly a result of the growing importance of innovation and the proliferation of product variety in developed economies. The overarching issue that is informed by these empirical studies is to what extent markets are characterised as reflecting the sale of heterogeneous products competing on quality, variety and price. This type of non-price competition is often qualified as Schumpeterian competition via both major and minor innovations. It ensures ever rising productivity, product quality and product variation in the modern economy.[4]

In the third and fourth chapter, I focus on the role of knowledge and innovation related activities in firm and industry performance. The OECD Oslo Manual identifies both aspects as relevant to innovation policy (OECD and Eurostat, 2005, pp. 41). To address the role of knowledge, it is necessary to distinguish between the different types of knowledge. Access to knowledge varies with type and affects the diffusion of it. Knowledge diffusion in turn determines the supply of potential entrants in an industry and thus firm entry (Winter, 1984). In chapter 3, I investigate empirically the effects of different knowledge types and innovation related activities on firm entry. In particular, I investigate an extension of an implicit hypothesis in Winter (1984): firm entry is roughly proportional to the number of individuals who are exposed to the knowledge required to operate in an industry, because these individuals generate innovative ideas that can lead to firm entry. To this end, I created a new German Firm-Level Intellectual-Property data set (GFLIP),

[4]See Greenhalgh and Rogers, 2012 for a recent discussion of this process.

covering the period 2002-12. I show that knowledge types and innovation related activities prevalent in an industry explain some of the cross-industry differences in firm entry, even though their marginal effects are small.

Successful entry is not only determined by knowledge types and innovation related activities. An idea is merely one ingredient for successful firm entry. Once entrepreneurs have an idea that is relevant to the industry, their post-entry performance depends on the remaining ingredients (Gort and Klepper, 1982; Winter, 1984). Entrepreneurs can enter an industry and stand up to established firms if the remaining ingredients are available to everyone and easy to learn. Nelson and Winter (1974) call such a situation an entrepreneurial regime. By contrast, if entry by an entrepreneur requires experience and routine in coordinating all the ingredients, successful entry by new firms is less likely to occur. This is a routinized regime. Both regimes are types of the technological regime prevailing in an industry. Following Audretsch (1991), I investigate the effect of the technological regime on firm entry by separately analysing innovation related activities by young firms.

Some of the barriers to entry identified in Bain's (1956) seminal work often fail to explain entry patterns. For instance, Acs and Audretsch (1989b; 1989a) find no significant effect of capital-intensity in an industry on firm entry. Summarizing the literature up to that date, Geroski (1995) notes that entry, even in large numbers, is not a rare occurrence in most markets in spite of high econometric measures of entry barriers. Some authors have claimed that it is survival and growth rather than entry that sustains employment, know-how and value added (Dunne, Roberts, and Samuelson, 1988a; Mata and Portugal, 1994; Wagner, 1994).

Previous studies of German post-entry performance focus on the effect of the characteristics of the founder (Brüderl, Preisendörfer, and Ziegler, 1992), on the choice of the form of ownership, liability and the age of the owner (Harhoff, Stahl, and Woywode, 1998), on employment growth just before entry (the "shadow of death") (Almus, 2004), and on regional differences (Fritsch, Brixy, and Falck, 2006). The role of knowledge and of innovation related activities prevalent in an industry in post-entry performance by German firms has not yet been analysed. I address this gap in chapter 4, where I show that high entry rates are correlated with high exit rates, innovation related activities contribute to the probability of successful entry, and more specialised knowledge in an industry appears to be associated with lower entry rates.

This thesis contains several contributions. First, I survey the existing empirical economic literature on trade marks to date and identify what is needed from future research in this field. Second, I examine the role of knowledge in firm creation, using national patent and trade mark data. Using national trade mark data for Germany is new. Previous studies on German firms only include Community trade marks or aggregated statistics from the World Intellectual Property Office (WIPO). Third, the period under investigation is particularly interesting because it includes the financial crisis. I follow two cohorts of new firms established in 2003 and 2006, respectively. Firms starting a business in 2006 did not know that that the financial crisis of 2007-08 was about to happen. In economic terms, the financial crisis presents a natural experiment for new firms. By comparing survival patterns of firms that were hit by the financial crisis in their first year with survival patterns of firms that had more time to establish themselves, I disclose unobserved effects that determine young firm survival and are much stronger than those of knowledge and innovative activity.

Chapter 1

European Patent and Trade Mark Systems

In this section I summarise the specific requirements to apply for a patent or to register a trade mark, and I discuss the different routes to obtaining patent or trade mark protection.

1.1 Patent systems[5]

A patent is an exclusive right granted for an invention. Following Article 27 of the TRIPS agreement, a patent can only be filed for inventions that are *new*, *industrially applicable* and contain an *inventive step.* These requirements make a patent a unique indicator for inventive output (Schmookler, 1966).

In particular, the exclusive rights granted by a patent are

> "(a) where the subject matter of a patent is a product, to prevent third parties not having the owner's consent from the acts of: making, using, offering for sale, selling, or importing (6) for these purposes that product;
>
> (b) where the subject matter of a patent is a process, to prevent third parties not having the owner's consent from the act of using the process, and from the acts of: using, offering for sale, selling, or importing for these purposes at least the product obtained directly by that process (TRIPS, Art.28, 1)."

[5]A more comprehensive introduction to patent systems and their implications for patent statistics can be found in the OECD Patent Statistic Manual (OECD, 2009).

Patents can be obtained via different routes. As I distinguish between European and German national patents in the following chapters, I provide a brief overview of the differences between German national, European and international patents.[6] The choice of the route depends on the geographical scope a patent shall have. While the requirements regarding the patentable subject matter do not differ much across levels and most high-income countries, the differences in formal requirements can be substantial.

The process of applying for and registering a *national patent* in Germany is governed by the "Patentgesetz" (patent law, PatG), which is largely harmonised with other patent laws in the European Union, although some differences between countries persist (Hall and Harhoff, 2012). Taking the **national route**, the inventor applies to the German Patent and Trade mark Office (DPMA). The first application is referred to as the *priority application* and is assigned a *priority date.* The content of the application will not be disclosed to the public until 18 months after the priority date (§31(2) PatG). Within the first 12 months after the filing of the priority application, the inventor can file additional patent applications at other national or regional patent offices, or at the International Bureau of the World Intellectual Property Organisation (WIPO) in Geneva. In each case, the applicant can only claim the priority date as the beginning date of the protection of the invention (§40(1) PatG).

The laws concerning the European patent are laid down by the European Patent Convention (EPC), which was signed by seven countries in October 1973 in Munich and entered into force on 7 October 1977.[7] While through the national route each application is considered and subsequently granted or rejected by the national patent offices independently, the European Patent Office (EPO) has the authority to grant or reject patent applications for the whole region (Article 1 and 2 EPC). The goal of the EPC was to establish a

[6] A current development is the establishment of the Unitary Patent, which will allow inventors to file a single patent that would be valid in 25 countries and covered by only one patent court (Unified Patent Court). While this is "history in the making," it is an ongoing process and does not affect the analysis in this thesis. For more information see http://www.epo.org/news-issues/issues/unitary-patent.html, last accessed 27/11/2014.

[7] The contracting countries on the date of entry into force were: Belgium, West Germany, France, Luxembourg, Netherlands, Switzerland and the United Kingdom

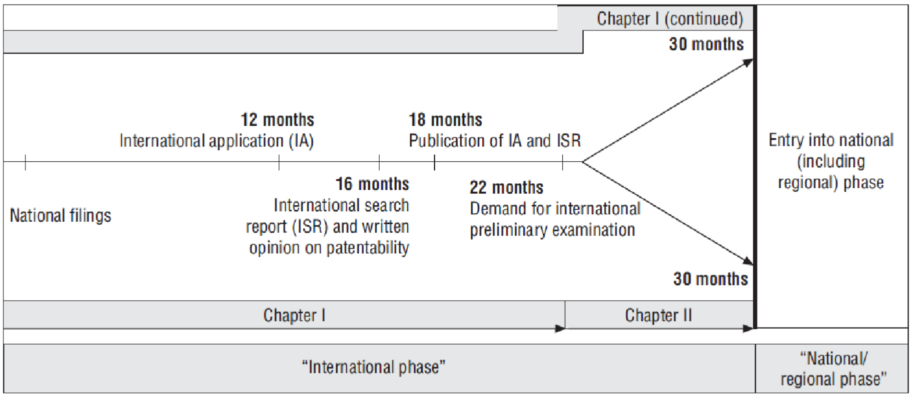

Figure 1.1.1: Time line for the international route
Source: OECD Patent Statistic Manual 2009, p.54

single patent system providing the same legal protection of industrial property in the contracting states on the basis of a single application (Article 2(2) EPC). Taking the *European route*, the applicant files an application with the EPO or under certain conditions with the central industrial property office (Article 75(1) EPC) and designates the contracting states in which the patent shall be validated (Article 3 EPC). As all granted patents ultimately obtain national status (Article 66 EPC), however, the applicant may have to submit a translation into a recognized language of the designated country within three months after the patent is mentioned in the European Patent Bulletin before its legal protection can be enforced in designated countries (Article 65(1) EPC). Designation can also require payment of a designation fee (Article 79(2) EPC), which can vary across countries.

Alternatively, applicants can take the *international route* and file a request for an *international application* (IA) under the Patent Cooperation Treaty (PCT). The PCT was concluded in 1970 and had 148 Contracting Parties as of November 2014.[8] It is administered by the World Intellectual Property Organisation (WIPO). Although international applications can be filed with the International Bureau of WIPO in Geneva, residents of contracting states usually file the application at their national or regional office. Applicants designate the

[8]http://www.wipo.int/treaties/en/ShowResults.jsp?lang=en&treaty_id=6, last accessed 27/11/2014

countries in which protection is desired in the application (Article 4(1) PCT). One of the major patent offices, which has been appointed by the PCT Assembly as an International Searching Authority (ISA), then conducts the *international search* to establish the current state of the art (Article 15(1) and 15(2) PCT). This results in an *international search report* (ISR) (Article 18 PCT), which is essentially a list of citations of prior art that may affect the patentability of the invention - i.e. knowledge of methods and technology that is related to, and existed before, the application was filed. The IA and the ISR are published 18 months after the priority date (Article 21 (2a) PCT). Within three months after this or 22 months after the priority date, whichever is later, the applicant can demand an *international preliminary examination* (IPE) (Article 31(6); Rule 54bis PCT), which results in an IPE report. These steps can delay the national procedure of the patent application (see figure 1.1.1). Finally, after a maximum of 30 months after the priority date, the IPE report will be made public (Article 21(3); Rule 44bis PCT) and the application enters into the national/regional phase.

There are at least two good reasons to file a request for an international application. Firstly, the international phase of the PCT route is not very costly and buys a substantial amount of time to improve and evaluate the economic value of an invention. Thus, inventors may file an application 'just in case'. Secondly, if the invention is worthwhile seeking protection internationally, the PCT route provides an efficient way to reach a large number of countries with a single application.

1.2 Trade mark systems

The Agreement on Trade Related Aspects of Intellectual Property Rights (TRIPS), an international agreement within the World Trade Organisation, which came into effect 1 January 1995 and covered 160 member states as of June 2014, sets down minimum standards for the different types of intellectual property that are binding for the member parties. It defines a trade mark as

> "any sign, or any combination of signs, capable of distinguishing the goods or services of one undertaking from those of other undertakings, shall be capable of constituting a trademark (Article 15(1) TRIPS)."

If such a sign is representable graphically, e.g. in words (including personal names), designs, letters, numerals, or by the shape of goods or their packaging, it is, in principle, eligible for registration by legal and natural persons. In countries that are members of the agreement, the issuing authorities are expected to promptly publish trade mark applications before registration and allow third parties to oppose an application (Article 15(5) TRIPS).

Based on the Agreement, members can specify detailed rules for the provision of trade mark protection. As I study Community and German trade marks in this thesis, and the national laws are by and large harmonized with the regional laws in the EU, I will refer to Council Regulation (EC) No 207/2009 on the Community trade mark where TRIPS does not provide guidelines to illustrate the requirements and exceptions for trade mark registration. For instance, registration can be rejected based on absolute grounds if the trade mark is devoid of any distinctive character, if it is purely descriptive, or if it consists exclusively of signs or indications which have become customary in the current language (Article 7 EC 207/2009). If no grounds for absolute refusal exist, a trade mark can be rejected, opposed, or cancelled if there exist relative grounds for refusal, e.g. if it is similar to or identical with an earlier trade mark, and the product for which registration is applied is similar to or identical with the product the earlier trade mark protects (Article 8(a) EC 207/2009). Registration can also be rejected if this identity or similarity creates *likelihood for confusion* (Article 8(b) EC 207/2009). This is a situation in which the average consumer may be confused as to the true origin of a product because of the similarity of the signs. Moreover, a trade mark registration can also be rejected or cancelled in case the product is not similar or identical. This can happen when the similarity of the newly registered trade mark with an existing one creates an association with the owner of the senior trade mark that does not actually exist, or if it causes damage to the established owner when used (Article 16(3) TRIPS). The agreement leaves discretion with member countries with regard to the use requirement. In most legal systems, owners of trade marks have a minimum grace period of three years of non-interrupted non-use before the registration can be cancelled (Article 19 TRIPS). If a trade mark owner in these jurisdictions cannot prove having used the trade mark in commerce, a third party can request the cancellation of that trade mark (Article 15 EC 207/2009).

There are different routes to registering a trade mark: the domestic route by applying directly at a country's trade mark office, the regional route where applicable, e.g. at the Office for Harmonization in the Internal Market (OHIM) for the Community trade mark (CTM) covering the European Union (EU), or the international route via the Madrid protocol of 1989 which relates to the Madrid Agreement of 1891. OHIM was established in 1996, but elements of the CTM regulation are still controversial and debated among legal scholars, for instance the fact that it grants full protection in all Member States of the EU, even if a CTM is only used in a small region. This and further issues regarding the European trade mark system are thoroughly discussed in a study by the Max Planck Institute for Innovation and Competition (Knaak, Kur, and von Mühlendahl, 2012). The international application, by contrast, is a territorial extension of existing trade mark protection and cannot establish first protection (Article 1(2) Madrid Agreement). A trade mark therefore has to be registered at a national or regional office of a member nation, before further countries or regions can be designated in an international application.

Trade marks are registered for particular classes of goods and services (Article 28, EC 207/2009). In most jurisdictions, the classification scheme used is the Nice classification (NCL), which is based on the Nice Agreement Concerning the International Classification of Goods and Services for the Purposes of the Registration of Marks of 15 June 1957. The agreement has 84 contracting parties as of November 2014, and as of 2012 the NCL is reviewed every year. The NCL 2014 consists of 35 goods classes and 11 services classes.[9] In principle, a trade mark application can include all classes of goods and services, but in most jurisdictions additional classes cost extra. Thus, the large majority of trade marks is only registered in as many classes as are included in the basic price.(von Graevenitz et al., 2012) In most legislations, the basic registrations is for one class, but somewhat controversially the Community trade mark registration includes three classes by default.

The costs of registering and renewing trade marks do vary across jurisdictions. For instance, as of 2014, registering a trade mark in three classes in Germany (OHIM, USPTO) cost €290 (€900, €661).[10] After at least seven years (ten in most jurisdictions), a renewal fee has to be paid, otherwise the trade mark is deleted from the register. In 2014, the renewal fee for three classes in Germany (OHIM, USPTO) was €750 (€1500, €964).[11] The different requirements to obtain a trade mark, e.g. the stronger enforcement of a use requirement in the U.S., the differences in geographical coverages, e.g. Community versus national trade marks, and the differences in the route to a trade mark registration need to be accounted for in studies that analyse more than one type of trade mark. The unitary character of CTMs, for instance, not only grants wider protection, but also exposes owners to a larger pool of senior or other similar trade marks. Studies that only focus on one type of trade mark data where more types are possible inevitably miss out on some information. European firms, for instance, are likely to either apply for national or Community trade marks, but rarely for both. I discuss these issues as they occur throughout chapter 2.

[9] For more information, see http://www.wipo.int/treaties/en/classification/nice/, last accessed 27/11/2014

[10] Three classes at $275 per class at €0.8/$ on 27/11/2014. Source: DPMA: http://www.dpma.de/english/trade_marks/fees/index.html; OHIM: https://oami.europa.eu/ohimportal/en/fees-and-payments; USPTO: http://www.uspto.gov/trademarks/tm_fee_info.jsp, last accessed 27/11/2014.

[11] Renewing three classes at $400 per class at €0.8/$ on 27/11/2014

Chapter 2

Empirical Studies of Trade Marks: The Existing Economic Literature

2.1 Introduction[12]

For over three decades many economic studies of innovation and intellectual property have focused on the analysis of R&D and patents, which are activities predominantly observed in some manufacturing sector (Griliches, 1981, 1990; Hall and Harhoff, 2012). Less attention has been paid to trade marks, even though these intellectual property rights (IPRs) are more widely used by firms of all types across the whole economy.

Trade marks allow their owners and licensees to prohibit others to sell the same or similar products using the protected mark. Trade marks have four main functions: indicating origin, signalling, incentivising investment and facilitating product differentiation.

The *indication of origin* is the oldest and primary function of trade marks. It ensures that consumers can identify a specific product without investigating each alternative before purchase. Trade marks therefore lower the costs of the search consumers undertake to find their most preferred product bundle (Landes and Posner, 1987). Being able to save time on studying each product for its attributes presumes that it is possible for consumers to learn about all product attributes. Products, however, often have credence attributes as well as search and experience attributes (Nelson, 1970; Darby and Karni,

[12]This chapter is joint work with Christine Greenhalgh, St. Peter's College, University of Oxford, and has been published as a working paper in 2013: Schautschick and Greenhalgh (2013).

1973). Consumers can discover the search attributes prior to purchase, e.g. the colour of an apple, and they learn experience attributes by consumption, e.g. the taste of an apple. It can take a while or even be impossible for the average consumer, however, to find out about credence attributes, such as whether the apple was organically grown. While producers know the attributes of their products, consumers may not. If information is distributed asymmetrically between buyers and sellers, markets can fail to perform efficiently (Akerlof, 1970). Trade marks can reduce information asymmetries between firms and consumers by *signalling* (Akerlof, 1970; Spence, 1973; Shapiro, 1982). They can also lower the relevance of information asymmetries on the purchasing decision once consumers trust the signal. In the latter case, firms reduce asymmetric information by simplifying the communication of facts ("Product A uses the same ingredients as product B"), and by relying on trust ("If you liked product A, you will also like product B"). This can only work if firms send signals that are reliable over time and across products. This consistency requirement facilitates the signalling function of a trade mark.

The signalling function creates *investment incentives* for firms to improve their products in the first place, and to keep constant or improve the quality of their products over time to build a reputation (Chamberlin, 1933; Landes and Posner, 1987; Economides, 1988). Firms that are not willing or able to keep their promises are not likely to file and maintain trade marks. The signalling function also creates incentives for firms to offer varieties that without trade marks might not find buyers. Hence, trade marks support *product differentiation*. In a homogeneous product market, product differentiation allows firms to move away from pure price competition and to make strictly positive profits, at least in the short run (Hotelling, 1929; Chamberlin, 1933).

Our aim in this paper is to survey the existing empirical economic literature to inform the reader by summarising what has been established to date and to identify what is needed from future research. This growing body of literature explores the expanding use of trade marks. The rising interest in the economics of trade marks is partly due to the large amount of trade mark data that have become available, but mainly a result of the growing importance of innovation and the proliferation of product variety in developed economies. The overarching issue that is informed by these empirical studies is to what extent markets are better characterised as reflecting the sale of heterogeneous products competing on quality, variety and price. This process is often characterised as Schumpeterian competition via both major and minor innovations. It ensures ever rising productivity, product quality and product variation in the modern economy (See Greenhalgh and Rogers, 2012 for a recent discussion of this process).

The theory outlined above is our collection and abstraction of existing theory of trade marks and its various interpretations in the studies analysed in this paper. Most studies, however, either focus only on individual aspects of the four functions or use trade marks as a proxy for innovation. For the reader's convenience we therefore outline the main theoretical predictions, which form the basis for the individual empirical models, within each section rather than here.

In section 1, we document the use of trade marks by firms in several advanced countries, including Australia, the United Kingdom and the United States, and by firms of different sizes and in different industries. In section 2, we review attempts to gauge the function of trade marks as indicator of innovation and product differentiation. In section 3, we survey studies that demonstrate firms' incentives to trade mark, including transferring information to consumers, realising synergies between different types of IPRs and attempting to raise rivals' costs. In section 4, we provide an overview of the importance of trade mark use for firm survival and the association of trade marks with several dimensions of firm performance and productivity, including their ability to generate well-paid jobs. In the last section we conclude with some remarks on common weaknesses in the studies surveyed and suggestions how they can be overcome.

2.2 The use of trade marks in the UK, US, and Australia

2.2.1 Cross country comparisons

Trade marks have been in existence for more than a century in high-income countries. But whichever country is examined, the growth of trade mark registrations has been astonishingly rapid in the period since 1975. Taking first the long view of earlier history, we consult Duguid, Da Silva Lopes, and Mercer (2010). These authors construct three series of data on trade mark registrations for France, the UK, and the US for the century leading up to 1970. While they acknowledge that the data sources are not without difficulties for making comparisons over such a long period, they conclude that France and Britain had both an earlier and more enduring interest in trade-marking than the U.S. Even so, in all three countries the gradual rise in trade mark activity was very modest over this 100 year period in comparison with what occurred in the latter part of the 20th century.

The increased growth in trade mark registrations in recent decades began about ten years earlier than that for patents, which only took off from the mid-1980s (figure 2.2.1). Jensen and Webster (2004) date the upsurge in Australian trade mark registrations to the mid-1970s, calculating that this growth exceeded that of real GDP by 2.3% p.a. between 1975 and 2002, having previously only just kept pace. Trade-marking activities in the US, UK, and Australia show a remarkable degree of correspondence in their patterns of growth from 1975 to 2002 (figure 2.2.2). Applications for both types of IPRs seem to be impeded by recessions (von Graevenitz et al., 2012), and each country sees rapid contraction in IPR applications during 2000 to 2002. Trade mark growth was somewhat more volatile in the UK than in the US and Australia, dipping during 1991-1992 in what was for the UK a significant recession. Compared with activity in the 1980s, Greenhalgh, Longland, and Bosworth (2003) identify considerably faster growth in trade-marking activ-

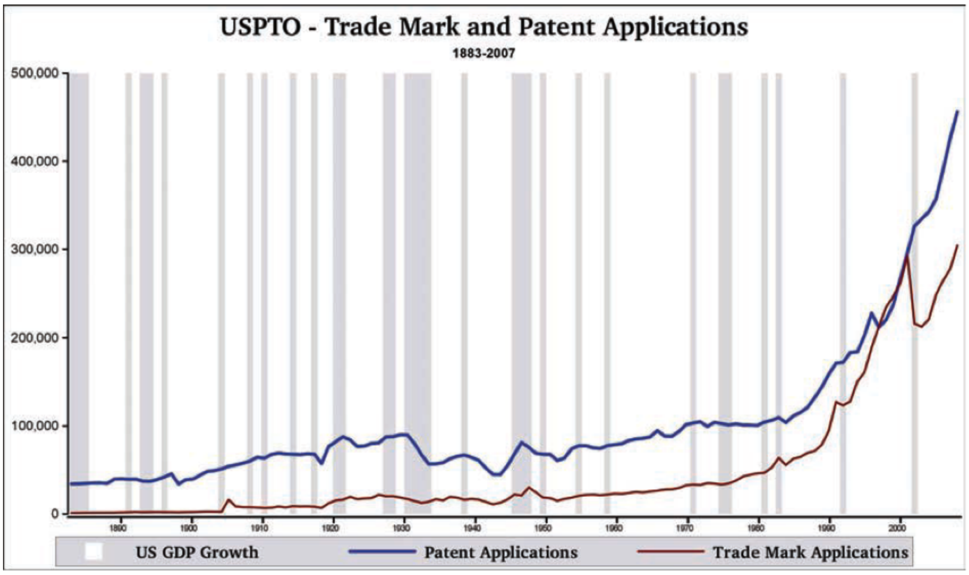

Figure 2.2.1: Demand for patents and trade marks at USPTO
Source: Figure 1 in von Graevenitz et al. (2012)

ity following the recovery from the recession of 1991-1992.[13]

Lybbert, Zolas, and Bhattacharyya (2014) report that trade mark growth in high-income countries increased by around 50% between 2004 and 2008, and middle-income countries experienced even faster growth in trade mark output. By contrast, low-income countries hardly experienced any growth. A recent report by the World Intellectual Property Organisation, WIPO (2013, Figure 3) compares trade mark applications relative to GDP in high- and middle-income countries from 1985 to 2011. Trade mark intensity (measured as the number of trade marks per dollar of GDP) in high-income countries increased rapidly until a peak in 2000. Following this it reverted to and stabilised around the average levels of the 1990s. Trade mark growth remained proportional to GDP in middle-income countries until the 1990s, after which it grew rapidly without showing any similarities with the reversal of trade mark growth in high-income countries at the turn of the millennium. What explains the worldwide increase of trade mark registrations?

There are two candidates as reasons for this rapid growth. First, the demand for differentiated and higher quality products has been increasing due

[13]In figure 2.2.1 we can see that for the U.S., trade marks recovered quite rapidly after this downturn during the 'dot.com' bust.

Figure 2.2.2: Recent Trends in Global Trade Marking Activity, 1975-2002
Source: WIPO data base as represented in Jensen and Webster (2004).

to rising consumer incomes. Second, production has been growing, which leads to the existence of more firms and products. The findings by Jensen and Webster (2004) suggest that the demand effect (measured as GDP per capita) is stronger than the growth effect (measured as change in industry production). If the national firms are not behind this growth in trade marks, who is?

Baroncelli E. (2005) study the shares of foreign and domestic residents registering trade marks and find clear differences by level of development. Their analysis of over 100 countries observed during 1994-1998 shows that the foreign residents' share of registrations was inversely related to the level of income per capita. In high-income countries it was 34% on average, rising to 46% in middle-income, and to 81% in low-income countries. They interpret these differences as indicating that higher development is associated with a greater degree of dominance of domestic brands in the home market and a stronger presence of these same brands in foreign markets. This relationship, however, is likely to differ between countries within each of the three groups and will also change over time.

Falling transport and communication costs as well as the rising globalisation of the world economy make it easier for firms to extend their business beyond national borders (Jensen and Webster, 2004). This could explain the rise in the share of registrations of trade marks by foreign nationals in Australia from 23% to 31% between 1985 and 2002. It is also a likely explanation for the rapid changes in the origins of foreign registrations that Baroncelli E. (2005) observe for countries of all income groups in their sample: during the five years 1994-1998, middle- and low-income countries displaced shares previously held by high-income countries by 3% in high-, 4% in middle-, and 16% in low-income countries. Yet, analysing the intensity of foreign trade marks relative to the value of exports received from the foreign countries shows that high-income countries file more foreign trade marks per dollar export value than countries from lower income groups (Lybbert, Zolas, and Bhattacharyya, 2014). To get a better idea of the changes in trade marking patterns worldwide, we now look in more detail at selected countries' trade marking landscapes.

2.2.2 Sector and industry differences

Starting with the large cross-country database of Baroncelli E. (2005), these authors find that the highest use of trade marks across the world occurs in the R&D intensive scientific equipment and pharmaceuticals sectors. Also present in the top ten sectors are advertising-intensive manufacturing industries, such as clothing, footwear, detergents and food products. Greenhalgh, Longland, and Bosworth (2003) study UK trade marks from 1989 to 2000 and find that the fastest expanding product classes of trade marks over this period were predominantly service marks. Registrations in these classes expanded seven-fold from 1993 to 2000.

While these two studies are conducted using the Nice classification system for trade marks, the following studies use industry classification codes after trade marks were matched to their owners. When matching IPRs to financial data, we need to carefully think about the consequences of varying firm-IPR ownership structures. For stand-alone firms there is no issue. For subsidiaries or parents, however, the question arises how to allocate the IPRs owned by other parts of the group. In the case where each subsidiary operates independently and files their IPRs individually, nothing needs to be done. It is often the case, however, that the parent firm holds all IPRs and subsidiaries are free to use them or to acquire exclusive licences. Alternatively, there may exist an individual subsidiary that is solely devoted to deal with the group's IPR holdings. Unless we indicate otherwise, the studies we review in this paper take account of this by adding up all IPRs for a group and then allocating the aggregate number of rights to each firm within the group. While this is a consistent approach, it probably overstates the IPR holdings by individual subsidiaries significantly and thus may lead to severe underestimation of the impact of IPRs.

Jensen and Webster (2004) find that service industries in Australia, including communication, education, and personal services, also experienced particularly strong growth in trade mark applications between 1975 and 2002. Moreover, trade mark applications in industries subject to considerable economic deregulation and restructuring over this period - such as electricity, gas and water - grew stronger than in most other industries. Besides back office services such as call centres and digitalisation tasks, it is not obvious how services can easily be exported. We might thus expect to find growing numbers of service marks mainly for national trade marks. But we would be wrong.

Greenhalgh and Rogers (2008) document four types of IPR activity in the UK over the period 1996-2000, namely domestic and European trade mark and patent activity for large and medium-sized firms. These authors compare IPR activity in eight service sectors with that in agriculture, manufacturing, utilities, and construction sectors. Manufacturing and utilities sectors dominated patents as well as recorded R&D expenditures, but the differences by sector in trade mark activity were much less dramatic. The eight service sectors all showed considerable percentages of firms applying each year for trade marks both in the UK and at the EU level. Looking at UK trade marks, retail firms were more frequently active than manufacturing firms, with more than 40% of retail firms applying for trade marks in any given year. The hotel and catering trade also showed rising UK trade mark activity, exceeding that of manufacturing by the year 2000. But despite the historic importance of UK marks, in general the growth in trade mark activity for most categories of service firms at this time was in their applications for Community trade marks. This indicates their positive appraisal of the wider remit of such marks, which only came into existence in 1996.

It is difficult to assess whether allocating trade marks to industries using their owner's primary economic activity classification is more or less appropriate than using NICE classes. Firms that are mainly active in one industry might be active in other industries, too, so matching is not a perfect allocation mechanism. But NICE classes are not perfectly informative about the product category or industry of a trade-marked product either. The leading example for their lack of precision is the fact that both the product categories of computers and fire-extinguishing apparatus are classified as NICE class 9. Matching trade marks at the firm level and cross-referencing the NICE classes covered by firms' trade marks and those firms' industry classifications could provide a more accurate correspondence. This approach, however, requires access to the individual trade marks and to firm-level data. Lybbert, Zolas, and Bhattacharyya (2014) propose a more flexible approach to create a more accurate correspondence. These authors use a sophisticated matching algorithm, which allocates industry codes to NACE classes using millions of U.S. trade mark descriptions and a list of keywords for each industry. Using this correspondence to match OECD industry data to NICE classes, these authors report that trade marking activity scaled by value-added is in fact similar across all industries, with on average 50-100 domestic trade marks per $billion valued-added.

2.2.3 Differences between large and small firms

One of the perennial questions in the study of innovation is whether large or small firms are more prolific, as this may affect the returns to public policy in areas such as R&D subsidies and other support for innovation. If large firms were less than proportionately active, then society might prefer to have two smaller firms, each of half the size of the larger firm, to generate more new products. Several studies using UK data have explored this issue by investigating whether (pro rata for their size) smaller firms are more or less IPR active than larger ones.

Greenhalgh, Longland, and Bosworth (2003) examine medium-sized and large UK production firms between 1986 and 2000, most of which were listed on the stock market. Trade mark intensity is measured as the number of trade marks relative to firm sales or employment, and their analysis shows a higher intensity of UK trade marks for the medium-sized firms compared to large firms.[14] Greenhalgh and Rogers (2008) expand this database by including a parallel panel of service sector firms for the period of 1996-2000. This addition reveals that in the service industries IPR intensity also falls as firm size increases. To study whether this relation is consistent across all size categories, Rogers, Helmers, and Greenhalgh (2007) create a database for the whole population of firms in the UK for the period 2001-2005, drawing on the commercially available FAME database of registered companies. Descriptive statistics of median values as well as multivariate statistical methods confirm that, in proportion to their asset base, IPR-active SME and micro firms are more IPR intensive than large firms. This is also consistent with the notion that IPR-active firms require a critical mass of IPRs to achieve a useful portfolio of intangible assets. In addition, Jensen and Webster (2006) argue that the more intense use of IPRs by SMEs in Australia is evidence that the design of the IPR system does not put small and medium-sized companies at a disadvantage compared to large firms. These authors also point out that more

[14] See Greenhalgh, Longland, and Bosworth (2003) tables 11a, 11b, and figures 7a, 7b.

intense IPR use is a sign of a lower level of trust between smaller firms, resulting from less integration and interaction among them. This then makes the use of the IPR system more attractive for smaller firms. But does this imply that small firms are more likely to use IPRs?

Rogers, Helmers, and Greenhalgh (2007) report that less than 5% of the SMEs applied for one or more of the IPR types at some point in the 2001 to 2005 period. UK trade marks were the most commonly sought IPR type, followed by Community marks, UK patents, and lastly EPO patents. The ratio of SME to large firm IPR activity varied across IPR type and region, but for trade marks it was around 74% and for patents it was around 60%. Nevertheless, because of the very large number of such firms in existence, the absolute number of trade mark applications by SME and micro firms taken together considerably exceeded that of all large firms in each year of the study even though only a small proportion of such firms are IPR-active. These findings suggest a considerable untapped potential for innovation in SME and micro firms that might be encouraged by innovation incentives to smaller firms.

2.2.4 Universities

In contrast to the rich body of literature on the use of trade marks by firms, we are only aware of one study that explicitly focuses on IPR use by universities. Squicciarini, Millot, and Dernis (2012) present a novel IPR data set of 621 U.S. universities observed over the period 1997-2007. These authors relate the trade mark use by universities to characteristics that strongly influence universities' products, such as teaching quality and innovative output. The share of trade marks filed by universities relative to all trade mark applications has increased slowly but steadily since 1983. Furthermore, trade mark activity is positively associated with the number of students enrolled, the share of graduate students, the presence of medical schools, the share of federal funds received, as well as being a private institution. While some of these variables are likely to be pairwise correlated, the findings are intuitive. Larger universities with more funds likely produce more innovative output and may have stronger links with the industries to which they can transfer research outputs. Similarly, private institutions depend more on their reputation and often adopt a more entrepreneurial culture compared to public institutions, which encompasses more intense use of IPRs.

With this overview of global trade marking trends in mind we now turn to the more specific questions of how trade mark data can be used empirically, why firms use trade marks, and what performance effects can empirically be associated with trade marks.

2.3 What trade marks can proxy

Above we saw that trade marks have become an increasingly attractive part of firms' strategies worldwide. What does this tell us? In this section we discuss literature that has empirically examined whether trade mark data can reliably indicate innovation and product differentiation, as argued by Mendonca, Pereira, and Godinho (2004), Fink, Javorcik, and Spatareanu (2005), and Mangani (2007). One difficulty is that authors and survey designers differ in what they consider to qualify as 'innovation'. Many economists prefer to confine the use of this term to items that are new to the market, whether product or process. Other writers and surveys, including the Community Innovation Survey, define innovation more broadly to include items and activities that are new to the firm even if these are not highly original in the market context. Many such activities would be classified in economic thinking as imitation arising from the diffusion of innovation. Similarly there is a distinction within the broad term 'product differentiation' between vertical (or quality) differences and horizontal variety, with the latter adding little or no quality improvement to a product or its manufacture, but satisfying a selection of consumers by its new combination of product characteristics. In this section of the paper we are constrained to follow whatever choices have been made by the writers whose work we survey, but we shall highlight instances where findings are derived with different definitions.

2.3.1 Proxy for innovation

It is difficult to firmly establish the link between trade-marking and innovation activity, because innovation is itself hard to measure. Before trade mark data became available and large scale surveys were conducted, the most common variables used as proxy for innovation were R&D activity and later patent counts. Firms operating in the service sector, however, are not always able to patent their innovative service products and often don't engage in R&D. One of the biggest gaps in our measurement of innovation therefore arises in this sector. Trade marks are more commonly used in service industries and the following studies investigate whether trade marks can be used as an additional proxy for innovation. In an early study, using a survey of 2,500 Benelux SMEs, Allegrezza and Guard-Rauchs (1999) find a positive, significant relationship between trade-marking and R&D activity. Considering that R&D is often used as a proxy for innovation activity, this could indicate links between innovation and trade marks. Given the small range of industries, however, in which firms conduct formal R&D, this study is by no means conclusive.

Schmoch (2003) analyses the responses of 377 German firms to the 2001 Community Innovation Survey (CIS), which contains information about recent innovation activities. He finds a significant correlation between the share of turnover from innovation and the use of trade marks in knowledge-intensive service sectors. Gotsch and Hipp (2012) present further work using the German part of the 2005 CIS, including answers from over 4000 firms. These authors confirm that the use of trade marks is positively and significantly associated with innovation in high-tech manufacturing and in knowledge-intensive service sectors. In low-tech manufacturing or in other service sectors, however, the link is not significant. Millot (2012) investigates the French part of the 2008 CIS, covering over 20,000 firms. She distinguishes between product, process, marketing and business organisation innovations. She finds that in contrast to process and organisational innovations, product and marketing innovations are significantly correlated with trade mark activity in the whole sample and in all sub-sectors. However, in high-technology manufacturing sectors, patents also predict trade marking, which weakens the link between product innovation and trade marks.

Jensen and Webster (2009) (henceforth JW) conduct a similar analysis of more than 1000 Australian firms that responded to the Melbourne Institute Business Survey between 2001 and 2007. The firms are drawn from all sectors of the economy and the sample is broadly representative of the underlying economic structure. For the whole sample (JW Table II), there are statistically significant correlations between innovation, patents and trade marks, but the level of these correlations is not very high. The correlations between reported R&D activity and use of the three types of IPRs are actually much higher. Why should this difference in correlations exist? It is perhaps the case that firms that are attempting to innovate by conducting R&D, even if they are only occasionally successful at doing so, are more likely to be using IPRs. When the overall results are broken down by sector, or by type of innovation, there is more to report. In manufacturing (JW Table III), innovation is correlated with both R&D and trade marks almost equally strongly. In services (JW Table IV), there is a weaker correlation with trade marks, but not with the other measures. Looking across the four innovation types (JW Table V), product innovation is correlated with patents and trade marks, as well as R&D, but not with design rights. Process innovation is weakly correlated with trade marks, but not with other indicators. Marketing innovation is significantly correlated with trade marks but only to a minor level, and organisational innovation shows nil or negative correlations with each of the proxy variables. Jensen and Webster argue that their findings arise because process and organisational innovation can be more easily protected by secrecy. These innovations therefore do not impact directly on consumers as is the case with product and marketing innovation. Overall, the authors of these studies conclude that trade marks are a useful innovation indicator, while cautioning about the need to recognise the differences in correlations by sector and innovation type.

In-depth studies of particular industries reveal further differences between types of innovation and trade mark practices. Malmberg (2005) compares historic IPR activity of selected Swedish firms in the electromechanical, automotive, and pharmaceutical industries over time. This author finds very large differences in trade-marking in relation to product innovation in these three industries. In both the electromechanical and automotive industry, new products are often identified by model numbers, obviating the need to register new trade marks. By contrast, most new products in pharmaceuticals are trade marked. Pharmaceutical companies face particularly fierce competition after the expiry of a patent, because generic drugs are chemically equivalent to the patented original and are thus physically perfect substitutes. Several authors have therefore referred to the objective for building brand names to sustain customer loyalty after the expiry of their patents.

How closely in time are trade marks filed after the event of related innovation? Flikkema, de Man, and Wolters (2010) survey 660 companies that had applied for trade marks at the Benelux office between 2007 and 2008 given they provided valid e-mail addresses. These authors find that about 60 percent of recent Benelux trade mark applications refer directly to a broad range of innovation activities. In addition, most of the trade marks were filed close to the market introduction of products. Hence, trade marks are useful to measure product innovations in the late stages of their development, something that is not always captured by either patents or the bulk of R&D expenditure occurring earlier in time. Trade marks also capture innovation activity other IPRs cannot. This is the case particularly for innovation in small firms that often rely on developing new products from existing technology.

The different approaches used to test the suitability of trade marks as proxy for innovation stress the difficulty of this undertaking. A trade mark is a good proxy for innovation if two conditions hold simultaneously:

i) trade mark using firms are innovative firms and

ii) innovative firms use trade marks.

Assume only i) holds but ii) does not hold strictly, that is, there exist innovative firms not using trade marks. Then a trade mark tells us that the owner is innovative, but there might be many other innovative firms that do not use trade marks. Conversely, if ii) is true but i) does not hold strictly, a trade mark only tells us that a firm could be innovative, but not whether it is. It follows that both directions need to be tested simultaneously to assess the suitability of trade marks as proxies for innovation. The data used must therefore include all trade marks of firms, related to innovation or not, and all firms, innovative or not. The question regarding the use of trade marks in the CIS 2001 questionnaire, however, explicitly asks for trade marks to "protect inventions or innovations developed in your enterprise". The firms indicating to be trade mark active in the Schmoch (2003) sample are therefore all innovative by default. Likewise, Malmberg (2005) only investigates product launches. In both cases it is impossible to test i). Flikkema, de Man, and Wolters (2010), by contrast, only look at firms that registered trade marks, which makes it impossible to test ii). To some extent, however, these studies complement each other. The CIS question was changed for the 2005 survey to include all trade marks, and it was dropped completely from the 2008 and 2010 CIS. The samples by Jensen and Webster (2009) and Millot (2012), who match trade mark data to their owners, and by Gotsch and Hipp (2012), who use the CIS 2005, look at both conditions. Yet, these studies cannot be directly compared. While Jensen and Webster as well as Millot take into account innovations "new to the firm" (in line with the Oslo Manual), Gotsch and Hipp only consider innovations "new to the market."

2.3.2 Proxy for product differentiation

Fink, Javorcik, and Spatareanu (2005) as well as Mangani (2007) relate trade mark registrations and applications, respectively, to country- and industry-specific characteristics. The underlying assumption is that larger and more developed countries consume and produce a wider range of products, which is reflected in trade mark registrations.

Fink, Javorcik, and Spatareanu (2005) use trade mark data from the World Intellectual Property Organization (WIPO) database and trade data from the UN COMTRADE database for 22 exporting countries and 100 importing countries between 1994 and 1998. Trade marks are allocated to industries using NICE classes. At the country level, the findings suggest a positive relationship between trade mark registrations and the income per head. At the industry level, import and export volumes are both positively correlated with the number of trade mark registrations in that industry. Because more trade in terms of quantity and value indicates a wider range of products, the number of trade mark registrations does appear to indicate the level of product differentiation.

Similarly, Mangani (2007) relates countries' GDP and population size to the number of trade marks filed by that country to infer the degree of product differentiation across and within categories of products. This author uses a cross-section of trade mark application counts of 35 countries that filed Community trade mark applications in 2003. He shows that the variation of products across categories is positively and significantly correlated to the applicant-country's GDP. Specifically, an increase of total GDP by one percent leads to a proportionate rise in the level of product differentiation. This total increase consists of a growing product variety across categories (41 percent) and an appreciation in the product variation within categories (59 percent). This variation within categories consists of additional products (93 percent) and quality levels (7 percent).

The results of the two studies cannot directly be compared for two reasons. Fink et al. allocate trade marks to industries according to an original correspondence between NICE classes and national industry class codes. Mangani, by contrast, interprets NICE classes as product categories and ignores industry-level data. Moreover, Fink et al. consider national, Community and international trade mark registrations, while Mangani focusses his analysis on Community trade mark applications at the NICE-class level. As regards coverage, leaving out national trade mark data inevitably biases the sample towards firms that are exposed to international competition, either via multinational activity or via competition from abroad.

To sum up this wide literature, studies for many countries and economic sectors generally support the view that trade marks are a useful addition to the list of measures that can inform us about innovation activity and product differentiation at the firm, industry, and country level. Not all innovative firms, however, use trade marks to protect their innovation, and not all trademarking firms are innovative. Other factors, as for instance the choice of target groups, advertising intensity and import competition, might also affect the trade marking decision. Thus, trade marks are not equally valid for all firms or countries, not always superior to other measures for a given industry, and do not provide coverage for all types of innovation. Nevertheless, they do contribute to a field where measurement is inherently difficult and expensive if survey data have to be collected. As regards product differentiation, there is some evidence that trade mark activity at the country and industry level can be informative about levels of horizontal (variety) and vertical (quality) product differentiation.

2.4 The incentives to use trade marks

Not all innovation types can be protected by patents or secrecy (Hall et al., 2013). Often, trade marks can help to appropriate rents from innovation nevertheless. In fact, Frey (2012) reports that IPR management in firms as a whole supports R&D, business development and marketing efforts. This author summarises a series of semi-structured interviews with IPR experts in European and U.S. pharmaceutical firms as well as reporting findings from a survey of pharmaceutical firms listed either in the EU or the U.S. Both the interviews and the survey show that the primary objectives of firms' IPR management are securing freedom-to-operate and maximising exclusivity and the duration thereof. Moreover, the interviewees rank the protection and the identity provided by trade marks, as well as their function to communicate with customers, as trade marks' most important functions. Together with the fact that these firms spend a quarter of their annual turnover on average on marketing activities, these findings underline their intent to build a strong brand. What drives this intent, however, remains unanswered - is it the necessity to keep up with competitors, or the desire to keep them at bay by creating market power? In this section we present studies analysing different motives to obtain trade marks, including legitimate reasons such as informing the consumer as well as more questionable strategies such as raising rivals' costs.

2.4.1 Informing the consumer

When investigating the use of trade marks to inform the consumer, it is sensible to first think about how trade-marking and brand-building interact. Creating and registering a trade mark is a one-off event. Building a brand, however, involves long-term commitment and includes the provision of customer service, activities for reputation-building and the reliable delivery on promises. Greenhalgh et al. (2011) investigate the interplay between trade marks and brands. These authors use the Annual Respondent Database (ARD2) from the UK Office for National Statistics (ONS) for the period 2000-2006 in combination with the Oxford Firm-Level Intellectual Property Database (OFLIP). They report that both advertising and trade-marking activity contribute positively to the value generated by the average firm. There is also some evidence implying that trade-marking and advertising are (imperfect) substitutes. Advertising is often directed at building-up brand reputation, and trade marks are the legal basis for a brand. Intuitively, we would therefore expect trade-marking and advertising to be complementary activities. Registering, maintaining and monitoring a trade mark as well as advertising, however, are costly activities. Any resources allocated to trade-marking are therefore resources directed away from brand-building. This could explain the observed substitutive effects of trade-marking and advertising on added value. Further analyses show that trade-marking and advertising activities are associated with an employment and a turnover premium. But are these premiums due to consumers being better informed about the firm's product or to reduced competition?

Jensen and Webster (2008) study how adding informative labels about unobservable attributes on retail grocery products affects consumer demand. To identify the effect of communicating unobservable product attributes, these authors select brand-unrelated labels for their analysis. These authors use commercially available monthly data on a bundle of 92 goods in 12 categories from major supermarkets across Australia over the period 2002-2005. They investigate only mature product categories, where the products are sufficiently homogeneous, so they can compare the effects of the labelled attributes. The results regarding the attributes are mostly as expected - consumers are more attracted towards products containing recycled materials, are certified to be made in Australia, are health-conscious or offer support for a charity. But eco-friendly products, non-certified Australian-made products, and those that offer entry into a raffle have a negative impact on demand. Labels therefore seem to convey information that can affect the demand for the labelled product. This also supports the position that trade marks have more functions than indicating a product's origin. Perhaps more relevant for the discussion of the relation between trade marks and competition, however, is another finding by these authors: up to a certain point, each additional year a brand exists leads to an increase in the demand for that brand. Beyond that point demand decreases. Moreover, the more brands there are in a given product category, the lower is demand for each brand in that category. Although at first sight this speaks for healthy competition, it is not clear whether we can make this connection. After all, several brands in one category often belong to the same company and therefore only seemingly compete against each other. An analysis of brand competition thus needs to allocate brands to the relevant decision maker (which need not be the same as the ultimate owner). Nevertheless, it is evident that the number and the age of brands do affect competition. What does it take for a trade mark to achieve this function?

Trade marks can only serve as communication channel if their reliability has been established over time. Even so, once a critical level of trustworthiness is reached other parties have an incentive to 'borrow' an established mark. They attempt to free-ride on the original firm's reputation by signalling to potential customers the information inherent to the 'borrowed' mark. It is often posited that if such unauthorized activity occurs frequently, the trade mark will 'dilute', which means it slowly loses its informative value. Heald and Brauneis (2011) conduct an empirical study on (involuntary) brand sharing and potential trade mark dilution. These authors investigate whether the Federal Trademark Dilution Act of 1995 (FTDA[15]) in the U.S. was a needed response to frequent unauthorized use of famous brands for non-competing products, or whether it was a result of extensive special-interest group lobbying. They search evidence for brand-sharing of 33 selected famous brands in corporation and trade mark registers, national newspapers and in recorded dilution litigation. Their findings suggest that the unauthorized use of famous marks for non-competing products did indeed occur often. The vast majority of those unauthorized uses, however, were used for local business names, as for instance the CADILLAC Lounge, and not for products or businesses at the national level. Assuming consumers are capable of distinguishing between different meanings of an expression, famous brands are deemed immune to dilution through unauthorized use if it draws on the secondary meaning of the brand. In the example of the CADILLAC Lounge, the unauthorized use refers to the quality aspect of the CADILLAC and not to the origin-function. Their comprehensive investigation therefore does not find any evidence that unauthorized use of famous marks was an issue before or

[15]The Federal Trademark Dilution Act of 1995 is a U.S. federal law that protects well known trade marks from uses by others that could dilute their distinctiveness. This protection does not require the presence of a likelihood of confusion. "[T]he potency of a [trade]mark may be debilitated by another's use. This is the essence of dilution. Confusion leads to immediate injury, while dilution is an infection, which if allowed to spread, will inevitably destroy the advertising value of the mark. –Federal Trademark Dilution Act of 1995" See Federal Trademark Dilution Act of 1995, H.R. Rep. No. 104-374, at 3 (1995), reprinted in 1996 U.S.C.C.A.N. 1029, 1030 (citing Mortellito v. Nina of Cal., Inc., 335 F. Supp. 1288, 1296 (S.D.N.Y. 1972)).

after the introduction of the FTDA.

2.4.2 Realising synergies

In addition to their direct contribution to firm value by appropriating rents from innovation and brand building, trade marks might indirectly contribute by generating complementarities with other types of intellectual property rights. Following Somaya and Graham (2006), we distinguish between demand-side effects, where the use of one IPR type affects the marginal revenue of other IPR types, and supply-side effects, where the use of one IPR-type affects the marginal costs of other IPR types. In this subsection we explore evidence of such synergies between different types of IPRs starting with demand-side effects.

We find the first joint analysis of patent and trade mark protection in Parchomovsky and Siegelman (2002). These authors argue that building-up brand loyalty can be an attempt to extend the patent lifetime. To maximise profits over a product's entire lifetime, the patent owner charges less than monopoly prices during the patent period to encourage sales growth, but can then charge more than marginal costs thereafter due to the brand loyalty established during the patent period. To support their theoretical assertions, these authors present five case studies in which firms successfully used the patent period to build-up brand loyalty and reputation. This allows them to charge a mark-up over their competitors' prices after the patent period without losing all their customers: Monsanto Roundup, Nutrasweet, GSK Tagamet and Zovirax, and Bayer Aspirin.

In a similar vein, Davies and Maniatis (2010) discuss two cases in which firms tried to use trade marks to protect what was previously protected by a patent, namely Philips' three-headed shaver and Dyson's transparent vaccuum container. In both cases the firms argued that these distinctive features of their products were unique and thus indicated origin, which is why they should be protectable under trade mark law. Both attempts, however, failed: a distinct feature that was patented is almost by definition also functional, that is, it is required to obtain a technical result. As outlined above, functional features or marks are not eligible for protection under trade mark law. From the two studies it seems that patents and trade marks can generate complementarities when firms use the temporary monopoly granted by the patent to build-up brand reputation and consumer loyalty. Firms cannot, however, use trade marks to simply replace a patent after its expiration date.

In contrast, Frey's (2012) interviews suggest that combining trade marks and patents to increase exclusivity, or the duration thereof, plays a secondary role for firms. In fact, according to this latter study, most firms consider that the trade marks' function as a substitute for other IPRs is irrelevant for their decision to trade mark. These differing findings stress the limited extent to which results from case studies, interviews or small scale surveys can be generalized even within the same industry.

Cross-industry studies potentially provide more general insights. In a recent study, Llerena and Millot (2013) investigate the interplay of patents and trade marks by analysing French firm-level data to measure the impact of different IPR strategies on firm performance. These authors argue that the direction of the relationship between trade marks and patents depends on industry characteristics: if the effects of advertisement are persistent but the returns are difficult to appropriate, as for instance in the pharmaceutical industry once patent protection has lapsed or where it is not available, trade marks can complement patents (as discussed by Parchomovsky and Siegelman (2002). These authors use data on 785 French publicly traded firms in the year 2007 including their corresponding patent and trade mark applications between 1998 and 2007. They estimate a market value equation containing four dummy variables, each of which represented one possible patent - trade mark strategy. As predicted, the results show that the sign of the relationship between patents and trade marks depends on exogenous variables such as advertisement depreciation and spillovers. In high-tech business sectors, where effects from advertising are short-lived, these IPR types appear to be substitutes. In contrast, the authors find complementary effects in more traditional sectors such as the pharmaceutical and chemical sectors. These results should be treated with caution, however. The complementarity effects in the theory only occur after the patent expired. Assuming firms renew valuable patents until the maximum duration is reached, the sample cannot include cases in which a trade mark could act as complement, because the observation period does not contain patents older than nine years. One could argue, however, that the stock market already values the future effect of the trade mark complementing the patent before this actually occurs. But according to their theory, the value added by the trade mark depends on the goodwill built up during the patent period, which is a volatile process that is still ongoing at the time of observation. It is therefore likely that the complementary (substitutive) effects are underestimated (overestimated). This might also explain why the results for the full sample indicate no interplay between patents and trade marks with respect to market value. Moreover, using a product-level approach, Helmers and Schautschick (2013) analyse 300 small UK firms and show that of the firms that own both IPR types, only a small share of about 5 percent use bundles to protect the same product or product type. Results from empirical analyses should therefore be assessed critically if ownership of both patents and trade marks is assumed to be equivalent to an IPR bundling strategy by that firm. The evidence with regard to demand-side complementarities between patents and trade marks is therefore inconclusive, and we now discuss a study analysing supply-side effects between copyrights, patents and trade marks.

Somaya and Graham (2006) suggest that different types of IPRs act as complements due to economies of scope. Complementarities between IPR types in the form of economies of scope occur if the existing know-how and experience with one IPR type makes it cheaper to introduce other types of IPRs. These authors report on unstructured interviews with six employees of five software firms who all indicate that economies of scope regarding IPR types exist. Based on these interviews, the authors suggest that the more a firm is aware of the importance of intellectual property protection and the more resources a firm allocates to IPR related matters, the more likely it is to use more than one type of IPRs.

These authors use an original database of information concerning 85 of the top 100 PC software firms in the U.S. over the time period 1985-1999. It contains firms' litigation and IPR activity matched with accounting data. By using IPRs that have been subject of litigation, these authors ensure that the IPRs under consideration were actually used and therefore of value to their owner. Moreover, to take account of the significance of a particular copyright or trade mark for the company, as dependent variables the authors calculate copyright and trade mark years-in-litigation instead of mere counts of the suits. Patent counts and the number of patent attorneys used by a company serve as proxies for management attention to IPRs and IPR-related organisational resources, respectively. The results suggest that the more a firm is involved in trade mark litigation, the more likely it is to be involved in copyright litigation, and vice versa. Moreover, patenting activity is highly correlated with both trade mark and copyright litigation activity: filing an additional patent or hiring an additional patent lawyer are both correlated with a higher number of suit-days in copyright and trade mark litigation. The authors repeat the analysis without Microsoft, by far the largest firm in the sample. The complementarity between trade mark and copyright litigation remains statistically significant. This supports the view that concurrent movements of different IPR types within a firm are often due to economies of scope rather than demand-side synergies between the different IPR types.

2.4.3 Raising rivals' costs

A number of legal cases presented in Greenhalgh (2012) suggest that owners of strong brands with 'deep pockets' seek to prohibit the use of any similar marks, even if the allegedly infringing product shows significant differences to those marketed under the strong brand. The cases discussed include Coca-Cola's claim over the slogan "World Famous in New Zealand", the US-Australian "Ugh boots" dispute, Cadbury's "purple" dispute in Australia, McDonald's versus "MacTea" in Singapore and versus "McCurry" in Malaysia. Courts in the various jurisdictions found differentially in favour or against the complainant. While the true intent of these legal actions often remains blurry, it is clear that they raise the legal costs of the alleged infringers. The following study presents empirical evidence that raising rivals' costs could indeed be a strategic goal of some legal action.

Being at the receiving end of a trade mark opposition requires the reallocation of resources to the opposition proceedings and interrupts the marketing process for the duration of the proceedings. The latter can even be prolonged if one of the parties requests a delay. Collette (2012) presents a new data set on completed trade mark opposition cases in Canada between 1996 and 2009. This author investigates whether incumbent firms with deep-pockets use the possibility of opposing trade mark applications by rivals and then also delays the proceedings to burden them. The sample consists of 2,575 opposition cases, for which both the applicant and the opponent could be matched to a firm-level company accounts database. In this sample, complainants use at least one delay 45 percent of the time, and the mean complainant is 30 percent larger in terms of revenue than the mean applicant ($13.3 billion compared to $US 10.2 billion). Very large firms are 6 percent more likely to delay the proceedings and 4 percent more likely to be successful with their opposition. This effect is stronger for larger firms as well as for incumbent firms. The more often firms start opposition proceedings, however, the less likely they become to request more time, while they become more likely to win the proceedings. Likewise, complainants are more likely to request a delay, yet are less likely to win, if the defendant is more experienced. The author argues that the results provide evidence that large firms oppose and delay strategically. It might also be the case, however, that the requirement of additional time depends on the experience of both parties individually and perhaps the ratio thereof, too. Nevertheless, the study provides detailed insights into the patterns of use of oppositions, proceedings, and their outcomes depending on firm characteristics such as size and experience. Further investigation of litigation and opposition data is still needed with a focus on oppositions to trade mark registrations for products that do not compete with the products offered by the defendant.

The studies in this section are concerned with firms' incentives to use trade marks. The different contributions address three main themes - the use of trade marks and labels to inform the consumer, to realise synergies with other IPR types and to raise rivals' costs. There is evidence that firms invest in trade marks to inform their consumers, and that consumers respond to additional information about available products. Instead of investing in their own trade marks, some firms try to free-ride on famous brands' reputation. While it is not clear whether this is a successful strategy, it does not seem to harm the famous brand. The findings of the rare attempts to measure synergies between different IPR types suggest weak but significant complementary effects between copyrights and trade marks, and the existence of both effects, depending on the environment, between patents and trade marks. Strategic behaviour might partly explain the observation that large firms are more likely to start opposition proceedings and smaller new firms are significantly more prone to lose them.

Putting aside the methodological issues, there is evidence that the trade mark system does create incentives for firms to engage in costly actions targeted at building or preserving market power. This leaves fewer resources for optimisation and innovation. The impact of those actions, however, is limited, because judges are well aware of the trade-off between protecting valuable brands and preserving competition. Although only a fraction of trade mark related legal disputes is taken to court, the interpretation and application of the law by the judges in those cases most likely has a moderating influence improving the net social value of trade marks through the signalling function to all agents in the economy. More thorough investigation of the impact of brands and trade marks on competition and the economy as a whole will help the courts to make even better informed decisions.

2.5 The relation between trade marks and firm performance

Innovation activity is aimed at a temporary improvement in firm performance, and we find positive associations between innovation and trade mark activity in several of the studies reviewed above. Therefore, we expect to find measurable positive impacts of trade-marking activity on firm performance.

We start this section with the review of studies investigating the role of IPRs in firm survival. We then turn to studies analysing the links between trade-marking activity and the stock market value of the firm. Market value, however, is a forward-looking measure of performance, which depends on investors' expectations of firms' future success. Productivity and profitability are more immediate measures of performance, and we review studies investigating the link between trade marks and these measures to complete this section.

Trade marks reduce search costs and asymmetric information, facilitate product differentiation and incentivise investment in goodwill. These effects should contribute to firm performance, regardless of whether they are linked to innovative activity or not. Attributing positive associations found for trade marks in performance studies to innovative activities might thus overstate the impact of innovation on performance, or by the same logic, understate the risk inherent to innovative activity. We therefore refrain from interpreting effects found for trade mark activity in the studies reviewed below as effects related to innovation, unless the link is clearly established.

2.5.1 Survival

Firm survival studies try to identify and measure the influence of firms' decisions, of firms' characteristics and of the actions by their competitors on the likelihood to survive. The existing studies that analyse the effect of innovation activity on survival using trade mark data differ in two important

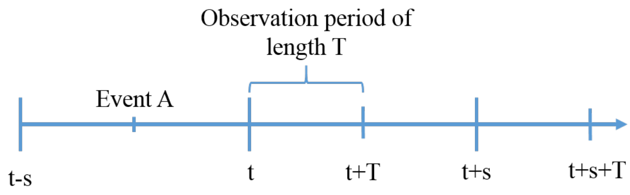

Figure 2.5.1: Timeline illustrating differences between observation periods

aspects: sample selection and estimation method.

Helmers and Rogers (2010) choose to observe for five years a cohort of young firms established in the UK in 2001, and Jensen, Webster, and Buddelmeyer (2008) as well as Buddelmeyer, Jensen, and Webster (2010) observe entry and exit activity of all firms over fixed periods of time. Both approaches must account for the fact that many firms survive beyond the end of the observation period (right-censoring). In addition, in studies that analyse not only survival of young firms but also of existing firms must account for the fact that many firms existed and also closed long before the start of the observation period (left-censoring).

The presence of left-censoring has implications for the interpretation of the results. Suppose that most firms face some challenges throughout their lifetime. We can measure the impact of firm, industry and competitor characteristics on firms only during the period of observation, and we can only measure them for the types of firms that entered during the observation period and for those that survived previous challenges. The types of firms that survived previous, unobserved challenges can differ from the types of firms that survive the challenges to come. The timeline in figure 2.5.1 illustrates such a situation.

Let event A occur only between [t-s,t] and significantly change the economic situation of an industry. For the UK, the introduction of the Euro as accounting currency in the Euro-zone on 1 January 1999 could mark such an event. This put some UK firms at a disadvantage relative to firms in the Euro-zone, because the trade between firms in the Euro-zone is no longer subject to uncertainties due to fluctuations in the exchange rate. It is possible that among the firms that exited shortly after this event would have survived until the beginning of the observation period if it had not been for this event. The set of active firms in the observation period is therefore potentially different from a set of firms of the same age that did not witness such an event. Hence, the results of a survival analysis for firms that existed before the observation period begins are only valid for these types of firms. More generally, unless the challenges for firms established in t in the period [t, t+s] have the same effect on the composition of firms in an economy as unobserved challenges during the period [t-s, t], we cannot use the effects of x on survival that we find in [t, t+T] for firms established in t-s to predict the effect of x on survival in [t+s, t+s+T] for firms established in t.

All three papers estimate firms' risk of exit in period t conditional on having survived until period t, i.e. the hazard rate. The empirical models differ, however. Helmers & Rogers (2010) estimate a probit,model, while the authors of the other two papers estimate a piecewise-constant exponential function (PCEF). The two main differences are: i) the probit model explicitly accounts for the fact that survival time is measured in intervals, that is, discretely, while the PCEF implicitly assumes survival time to be measured continuously; ii) the PCEF is a semi-parametric model, in which the baseline hazard is a non-specified function of time and is therefore a more general version of the intercept in the fully parametric model.

Buddelmeyer, Jensen, and Webster (2010) elaborate on the model underlying the basic hazard function they estimated in both papers. These authors argue that firm exit occurs if revenues are insufficient to cover costs and thus model the probability of a firm to de-register as a multiplicative function of three components: the basic propensity to exit only depending on firm age, $h_0(t)$; the firm specific, time-invariant characteristics (α_i), which cannot be observed but affect the basic hazard rate proportionately; and the vector ($x'_{it}\mathbf{b}$) of explanatory variables that have an exponential impact on the firm-specific baseline hazard. The estimated piecewise-constant exponential function with proportional unobserved heterogeneity reads $h_i\left(t|\mathbf{x}\right) =$

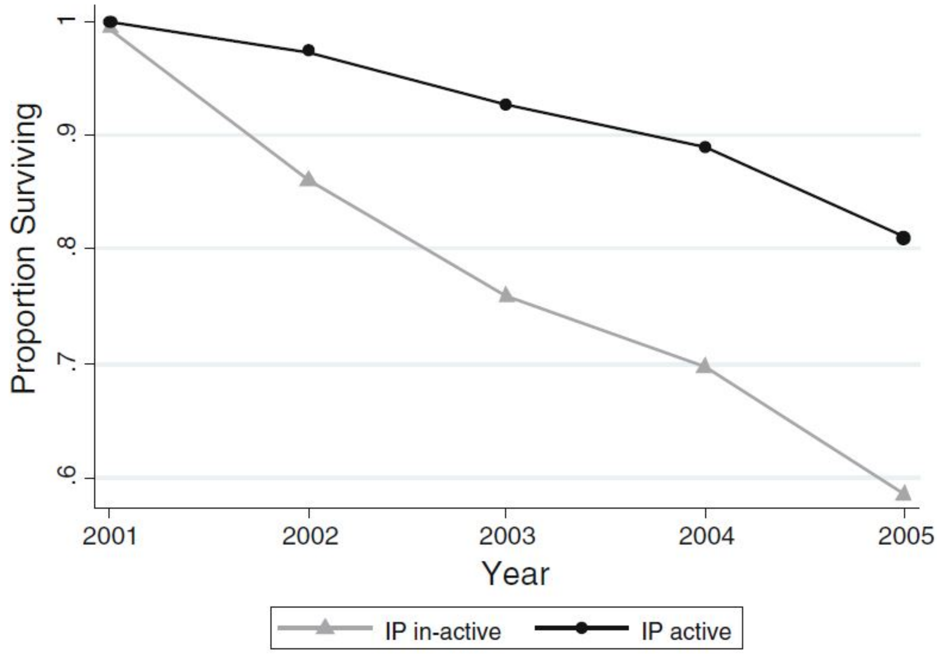

Figure 2.5.2: Survival rates for IPR-active and IPR-inactive firms
Source: Helmers & Rogers (2010), figure 2, p. 235

$h_0\,(t)\,\alpha_i \exp\,(x_{it}'\mathbf{b})$.

One possibility of avoiding biases due to left-censoring is to select a cohort of new firms at a given point in time and then follow their development for some time. For a period of five years, Helmers and Rogers (2010) track the development of the entire cohort of over 160,000 limited companies newly incorporated in the UK in 2001. Registered IPRs are matched to firms using the string match algorithm described in Helmers, Rogers, and Schautschick (2011), and ownership structure is not accounted for, so that firms in the data only have the IPRs they applied for or registered using their own name. First, these authors compute non-parametric Kaplan-Meyer survival estimates for the first five years of existence, distinguishing between IPR-active and IPR-inactive firms. This yields two survival curves (figure 2.5.2), which show the rate of survival as a function of time. In every year, the survival rate of IPR-active firms lies strictly above that of IPR-inactive firms.

To take advantage of the firm- and industry level variables at hand, the relationship between them and the risk of a firm exiting a market can be analysed. Of relevance for such an analysis are variables that represent the firms' ability to compete successfully and others that reflect the conditions in which the new firms operate. To characterise each firm sufficiently, the authors include counts of firms' patent and trade mark applications, total assets, a variable indicating whether it is part of a group and if so, whether it is owned by a domestic or a foreign entity. Including a measure of the competitive conditions and of growth for each industry, the authors account for the industrial environment of each firm. Moreover, regional unemployment rates and house prices are included, as well as a dummy variable indicating if a firm is located close to a university, to control for spatial effects.

The results at the firm level suggest that new firms that applied for at least one trade mark (patent) had a 16% (14%) lower probability of exiting during the observed 5-year period compared to IPR-inactive firms. A more disaggregated regression using patent and trade mark counts reveals that registering national trade marks is correlated with a lower likelihood of exit than registering Community trade marks. By contrast, a patent filed at the EPO is correlated with a higher increase in the expected life span of a new firm than a national patent. This might reflect the fact that firms wish to protect more promising inventions at a larger scale. Trade marks, however, can differ across countries, so that wider protection is considered necessary at the early stage of an innovation. Community trade marks thus often follow national trade marks instead of replacing them, as is the case with EPO patent.

The base for the analyses in (Jensen et al., 2008) and (Buddelmeyer et al., 2010) is the stock of registered Australian companies in 1997 where all data were available, which left 229,869 companies or roughly 65% coverage. In their two papers these authors track all incumbents as well as new-firm registrations and de-registrations during the period 1997-2005 (Jensen et al., 2008) and 1997-2003 (Buddelmeyer et al., 2010), respectively. In their 2008 paper, the authors distinguish between new firms and incumbents by defining as incumbents all firms that were already registered in 1988. However, firms of different ages and sizes react differently to macroeconomic fluctuations and business cycles, which is why some economy-wide indicators are included to separate the impact of innovation from that of the general environment. In these studies, renewed patents are associated with a lower probability of exit, while applying for a patent increases the risk of de-registration significantly. In addition, distinguishing between new firms and incumbents shows that patent applications only affect incumbents, while they have no significant effect on new firms. Both findings are in contrast to those in Helmers & Rogers (2010). Recent IPR applications are proxies for more risky innovation than established IPRs. For the median firm of the 1997-2003 sample the calculations show that registering for a patent decreases the expected life span of an Australian firm by 7.6 years on average, while increasing the stock of renewed patents from zero to five years increases it by 13.5 years.

The findings related to trade marks are even more pronounced. Applying for the first trade mark prolongs the expected life span of the median firm, on average, by 6.6 years, while extending the incremental innovation capital by five years, that is, the stock of renewed trade marks, yields 19.5 additional operating years for the median firm. However, neither the impact of design right stocks, nor that of recent design right applications is a significant contributor to firm survival. The results in both papers by Jensen et al. and Buddelmeyer et al. are very similar. Overall, the authors show in a novel way that innovative activity associated with trade marks is less risky than that associated with patents, and that renewed IP rights, which are proxies for solid innovation capital increases the expected life span of an average Australian firm. So far, it appears as if firms that engage in successful or incremental innovation fare better, or at least live longer, than their IPR-inactive peers. Perhaps this can be interpreted as a direct effect of innovation, which implies that it might be worthwhile to also look at indirect effects. For instance, how does innovation by one firm affect the survival chances by other firms? Because it might not be possible to ever measure direct spill-over effects or externalities, a picture of the general nature of these effects can be drawn by looking at the industry level. In other words, do firms survive longer in highly innovative industries, and does this hold for new as well as for incumbent firms? To this end, Helmers & Rogers (2010) include the share of trade-marking and patenting firms in a sector as a measure of industry innovativeness. A higher share of trade-mark-active firms within an industry is correlated with a higher risk of exit, while a higher share of patent-active firms is correlated with a lower risk of exit. As interpretation of this result, the authors suggest that a more patenting intensive sector is one that is subject to rapid technological change. This makes survival of new firms more likely, because it reduces incumbents' ability to displace the new entrants. More trade mark activity, on the other hand, could be a result of more marketing intensive industries where reputation plays an important role, which is difficult and costly for a new firm to build up and maintain. The estimated exit propensities at the sector level reveal significant heterogeneity across sectors. For instance, while in all but three sectors trade-marking is associated with a statistically significant drop in risk of exit, the same can be said for only four out of ten sectors with regard to patents. These results thus show that the roles played by the different types of innovativeness vary significantly across industries.

Jensen et al. (2008) construct as an innovation index at the industry level a weighted average of R&D intensity, R&D employment, patents, trade marks, resources allocated to organisational change, and productivity. Including this measure in the regressions has virtually no effect on the coefficients of the restricted regressions summarised above. The main findings of the three studies are that innovation as measured by trade marks at the firm level increases the likelihood of survival for new firms significantly, while it appears that additional patent applications decrease incumbents' expected life span. Moreover, as often assumed, the researchers suggest that a more inventive and more competitive environment benefits the survival chances of new firms at the cost of incumbents' propensity to survive.

2.5.2 Market value

The relationship between a firm's stock market value and its underlying intangible assets is explored in a literature that goes back a long way - for a useful discussion of the underlying theory and empirical methodology, and a survey of pre-existing studies at that date see Hall (2000). The empirical equation specified in these studies reflects the idea that both the book value of tangible assets (known from firm accounts) and the value to firms of a range of intangible assets (not formally assessed by accountants) contribute to the determination of the stock market value of the firm. Thus the market value (V) of the firm is given by $V = q\left(K_1 + K_2\right)^{\sigma}$, where K_1 is the book value of total tangible assets of the firm, K_2 is the stock of intangible assets not included in the balance sheet, q is the 'current market valuation coefficient' of the firm's total assets, and σ allows for the possibility of non-constant returns to scale in the market valuation of assets. By taking natural logarithms and using the approximation of $ln\left(1 + \frac{K_1}{K_2}\right) \approx \frac{K_1}{K_2}$, this equation can be rearranged to the following for estimation: $ln\left(\frac{V}{K_1}\right) = ln\left(q\right) + \left(\sigma - 1\right) ln\left(K_1\right) + \sigma \frac{K_2}{K_1}$.

At the time of Hall's survey, the measures used to proxy the intangible assets were solely R&D and patents. In addition, almost all of the studies used US data on manufacturing firms for their investigation (see Hall, 2000, Table 7.1). As noted by Hall, the stock market value of the firm offers a measure by which we can observe the changes in the overall price of the firm caused by rises in assets that are not generally traded separately in the market. Even so, the analysis has to be limited to private firms that are listed on the stock market, so this is still rather restrictive compared with the whole range of firms operating in the economy.

A paper by Bosworth and Rogers (2001) marks an early attempt to investigate the impact of trade marks on market value. The authors use data for a small sample of 60 large Australian firms observed in 1994-1996 and include an exploration of the value of trade marks and design rights in addition to the value of R&D and patents. In their first analysis of market value using all firms in the sample, whether in manufacturing or other sectors, and including as explanatory variables both R&D and patents, the effects of trade marks and designs are positive but not statistically significant. Limiting their analysis to non-manufacturing firms partly reverses their results, as there is a statistically significant positive impact for trade marks, but not for R&D, patents, or designs. Even so, the coefficient magnitudes suggest that the value of a trade mark (to a non-manufacturing firm) is less than half the value of a patent as recorded for all firms (with this result having been clearly dominated by returns to manufacturing firms). Nevertheless, it is likely that the R&D cost of developing what is eventually patented is much higher than the design and marketing activities leading to the trade mark, so the net return for each type of IPR investment is unknown.

The early positive findings by these authors encouraged the development of more extensive firm-level databases, both in the UK at Oxford University's Intellectual Property Research Centre (OIPRC) and in Australia at Melbourne University's Intellectual Property Research Institute of Australia (IPRIA). In both centres the IPR activity of larger samples of firms could be catalogued through several years, giving rise to panel data. Two studies published in the same volume by Greenhalgh and Rogers (2006) and by Griffiths and Webster (2006) present further evidence of the positive value investors assign to the acquisition of trade marks by firms.

The sample analysed by Greenhalgh and Rogers (2006) of over 670 UK firms is sufficiently large to be able to compare results for manufacturing firms with two sets of non-manufacturing firms: firstly a group of financial services (finance, insurance, and real estate), and secondly a broad utilities sector (transport, communications, gas, electricity, and water), all observed from 1996 to 2000. Like the earlier study by Bosworth and Rogers (2001), the benefit effect of applying for UK trade marks is weaker for the whole sample than for the financial service sector, whose use of trade marks had been growing very strongly and where the stock market return to trade marks is high. However, despite a high level of use of trade marks by the utilities sector, firms in this sector do not show any significant increase in market value for acquiring any type of IPRs, so the results are not uniform across the two service sectors. For manufacturing firms, the key variables are doing R&D, acquiring European patents, and buying intangible assets such as goodwill through takeovers.

The study by Griffiths and Webster (2006) analyses around 300 publicly listed Australian companies from 1989 to 2002. As well as exploring the existence of significant positive returns to Australian trade marks and patents, they also investigate whether these returns are rising or falling over this period. These authors go to some lengths to remind the reader that, without full costing of different types of innovative activity, the analysis cannot tell us whether or not the investment in inventive activity is profitable. However, they are confident that their estimates of the trends in the average net present value accorded by the stock market to a patent or trade mark are reliably estimated (but again making no claims that the net returns have risen or fallen, as this would depend on costs). Their finding is that the average value accorded to trade marks was rising over the 1990s, whereas that for patents was falling over the same period, and that there is no discernible trend for design rights. They speculate that the rise in the value of trade marks may reflect the increasing extent to which new brands are seen as critical to the marketing and commercialisation of product lines.

Sandner and Block (2011) developes a multi-country database of around 1,200 large firms observed for the period 1996-2002 yielding nearly 7,000 data points. Their sample selection is based on the requirement that all the firms being analysed are trade mark active in Europe at some point in this seven year period. Their analysis focuses on the impact of European Community trade marks applied for by these firms, but does not include any analysis of their domestic trade marks. As well as recording the instances of European trade-marking over this period (which coincides with the start-up of the European mark in 1996 and thus reflects the firms' entire stocks of these assets), the authors develope four value indicators to try to differentiate between high and low value trade mark activity by firms. These measures are i) the breadth of the trade mark, measured by the number of classes applied for; ii) the seniority of the mark claimed at the time of registration; iii) oppositions to other firms' marks made by the firm; and iv) oppositions received by the firm to its own marks.

In this study the stock of Community trade marks exerts a strongly significant positive impact on stock market value of these firms. Of the four 'value' indicators, two show positive significance - the holding of senior trade marks and the conducting of oppositions against other firms' trade marks. Insignificant results can be seen for the other indicators - the breadth of the trade mark and opposition activity received by the firm from competitors. The authors' comment on this that trade marks appear to differ from patents, where the level of opposition has been found to be informative about the value of the patent.

Greenhalgh and Rogers (2012) put together a database for the period 1996-2000 covering 1,600 large and medium-sized firms operating in all economic sectors of the UK. This large sample of more than 6,000 observations permits them to break down the statistical analysis to compare firms in the manufacturing and service sectors. The extent of trade mark activity via the domestic application route and the European route are both monitored. They also investigate trends in returns over the late 1990s. Here, the impact of doing any trade mark activity in a given year is positive on market value in the full sample, with a slightly bigger impact of taking out a Community trade mark compared with just a UK mark. Comparing sectors, these 'news' effects of new trade marks on stock market value are much larger and more significant in services than in manufacturing, where news about patents and R&D is already doing the job of informing stock markets.

In addition to studying the effect of doing any trade-marking, these authors also look at what impact arises from taking out more trade marks in a given year (relative to the size of the firm) - this variable is termed the intensity of trade mark activity. In the data as a whole there is no rise in stock market value associated with higher intensity, but this finding for the whole sample conceals a more complex story. When trade mark intensity is interacted with a time trend, initial gains from higher trade mark intensity surface. These higher gains, however, are eroded by a falling trend in this value over time. This is in sharp contrast to the results by Griffiths and Webster (2006) for Australia where the market value of trade marks is rising. We know from section 1 that trade mark activity was rising strongly in both countries, hence the UK result conforms to economic expectations that the marginal value of each extra trade mark would fall as their number increased. It is thus the contrary Australian result that remains to be investigated further.

Greenhalgh and Rogers (2012) also show that an increase in trade-marking by other firms in the same four-digit industry reduces a firm's value-added, confirming the immediate effect of innovation by competitors on a non- innovating incumbent. At the same time, this rise in industry trade-marking intensity yields an increase in the market-to-book value ratio, which indicates that investors expect the losing firms to respond by engaging in more intense innovation in order to generate higher future returns.

Fosfuri and Giarratana (2009) study this effect of rivals' innovation and advertisement activity on firms' market value in more detail. These authors argue that product innovation as well as advertising by one firm not only affects that firm's market value, but also that of their rivals. They hypothesise that the business stealing effect outweighs the market expansion effect of product innovation, such that rivals' market value decreases after the introduction of a new product or an incremental product innovation. In contrast, new advertisement is expected to increase overall demand and thus all firms' market value. To test their hypotheses, these authors regress firms' market value as well as their market-to-book value on product innovation and new advertisement as well as a number of control variables. The study focuses on the U.S. carbonated soda drink (CSD) industry during 1999-2003, in particular, on Coca Cola and Pepsi, as these firms account for more than 50% total CSD sales. In contrast to most of the other studies using trade mark data, here trade mark filings at the USPTO serve as proxy for new advertisement. Data on product innovations stem from a commercial database containing information on announcements in trade journals, magazines, and other specialised publications around the world. Their results match the findings from

Greenhalgh & Rogers (2012): new trade marks by either firm increase the market and market-to-book values of both firms. Product innovation, however, increases own market values, while it decreases the rival's market values. Additional regressions analysing the channels through which each action affected firms' market value reveal that product innovations generate their impact through market shares but not through changes in total demand, whereas total demand is increased by new trade marks and market shares remain unaffected.

While these results confirm the positive impact of trade marks on all firms' market value, their choice of interpretations of the proxies' functions is not compelling. Intuitively, firms would protect the name of a new product before they announce it. It seems thus more likely that trade marks in fact proxy new product innovation which expands demand for all firms, while a product announcement may indicate the innovating firm is going to market soon, shifting some of the existing demand from the rivals to the innovative firm. This interpretation would also be more in line with the findings in section 2) and by Greenhalgh and Rogers (2012).

2.5.3 Trade marks, productivity, and profitability

While studies of stock market value are useful in reflecting the estimated future profits from innovative activity, it is also of interest to examine the actual observed returns. Studies of productivity and profitability can show how far trade mark activity is affecting the immediate performance of firms. Furthermore, these studies can include observations on firms that are not listed on the stock market. Therefore, they are more general in terms of the sample of firms that can be studied, although they are partial in terms of the time over which the benefits of trade marks are observed. Using a standard production function relating output to inputs such as $Y = AL^{\alpha}K_1^{\beta}$, this can be linearised in natural logs to the following for estimation: $ln\,(Y) = ln\,(A) + \alpha ln\,(L) + \beta ln\,(K_1)$, where Y is value added, L is labour (total employment), K_1 is the stock of tangible capital and A represents knowledge and ability to produce high quality output. There is a large range of factors affecting the level of A, including intangible assets, K_2.

An early study of the impact of trade marks on productivity is that of Greenhalgh and Longland (2005), who use this approach to examine whether trade marks were associated with increases in the real value of firms' output for given factor inputs, i.e. with higher productivity. The sample of firms analysed contains 740 manufacturing firms observed from 1988 to 1994. For these firms the records of R&D (if reported) as well as patent and trade mark applications are observed, together with information on real net output (measured as the value added by the firm to material inputs) and inputs of labour and capital. Given that this database contains repeated observations on firms, it is possible to differentiate the short term impact of new trade marks on productivity within the firm and the longer term contribution of trade mark activity to persistent differences in productivity between firms.

The study finds that increasing the intensity of trade mark activity (i.e. the number of trade marks relative to the size of the firm as measured by employment) for the whole sample of firms has a significant positive impact on next years' output. This result holds when the researchers control for both UK and EU patents as well as firm-level R&D intensity. The results also remain significant when persistent productivity differences between firms are eliminated using appropriate statistical methods. When these persistent differences are examined in a separate cross-section analysis, trade mark activity is also shown to be correlated with permanent productivity differences between firms.

Nevertheless, when the full sample of firms is split into high-tech and low-tech industry sectors, the analysis reveals significant differences between sectors - in particular, trade marks are important in influencing both short and long term productivity in the low-tech sector, whereas for high-tech firms their R&D activity is the most telling factor followed by patents. This sample does not include service firms so the study does not permit exact comparison with the later stock market studies described above. Even so, the differences between high- and low-tech manufacturing suggest that stock markets are right to value R&D and patents for those sectors where these are important types of intangible investment, but also that they can draw useful inferences about firm productivity from the trade mark activity of firms in other sectors.

In their later work, Greenhalgh and Rogers (2012) examine the productivity of a broader sample of firms, covering both manufacturing and service firms. In this paper, direct comparison between productivity changes and stock market valuation are possible as these authors provided both types of analysis. Trade mark activity shows a large value-added premium for firms that applied for trade marks in the previous year, by between 10 per cent and 30 per cent, depending on the type of trade mark averaged across all firms. For service firms that applied for both UK and European Community trade marks in a given year, their value-added is around 47 per cent higher than that of other firms. The value-added premium for manufacturing firms that were also seeking both UK and Community trade marks in the previous year is lower (at 16 per cent) than that for service firms. These authors conclude that:

> "In the analysis of the firm's net output, the results were broadly consistent with those derived using the market value approach, suggesting that stock markets are efficient in estimating the likely benefits of new intangible assets and that managers do not seek trade marks to follow a management fad, but can expect to receive real returns from innovative activity."

Turning now to the issue of how much intangible assets can enhance firm profitability, Griffiths, Jensen, and Webster (2011) analyse the determinants of financial profitability for a sample of nearly 2,700 mainly public and private Australian firms observed from 1990 to 2006. In this study, the authors are able to measure each firm's stocks of registered patents, trade marks, and designs, as well as several other control variables, such as tangible capital and the age of the firm. While the ultimate focus of the paper is to examine the determinants of persistent excess profits, distinguishing between innate cost advantages and artificial barriers to market entry, their empirical analysis begins with an estimating equation relating actual gross profits to both tangible and intangible capital stocks. This shows that both patent and trade mark stocks are key contributors to profits, although rather surprisingly design rights are not significant determinants. These authors conclude that firms and regulators ought to collect better data on intangible assets, so that the returns to intangibles can be monitored alongside the returns to tangible assets.

So far most of the empirical analyses of share prices and productivity that we have quoted are conducted using data on large firms. Studies of small firms are rare, but that undertaken by Rogers, Greenhalgh, and Helmers (2007) covers UK registered small and medium-sized enterprises (SMEs), a population of around 140,000 firms, observed over the period 2001-2004. This study relates firm profitability over the three years 2002-2004 to the acquisition of a new trade mark during 2001. It is posited that, because of investment in launching an innovation, profits may be low or even negative for a number of years, even if the new product is ultimately successful. The findings show that, in comparison with firms not acquiring any marks, trade mark active firms are more concentrated in the lowest and highest quartiles of the profits distribution. The negative effect is particularly strong for those acquiring a European Community trade mark, where the proportion falling into the lowest quartile of profits is 44% compared with 25% of inactive firms. Also, this hollowing out of the profits distribution is most pronounced for the youngest firms aged less than five years old; it continues for firms aged five to ten, but virtually disappears for trade mark active firms aged more than ten years.

2.5.4 Employment and wages

Firms that innovated and marketed successfully can invest some of their premium profits into their workforce, either via higher wages to keep the existing staff motivated, or by hiring more skilled personnel for future research, development, and marketing. In other words, a link is likely to exist between a firm's innovative activity and the size and remuneration of its workforce. In their early study, Greenhalgh and Longland (2001) are the first to model UK employment as a function of a firm's sales, industry levels of wages, costs of capital and materials, R&D expenses, and a range of IPR variables (including trade marks) to proxy innovation. These authors analyse a panel of about 500 large UK production firms operating between 1986 and 1995. In the initial regression, firm specific time-invariant effects are included, showing no effect of trade marks on the number of jobs in a firm. However, a supplementary analysis of the firm specific effects shows that there are persistent differences between trade-marking firms and those that never register trade marks. In particular, trade-mark-active firms consistently employ significantly more workers than firms without trade marks. Further analysis of the impact of trade marks on firm wages shows that registering trade marks is also significantly associated with rising wages. Viewing these results together shows that innovative activity is associated with more jobs at higher wages, albeit unclear to the researchers whether the extra returns are being shared with the existing workforce, or whether higher wages are paid to attract better skilled personnel.

These results are confirmed in the UK IPO report on trade mark incentives mentioned above. In this report, Greenhalgh et al. (2011) essentially repeat these analyses using more recent ONS-ARD data, which then includes service firms as well as Community trade marks. The results suggest that trade mark active firms employ, on average, 20% more workers than trade-mark-inactive firms with the level of sales held constant, implying that trade-marking firms are more labour intensive than their non-trade-marking counterparts. Moreover, wage regressions show that trade marks alone imply a 0.7% wage premium and trade marks in conjunction with patents a 2% wage premium over and above industry average wages. Similar to the earlier results, including firm fixed-effects left trade marks and patents insignificant indicators of wage differences. This confirms that the higher levels of employment and wages are time-persistent characteristics of IPR-active firms.

Taken as a whole, this developing literature indicates that stock market analysts take note of trade mark activity and value firms more highly as a result. This news about the firm appears to be more important in the service sector, where investors often lack the information provided by R&D and patent activity available in manufacturing. Where the studies make comparisons over time, we see conflicting evidence about the trends in rewards between countries.

The findings from the productivity and profitability studies are consistent with the results from the studies on market value. Both patent and trade mark stocks are key contributors to profits, but the results of these investigations also emphasise the risks of innovation for smaller firms, especially the youngest ones that are likely to have less experience and resources, by showing that there are losers as well as winners from attempts to innovate.

2.6 Conclusion

The purpose of this paper is to collect and summarise the existing body of descriptive and inferential economic empirical analyses of trade mark data and to identify what is needed from future research. Despite the widespread perception that trade marks and trade mark data have received little attention by economists, we find that this body of literature addresses a broad range of questions using trade mark data at all levels of aggregation from different countries.

In table 2.6.1 we summarise the findings of 46 empirical studies of trade mark data, covering the UK (13 studies), Australia and the U.S. (8), France (5), Germany (4), as well as Canada, Benelux countries, and Sweden. The majority of these studies use firm-level data (29), followed by country-level studies (7), and a few that look at specific trade marks or products (3). We summarise the main findings at the end of each section. We want to use this section to emphasise common weaknesses and to give some first ideas how to overcome them in future research.

First, some studies use trade mark applications and others use trade mark registrations. Although the type of trade mark data required may vary with the question, using different types limits the comparability of the results across studies.

Second, only few studies concerned with countries within the EU, where supra-national trade marks compete with national trade marks, take explicit account of the differences between the effects of Community trade marks (CTM) and national trade marks. Analysing only the use of CTMs leaves the impact of national trade marks unaccounted for. This exclusion can lead to biased results, as small and young firms using only national TMs are shown to be significantly more productive and profitable than firms that use only CTMs.

Third, different studies use different approaches to allocate trade marks to industries: some use NICE classes, some match trade marks to their owners at the firm level and use the firms' standard industry classification (SIC), and a recent approach is to create a NICE-SIC concordance through matching trade mark descriptions to keywords for each industry. To this date, there is no work comparing the effects of the different allocation mechanisms. Undertaking such an exercise could guide the decision which approach to use for what type of study.

Fourth, in assessing the suitability of trade marks as proxies for innovation activity, researchers should clearly state what makes a "good" proxy for innovation. In our opinion, a trade mark is a good proxy for innovation activity if trade mark using firms are innovation active and innovation active firms are using trade marks. Hence, to test the suitability of trade marks as a proxy for innovation activity, the data used must include all trade marks of firms, related to innovation or not, and all firms, innovative or not.

Fifth, the results concerning the incentives to trade mark are at times weak and speculative. The root causes for the different results of case studies, interviews, surveys and cross-section studies are the lack of a common set of hypotheses and the corresponding empirical methodology. Some authors derive their hypotheses from the management and marketing literature, some from the law and economics literature and others from the international trade literature. The empirical methods include ordinary least square, logit and seemingly unrelated regressions, and often only measure an ad-hoc linear relationship between IPRs and other firm variables. A successful investigation should follow certain qualitative and quantitative guidelines. Qualitative requirements include that the methodology is capable of disentangling supply- and demand-side effects of IPRs on firm performance. Also, interview and survey questions need to clearly ask for either effect, in a way that an IPR-expert without training in economics understands it. With regard to quantitative requirements, firm-level IPR-databases need to contain sufficient data, in terms of subjects and duration, so that the conjectured effects can actually occur.

Neither the list of papers reviewed in this survey nor the range of questions addressed thus far is exhaustive. Nevertheless, the work done using trade mark data in a time-span of just over a decade has vastly contributed to a better understanding of the use of intellectual property by firms, its impact on firm behaviour and thus on the economy as a whole. It is most likely that new insights will appear as more data from more countries become available.

Moreover, not all possibilities of the existing IPR data have yet been exploited, but a need for more specific product- and case-level data has become apparent. This would help not only to better understand and underpin some of the findings of the aggregate studies, but also to answer questions regarding the misuse of IPRs and the success of the regional harmonization of the law.

The review also makes apparent at least two gaps in the literature - there are no studies investigating the impact of trade mark use on the firm entry rate, and only few studies that investigate the impact of patent and trade mark patterns on post-entry survival in Germany. The rest of this thesis addresses these two gaps, starting with an analysis of the relationship between IPR activity and firm entry at the German industry-region level in the next chapter.

Paper	Countries	Period	Level	Type	Source
Allegrezza and- Guard-Rauchs (1999)	Benelux countries	1999	Firm level	Mark registrations	Survey
Baroncelli et al. (2005)	>100 countries	1994-1998	Country-Nice class level	Mark registrations	WIPO
Bosworth and Rogers (2001)	Australia	1996	Firm level	Mark applications	IP Australia
Buddelmeyer et al. (2010)	Australia	1997-2003	Firm level	Mark applications	IP Australia
Collette (2012)	Canada	1996-2009	Mark level	Completed oppositions	TMOB Canadian IPO
Duguid et al. (2010).	France, UK, US	1870-1970	Country level	Mark registrations	Different historic and recent
EPO and OHIM (2013)	EU	2004-2008	4-digit industry level	Mark registrations	OHIM
Fink et al. (2005)	>100 countries	1994-1998	3-digit ISIC - Nice class level	Mark registrations	WIPO
Flikkema et al. (2010)	Benelux countries	Jan 2007 - March 2008	Firm level	Mark applications	Benelux Office for IP
Fosfuri and Giarratana (2009)	US	1999-2003	Product level	Mark applications	USPTO
Goetsch and Hipp (2012)	Germany	2005	Firm level	Survey question: TM use yes/no	Consumer Innovation Survey
Greenhalgh and Longland (2001)	UK	1986-1995	Firm level	Mark applications	Marquesa Search Systems
Greenhalgh and Longland (2005)	UK	1988-1994	Firm level	Mark applications	Marquesa Search Systems
Greenhalgh and Rogers (2006)	UK	1996-2000	Firm level	Mark applications	Marquesa Search Systems
Greenhalgh and Rogers (2008)	UK	1996-2000	Firm level	Mark applications	Marquesa Search Systems
Greenhalgh and Rogers (2012)	UK	1996-2000	Firm-Nice class level	Mark applications	Marquesa Search Systems, OHIM
Greenhalgh et al. (2003)	UK	1989-2000	Firm-Nice class level	Mark applications	Marquesa Search Systems
Greenhalgh et al. (2003)	UK	1989-1995; 1996-2000	Firm level	Mark applications	Marquesa Search Systems
Greenhalgh et al. (2011)	UK	2000-2006	Firm level	Mark applications	UK IPO, OHIM
Griffiths and Webster (2006)	Australia	1989-2002	Firm level	Mark registrations	IP Australia
Griffiths, Jensen, and Webster (2011)	Australia	1990-2006	Firm level	Mark registrations	IP Australia
Heald and Brauneis (2011)	US	1946-2010	Mark level	Mark registrations	Various databases, media, FJC
Helmers and Rogers (2010)	UK	2001-2005	Firm level	Mark applications	Marquesa Search Systems, OHIM
Jensen and Webster (2004)	Australia, UK, US	1975-2002	Country level	Class applications	WIPO
Jensen and Webster (2006)	Australia	1989-2001	Firm level	Mark applications	IP Australia
Jensen and Webster (2008)	Australia	2005-2005	Product level	Product label	Authors
Jensen and Webster (2009).	Australia	2001-2007	Firm level	Survey matched to applications	IP Australia
Jensen et al. (2008)	Australia	1997-2005	Firm level	Mark applications	IP Australia
Jensen et al. (2008)	Australia	1997-2005	Firm level	Mark applications	IP Australia
Llerena and Millot (2012)	France	1998-2007	Firm level	Mark applications	OHIM, INPI
Lybbert et al. (2014)	Selected WIPO countries	1990-2012	Country-Nice class level	Mark applications and registrations	WIPO
Malmberg (2005)	Sweden	1935-2000	Mark level	Mark registrations	PRV
Mangani (2007)	OHIM applicants	2003	Country-Nice class level	Mark applications	OHIM
Mendonca et al. (2004)	EU-15	1996-2002	Country-Nice class level	Mark applications	OHIM
Millot (2011)	France, Germany	2005-2006	Firm level	Mark applications	OHIM, INPI
Millot (2012)	France	2008	Firm level	Survey matched to applications	OHIM, INPI
Rogers et al. (2007)	UK	2001-2005	Firm level	Applied UKTM, reg. CTM	Marquesa Search Systems
Rogers, Greenhalgh, and Helmers (2007)	UK	2001-2004	Firm level	Mark applications	Marquesa Search Systems
Sandner and Block (2011)	Europe	1996-2002	Firm-Nice class level	Mark applications	OHIM
Schmoch (2003)	USA, Germany, France, UK	1990-2000	Class level	Mark applications	Dialog, Questel-Orbit or STN
Schmoch (2003)	Germany	2001	Firm level	Survey question: TM use yes/no	Consumer Innovation Survey
Somaya and Graham (2006)	US	1985-1999	Firm level	Litigated marks	Federal Judicial Center (FJC)
Squicciarini et al. (2012)	US	1997-2007	Firm level	Mark applications	USPTO
von Graevenitz et al. (2012)	US	1883-2007	Country level	Mark applications	WIPO
WIPO (2013)	Selected WIPO countries	1974-2011	Country-Nice class level	Mark applications and registrations	WIPO

Table 2.6.1: Overview of the samples used by the reviewed trade mark studies

Chapter 3

The Effect of IPRs and Different Knowledge Types on Firm Entry

3.1 Introduction

An old controversy in economics is the nature of the effect of intellectual property rights (IPRs) on competition and welfare. IPRs can be associated with monopolistic elements (Chamberlin, 1933), because they can be used to increase consumers' willingness-to-pay by changing their perception of a brand (Scherer, 1980). IPRs can also constitute barriers to entry due to cost advantages (Bain, 1956). In contrast, IPRs are also said to stimulate competition in innovation (Chamberlin, 1933), reduce information asymmetries (Akerlof, 1970; Shapiro, 1982), lower search costs for consumers (Landes and Posner, 1987), and incentivise investment in goodwill (Economides, 1988). To date, empirical studies on the effect of IPRs on competition are rare (for surveys, see Griliches, 1990; Hall and Harhoff, 2012 and chapter 2).

IPRs incentivise firms to create specialised knowledge and they can advance the diffusion thereof. The generation and the diffusion of knowledge stimulates new innovative ideas (Arrow, 1962; Winter, 1984), and new ideas often lead to the foundation of new firms. As entry by new firms in the long run is one of the essential requirements for markets to be competitive, it provides the link between IPRs and competition that I analyse in this chapter.

To this end, I created the German Firm-Level Intellectual Property database (GFLIP) of German firms between 2002 and 2012. Using ordinary least squares (OLS) techniques and generalized method-of-moments (GMM) for static and dynamic linear panel models, I measure whether varying access to specialised knowledge across industries affects competition, whether the anti-competitive effects of patents and trade marks diminish or even outweigh the pro-competitive effects, and whether export-active industries offer more opportunities for new firms to enter than less-export-active industries.

As a measure of competitiveness, I use the firm entry rate at the industry-region level, and I interpret IPRs as proxies for innovation related activities as they can be means to reduce the market failures stemming from the public good properties of explicit knowledge and from the information asymmetries due to tacit knowledge. Therefore, I use the shares of national-patent- and national-trade-mark-active (NP- and NTM-active) firms at the industry level as measure of the requirements of and access to specialised knowledge in an industry, and the flows and stocks of NPs and NTMs at the industry-region and industry level, respectively, to measure the effect of innovation related activities on competition. Furthermore, I use the share, the stocks and the flows of European patents and Community trade marks (EPs and CTMs) as proxies for the extent of export-activity in an industry.

Gort and Klepper (1982) and Winter (1984) put forward the hypothesis that the technological regime as defined in Nelson and Winter (1974) determines the ease of entry and innovation. Following Audretsch (1991), I investigate the effect of the technological regime on firm entry by separately analysing innovation related activities by young firms.

I intend to contribute to the literature by providing evidence for the significance of access to knowledge for firm entry as a guide for future research that investigates whether limited access to the different types of knowledge can lead to an under-provision of firm entry relative to the socially desirable level. If it turns out that limited access to some types of knowledge suppresses *a priori* socially desirable firm entry, we should ask whether the limitations can be justified *a posteriori*. This could be the case if profits with free entry did not provide the necessary incentives to operate and invest in these industries in the first place. The findings can then be used as input to evidence-based policies that address issues of accessibility to knowledge such as the EU's scientific information package adopted in June 2012 as part of the Digital Agenda For Europe,[16] or programmes of organisations such as the Global Knowledge Initiative that *"help partners access the global knowledge, technology, and human resources needed to sustain growth and achieve prosperity for all."*[17]

In section 2, I introduce the different types of knowledge and establish the theoretical link between knowledge, innovation related activities and their effect on competition. In section 3, I explain the regression strategies, and in section 4 I describe the methods and sources used to create the GFLIP database and discuss the variables used. I present descriptive statistics in section 5. Section 6 contains the results and a discussion thereof, and I conclude in section 7.

3.2 Theory

Firm entry directly affects the degree of competition in the long run. Successful entry intensifies competition either because the new firm replaces a less efficient existing firm, or because it increases the number of competitors. Unsuccessful entry still positively affects the degree of competition by reminding the incumbents that there are firms waiting to enter in case they become less competitive. Hence, firm entry seems to be a good indicator of the degree of long-run competition.

The recipe for firm entry, successful or not, is complex. Winter (1984) posits that the supply of potential entrants depends on the union of entrepreneurial traits and a relevant innovative idea. According to Winter, the occurrence of the latter is roughly proportional to the number of people exposed to the knowledge that is required to have an innovative idea. To ad-

[16]This package consists of a Communication "Towards better access to scientific information: Boosting the benefits of public investments in research" and a Recommendation to Member States "on access to and preservation of scientific information (EC, http://ec.europa.eu/digital-agenda/en/open-access-scientific-information, last accessed 27/11/2014)".

[17]http://globalknowledgeinitiative.org/, last accessed 27/11/2014

dress the diffusion of knowledge, it is necessary to distinguish between the different types of knowledge. Access to knowledge varies with type and affects the diffusion of it. Knowledge diffusion in turn determines the supply of potential entrants and thus firm entry (Winter, 1984).

On one end of the spectrum is knowledge that can only be transferred by showing or teaching someone how something is done, e.g. producing a particular wine or cheese. On the other end of the spectrum is knowledge that can be transferred without any interaction, such as putting together an Ikea table. Polanyi (1958) refers to these knowledge types as tacit and explicit knowledge, respectively. In addition to this distinction, Winter (1984) separates specialised from generic knowledge. As knowledge becomes more specific for individual tasks, the less transferable it is to other tasks. For instance, the knowledge that is required to put together an Ikea table is more specialised than that required to use a screwdriver, and the knowledge required to build a hybrid-car engine is more specialised than that required to sell hybrid-cars. I combine both notions so that there are four types of knowledge - explicit and tacit generic knowledge, and explicit and tacit specialised knowledge.

Most individuals are exposed to the knowledge that is relevant for operating in an industry if an industry's activities involve generic knowledge. Fewer individuals are exposed to the relevant knowledge if an industry's activities do involve explicit or tacit specialised knowledge that is freely accessible. The least individuals are exposed to the relevant knowledge if an industry's activities do involve explicit or tacit specialised knowledge that is not freely accessible.

In this chapter I use the proportion of firms that use national patents (NP) or national trade marks (NTM) in an industry as indicators of the degree of explicit and tacit specialised knowledge, respectively, that is required to operate in an industry. Patents seem suitable because their application is required to contain explicit specialised knowledge about the invention they protect. A larger share of NP-active firms in an industry then indicates the degree to which explicit specialised knowledge is required to operate in an industry. A larger extent of explicit specialised knowledge required to operate in an industry reduces the exposure of individuals to knowledge that is relevant for an innovative idea, and fewer innovative ideas lead to less firm-entry activity. This implies the following testable hypothesis:

H1a: *The share of NP-active firms in an industry is negatively correlated with the firm entry rate into that industry.*

Firms file not only NPs, but also European patents (EP). However, most firms that file EPs also file NPs.[18] NPs thus capture the effect of the degree of explicit specialised knowledege required to operate in an industry. The share of EP-active firms in an industry is then informative about the degree to which firms in an industry are (or intend to be) export-active. Being able to export increases the number and the size of potential markets for firms' products, and thus the number of opportunities for new firms to enter. Hence, the share of EP-active firms in an industry indicates the level of opportunities for firm entry due to the demand for national technologies from abroad, leading to hypothesis H1b:

H1b *The share of EP-active firms in an industry is positively correlated with the firm entry rate into that industry.*

Parallel to the use of NPs, the use of NTMs in an industry implies the presence of tacit specialised knowledge. The presence of tacit knowledge potentially leads to information asymmetries between buyers and sellers. Trade marks can reduce information asymmetries because consumers remember the attributes of products of firms they recognize, and consumers recognize firms that can reliably signal their identity. Trade marks allow firms to reliably signal their identity, so firms can signal which products truly contain the promised attributes. This is possible even if they do not reveal the true attributes (Akerlof, 1970; Spence, 1973; Shapiro, 1982). As the tacit (or hidden explicit) knowledge relevant in an industry becomes more specialised,

[18]See table A.2.5 in appendix.

more firms will be trade mark active to signal the origin of their products without disclosing their knowledge. The share of NTM-active firms in an industry thus indicates the degree to which tacit (or hidden explicit) specialised knowledge is required to operate in that industry. Hypothesis H2a posits the corresponding testable implication.

H2a: *The share of NTM-active firms in an industry is negatively correlated with the firm entry rate into that industry.*

Just as most EP-active firms are also NP-active, most Community-trade-mark-active (CTM-active) firms are also NTM-active. Thus, the share of NTM-active firms captures the negative effects of tacit-knowledge requirements on firm entry, so that the share of CTM-active firms in an industry is informative with regard to the export activity of the firms in that industry. The argument made above is still valid: the ability to export products opens up more and potentially larger markets, which creates more opportunities for new firms to enter. But the presence of tacit-specialised-knowledge requirements implies the presence of information asymmetries. The ability to sucessfully signal the true origin strongly depends on reputation, which takes time and significant investments to be established. For new firms it might be harder to set foot in export-active industries that involve a high degree of tacit specialised knowledge, which is stated in hypothesis H2b:

H2b: *The share of CTM-active firms in an industry is negatively correlated with the firm entry rate into that industry.*

The role of patents and trade marks is not restricted to making available or signalling knowledge, respectively. Recall that explicit knowledge has a public good character, and that the appropriability of public goods is limited (Arrow, 1962). The benefits from generating explicit knowledge can therefore often not be internalised by the inventor. However, generating explicit knowledge is costly. If all the costs of the knowledge generation are borne by the inventor, too little explicit knowledge will be generated. As explicit knowledge is part of many innovations, an under-production of explicit knowledge will lead to an under-provision of innovation. Patents are a partial remedy for the under-provision of innovation stemming from the public good character of explicit knowledge.

Patent holders obtain the legal right to temporarily exclude anyone from using or selling their inventions within the designated geographic area, so they temporarily limit the public good character of newly generated explicit knowledge. The benefits from inventing can be internalized during that period, so patents can reward inventors for successful invention and thus provide incentives to conduct research and development (R&D). Innovation then follows discovery and invention.

Critics of the patent system argue that exclusive access to explicit knowledge might increase the price of using it for others. A higher price of using knowledge inhibits competition and diffusion. But diffusion of knowledge stimulates innovation, so critics conclude that patents could stifle competition and innovation (Greenhalgh and Rogers, 2010). Nevertheless, everyone can use the information disclosed in a patent to invent around the protected matter or identify additional applications of it. Thus, patents can also lower the price of access to specialised explicit knowledge, thereby fostering competition and innovation. Proponents of the patent system argue that the disclosure and the incentive functions of patents counterbalance the adverse effects.

While there is little evidence for or against the posited importance of disclosure, theoretical considerations indicate that the social value from disclosure is likely to be small (Hall and Harhoff, 2012). The two main tools to protect a (patentable) invention are patents and secrecy, and inventors are more likely to choose patents if the invention can be re-engineered from the end-product. In that case, the patent does not reveal much that cannot be inferred from the end-product. If, by contrast, the patent reveals much of the invention, secrecy as method of protection will becomes more attractive (Levin et al., 1987; Moser, 2005).

With regard to the innovation-incentive function of patents, Hall and Harhoff (2012) conclude that patents are important and essential as innovation incentive only to a small set of industries, mainly pharmaceuticals. Yet, firms may have patents for strategic reasons, for instance to prevent competitors from using a technology that could be a substitute for the actually used patented technology (Harhoff, Scherer, and Vopel, 2003).

In industries where patents are necessary for strategic but not for incentive reasons, it is likely that their negative effects on competition and innovation dominate, while in industries where they provide essential incentives to innovate, these positive effects outweigh the negative effects. As the positive effects only occur in a small set of industries, the overall effect of patents on competition is likely to be negative. The average patent intensity, that is, the average number of patents per firm in an industry, indicates to what extent patents are deemed necessary either to protect inventions or for strategic reasons. Together with the preceding discussion, this motivates the following hypothesis:

H3a: *More NPs per firm are negatively correlated with the firm entry rate.*

Again, NPs capture the negative effects on firm entry. EPs per firm, by contrast, again signal the degree to which foreign markets are addressed. Hence, EPs are a simple proxy for the potential market size and thus for opportunities for new firm entry. Moreover, even if the disclosure effect of patents is small, its cumulative effect across markets might be significantly larger, because market size stimulates the diffusion of innovation (Griliches, 1957; Moser, 2005). Hypothesis H3b states:

H3b *More EPs per firm are positively correlated with the firm entry rate.*

Trade marks can reduce information asymmetry and search costs stemming from the presence of tacit knowledge. Owners and licensees of trade marks have the right to prohibit others to sell the same or similar products using the protected mark. This ensures that trade marks signal the true origin of a product.

Recall that consumption decisions are based on tastes for explicit (search) and tacit (experience, credence) product attributes. Consumers can inform themselves at low costs about explicit product attributes (Nelson, 1970; Darby and Karni, 1973), so they can easily distinguish between different products and lookalikes with only explicit attributes. The search or information costs to find out about tacit attributes can be much higher. Consider production methods and technologies that cannot or shall not be codified explicitly, e.g. Bavarian beer-brewing traditions or the Coca-Cola recipe. Competitors of a firm that uses the technology most valued by consumers could simply claim that they are using the same technology, even if that were not the case. It would be very tedious and perhaps even impossible for consumers to find out about the true product attributes. To prevent such a situation where information is asymmetrically distributed between producers and consumers, firms use trade marks to differentiate their products from competing products (Akerlof, 1970; Spence, 1973; Shapiro, 1982).

With a few exceptions, the nature of the effect of trade marks on competition and innovation is less controversial than that of patents. Adverse effects of trade marks on competition can result from the strategic use of trade marks to weaken competitors or from trade marks' function to facilitate product differentiation.

Strategic uses predicated on observation are firms' attempts to raise rivals' costs by opposing competitors' trade mark applications or by delaying opposition proceedings beyond necessity (Collette, 2012). Other observed attempts to reduce competition include the proliferation of brands to foreclose competitors (Schmalensee, 1978; Scherer, 1982; Economides, 1988). While consumers can benefit from product differentiation, it can lead to market power in the short run by creating monopolistic niche markets (Chamberlin, 1933; Economides, 1988) and in the long run by hampering new firm entry (Bain, 1956).

Trade marks, however, can stimulate competition in industries that require tacit or hidden explicit specialised knowledge by providing incentives to generate knowledge. Trade marks also enable firms to build a reputation or to otherwise differentiate their products, both of which can lower competitive pressure. Reduced competition allows firms to charge a higher price, which in the long run attracts new firms to enter so they can also benefit from the higher profits. This motivates hypothesis H4:

H4 *In industries that require tacit knowledge, and where trade marks are a suitable tool to reduce information asymmetries between buyers and sellers, more trade marks per firm are positively correlated with the firm entry rate.*

In the next section, I discuss the methods used to test hypotheses H1-H4.

3.3 Empirical methodology

I estimate two types of firm entry models - a static linear model and a dynamic linear model. In the static linear model I assume that each period, the firm entry decision is made independently of previous firm entry and only depends on the independent variables observed in the previous period in addition to a contemporaneous idiosyncratic shock. In the dynamic linear model, I explicitly allow for inter-temporal dynamics so that the firm entry decision in period *t* can also depends on the firm entry decision in *t-1*. The unit of analysis is the two-digit level industry at the two-digit postal code level.

A static linear model

Within their region, potential entrants observe the industry of interest in period t and make their decision whether to enter in $t+1$ or not. Actual entry occurs in $t+1$. I assume the number of new firms in an industry i in a particular region r per period t, $n_{ir,t}$, to be a linear function of the size of an industry in a region (in terms of number of firms) in addition to a set of observable variables at the industry level and the regional-industry level, denoted by the vectors $\mathbf{K_{i,t-1}}$ and $\mathbf{X_{ir,t-1}}$, respectively. Some fixed region and industry-specific variables are observed by the firms but not by the researcher, C_i^I, C_r^R, and a contemporaneous idiosyncratic shock is observed by neither the firms nor the researcher, $U_{ir,t}$:

$$n_{ir,t} = \alpha N_{ir,t} + \beta \mathbf{K_{i,t-1}} + \gamma \mathbf{X_{ir,t-1}} + C_i^I + C_r^R + U_{ir,t} \tag{3.1}$$

Dividing (3.1) by the number of active firms in each industry yields the firm entry rate and the following static estimation regression

$$r_{ir,t} = \alpha + \beta \mathbf{k_{i,t-1}} + \gamma \mathbf{x_{ir,t-1}} + \nu_{ir,t} \tag{3.2}$$

where $r_{irt} = \frac{n_{irt}}{N}$, $\nu_{ir,t} = c_i^I + c_r^R + u_{ir,t}$, and lower-case letters represent their upper-case counterpart divided by the total number of active firms in the industry-region in t, $N_{ir,t}$. The $(K \times 1)$ vector $\mathbf{k_{i,t-1}}$ contains K lagged proxies for specialised knowledge at the industry level, the $(L \times 1)$ vector $\mathbf{x_{ir,t-1}}$ contains L lagged variables of patent and trade mark applications and other control variables for each industry-region unit. The $(1 \times K)$ and $(1 \times L)$ parameters β and γ, respectively, are the parameters of interest. c_i^I and c_r^R are industry and region dummies, capturing the unobserved fixed effects across industries and across regions.

Next, I assume

$$E[u_{ir,t}] = E[c_i^I u_{ir,t}] = E[c_r^R u_{ir,t}] = 0 \tag{3.3}$$

$$E[u_{ir,s} u_{ir,t}] = 0, \; for \; s \neq t \tag{3.4}$$

$$E[r_{ir,s} u_{ir,t}] = 0, \; for \;\; s < t \tag{3.5}$$

$$E[\mathbf{k_{i,s}} u_{ir,t}] = E[\mathbf{x_{ir,s}} u_{ir,t}] = 0, \; for \; s < t \tag{3.6}$$

Equation (3.3) implies mean-zero idiosyncratic shocks and zero correlation with unobserved fixed industry and region effects, (3.4) rules out serial correlation of the idiosyncratic shocks, and (3.5) rules out feedback from current or past realisations of the firm entry rate to future shocks. Moreover, past realisations of the independent variables do not feed into future shocks (expression (3.6)). Given these assumptions, I estimate equation (3.2) using ordinary least squares methods.

A potential issue arises if there are unobserved fixed effects that are specific to an industry but vary across regions, or fixed effects that are specific to a region but vary across industries. Then the industry and region dummies alone do not capture them and the estimated parameters will be biased and inconsistent. The traditional approaches to resolve this in panel data sets are to use a fixed-effects estimator or equivalently, allowing for a unit-specific constant by including a dummy per industry-region observation (dummy variable estimator). An alternative transformation is to take first-differences of all variables, as this would also eliminate the fixed terms. This comes at a cost, however. De-meaning or first-differencing removes not only unobserved fixed effects, but also observed fixed effects. If the knowledge requirements in industries change only very little over time, the fixed-effects or the first-differences estimators might no longer identify the parameters on the knowledge variables.

I therefore explicitly account for fixed industry-region effects and for possible feedback effects from past decisions to current decisions by including a lagged dependent variable to model firm entry as a dynamic process.

A dynamic linear model

The dynamic linear equation based on (3.1) reads

$$r^d_{ir,t} = \alpha_0 + \alpha_1 r^d_{ir,t-1} + \beta \mathbf{k_{i,t-1}} + \gamma \mathbf{x_{ir,t-1}} + c^{IR}_{ir} + \nu_{ir,t} \tag{3.7}$$

and I impose the following assumptions

$$E[r^d_{ir,t-1}\nu_{ir,t}] \neq 0 \tag{3.8}$$

$$E[x_{ir,t}c^{IR}_{ir}] = \sigma_{\mathbf{ir}} \neq 0,\ for\,all\,t \tag{3.9}$$

in addition to (3.3) to (3.6).

Note that $E[r^d_{ir,t-1}\nu_{ir,t}] \neq 0$ by definition as $r^d_{ir,t-1}$ contains $c^{IR}_{ir} + \nu_{ir,t-1} = c^{IR}_{ir}+c^I_i+c^R_r+u_{ir,t-1}$, and I am explicitly allowing for the industry-region variables to be correlated to the unobserved, fixed industry-region fixed effects, but assume that this correlation is constant over time (expression (3.9)). Nickell (1981) shows formally that in this case the OLS and the fixed-effects estimators are likely to be biased (upwards and downwards, respectively), and that the fixed-effects estimator would in addition be inconsistent, because the number of periods available is not large. First-difference OLS is also not consistent under these assumptions, because the first difference of the lagged dependent variable is negatively correlated with the first difference of the contemporaneous shock, i.e., $E\left[\left(r^d_{ir,t-1} - r^d_{ir,t-2}\right)(u_{ir,t} - u_{ir,t-1})\right] < 0$.

Under additional assumptions, general method-of-moments (GMM) can overcome these obstacles. The general method-of-moments formulates a set of orthogonality restrictions (moment conditions) related to the econometric model. These conditions are then used to find parameter estimates that come as close as possible to achieving these orthogonality properties in the sample. The formulation of the moment conditions has to account for the endogenous variables on the right hand side. As the share of IPR-active firms and the IPR-stocks in an industry are not likely to be endogenous with respect to the idiosyncratic shocks, I only need to find valid and informative instruments for the lagged dependent variable and the patent and trade mark flow variables. With the additional assumptions that

$$E\left[(\mathbf{x}_{ir,t} - \mathbf{x}_{ir,t-1})\,c^{IR}_{ir}\right] = 0 \tag{3.10}$$

and

$$E\left[\left(r_{ir,2}-r_{ir,1}\right)c_{ir}^{IR}\right]=0 \tag{3.11}$$

the problems stemming from (3.8) and (3.9) can be overcome. Assumption (3.10) follows from (3.9) and implies that first-differencing the explanatory industry-region variables eliminates the component that is potentially correlated to the unobserved industry-region fixed-effect. This approach goes back to Hausman and Taylor (1981) and is further elaborated in Arellano and Bover (1995). Assumption (3.11) is a restriction on the initial values of the time series - if the same process has generated the firm entry rates long enough, it is probable that the first difference of the dependent variable is independent of the fixed industry-region effect. Equations (3.10) and (3.11) can thus be used to formulate a set of linear moment conditions, and the lags of the first-differences can be used as instruments. Based on these additional assumptions, I use lagged first-differences of the explanatory industry-region variables as instruments for their current first-differenced values, and lags of the lagged first difference of the dependent variable as instrument for its current values on the right hand side of (3.7). I use the robust two step estimation method yielding Windmeijer's corrected finite sample standard errors (Windmeijer, 2005).

3.4 Data and variables

The German Firm-Level Intellectual Property database (GFLIP) is an integrated database consisting of two components from four sources: a firm-level data set and IPR data.[19] The source of the firm-level data is the commercial database AMADEUS provided by Bureau van Dijk. This database contains structural and financial information on firms from 24 European countries. I extracted data covering the population of limited corporate enterprises (AG,

[19]In creating the database for this thesis, I could rely on the cooperation with Heike Mittelmeier at the LMU-ifo EBDC, Gabriele Niggebaum at the DPMA, Georg von Graenenitz, Michał Kazimierczak at OHIM, and Peter Evans at the UK IPO.

GmbH, KGaA) in Germany for the years 2002-12. Unlimited companies as well as banks and insurances are not included.

The exclusion of unlimited companies must be considered when interpreting the findings. Establishing a limited company (GmbH) requires a minimum of €25,000 as liable capital (§5 (1) GmbHG), and establishing a public limited company (AG) requires a minimum of €50,000 as share capital (§7 AktG). Limiting ownership liability comes at the cost of increased tax liability and potentially higher costs due to the additional legal requirements for operation and transaction costs (Harhoff, Stahl, and Woywode, 1998). In 2010, limited companies accounted for approximately 19 percent of all companies in Germany, and about 55 percent of all employees were employed by limited companies (Rink, Seiwert, and Opfermann, 2013). Limited companies also account for 14 percent of all new companies and for 44 percent of employment created by new companies. While focussing on limited companies does not give a full picture of the economy, it is yet informative of a very important part of it in terms of employment and economic activity.

In AMADEUS, the term "firm" represents a registered legal entity which organises operations. Census-type data, by contrast, often is collected at the level of the plant or production unit. In Germany, the firm-level data is retrieved from the private credit rating agency CREDITREFORM and CREDITREFORM RATING AG. To construct the latest version of the database, I used thirteen versions of AMADEUS: October 2002 through 2013 and AMADEUS April 2014.

There are two main reasons for using multiple annual versions. First, AMADEUS versions before 2006 keep details of 'inactive' firms only for two years, and later versions for a period of four years. The term 'inactive firms' includes firms that are bankrupt, in liquidation or dissolved. Note, however, that bankruptcy and liquidation does not necessarily imply that these firms are economically inactive. Amadeus is available prior to 2000, but I use data starting in 2002 because some of the relevant variables are not available for years before 2002, and coverage is significantly restricted. As there are reporting delays of up to a year by firms, using the AMADEUS April 2014 version means that the latest year for which I can use firm-level data reliably is 2012.

I match the financial data to patents and trade marks using a string match algorithm outlined in Helmers, Rogers, and Schautschick (2011). The German Patent and Trade Mark Office (DPMA) provided raw national trade mark (NTM) data, and the Office for Harmonisation for the Internal Market (OHIM) made available raw Community trade mark (CTM) data. I downloaded raw information on patent publications by German entities from the international patent database maintained by the European Patent Office, PATSTAT, version April 2014. Between the filing and the publication of a patent is a delay of at least 18 months, which implies that firms become aware of patents filed by (potential) competitors long after the filing date. In this thesis I am concerned with firm entry and exit, which are arguably related to patents filed by potential competitors. The relevant date for a patent to show up in the regression is therefore its publication date. As I am using lags of IPR flows and stocks, using the April 2014 version of PATSTAT allows me to include the year 2012 in my firm entry analysis in this chapter and in the survival and performance analyses in the next chapter.

I deflated all monetary values with base year 2010 using two–digit industry deflators obtained from the OECD STRUCTURAL ANALYSIS DATABASE (STAN).

Firms are allocated to industries according to the two-digit level Statistical Classification of Economic Activities in the European Community from 2007 (NACE Rev. 2).[20] Because industrial activity varies a lot across regions, I am not aggregating at the industry level, but at the regional level within an industry. I use the first two digits of firms' postal codes to allocate firms to regions. The advantage of the postal codification is that it covers the entire country. Its borders are usually real borders such as rivers, roads or the

[20] The NACE classification is used by Eurostat, and it classifies economic activity into 21 sections, which comprise 88 divisions (the "two-digit level"), 272 groups ("three-digit level"), and 615 classes ("four-digit level"). See http://epp.eurostat.ec.europa.eu/portal/page/portal/nace_rev2/introduction, last accessed 27/11/2014

outskirts of a city, and the regions are often similar in population and economic activity. There are 95 regions and 87 economic divisions without the insurance industry, leading to a maximum of 8,265 observations per year and 90,915 for the whole period. However, not all industries are active in all regions in all years,[21] so that the total number of observations in the original database is 83,155. Next, there are 13,290 industry-region observations for which values of either turnover, employment or total asset are missing. The average number of firms is much smaller in the regions with missing observations than in those where observations on turnover, employment, and total assets are available, so the results might not be applicable to regions in which a particular industry is not well represented. Omitting observations with missing values leaves 69,865 observations for 7,352 industry-region units of analysis.

3.4.1 Construction of variables

Dependent variable

The dependent variable of interest is the gross entry rate of new firms at the industry-region level. While there exist databases tracking mergers and acquisitions, the current data set only contains the incorporation date of legal entities. Therefore, I do not observe firm entry by brand extension, acquisition, or merger that does not result in a new legal entity. While these cases often involve large and well–known firms, the total number of this type of

[21] Industries that are not active in all regions: Forestry and logging; Fishing and aquaculture; Mining of coal and lignite; Extraction of crude petroleum; Mining of metal ores; Other mining and quarrying; Mining support service activities; Manufacture of beverages; Manufacture of tobacco products; Manufacture of wearing apparel; Manufacture of leather and related products; Manufacture of coke and refined petroleum; Manufacture of basic pharmaceuticals; Manufacture of basic metals; Water collection, treatment and supply, Sewerage; Remediation activities; Retail trade w/o motor vehicles; Water transport; Air transport; Programming and broadcasting activities; Telecommunications; Information service activities; Advertising and market research; Veterinary activities; Human health activities; Creative, arts and entertainment activities; Libraries, archives, museums and other; Activities of professional and other membership organisations; Activities of households as employers; Undifferentiated products; Activities of extraterritorial organisations

Summary of variables							
Variable	Description	Source	Mean	Std. Dev.	Min	Max	Obs
Industry-region level							
Log of gross entry rate	Logarithmic share of new firms relative to all firms	BvD Amadeus	1.53	0.9	0	4.61	69865
(Log of grossentry rate)^2		BvD Amadeus	3.18	2.6	0	21.29	69865
Log of turnover	Logarithmic mean of firm turnover	BvD Amadeus	3.97	1.98	0	15.12	69865
Log of capital intensity	Logarithmic mean of total assets/employment	BvD Amadeus	1.77	1.78	0	13.21	65732
Log of total assets	Logarithmic mean of total assets	BvD Amadeus	3.28	2.09	0	15.49	69865
Log of employment	Logarithmic mean of firm employment	BvD Amadeus	2.3	0.85	0.69	12.72	69865
(Log of total assets)*(Log of employment)	Interaction term	BvD Amadeus	7.65	6.66	0	178.66	69865
Log of firm age	Average firm age	BvD Amadeus	2.76	0.54	-1.1	6.79	69865
(Log of age)2		BvD Amadeus	7.94	3.03	0	46.21	69865
Subsidiary rate	Share of subsidiary firms	BvD Amadeus	0.12	0.11	0	1	69865
Diversification rate	Share of diversified firms	BvD Amadeus	0.65	0.18	0	1	69865
PLC rate	Share of public limited firms	BvD Amadeus	0.11	0.11	0	1	69865
Bankrupcty or liquidation rate	Share of firms that went bankrupt or into liquidation	BvD Amadeus	0	0.01	0	0.5	69865
National TM apps per firm	Logarithmic mean of national trade mark applications per national TM-active firm per year	DPMA	0.08	0.16	0	3.36	69865
CTM apps per firm	Logarithmic mean of CTM applications per CTM-active firm per year	OHIM	0.08	0.22	0	4.3	69865
National patent apps per firm	Logarithmic mean of national patent applications per national-patent-active firm per year	PATSTAT	0.22	0.49	0	7.05	69865
EP apps per firm	Logarithmic mean of EP applications per EP-active firm per year	PATSTAT	0.2	0.54	0	6.91	69865
Industry level							
National TM-activity rate	Share of firms that applied for at least one national trade mark	DPMA	27.57	12.83	0	77.77	69865
CTM-activity rate	Share of firms that applied for at least one Community trade mark	OHIM	8.12	4.78	0	44.44	69865
National patent-activity rate	Share of firms that applied for at least one national patent	PATSTAT	9.44	6.16	0	70	69865
EP-activity rate	Share of firms that applied for at least one European patent	PATSTAT	5.75	4.3	0	60	69865
National TM stock per firm	Logarithmic mean of stock of national TMs per firm	DPMA	0.79	0.46	0	3.1	69865
CTM stock per firm	Logarithmic mean of stock of CTMs per firm	OHIM	0.59	0.47	0	2.58	69865
National patent stock per firm	Logarithmic mean of stock of national patents per firm	PATSTAT	0.81	0.83	0	5.2	69865
EP stock per firm	Logarithmic mean of stock of EPs per firm	PATSTAT	0.9	0.93	0	5.04	69865
Global and dummies							
Real GDP growth rate	Real GDP growth rate	Eurostat	1.22	2.56	-5.1	4	69865
Industry Dummies	87 two-digit level NACE Rev. 2 (2007) dummies	BvD Amadeus					69865
Region Dummies	95 two-digit postal code dummies	BvD Amadeus					69865
Year Dummies	13 year dummies						69865

Table 3.4.1: Summary statistics - Firm-entry estimation

entry is negligible relative to the number of observable entry at the two–digit industry level (Jensen, Webster, and Buddelmeyer, 2008; Helmers and Rogers, 2010). Thus, I define gross entry as the number of legal entities that are new in industry i in region r in time t. The gross entry rate is then the ratio of new firms to the total number of active firms in period t and is denoted as $r_{irt} = \frac{entry_{irt}}{N_{irt}} \times 100$.

Proxy variables

Patent families (equivalents): I first identify the priority applications of patents that German applicants or entities filed in Germany and then allocate to the owners of these priority applications all patents related to these priorities. The set of patents related to the same priority patent(s) is known as *patent equivalents*, which is a more restrictive definition of patent families (OECD, 2009, p.72). Patent families account not only for patents filed in the domestic country or at the EPO, but also for patents filed in other jurisdictions. Using patent equivalents yields a better representation of the value of an invention than individual patent counts. The equivalent patents are allocated to firms in the publication year of the priority application, which is usually 18 months after the priority application was filed.

Next, I assume patent stocks depreciate at a rate of 15 percent per year to reflect the decreasing value of the protected knowledge over time, which is in line with the literature using stocks of patents as proxy for knowledge (see for instance Hall, Jaffe, and Trajtenberg, 2005).

PATSTAT also makes available legal events related to a patent, from which I derive patent lifetime data. If a patent is withdrawn, cancelled, suspended or not renewed, its depreciated value is deducted from the firm's stock of patents in the year of the event.

Neither the extent to which industry entry and activity requires explicit knowledge, nor the the stock of knowledge available in an industry varies across regions. By contrast, the extent to which firms are R&D or innovation active may vary across regions. On the one hand, firms located in an R&D

and innovation active region benefit more from knowledge spillovers, but on the other hand, employees with more exposure to knowledge might be more likely to leave to competitors or to establish their own business. The effect of a firm's proximity to R&D and innovation active regions is therefore ambiguous (Silva and McComb, 2012) and varies across regions. I thus calculate the flow of patents per firm at the industry-region level. To capture the stock of knowledge available in an industry, I calculate patent stocks at the industry level. Moreover, I use the proportions of patent-active firms at the industry level as proxies for the prevalence of specialised knowledge.

Trade marks: A novelty of this database is that NTM data in addition to CTM data are available for Germany. I follow the reasoning above and calculate trade mark stocks and activity variables at the industry level, and trade mark flows at the industry-region level. Renewal data is available for both types of trade marks, so I consider only new or renewed trade marks in the analyses. The value of trade marks can increase or depreciate over time, depending on the owner's investment and the success of trade marked products. Therefore, I do not depreciate firms' trade mark stocks.

Control variables

Firm size and age: To account for *"conventional [...] measures of entry barriers" (Geroski, 1995, , p.430)*, I compute average firm age in addition to average firm size in terms of total assets, turnover, and employment and capital intensity as the ratio of assets to labour. I compute these variables within each industry-region to account for geographical differences in industry structure. For instance, renting or buying space is more expensive in and around cities than it is in the countryside. It is therefore likely that the concentration of large firms (in terms of assets) is higher in remote areas than in cities, and that more small firms set shop in or near big cities.

Legal form: Without having data for unlimited firms, the firms in the data-set at hand fall into two categories (following Harhoff, Stahl, and Woywode (1998)). The first category, *Limited liability,* contains private limited liability firms (Gesellschaft mit beschränkter Haftung, GmbH) and limited commercial partnerships joint with a limited liability firm (GmbH & Co. KG). The second category, *Stock companies,* contains public limited companies and partnerships limited by shares (Aktiengesellschaft und Kommanditgesellschaft auf Aktien).

Ownership: A firm is marked a subsidiary if more than 50 percent of it is owned by another firm. A firm is marked a group if it holds more than 50 percent of any other firm. A group can also be a subsidiary. A firm is marked foreign owned more than 50 percent of it are owned by a foreign firm.

Diversification: A dummy variable indicates whether a firm operates in industries other than its primary industry of economic activity. A higher share of diversified firms in an industry could indicate a higher degree of competitiveness or uncertainty, because focussing on one economic activity might be too risky or volatile, respectively.

Economy: Global effects such as the dot.com bubble and the financial crisis affect more than one industry. The effect of such crises on the general economic environment is captured by the inclusion of time dummies and the rate of real GDP growth.

3.5 Descriptive statistics

3.5.1 Sample composition

The top panel of table 3.5.1 contains the distribution of firms over size (left panel) and age (right panel) within a sector and the last column contains the distribution of firms across sectors. Service firms account for 48 percent of all firms, followed by trade firms (22 percent) and manufacturing firms (11 percent). Construction firms make up almost 10 percent, ICT firms 6 percent, agricultural firms 2 percent and electricity, gas, water (EGW), R&D and mining the rest. Size is measured in terms of turnover, total assets and employees, following the Eurostat definition. The majority of firms (87 percent) are micro firms, accounting for particularly large shares in the service, trade, EGW and ICT sectors. Small firms are most common in the agricultural, manufacturing and construction sectors (14, 14 and 12 percent). Medium and large firms have the largest shares in the manufacturing sector (6 and 2 percent), and the lowest share in the service sector (one percent each). It thus seems that there are sector-specific characteristics that affect the optimal size of a firm. In contrast, the distribution of firm age varies less across sectors. In manufacturing, trade, construction and mining sectors, more than 60 percent of firms are more than ten years old, half of which are 25 years and older. Roughly a quarter of all firms are five to ten years old, and 20-30 percent of firms are less than five years old. The second panel presents firms' IPR activity in each sector.

3.5.2 IPR activity

Service and trade firms are least likely to use IPRs of some sort (table 3.5.1, second panel). Only 14 percent of service firms are trade mark active, and 4 percent are patent active. 24 percent of trade firms are trade mark active, and 8 percent applied for at least one patent. A quarter of firms in manufacturing owns only trade marks, 4 percent only use patents and 10 percent use both. Over 50 percent of R&D and mining firms use trade marks, and about a quarter applied for at least one patent. Overall, firms are more likely to use patents in addition to trade marks rather than only patents. The share of firms using only patents ranges from 1 to 6 percent (service and mining, respectively), and the share of firms using both, patents and trade marks, ranges from 3 to 22 percent (also service and mining).

Looking at firms' IPR-activity in the two years following establishment, we can see that the overall IPR-activity pattern across and within sector does

	Size				Age					*Share*
Sector	Micro	Small	Medium	Large	0-1	2-4	5-10	11-24	25+	%
Agriculture	87	14	2	0	14	18	22	36	11	1.82
Manufacturing	78	14	6	2	7	9	17	34	34	10.95
Service	94	4	1	1	13	18	27	27	15	48.56
Trade	90	8	2	0	9	12	20	32	29	21.41
Construction	86	12	2	0	7	11	21	33	27	9.52
EGW	90	6	3	1	19	22	28	23	8	1.60
ICT	91	7	2	0	15	20	28	28	9	5.52
RD	89	8	3	1	14	21	33	26	5	0.44
Mining	78	18	5	1	6	8	16	29	43	0.18
Weighted average	90.19	7.16	1.99	0.72	11.11	15.21	23.8	29.6	20.77	
	IPR activity all firms				**IPR activity young firms**					
Sector	No IPRs	Patents only	TMs only	Both	No IPRs	Patents only	TMs only	Both		
Agriculture	51.1	4.4	33.3	11.2	88.6	1.4	9.5	0.5		
Manufacturing	60.0	4.1	25.7	10.3	72.5	5.7	16.6	5.2		
Service	84.4	1.3	11.3	2.9	92.6	1.0	5.5	0.9		
Trade	73.4	2.3	18.6	5.7	92.1	1.5	5.1	1.2		
Construction	60.6	3.5	26.6	9.2	92.8	1.5	4.6	1.1		
EGW	51.5	3.6	34.2	10.8	92.2	1.2	5.7	0.9		
ICT	55.7	3.6	30.8	9.9	85.9	1.7	10.7	1.7		
RD	36.3	6.2	36.5	21.0	61.1	12.3	16.6	10.0		
Mining	32.7	6.4	39.3	21.6	93.8	1.1	3.9	1.1		
Weighted average	73.98	2.29	17.97	5.71	89.70	1.77	6.97	1.53		
	IPR use all IPR users				**IPR use young IPR users**					
Sector	National TM	OHIM TM	National Patents	EP Patents						
Agriculture	0.4	0.1	0.1	0.1	0.2	0.1	0.1	0.2		
Manufacturing	2.0	1.5	5.7	6.2	0.9	0.8	2.0	2.2		
Service	1.0	0.6	1.1	1.7	0.6	0.4	0.5	0.5		
Trade	1.1	0.8	0.9	1.1	0.6	0.4	0.4	0.4		
Construction	0.2	0.1	0.3	0.4	0.1	0.1	0.1	0.1		
EGW	0.3	0.2	0.2	0.1	0.1	0.1	0.1	0.1		
ICT	0.9	0.7	0.4	0.6	0.5	0.5	0.2	0.2		
RD	1.2	1.1	6.6	8.8	0.6	0.8	3.0	3.9		
Mining	0.3	0.2	0.2	0.1	0.2	0.3	0.2	0.1		
Weighted average	1.03	0.69	1.44	1.85	0.56	0.41	0.59	0.61		
Number of industry-region observations 69,865										

Source: Own calculations based on BvD Amadeus, DPMA, OHIM and PATSTAT data

Table 3.5.1: Distribution of firm characteristics across sectors

Top panel: Statistics for German firms, 2002-2012. Left panel: Average shares of firms in respective size category. Right panel: Average shares of firms in respective age category. The rows in each panel add up to 100 percent. The last column shows the shares of each sector in the economy in terms of numbers of firms.

Middle panel: Left panel: Average shares of all firms in respective IPR-activity category. Right panel: Average shares of firms that were less than two years old on entering the respective IPR-activity category. Rows in each panel add up to 100 percent.

Bottom panel: Left panel: Average number of patent applications or trade mark registrations by IPR-activity types. Right panel: Average number of patent applications or trade mark registrations by young IPR-active firms.

not emerge early on. Young manufacturing and R&D firms are most likely to use some form of IPRs (27 percent and 39 percent, respectively), compared to roughly 10 percent of firms in the other sectors. Most of the IPR-active firms use only trade marks, specifically, 17 percent of the manufacturing and R&D firms and 4-11 percent of the firms in the other sectors. R&D and manufacturing firms are most likely to use only patents (12 and 6 percent) or patents in addition to trade marks (10 and 5 percent).

IPR intensity, which is defined as the number of IPRs per firm, can be described by three categories: manufacturing and R&D firms are most IPR intensive, with 2 and 1 NTMs, on average, 1.5 and 1 CTMs, 6 and 7 national patents, and 6 and 9 European patents, respectively (table 3.5.1, third panel). The average IPR-active service or trade firm owns one national and 0.6 CTMs in addition to 1 national and 2 European patents. IPR-intensity is lowest for agriculture, construction, EGW, ICT and mining industries. Firms file about half of their national IPRs in the first two years of their existence, and slightly more than half of their regional IPRs.

Thus, the extensity and the intensity of IPR activity differs across sectors but not so much between old and young firms. More old firms are IPR active, and IPR-active firms file half of their IPRs in their first two years after establishment.

3.5.3 Firm entry

The sector-specific difference are also reflected in the average annual entry rates. Figure 3.5.1 shows average entry rates for all sectors over the period 2002 and 2012. There appear to be three types of sectors in terms of entry - high, medium and low entry rate sectors. Entry rates are lowest in the mining sector, medium in construction, manufacturing and trade sectors, and highest in service, ICT, EGW, R&D and agriculture sectors. With the exception of EGW industries, firm entry rates follow a similar pattern across sectors - following the dot.com crisis, the entry rates slowly decline between 2003 and 2008, after which they peak in 2010 at levels above the 2003 levels

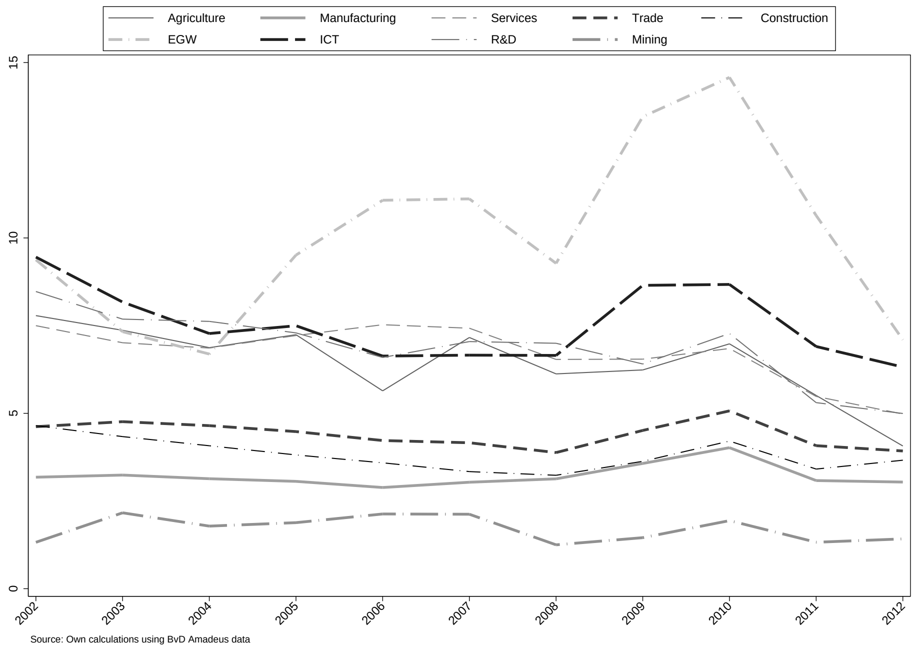

Figure 3.5.1: Average gross entry rates across sectors
Gross entry is calculated as the proportion of new firms in a given industry and region. Industries and regions are weighted by their relative size (in terms of number of firms) within a sector.

and then sharply decline as a consequence of the Euro crisis. The EGW sector marks an exception for two reasons: first, entry rates are higher than in other sectors because the number of firms was relative small at the turn of the millennium. Second, in 2000, the German government passed the German Renewable Energy Sources Act (EEG), with amendments in 2004, 2009 and 2012 that significantly affected firm entry into these industries (Rink, Seiwert, and Opfermann, 2013, footnote 22). I therefore exclude this sector from the regression analyses. Moreover, firm entry activity is almost static in the mining sector, so that after the fixed-effect or the first-difference transformations hardly any observations are left. Hence, I also exclude the mining sector from the firm entry regressions.

3.6 Results

In this section, I first discuss the different estimations and then summarise them jointly. I start with OLS and GMM regression results across all sectors, before I break up the sample by sectors.

3.6.1 Cross-sector regressions

Columns 1 and 2 in table 3.6.1 contain the results of estimating the static and the dynamic model, respectively, using the OLS fixed-effect method. In the static model, capital intensity and firm age, which are often associated with lower entry rates, are significantly negatively correlated with the firm entry rate. Economic growth, the share of firms with subsidiaries, and the squared firm age are positively correlated with the firm entry rate. In column 2, I include the previous gross entry rate, assuming that previous entry also effects current entry. Indeed, the coefficient is significantly negative. Note that the inclusion of the lagged gross entry rate hardly affects any of the coefficients or the significance of the other explanatory variables. This suggests that the fixed effect transformation of the data successfully removed unobserved fixed effects that were potentially correlated to the explanatory variables. The tests for joint validity of the three sets of IPR variables, i.e., the activity rate, the stocks and the flows, all suggest that the variables in each set are jointly significant at the 1 percent significance level. The tests for joint validity of turnover and capital intensity, as well as for other controls (share of holdings in the industry-region and the real growth rate) also indicate joint significance of these variables at the 1 percent level. Even so, these models explain only a fraction of the variation over time. Columns 3 to 5 present results of the difference GMM regressions. Here, the variables are in first-differences rather than in levels.

In column 3, I estimate the static model using GMM methods.[22] Under

[22]The industry-level variables, the year dummies and the control variables act as instruments for themselves, yielding 12 instrument variables. In addition, I am using further lagged differences of the flows of IPRs and the gross entry rate as instruments for the first lag of the

	OLS - fixed effects		Difference GMM		
Dep. var.: Log of gross entry rate	Static	Dynamic	Static	Dynamic	Young IPR activity
Lag-logarithmic gross entry rate		-0.0177^{**}		-0.366^{***}	-0.396^{***}
		(0.00715)		(0.140)	(0.136)
Industry-region level effects					
Lag-log of turnover	0.00720	0.00721	-0.222	-0.188	-0.162
	(0.0103)	(0.0104)	(0.217)	(0.192)	(0.194)
Lag-log of capital intensity	-0.0330^{***}	-0.0332^{***}	-1.123^{*}	-1.062^{**}	-0.969^{**}
	(0.0102)	(0.0103)	(0.576)	(0.470)	(0.466)
Lag-log of national TM apps per firm	-0.0247	-0.0249	-0.158	-0.0154	0.127
	(0.0351)	(0.0351)	(0.377)	(0.361)	(0.366)
Lag-log of CTM apps per firm	-0.0106	-0.0107	-0.463	-0.566^{*}	-0.483
	(0.0202)	(0.0202)	(0.328)	(0.292)	(0.308)
Lag-log of national patent apps per firm	0.00286	0.00288	0.194	0.0412	-0.208
	(0.0157)	(0.0158)	(0.205)	(0.225)	(0.200)
Lag-log of EP apps per firm	-0.0147	-0.0151	-0.456^{**}	-0.293	-0.161
	(0.0122)	(0.0122)	(0.204)	(0.204)	(0.187)
Industry effects:					
Lag-log of national TM stock per firm	-0.146	-0.146	-0.467^{*}	-0.372	-0.258
	(0.119)	(0.120)	(0.265)	(0.237)	(0.164)
Lag-log of CTM stock per firm	0.384^{***}	0.389^{***}	0.615^{***}	0.535^{***}	0.133
	(0.0626)	(0.0633)	(0.187)	(0.171)	(0.104)
Lag-log of national patent stock per firm	-0.202^{***}	-0.202^{***}	-0.0271	0.00957	-0.0966
	(0.0396)	(0.0398)	(0.0952)	(0.0837)	(0.0635)
Lag-log of EP stock per firm	0.108^{***}	0.108^{***}	0.119^{**}	0.0617	0.0217
	(0.0255)	(0.0256)	(0.0481)	(0.0488)	(0.0468)
Lagged national TM-activity rate	-0.0162^{*}	-0.0156^{*}	-0.0308	-0.00445	0.00343
	(0.00832)	(0.00837)	(0.0212)	(0.0190)	(0.00899)
Lagged CTM-activity rate	0.00631	0.00553	-0.0454	-0.0741^{**}	-0.0614^{***}
	(0.0186)	(0.0187)	(0.0442)	(0.0362)	(0.0162)
Lagged national patent-activity rate	-0.100^{***}	-0.101^{***}	-0.0807^{**}	-0.0700^{**}	-0.0121^{**}
	(0.0225)	(0.0227)	(0.0362)	(0.0310)	(0.00488)
Lagged EP-activity rate	0.114^{***}	0.114^{***}	0.119^{**}	0.103^{**}	0.0332^{*}
	(0.0301)	(0.0303)	(0.0552)	(0.0485)	(0.0175)
Control variables					
Lag-log of age	-0.334^{*}	-0.365^{*}	2.635^{***}	1.176	0.975
	(0.202)	(0.205)	(0.749)	(0.748)	(0.720)
(Lag-log of age)^2	0.158^{***}	0.157^{***}	0.183	0.157^{*}	0.169^{**}
	(0.0385)	(0.0389)	(0.138)	(0.0861)	(0.0792)
Holding rate	0.843^{***}	0.830^{***}	2.447^{***}	1.552^{***}	1.553^{***}
	(0.205)	(0.206)	(0.558)	(0.563)	(0.554)
Real growth rate	0.0289^{***}	0.0288^{***}	0.207^{***}	0.163^{***}	0.103^{**}
	(0.00566)	(0.00569)	(0.0555)	(0.0521)	(0.0435)
Constant	1.976^{***}	2.094^{***}			
	(0.324)	(0.332)			
Year dummies	Yes	Yes	Yes	Yes	Yes
TM use F-stat	9.71	9.74			
PAT use F-stat	7.11	7.09			
Industry IPR activity	9.96	9.85			
Size F-stat	5.28	5.28			
Controls F-Stat	25.1	24.2			
Year F-stat	35.9	35.5			
R^2	.0252	.0255			
Sargan J p-value			.0788	.149	.0665
Hansen robust p			.277	.357	.343
Arellano-Bond AR(1) p			$2.49e{-31}$	.0452	.0704
Arellano-Bond AR(2) p			.393	.0061	.00249
Arellano-Bond AR(3) p			.124	.344	
χ^2			1,094	1,839	2,085
Number of instruments			72	81	81
Obs	53,127	53,127	45,744	45,744	45,744

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.6.1: Firm entry all sectors, OLS and GMM

Summary of results from estimating equations (3.2) and (3.7). Standard errors in the OLS models are robust and clustered at the industry-region level. Standard errors in the GMM models are Windmeijer's robust finite sample errors (Windmeijer, 2005).

strict exogeneity of the explanatory variables and no unobserved fixed effects, the coefficients should not change from one method to the other. The results suggest the presence of unobserved effects or endogeneity of some of the explanatory variables. The coefficient for capital intensity increases more than 30 fold. The magnitude of the coefficients for the average age, the share of firms with subsidiaries and the real growth rate also increase manifold. The panel bias stemming from unobserved fixed effects and endogeneity of some of the explanatory variables tends to lower the value of the fixed-effect estimators (Nickell, 1981; Bond, 2002; Roodman, 2009). Seemingly consistent and unbiased coefficients with values smaller than the fixed-effects coefficients should thus be viewed with suspicion.

Neither the Sargan-J tests (1956) nor the robust Hansen tests of over-identifying restrictions reject the validity of the additional moment conditions used for these two models. The Arellano-Bond autocorrelation tests indicate that the first-differenced shocks are serially correlated at order 1 without the inclusion of the lagged entry rate, and at order 2 with the inclusion of the lagged entry rate. I use the third and fourth lag of IPR flows and the fifth and sixth lag of the firm entry rate as instruments, so no endogeneity should occur from these variables.

3.6.2 Young firm IPR activity

Column 5 presents results from estimating the same model as in column 4, but only accounts for IPR-activity in the first two years after a firm was established. The Sargan-J test accepts the validity of the over-identifying restrictions at the 5 percent significant level, but rejects the validity at the 10 percent significant level. The robust Hansen test statistic confirms the validity of the over-identifying restrictions.

first-differences, because these variables likely violate the strict-exogeneity assumptions. In particular, I am using the 3rd and 4th lag of the differenced IPR flow variables as instruments, which yields 15 instruments for each of the four variables (the first instrument is available in t=6), and the 5th and 6th lag of the gross entry rate, which yields an additional 9 instrument variables.

3.6.3 Sector-level regressions

To further investigate the nature of the effect of IPRs on firm entry, I repeat the difference GMM estimations including the lagged dependent variable at the sector level (table 3.6.2). Table 3.6.3 summarises the effects of IPRs on firm entry.

3.6.4 Summary and discussion of findings

Industries with a higher share of NP-active firms are predicted to have lower entry rates, while industries with a higher share of EP-active firms are predicted to have higher entry rates. Both findings confirm hypothesis H1a and H1b. The quantity of knowledge generated and made available, as measured by patent stocks and flows, appears to have no robust effect on firm entry, rejecting hypothesis H3a and H3b for the full sample.

The extent to which tacit specialised knowledge is required to operate in an industry at the national level, measured by the share of NTM-active firms, does not appear to restrict the generation of new ideas and thus firm entry. By contrast, the degree to which firms in an industry are export-active lowers firm entry. Thus, hypothesis H2a cannot be confirmed, but hypothesis H2b is supported.

At the national level, the pro-competitive effects of trade marks seem to be diminished by their anti-competitive effects. CTMs, on the contrary, appear to be able to significantly reduce asymmetric information, and thereby attract more new firms. Presumably, CTMs are used when a minimum level of reputation has been established, at which point they have a stronger signalling function than NTMs without a regional counterpart. Trade marks with a stronger signalling function perform better at reducing information asymmetries, and so for CTMs, the pro-competitive effects outweigh the anti-competitive effects and thus support hypothesis H4.

	GMM					
	Manufacturing	Service	Trade	Construction	ICT + R&D	Agriculture
Dep. var.: First-differenced log of gross entry rate						
Lag-logarithmic gross entry rate	-0.415^{***}	-0.224^{*}	-0.249^{*}	-0.577^{***}	-0.163	-0.356^{*}
	(0.137)	(0.126)	(0.146)	(0.162)	(0.164)	(0.216)
Industry-region level effects						
Lag-log of turnover	-0.232	-0.321^{*}	-0.179	-0.112	-0.213	-0.231
	(0.238)	(0.194)	(0.289)	(0.350)	(0.292)	(0.352)
Lag-log of capital intensity	0.172	0.242	-0.912^{*}	-0.129	0.0274	-0.0338
	(0.516)	(0.296)	(0.538)	(0.391)	(0.252)	(0.263)
Lag-log of national TM apps per firm	0.149	0.0480	-0.414	-1.004^{*}	-1.008^{*}	-0.144
	(0.286)	(0.239)	(0.317)	(0.568)	(0.578)	(1.003)
Lag-log of CTM apps per firm	-0.0800	0.0104	0.154	-0.159	-0.458	0.713
	(0.247)	(0.176)	(0.134)	(0.210)	(0.465)	(0.597)
Lag-log of national patent apps per firm	0.0456	-0.00427	-0.0371	-0.235	-0.540^{**}	0.0310
	(0.234)	(0.155)	(0.0930)	(0.182)	(0.254)	(0.213)
Lag-log of EP apps per firm	-0.151	-0.144	-0.0779	-0.0521	0.538^{**}	0.0576
	(0.222)	(0.111)	(0.0618)	(0.178)	(0.224)	(0.404)
Industry effects:						
Lag-log of national TM stock per firm	0.355	-0.967^{***}	2.713	-0.819	0.550	0.653
	(0.466)	(0.266)	(2.208)	(1.716)	(0.683)	(2.320)
Lag-log of CTM stock per firm	0.00299	-0.0444	-0.0726	-0.479	0.179	-0.488
	(0.329)	(0.134)	(0.464)	(0.847)	(0.183)	(0.588)
Lag-log of national patent stock per firm	-0.117	0.0108	0.416^{*}	0.988^{*}	0.123	0.0782
	(0.167)	(0.0518)	(0.217)	(0.559)	(0.183)	(0.531)
Lag-log of EP stock per firm	0.182^{*}	-0.0561^{**}	-0.449	-0.195	0.0124	-0.188
	(0.108)	(0.0268)	(0.314)	(0.207)	(0.129)	(0.351)
Lagged national TM-activity rate	-0.0363	-0.0691	0.140	0.901	0.103	-0.257
	(0.0250)	(0.0470)	(0.162)	(0.660)	(0.0749)	(0.714)
Lagged CTM-activity rate	-0.00337	0.108	-0.398	-2.836^{*}	-0.472^{**}	2.018
	(0.0779)	(0.158)	(0.679)	(1.518)	(0.206)	(4.135)
Lagged national patent-activity rate	0.0157	-0.608^{**}	0.592	-0.598	0.330	1.358
	(0.0704)	(0.249)	(1.250)	(1.329)	(0.654)	(1.858)
Lagged EP-activity rate	-0.0195	0.263	-1.469	0.348	0.293	-2.527
	(0.105)	(0.316)	(1.894)	(2.708)	(1.029)	(2.493)
Control variables						
Lag-log of age	0.299	2.565^{**}	-5.789^{*}	-4.528^{**}	3.315^{*}	0.449
	(0.972)	(1.084)	(3.028)	(1.875)	(1.751)	(0.907)
(Lag-log of age)^2	0.297^{**}	0.0668	1.380^{**}	1.056^{**}	0.0783	0.115
	(0.138)	(0.170)	(0.639)	(0.466)	(0.309)	(0.249)
Holding rate	0.856	1.479^{**}	6.494^{***}	-2.577	0.543	-0.684
	(0.654)	(0.608)	(2.449)	(2.936)	(1.221)	(2.200)
Real growth rate	0.0868	0.0131	0.0296	0.155	0.217^{***}	0.00234
	(0.0692)	(0.0422)	(0.0585)	(0.128)	(0.0739)	(0.195)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Sargan J p-value	.000793	.921	.0827	.0834	.595	.192
Hansen robust p	.0958	.722	.488	.718	.619	.0918
Arellano-Bond AR(1) p	.164	.0299	.0378	.0857	.00228	.207
Arellano-Bond AR(2) p	.00119	.172	.268	.00334	.336	.192
Arellano-Bond AR(3) p	.968	.889	.743	.87	.495	.786
χ^2	817	1,267	495	281	382	93.3
Number of instruments	81	81	81	81	81	81
Obs	14,743	20,457	2,463	2,281	3,320	1,112

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.6.2: Firm entry by sector, Difference GMM

Results from estimating equation (3.7) for each sector. Standard errors in the GMM models are Windmeijer's robust finite sample errors (Windmeijer, 2005).

Summary of results		
Impact on firm entry rate	Significant positive	Significant negative
All sectors	European patent activity	National patent activity
	Community trade mark stocks	Community trade mark activity
Manufacturing	European patent stocks	
Service		National patent activity
		European patent stocks
		National trade mark stocks
Trade	National patent stocks	
Construction	National patent stocks	Community trade mark activity
		National trade mark applications
ICT & R&D	European patent applications	National trade mark applications
		National patent applications
		Community trade mark activity

Table 3.6.3: Summary of results - Firm-entry estimation

The specialised knowledge required to operate in an industry varies across industries, but more so across sectors. The variation in the use of patents and trade marks across sectors confirms this. The positive effect of more EPs in the manufacturing sector supports hypothesis H3b: even within a sector that requires significant specialised knowledge, producing for a larger market can stimulate more ideas.

The findings for the service sector confirm commonly known patterns - knowledge is more difficult to keep from others, so overall more ideas are generated and relatively more firms enter. In cases where it is possible to exclude competitors through patents or where reputation matters as signalled by the use of trade marks, the firm entry rate is significantly lower, rejecting hypothesis H3b and H4 for service sectors.

The trade and the construction sectors benefit from newly generated knowledge published in NPs (rejecting H3a). In addition, the construction sector appears to be marked by significant tacit knowledge requirements to operate at the regional level, as indicated by the negative coefficient on the share of CTM-active firms (rejecting H4). Some fields of the construction business might be characterised by higher transaction costs than others, so that it is more difficult to enter. An established reputation helps to reduce these transaction costs, giving the owners of the reputation a comparative advantage over new firms. Facing such a disadvantage makes entry less attractive for new firms.

Some areas in ICT and R&D are also subject to long contract durations and high transaction costs, e.g. due to confidentiality requirements, so that again firm entry might be reduced where reputation can lower these costs (rejecting H4). ICT and R&D are also fast moving sectors in terms of technological evolution. The generation of new knowledge by competitors can thus reduce the value of existing technologies and set back potential new firms (confirming H3a). Again, larger markets due to demand from abroad appears to offer significant opportunities for firm entry, confirming H3b.

Table 3.6.4 lists the top ten industries in terms of IPR use and activity together with average entry rates for those industries. The last panel lists the top and bottom ten industries in terms of firm entry. A close analysis reveals that the industries that are either very NP-active, NTM-intensive or CTM-active (lowering factors) and at the same time not EP-active or CTM-intensive (increasing factors) have,[23] on average, lower firm entry rates than industries that have lowering as well as increasing factors,[24] which in turn have lower firm entry rates than industries that exhibit only firm-rate-increasing factors.[25] Full lists of IPR-activity and use in addition to firm entry rates by two-digit NACE Rev. 2 industries are provided in tables A.2.2, A.2.3 and A.2.4 in the appendix.

[23] Manufacture of fabricated metal products; Manufacture of rubber and plastic products; Remediation activities, other waste management services; Water collection, treatment and supply; Air transport; Manufacture of beverages; Manufacture of electrical equipment; Manufacture of paper and paper products; Programming and broadcasting activities.

[24] Manufacture of basic pharmaceutical products; Manufacture of chemicals and chemical products; Manufacture of computer, electronic and optical products; Manufacture of electrical equipment; Manufacture of machinery and equipment n.e.c.; Manufacture of motor vehicles, trailers; Manufacture of other transport equipment; Postal and courier activities; Scientific research and development; Extraction of crude petroleum and natural gas; Manufacture of coke and refined petroleum products; Manufacture of tobacco products; Mining of coal and lignite; Mining of metal ores; Mining support service activities; Other mining and quarrying;

[25] Other professional, scientific and technical activities

Top ten two-digit industries: IPR activity and entry rates			
Top ten national TM active two-digit industries		**Top ten Community TM active two-digit industries**	
Manufacture of basic pharmaceutical products	4.3	Manufacture of motor vehicles, trailers and semi	3.2
Manufacture of tobacco products	3	Manufacture of basic pharmaceutical products	4.3
Telecommunications	13	Telecommunications	13
Manufacture of beverages	3.4	Manufacture of chemicals and chemical products	4.6
Manufacture of motor vehicles, trailers and semi	3.2	Air transport	3.7
Manufacture of chemicals and chemical products	4.6	Postal and courier activities	9.6
Manufacture of food products	3.3	Manufacture of paper and paper products	2.7
Postal and courier activities	9.6	Manufacture of beverages	3.4
Manufacture of coke and refined petroleum products	5	Programming and broadcasting activities	6.3
Air transport	3.7	Manufacture of coke and refined petroleum products	5
		Manufacture of electrical equipment	3.3
Top ten national patent active two-digit industries		**Top ten European patent active two-digit industries**	
Manufacture of motor vehicles, trailers and semi	3.2	Manufacture of motor vehicles, trailers and semi	3.2
Manufacture of other transport equipment	4.9	Manufacture of basic pharmaceutical products	4.3
Manufacture of electrical equipment	3.3	Manufacture of chemicals and chemical products	4.6
Manufacture of chemicals and chemical products	4.6	Manufacture of other transport equipment	4.9
Manufacture of basic pharmaceutical products	4.3	Manufacture of electrical equipment	3.3
Manufacture of computer, electronic and optical products	3.9	Scientific research and development	7.1
Manufacture of machinery and equipment n.e.c.	4.2	Manufacture of computer, electronic and optical products	3.9
Scientific research and development	7.1	Postal and courier activities	9.6
Manufacture of rubber and plastic products	3	Manufacture of machinery and equipment n.e.c.	4.2
Manufacture of fabricated metal products	3.1	Other professional, scientific and technical activities	7.3
Top ten national patent using two-digit industries		**Top ten EP using two-digit industries**	
Mining of coal and lignite	0	Mining of coal and lignite	0
Extraction of crude petroleum and natural gas	6.8	Extraction of crude petroleum and natural gas	6.8
Mining of metal ores	0	Mining of metal ores	0
Other mining and quarrying	1.7	Other mining and quarrying	1.7
Mining support service activities	11.3	Mining support service activities	11.3
Manufacture of rubber and plastic products	3	Manufacture of chemicals and chemical products	4.6
Manufacture of computer, electronic and optical products	3.9	Manufacture of basic pharmaceutical products	4.3
Manufacture of electrical equipment	3.3	Manufacture of electrical equipment	3.3
Manufacture of machinery and equipment n.e.c.	4.2	Manufacture of machinery and equipment n.e.c.	4.2
Manufacture of motor vehicles, trailers and semi	3.2	Scientific research and development	7.1
Scientific research and development			
Top ten national TM using two-digit industries		**Top ten CTM using two-digit industries**	
Mining of coal and lignite	0	Mining of coal and lignite	0
Extraction of crude petroleum and natural gas	6.8	Extraction of crude petroleum and natural gas	6.8
Mining of metal ores	0	Mining of metal ores	0
Other mining and quarrying	1.7	Other mining and quarrying	1.7
Mining support service activities	11.3	Mining support service activities	11.3
Manufacture of chemicals and chemical products	4.6	Manufacture of tobacco products	3
Manufacture of basic pharmaceutical products	4.3	Manufacture of coke and refined petroleum products	5
Water collection, treatment and supply	2.7	Manufacture of chemicals and chemical products	4.6
Remediation activities, other waste mgmnt services	7.9	Manufacture of basic pharmaceutical products	4.3
Scientific research and development	7.1	Scientific research and development	7.1
Top ten average entry rates 2002-2012		**Bottom ten average entry rates 2002-2012**	
Electricity, gas, steam and air conditioning supply	13.9	Mining of coal and lignite	0
Financial service activities w/o insurance	13.8	Mining of metal ores	0
Telecommunications	13	Activities of households as employers of domestic personnel	1
Information service activities	11.9	Other mining and quarrying	1.7
Mining support service activities	11.3	Manufacture of other non	2.6
Employment activities	10	Manufacture of paper and paper products	2.7
Postal and courier activities	9.6	Water collection, treatment and supply	2.7
Office administrative activities	9	Manufacture of tobacco products	3
Social work activities without accommodation	9	Manufacture of rubber and plastic products	3
Other personal service activities	9	Printing and reproduction of recorded media	3.1
		Manufacture of fabricated metal products	3.1

The numbers next to the industries indicate that industry's firm entry rate in percent.

Table 3.6.4: Top ten industries: IPR-activity and firm-entry rates

3.6.5 Robustness

Tables A.2.6 and A.2.7 in the appendix present OLS and GMM estimations for the stepwise inclusion of the right-hand-side variables. They reveal that the effect of the number of IPRs per firm is related to the share of IPR-active firms in an industry. In particular, the trade-mark-intensity effects are significant in their own right (column 5), while the shares of CTM- and patent-activity in the GMM estimations are only significant after the inclusion of the intensity variables (compare columns 4 and 8). The joint inclusion of the intensity and the activity variables reduces the magnitude of the effect of the intensity variables, but does not change the sign of the coefficients.

The EGW sector is not part of the regression analysis for reasons explained in section 3.4. Robustness regressions including the EGW sector show that the coefficients on the IPR variables are robust to the inclusion. The coefficients on firm age change, however, indicating a positive relationship between average firm age and firm entry even after including the lagged dependent variable.

The set of potential instruments offered by the generalised method-of-moments can lead to "over-fitting", which is a situation in which too many instruments are used relative to the sample size. As the period of observation grows longer, this becomes more likely, because the number of possible instruments grows rapidly with the time dimension (Roodman, 2009). Over-fitting gives a downward finite sample bias, in the direction of the fixed-effects estimator. If the coefficients of the fixed-effects and the GMM regressions are too close, one can reduce the number of instruments to reduce the extent of the bias. Tables A.2.7, A.2.8, A.2.9 and A.2.11 in the appendix to this chapter present results from estimating variations of the models specified in table 3.6.1. The results concerning the IPR variables are robust to variations in the specification with regard to the dependent variable and with regard to the number of instruments used.

3.7 Conclusion

In this chapter I investigated the role of tacit and explicit specialised knowledge in firm entry, and how innovation related activities measured by intellectual property rights (IPR) affect this role. The marginal effects on the firm entry rate I found for these variables are small. Considering the range of values of the knowledge and IPR-variables across industries, however, these indicators explain a significant proportion of the variation of firm entry rates across industries. They should therefore be added to the list of informative indicators of firm entry.

The results give a picture of the current relationship between firm entry rates, knowledge and innovation related activities at the industry-region level. They cannot be used to assess whether firm entry rates are above or below a socially desirable level. But they inform the analysis of this question by pointing out that some of the differences in firm entry across industries are due to knowledge, innovation related activities, and the suitability of IPRs to reduce market failures. These factors need to be taken into account in deriving the socially optimal firm entry rate for each industry. Focussing on selected industries to better understand the role of knowledge and diffusion could thus be another avenue for future research. The findings in this chapter support the use of the degree of IPR activity in an industry as selection criterion for industries to focus on.

Firm entry may be necessary for competition, but it is certainly not sufficient. It may well be that more firms are attracted by supra-normal profits in concentrated industries than by competitive profits in other industries, but this does not imply that the industry becomes more competitive as a consequence. Attractive profits might be a result of entrants failing to survive after entry, in which case high firm entry rates could imply concentration and barriers to survival.

In the next chapter, I analyse whether high entry rates are correlated with low survival rates, whether firm innovation related activity contributes to the probability of successful entry and how survival is affected by competitors' innovation related activity. Moreover, I show that the effects of knowledge and innovation related activities are small compared to the effect of the financial crisis.

Chapter 4

The Role of Innovation and the Financial Crisis in New Firm Survival and Employment Growth in Germany

4.1 Introduction

The recent crises and resulting job losses worldwide add relevance to the research of the firm creation and employment generating processes in the economy. Despite the inherent risk, innovation activity is frequently found to increase firms' expected lifetime[26] and employment.[27] In this chapter I provide a first analysis of the effects of innovation related activities on young firm survival in Germany to follow-up on the findings on the role of knowledge and innovation related activities in firm entry in chapter 2. In addition, I investigate the effect of the financial crisis on young firm survival and employment growth in Germany, thereby providing a framework that can be used to find unobserved determinants of young firm survival.

Firms starting a business in 2006 did not know that the financial crisis of 2007-08 was about to happen. In economic terms, the financial crisis therefore presents a natural experiment for young firms. By comparing survival

[26] E.g. Audretsch and Mahmood (1995); Pérez, Llopis, and Llopis (2004); Cefis and Marsili (2005); Jensen, Webster, and Buddelmeyer (2008); Buddelmeyer, Jensen, and Webster (2010); Helmers and Rogers (2010); Colombelli, Krafft, and Quatraro (2013)

[27] E.g. Van Reenen (1997); Greenhalgh and Longland (2001); Greenhalgh et al. (2011)

patterns between firms that were hit by the financial crisis in their first year firms that had four years time to establish themselves, I can identify further unobserved variables that determine young firm survival. To this end, I follow two cohorts of new German firms for seven and ten years after establishment. In particular, I use the German Firm-Level Intellectual Property database (GFLIP) and focus on 45,186 and 53,593 new German firms established in 2003 and 2006, respectively.

The results confirm previous findings that innovation related activities significantly affect survival and employment growth. Compared to the adverse effect of the financial crisis on young firm survival, however, the effects of knowledge requirements and innovation related activities are small.

In section 4.2, I outline the findings in the related literature and motivate the methodology, and in section 4.3, I compare the samples used in the analysis. Sections 4.4 and 4.5 contain the survival and employment analyses, respectively, and I draw conclusions from this and the previous chapter in section 4.6.

4.2 Related literature

4.2.1 Survival

The surveys by Sutton (1997) and Caves (1998) in addition to the special edition of the International Journal of Industrial Organisation edited by Mata and Audretsch (1995) present marking points in the post-entry performance research literature. Since then the following statistical regularities are commonly accepted:

- The probability to survive increases with the size and age of firms.
- The relationship between age and survival is non-monotonic.
- Growth rates decrease as firms become larger and older, thus refuting Gibrat's 'law' of the independence between growth and size.

- As industries evolve, the number of producers first increases, reaches a peak, and then decreases to a level below the initial level, manifesting the existence of industry-life-cycles.

Several authors have since extended this literature by studying the importance of controlling for sample composition with respect to firms' self-selection into full and limited liability ownership forms (Harhoff, Stahl, and Woywode, 1998), innovation-active and innovation-inactive firms,[28] and their geographical or technological location decision (Colombelli, Krafft, and Quatraro, 2013). To date, we can roughly separate the post-entry performance literature into four themes: the role of the life-cycle of firms and industries; the role of ownership and exit decisions; the role of spatial effects; and the role of innovation and technology.

The role of the life-cycle of firms and industries: Learning-by-doing models predict that a firm's chance of survival increases with longevity (Jovanovic, 1982; Pakes and Ericson, 1998). Most studies of firm survival confirm this relation between firm age and survival; however, studies that include all firms, in particular firms older than ten years, show that this relation is non-monotonic. After a certain age, a firm's risk of exit increases again (Evans, 1987; Agarwal and Gort, 2002; Pérez, Llopis, and Llopis, 2004). Firms that fail to keep up with important changes in technology and business models will fall behind and be replaced by new entrants (Jovanovic and MacDonald, 1994; Christensen, 2013). Controlling for innovation capital and investment, in addition to the conventional variables, age ceases to be a significant determinant of survival (Buddelmeyer, Jensen, and Webster, 2010). This U-shaped relationship between the risk of failure and age (or the variables correlated to age) represents the life-cycle of a firm.

At the industry level, most entrants enter during the formative stage of an industry. At this stage, firms with a larger start-up size have a lower propensity to exit than firms starting out small (Agarwal and Audretsch,

[28] Pérez, Llopis, and Llopis (2004); Cefis and Marsili (2005); Jensen, Webster, and Buddelmeyer (2008); Helmers and Rogers (2010)

2001; Agarwal and Gort, 2002). This size-premium, however, vanishes for firms entering during a more mature phase of an industry.

The role of ownership and exit decisions: Post-entry performance also depends on the type of entrant and the type of exit under consideration. New firms that are subsidiaries are larger on average and account for a larger share of entrants' output and employment, but are also more prone to exit (Caves, 1998). Young subsidiaries benefit from experience, endowment, and a wider relational network compared to their independent counterparts; however, continuance of their operation is more dependent on their performance relative to the targets set by the parent company. In as much, subsidiaries are often deprived of the option to fight for survival until the very end. Most studies show that the latter effect is dominant and that subsidiaries are on average more likely to exit in general[29] and voluntarily rather than through bankruptcy in particular (Harhoff, Stahl, and Woywode, 1998).

Entrants are also distinct with regard to their degree of owner liability. Voluntary exit is more common under full ownership compared to limited liability firms (Harhoff, Stahl, and Woywode, 1998). If the proportion of limited and unlimited firms varies across industries, this has implications for the interpretation of the results from cross-industry studies. For instance, it seems reasonable to assume that firms reduce assets and employment before they exit (Almus, 2004). Studies that distinguish between voluntary exit and bankruptcy, however, reveal that this is mainly the case if firms exit voluntarily (Harhoff, Stahl, and Woywode, 1998).

The role of spatial effects: Although scarce, existing survival literature on regional effects clearly demonstrates that locating within an area that is spatially-concentrated with firms in the same industry significantly decreases young firms' life expectancy (Fritsch, Brixy, and Falck, 2006; Silva and McComb, 2012). However, young firms can benefit from locating near, rather than within, a cluster of rivals due to positive externalities (e.g., existing infra-

[29] E.g. Dunne, Roberts, and Samuelson (1988b); Audretsch and Mahmood (1995); Jensen, Webster, and Buddelmeyer (2008); Buddelmeyer, Jensen, and Webster (2010); Helmers and Rogers (2010)

structure and presence of skilled labour). Close proximity to universities is also shown to reduce the likelihood of exit (Helmers and Rogers, 2010). When the geographic source of input goods is relevant, e.g. for the production of wine or cheese, small firms can benefit from signalling place-of-origin via protected labels such as geographical indications, regardless of their age (Bontemps, Bouamra-Mechemache, and Simioni, 2013).

The role of innovation and technology: Manufacturing firms are more prone to exit if their plants employ more advanced technologies (Doms, Dunne, and Roberts, 1995). Likewise, conducting more R&D and employing more marketing personnel than the average firm of the same size decreases the chances of survival (Agarwal and Gort, 2002). High-tech industries attract more entrants than other industries (Agarwal and Audretsch, 2001; Samaniego, 2009), and the survival prospects of small firms, regardless of age, are significantly higher, while there is no difference for large firm survival between low- and high-tech industries (Agarwal and Audretsch, 2001; Cefis and Marsili, 2005). Despite the inherent risk often associated with innovation, several authors find an innovation premium for young firms in terms of survival.[30] In particular, process innovation - in contrast to product innovation - seems to drive this innovation premium in the manufacturing sector (Cefis and Marsili, 2005). Firms re-allocate resources away from product innovation over time: older firms apply for and hold more trade marks.[31] Both measures are associated with an increase in companies' expected lifetime, with process innovation, and with innovation in service industries (see chapter 2).

Innovation activity affects not only the performance of companies but also that of their rivals. A high degree of small firm innovation in an industry seems to constitute a barrier to survival for new firms in the first years after establishment Audretsch (1995). However, firms that manage to keep pace and to adapt benefit from a more innovative environment. In contrast,

[30] E.g. Pérez, Llopis, and Llopis (2004); Cefis and Marsili (2005); Jensen, Webster, and Buddelmeyer (2008); Colombelli, Krafft, and Quatraro (2013)

[31] E.g. Jensen, Webster, and Buddelmeyer (2008); Buddelmeyer, Jensen, and Webster (2010); Helmers and Rogers (2010)

in many industries, a larger share of IPR-active firms decreases incumbent firms' chances of survival, while it increases the expected lifetime of younger firms (Jensen, Webster, and Buddelmeyer, 2008; Helmers and Rogers, 2010). Why do these studies predict a different effect of innovation for new firm survival? The answer could be in the data. Audretsch uses the U.S. Small Business Administration Innovation Database to obtain data on innovation introduced by U.S. firms. These data probably consist mainly of product innovations. Jensen et al. and Helmers & Rogers use patent and trade mark data from Australia and the UK, respectively. Counts of IPRs include product and process innovations. This broader definition of innovation better captures the degree of non-price competition in an industry. IPRs might thus be better proxies for the competitive effect of innovation activity.

A thorough firm-survival analysis needs to account for innovation related activities at the firm and the industry level, industry life-cycle effects, regional effects, and ownership effects. The GFLIP database allows me to control for these characteristics, so I can identify the effects of innovation related activities and the financial crisis. Using IPRs as indicators for innovation related activities implies that I adopt the broader definition of innovation, including at least product and process innovation, and perhaps even marketing and organisation innovation (see 4.2.3).

4.2.2 Innovation and employment

A further dimension of the performance of firms in relation to innovation activity is its ability to create or sustain jobs. Such analysis of employment can give us metrics to assess some of the benefits to households from innovation activity.

The introduction of new technology (process innovation) can have positive and negative effects on employment. Some jobs will be destroyed by new techniques, while the demand for those with newer skills will tend to rise. At the same time, the introduction of new products into the marketplace (product innovation) will generally increase the demand for at least part of a firm's output, thus sustaining or increasing employment. Harrison et al. (2008) conduct a cross-country study using data from four European Community Innovation Surveys to model the general effect of innovation on employment. They estimate that, in 1998-2000, the effect of process innovation was usually negative for manufacturing but positive for services, although all these effects were very small in each country. In contrast, their estimates suggest that the effect of product innovation was uniformly large and positive in France, Germany, Spain and the UK. A fuller survey of these issues and the relevant literature can be found in Greenhalgh and Rogers (2010). As their survey shows, there have only been a handful of studies using UK firm-level data to explore the effect of innovation activity on jobs and wages, and very little attention has been paid to the role of trade mark activity within these studies. To the best of my knowledge, there are no such studies using German firm-level data to date.

4.2.3 Patents and trade marks

Section 2 of chapter 2 in this thesis discusses the use of trade marks as proxies for innovation. The survey by Griliches (1990) provides an excellent and still current discussion of the use of patents as an economic indicator, which is complemented by an overview of recent patent research in Hall and Harhoff (2012) and by a review of the literature concerned with the trade-off between formal and informal IPRs by Hall et al. (2014). The findings common to all these surveys are that there is substantial heterogeneity across sectors in the use and the perceived importance of patents and trade marks as instruments to appropriate returns from innovation. In fact, with the exception of pharmaceutical and chemical industries, and to some extent medical instrument industries, patents are not considered useful means to appropriate rents from innovation in most industries, and particularly not in isolation. Trade marks, however, are used more widely, and the empirical evidence suggests that trade marks are informative with regard to product and process innovation activity in manufacturing and knowledge-intensive service industries, and with regard to market innovation across industries. Using both patents and trade marks as indicators thus allows me to capture new firms' ability to offer innovative or differentiated goods and services, which is an important part of new firms' success (Spulber, 2009; Helmers and Rogers, 2010).

4.3 Data

I am using the German Firm-Level Intellectual Property (GFLIP) database, which is described in detail in chapter 3. GFLIP contains data on 1,481,112 limited corporate enterprises (AG, GmbH, KGaA) in Germany for the years 2002-2012. As I measure the effect of IPRs on new firm survival and growth conditional on the economic environment, I create two survival samples: the first sample contains ten years of data on all limited firms incorporated in 2003 (45,392 firms), just after the dot.com crisis, and the second survival sample contains seven years of data on all limited firms created in 2006 (53,634 firms), just before the financial crisis. Moreover, because not all firms report employment, for each sample I create a subsample containing only firms that do (32,254 and 41,429 firms, respectively).

Table 4.3.1 presents the distribution of firms within and across the four subsamples. Across all samples, service firms make up for 59.8 percent of all firms, followed by trade, construction and manufacturing firms (15.5, 7.3 and 7 percent). The distribution of firms does not vary systematically across the survival and the employment samples or across the 2003 and 2006 samples.

There are, however, differences in the characteristics of the firms in the respective samples. Tables A.3.1 and A.3.2 show the results of mean comparison tests between the subsamples. The last three years of the 2003 samples are excluded from this test to avoid biased results due to the additional time these firms had to grow. Fewer firms were created in 2003 compared to 2006, but firms established in 2003 are larger and more IPR-active on average. In

Sector	Survival 2003	Survival 2006	Employment 2003	Employment 2006	Total	Survival 2003	Survival 2006	Employment 2003	Employment 2006	Total
Agriculture	54.8%	23.5%	15.3%	6.4%	100.0%	2.1%	1.1%	2.2%	1.0%	1.7%
Manufacturing	47.0%	26.0%	16.3%	10.7%	100.0%	7.6%	5.3%	9.8%	7.0%	7.0%
Service	41.9%	37.5%	9.8%	10.8%	100.0%	57.7%	65.6%	50.3%	60.0%	59.8%
Trade	44.5%	30.1%	14.2%	11.2%	100.0%	15.9%	13.7%	19.0%	16.2%	15.5%
Construction	45.5%	27.6%	15.6%	11.3%	100.0%	7.6%	5.9%	9.8%	7.7%	7.3%
EGW	35.0%	44.2%	6.9%	13.8%	100.0%	1.8%	2.8%	1.3%	2.8%	2.2%
ICT	49.0%	28.9%	13.3%	8.8%	100.0%	7.3%	5.5%	7.4%	5.3%	6.5%
Mining	50.3%	32.3%	9.3%	8.1%	100.0%	0.1%	0.1%	0.1%	0.1%	0.1%
Total	43.5%	34.2%	11.6%	10.7%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
N						455,858	358,515	121,656	112,552	

Table 4.3.1: Distribution across sectors

particular, the ratio of total assets to employment (capital intensity) is smaller for firms established in 2003, indicating that these firms hired more workers per unit of assets than their 2006 counterparts. Omitting firms with missing employment observations biases the sample towards larger firms (table A.3.2), which is a direct consequence of the fact that smaller firms are not required to report employment.

4.4 Survival analysis

In this section I start with a univariate description of young firm survival in Germany to reveal systematic patterns between different types of firms that motivate the semi-parametric analysis in the second part of this section.

4.4.1 Non-parametric analysis

Tables 4.4.1 and 4.4.2 contain firm mortality rates after two and five years of existence for different types of firms established either in 2003 or in 2006. Wagner (1994) reports an average mortality rate of 20 percent for the cohorts of less than two year old manufacturing firms established in Lower-Saxony, West Germany between 1979-1982. Harhoff, Stahl, and Woywode (1998) report a 24 percent average mortality rate for two-year old West-German manufacturing firms established between 1987 and 1989. Fritsch, Brixy, and Falck

(2006), however, report mortality rates between 25-35 percent for West-German firms established between 1983-2000. The average mortality rate of firms after two years of existence in this sample is 17.6 percent in manufacturing, which is not far off from the values reported in Wagner (1994) and Harhoff, Stahl, and Woywode (1998). The sample used by Fritsch, Brixy, and Falck (2006) excludes firms with more than 20 employees in their first or second year, which leaves out many subsidiaries and potentially high-growth firms, but explains the higher mortality rates. The mortality rate after five years of existence is 35 percent in this sample compared to 29 percent in Wagner (1994).

The difference between the mortality rates reported here and in Wagner (1994) and Harhoff, Stahl, and Woywode (1998) are small enough to be explained by this chapter's focus on firms with limited liability and perhaps by the inclusion of firms established in the new federal states of Germany (former East-Germany).

With the data at hand I can compute mortality rates depending not only on the IPR-type used by firms, but also on the regional scope and on the success of patent applications.

The mortality rate of firms using any type of IPRs two years after establishment is lower than for IPR-inactive firms. For firms using patents in addition to trade marks, the two-year-mortality rate is lowest. After five years, however, mortality rates for patent or trade-mark-active firms established in 2003 are higher than for IPR-inactive firms or for firms that use both IPR-types. For firms established in 2006, this pattern is exactly reversed, perhaps indicating an adverse effect of the financial crisis on IPR-inactive firms and on those using patents and trade marks.

Similarly to the results found for patent activity, trade mark activity of any kind is associated with lower mortality rates. In particular, firms that use

Category	(2 years, 5 years) Number of firms								
	All sectors	Manufacturing	Service	Trade	Construction	EGW	ICT & R&D	Mining	Agriculture
IPR type									
No IPRs, est. 2003	(0.17,0.17)	(0.16,0.29)	(0.15,0.21)	(0.22,0.33)	(0.19,0.28)	(0.14,0.19)	(0.14,0.73)	(0.18,0.31)	(0.12,0.90)
	41075	2765	22163	6479	3178	682	4065	46	1697
Patents only, est. 2003	(0.12,0.21)	(0.12,0.21)	(0.12,0.18)	(0.09,0.18)	(0.04,0.16)	(0,0)	(0.13,0.53)	(-,-)	(0,1)
	387	124	126	78	17	3	31	0	8
Trade marks only, est. 2003	(0.11,0.18)	(0.09,0.20)	(0.09,0.13)	(0.15,0.21)	(0.14,0.22)	(0.10,0.10)	(0.08,0.42)	(0.5,0.5)	(0.06,0.97)
	2557	278	1047	579	95	27	384	2	145
Both IPRs, est. 2003	(0.09,0.15)	(0.10,0.16)	(0.07,0.13)	(0.09,0.16)	(0.09,0.12)	(0.2,0.2)	(0.09,0.43)	(-,-)	(0.8,1)
	407	122	131	84	23	5	37	0	5
No IPRs, est. 2007	(0.20,0.33)	(0.22,0.47)	(0.16,0.30)	(0.26,0.45)	(0.20,0.37)	(0.17,0.29)	(0.63,0.71)	(0.24,0.36)	(0.81,0.83)
	42915	2237	26130	5989	2556	1144	3487	32	1340
Patents only, est. 2007	(0.10,0.24)	(0.11,0.29)	(0.07,0.24)	(0.11,0.36)	(0.15,0.31)	(0.16,0.5)	(0.42,0.57)	(0,0)	(0.6,0.6)
	284	68	111	63	12	6	13	1	10
Trade marks only, est. 2007	(0.12,0.25)	(0.15,0.31)	(0.09,0.25)	(0.14,0.32)	(0.19,0.30)	(0.08,0.25)	(0.25,0.37)	(0,0)	(0.89,0.89)
	1997	170	948	438	52	30	295	2	62
Both IPRs, est. 2007	(0.10,0.27)	(0.05,0.30)	(0.13,0.30)	(0.11,0.31)	(0.17,0.29)	(0.5,1)	(0.19,0.35)	(1,-)	(0.5,0.5)
	222	61	79	46	11	2	20	1	2
Likelihood-ratio test	$\chi^2(7) = 3617.81$	$\chi^2(7) = 370.41$	$\chi^2(7) = 2346.28$	$\chi^2(7) = 746.60$	$\chi^2(7) = 262.96$	$\chi^2(7) = 93.44$	$\chi^2(7) = 1004.62$	$\chi(5)^2 = 5.69$	$\chi^2(7) = 612.36$
Log-rank test	$\chi^2(7) = 69837.45$	$\chi^2(7) = 4731.30$	$\chi^2(7) = 54019.17$	$\chi^2(7) = 11182.59$	$\chi^2(7) = 4875.26$	$\chi^2(7) = 2043.99$	$\chi^2(7) = 1624.75$	$\chi^2(5) = 73.51$	$\chi^2(7) = 129.55$
Trade marks									
No TMs, est. 2003	(0.17,0.27)	(0.16,0.29)	(0.15,0.21)	(0.22,0.33)	(0.19,0.28)	(0.14,0.19)	(0.14,0.73)	(0.18,0.31)	(0.12,0.90)
	41465	2890	22290	6559	3196	684	4097	46	1703
Only national TMs, est. 2003	(0.11,0.18)	(0.11,0.21)	(0.09,0.13)	(0.15,0.22)	(0.15,0.23)	(0.12,0.12)	(0.08,0.43)	(0.5,0.5)	(0.06,0.96)
	2258	275	919	485	93	21	337	2	126
Only CTMs, est. 2003	(0.10,0.15)	(0.01,0.15)	(0.11,0.13)	(0.13,0.16)	(0,0)	(0.11,0.11)	(0.07,0.35)	(-,-)	(0.13,0.93)
	274	36	100	72	10	9	37	0	10
National and CTMs, est. 2003	(0.08,0.15)	(0.07,0.13)	(0.06,0.10)	(0.13,0.18)	(0.07,0.15)	(0,0)	(0.05,0.38)	(-,-)	(0,1)
	431	88	158	105	18	4	46	0	12
No TMs, est. 2007	(0.20,0.33)	(0.21,0.47)	(0.16,0.30)	(0.26,0.45)	(0.20,0.37)	(0.17,0.29)	(0.63,0.71)	(0.23,0.35)	(0.81,0.83)
	43194	2305	26241	6052	2568	1147	3501	33	1347
Only national TMs, est. 2007	(0.12,0.25)	(0.14,0.31)	(0.09,0.24)	(0.14,0.32)	(0.18,0.29)	(0.08,0.26)	(0.27,0.37)	(0.5,0.5)	(0.88,0.88)
	1712	152	824	352	55	29	240	2	58
Only CTMs, est. 2007	(0.13,0.28)	(0.11,0.28)	(0.09,0.25)	(0.2,0.38)	(0.33,0.66)	(0.33,0.66)	(0.21,0.35)	(-,-)	(0.83,0.83)
	236	29	93	65	3	3	37	0	6
National and CTMs, est. 2007	(0.09,0.24)	(0.08,0.29)	(0.10,0.30)	(0.07,0.25)	(0.2,0.3)	(0,0)	(0.18,0.33)	(0,0)	(1,-)
	279	50	110	67	10	1	38	1	2
Likelihood-ratio test	$\chi^2(7) = 3612.34$	$\chi^2(7) = 365.08$	$\chi^2(7) = 2345.06$	$\chi^2(7) = 743.62$	$\chi^2(7) = 262.84$	$\chi^2(7) = 92.65$	$\chi^2(7) = 1000.96$	$\chi(4)^2 = 3.94$	$\chi^2(7) = 607.46$
Log-rank test	$\chi^2(7) = 69834.85$	$\chi^2(7) = 4714.84$	$\chi^2(7) = 54019.47$	$\chi^2(7) = 11181.42$	$\chi^2(7) = 4876.21$	$\chi^2(7) = 2040.24$	$\chi^2(7) = 1606.04$	$\chi^2(4) = 68.69$	$\chi^2(7) = 120.07$
Obs	681,680	42,167	429,672	97,883	48,167	16,449	40,355	373	6,614

Table 4.4.1: Mortality rates for different types of young firms (part 1)

Category	(2 years, 5 years) Number of firms								
	All sectors	Manufacturing	Service	Trade	Construction	EGW	ICT & R&D	Mining	Agriculture
Granted and non-granted patents									
No patents, est. 2003	(0.17,0.27)	(0.16,0.28)	(0.15,0.21)	(0.21,0.32)	(0.19,0.28)	(0.14,0.19)	(0.14,0.70)	(0.19,0.32)	(0.12,0.90)
	43636	3044	23211	7059	3274	709	4449	47	1843
Only granted patents, est. 2003	(0.22,0.88)	(-,-)	(0,1)	(0,1)	(1,-)	(-,-)	(0,0.5)	(-,-)	(0,1)
	9	0	4	1	1	0	2	0	1
Only non-granted patents, est. 2003	(0.17,0.30)	(0.28,0.48)	(0.06,0.13)	(0.22,0.36)	(0,0.2)	(0,0)	(0.10,0.31)	(-,-)	(0,1)
	75	17	21	15	5	1	13	0	3
Granted and non-granted patents, est. 2003	(0.09,0.16)	(0.10,0.16)	(0.10,0.15)	(0.08,0.15)	(0.05,0.11)	(0.14,0.14)	(0.11,0.51)	(-,-)	(0,0.88)
	715	229	234	147	36	7	53	0	9
No patents, est. 2007	(0.20,0.33)	(0.21,0.46)	(0.16,0.30)	(0.25,0.44)	(0.20,0.37)	(0.17,0.29)	(0.60,0.68)	(0.23,0.34)	(0.81,0.83)
	44916	2408	27078	6427	2609	1174	3784	33	1403
Only granted patents, est. 2007	(0,0.66)	(0,0)	(0,1)	(0,1)	(-,-)	(-,-)	(-,-)	(-,-)	(-,-)
	5	1	2	2	0	0	0	0	0
Only non-granted patents, est. 2007	(0.20,0.46)	(0.33,0.41)	(0.16,0.45)	(0.18,0.59)	(0.16,0.66)	(0,1)	(0.33,0.58)	(0,0)	(1,-)
	53	7	15	14	6	1	7	1	2
Granted and non-granted patents, est. 2007	(0.09,0.23)	(0.06,0.29)	(0.08,0.25)	(0.10,0.30)	(0.16,0.23)	(0.28,0.57)	(0.28,0.41)	(1,-)	(0.5,0.5)
	451	121	174	94	19	7	25	1	10
Likelihood-ratio test	$\chi^2(7) = 3576.06$	$\chi(6)^2 = 360.66$	$\chi^2(7) = 2331.59$	$\chi^2(7) = 725.81$	$\chi(6)^2 = 264.47$	$\chi(5)^2 = 92.66$	$\chi(6)^2 = 797.68$	$\chi(3)^2 = 5.42$	$\chi(6)^2 = 608.96$
Log-rank test	$\chi^2(7) = 69877.98$	$\chi^2(6) = 4708.90$	$\chi^2(7) = 54042.85$	$\chi^2(7) = 11174.04$	$\chi^2(6) = 4884.92$	$\chi^2(5) = 2046.73$	$\chi^2(6) = 1261.05$	$\chi^2(3) = 73.30$	$\chi^2(6) = 87.92$
Granted patents									
No granted patents, est. 2003	(0.17,0.27)	(0.16,0.28)	(0.15,0.21)	(0.21,0.32)	(0.19,0.28)	(0.14,0.19)	(0.13,0.70)	(0.19,0.32)	(0.12,0.90)
	43714	3063	23233	7075	3278	710	4463	47	1845
Only national granted patents, est. 2003	(0.10,0.17)	(0.12,0.19)	(0.10,0.14)	(0.09,0.19)	(0.09,0.09)	(0,0)	(0.08,0.48)	(-,-)	(0,1)
	376	116	121	86	21	4	25	0	3
Only European granted patents, est. 2003	(0.13,0.25)	(0.12,0.21)	(0.11,0.27)	(0,0)	(0,0.33)	(1,-)	(0.1,0.4)	(-,-)	(0,1)
	83	23	30	9	3	1	14	0	3
National and European granted patents, est. 2003	(0.07,0.13)	(0.07,0.11)	(0.09,0.13)	(0.06,0.10)	(0.05,0.15)	(0,0)	(0.18,0.68)	(-,-)	(0,0.75)
	257	88	84	51	13	2	15	0	4
No granted patents, est. 2007	(0.20,0.33)	(0.21,0.46)	(0.16,0.30)	(0.25,0.44)	(0.20,0.37)	(0.17,0.29)	(0.60,0.68)	(0.22,0.33)	(0.81,0.83)
	44975	2418	27095	6442	2613	1175	3793	34	1405
Only national granted patents, est. 2007	(0.10,0.23)	(0.09,0.32)	(0.07,0.24)	(0.10,0.10)	(0.16,0.16)	(0.25,0.5)	(0.30,0.34)	(-,-)	(0.5,0.5)
	255	61	96	63	11	4	14	0	6
Only European granted patents, est. 2007	(0.15,0.35)	(0.08,0.33)	(0.10,0.32)	(0.17,0.52)	(0.5,0.75)	(0.5,0.5)	(0.37,0.5)	(1,-)	(0,0)
	53	7	18	11	4	2	8	1	2
National and European granted patents, est. 2007	(0.06,0.20)	(0.03,0.23)	(0.10,0.26)	(0.06,0.27)	(0,0.12)	(-,-)	(0,0.33)	(-,-)	(-,-)
	144	50	59	21	8	0	6	0	0
Likelihood-ratio test	$\chi^2(7) = 3573.68$	$\chi^2(7) = 361.08$	$\chi^2(7) = 2329.59$	$\chi^2(7) = 725.53$	$\chi^2(7) = 263.88$	$\chi(6)^2 = 94.92$	$\chi^2(7) = 795.94$	$\chi(2)^2 = 5.33$	$\chi(6)^2 = 610.88$
Log-rank test	$\chi^2(7) = 69839.29$	$\chi^2(7) = 4709.85$	$\chi^2(7) = 54016.07$	$\chi^2(7) = 11162.49$	$\chi^2(7) = 4881.31$	$\chi^2(6) = 2046.4$	$\chi^2(7) = 1249.96$	$\chi^2(2) = 73.2$	$\chi^2(6) = 88.2$
Obs	681,680	42,167	429,672	97,883	48,167	16,449	40,355	373	6,614

Table 4.4.2: Mortality rates for different types of young firms (part 2)

both national and Community trade marks (NTM and CTM, respectively) show the lowest mortality rates, while the difference between firms using either NTMs or CTMs is negligible.

The effect of patent activity might also depend on its outcome. A patent application that is not granted reveals the invention but does not protect it. It is thus not likely to contribute to firm survival. In table 4.4.2 I distinguish between granted and non-granted patents. Patent-active firms that did not manage to obtain a patent grant within the observation period have a systematically higher mortality rate after five years than firms without patents or with both, granted and non-granted patents. Only very few firms have only granted patents, and their mortality rate is rather high. It is possible that these firms were acquired by another firm due to their success and this was not reflected in the database. It could also be a result of a measurement error, but this should not affect the analysis much due to the small number of such observations. Most patent-active firms have non-granted as well as granted patents, and their mortality rates are the lowest of all firms.

Within the group of firms that owns at least one granted patent, the mortality rate for firms owning only European patents (EP) is higher than for those owning only national patents (NP), which in turn is higher than owning both EPs and NPs. If successful, EPs may become more valuable than NPs, but on average they appear to be associated with a higher risk of failure.

The pattern observed for the whole sample by and large corresponds to the effects at the sector level. Construction and trade firms established in 2003 have lower mortality rates than their counterparts in other sectors when they use patents, but higher mortality rates when they use trade marks. This pattern can also be observed for service firms established in 2006.

Overall, mortality rates vary across sectors and cohorts, but less so across manufacturing, service, trade and construction sectors. The variation appears to be systematic within a given cohort. This variation can can be accounted for in a semi or full-parametric analysis by the inclusion of the re-

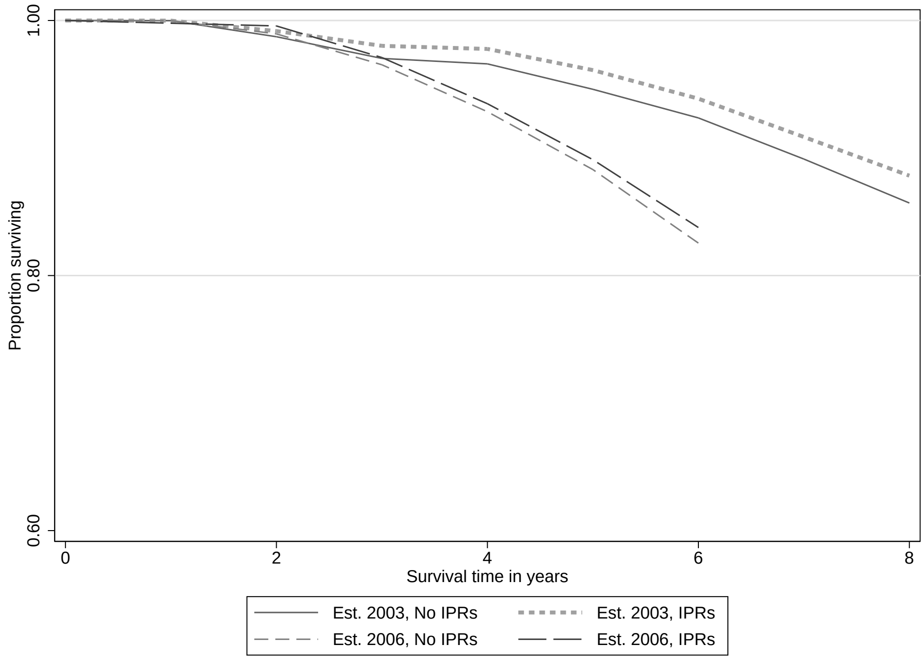

Figure 4.4.1: Kaplan-Meier survival curves by incorporation date and IPR-activity

spective controls. The log-likelihood tests and the log-rank tests suggest that the differences between the cohorts are significant.

Systematic differences between different types of firms over time can better be illustrated using Kaplan-Meier survival curves. The Kaplan-Meier estimator is of the following form:

$$\hat{S}(t) = \Pi_{t_i \leq t} \left(1 - \frac{d_i}{n_i}\right)$$

The number of firms that exit in period t is represented by d_i , and n_i is the total number of firms in t including those that exit during that period. In other words, the estimated probability of surviving t periods solely depends on the share of surviving firms in each period before and during period t.

As indicated by the mortality table, both cohorts of young IPR-active firms are systematically more likely to survive than their non-IPR-active peers (figure 4.4.1). Firms established in 2006 were clearly negatively affected by the financial and the Euro crisis: in 2009, three years after entry, their survival probability drops from a level just above that of firms at the same age

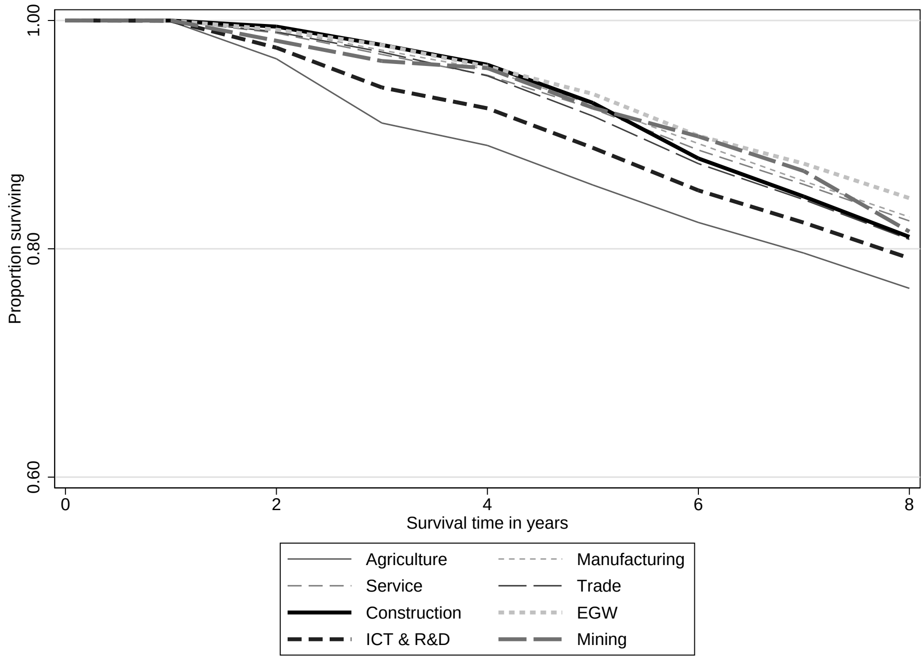

Figure 4.4.2: Kaplan-Meier survival curves by sector

established in 2003 far below that level. Thereafter it continues to decline at a faster rate. Throughout the whole period, the curves of the IPR-active firms remain in proportion to those of their IPR-inactive peers. Innovation activity thus seems neither to protect nor to aggravate the effect of the financial crisis on firm survival.

Figure (4.4.1) reveals little but persistent heterogeneity across sectors. Survival probabilities are lowest in the agriculture, ICT and R&D sectors, but there is little difference between the other sectors. The survival curves in figure (4.4.1) confirm the results found for young UK firms in Helmers and Rogers (2010), while the heterogeneity across sectors is less pronounced in Germany than that reported by these authors for the UK.

The Kaplan-Meier frequency measure discloses only little about the sources of these differences. A parametric analysis of firm survival is better suited to disentangle the effects of different firm characteristics on firm survival.

4.4.2 Semi-parametric analysis

(Cox, 1972; 1975) develops an estimation model that takes into account subject-specific variables. This model is later extended to capture time-varying components. Variations of this method are frequently used in economic survival analyses.[32] I follow this approach and estimate a piecewise-constant proportional hazard function. This type of model is called a semi-parametric model because it assumes a non-parametric basic hazard for each time interval. The basic hazard is then shifted proportionately according to each subject's characteristics.

To characterise each firm sufficiently, I include firms' lagged patent and trade mark flows and stocks as proxy for innovation related activities, following (Jensen, Webster, and Buddelmeyer, 2008; Buddelmeyer, Jensen, and Webster, 2010; Helmers and Rogers, 2010). A more inventive and more competitive environment benefits the survival chances of new firms. In contrast, industry size and age indicate later stages in the life-cycle, when entry is less common and young firm survival more difficult. Hence, I include industry IPR activity, age and size variables to control for the industry life-cycle effects. Following Helmers and Rogers (2010), I include region dummies at the two-digit postal code level to account for spatial effects. The GFLIP database only contains limited liability firms and information on firms' ownership structure. With this information I can identify parent firms, subsidiaries and subsidiaries owned by foreign parents. I account for the industrial environment of each firm by including the mean capital intensity and the lagged gross entry rate as well as industry dummy variables at the two-digit industry level. The lag of the real GDP growth rate acts as proxy for the macroeconomic environment. The model takes the following form:

$$h_i\left(t|\mathbf{x_{i,t}}\right) = h_{Cjr,0}\left(t\right) exp\left\{\beta_\mathbf{C}\mathbf{k_{i,t-1}} + \gamma_\mathbf{C}\mathbf{x_{ij,t-1}}\right\} \tag{4.1}$$

or in logs

$$\eta_{i,t} = \eta_{Cjr,0,t} + \beta_\mathbf{C}\mathbf{k_{i,t-1}} + \gamma_\mathbf{C}\mathbf{x_{ij,t-1}}$$

[32] E.g. Audretsch and Mahmood (1995), Harhoff, Stahl, and Woywode (1998), Jensen, Webster, and Buddelmeyer (2008), and Buddelmeyer, Jensen, and Webster (2010)

where $\eta_i = log\left(h_i\left(t|\mathbf{x_{i,t}}\right)\right)$ and $\eta_{C,0} = log\left(h_{Cjr,0}\left(t\right)\right)$. The left hand side variable, $h_i\left(t|\mathbf{x_{i,t}}\right)$ is firm $i's$ hazard rate, i.e. the probability that it will exit in t, given that it has not exited as of time t, and $h_{C,0}\left(t\right)$, is the base level hazard each firm in a given cohort C is exposed to in period t in the two-digit level industry j in the two-digit postal code region r. The row vectors β_C and γ_C are the coefficients for the vector $\mathbf{x_{ij,t-1}}$, which contains lagged variables of patent and trade mark activity and other control variables at the industry level, and the vector $\mathbf{k_{i,t-1}}$ contains lagged proxies for innovation activity, i.e., patent and trade mark stocks and flows, in addition to the other conventional firm-level variables.

The unit of analysis is the age of the firms, so that survival probabilities can be compared across the two cohorts. For non-IPR firm level variables, I fix the values at the time of firm establishment to avoid endogeneity issues. For the same reason, I use first lags of IPR-related variables. Buddelmeyer, Jensen, and Webster (2010) show that using first or second lags affects the results only marginally. I can confirm this for the 2003 sample, but not for the 2006 sample, as too few IPR-active observations are left after calculating second lags.

In columns 1-5 of table 4.4.3 I present the results of estimating equation (4.1) for different specifications. All specifications include region, industry and year dummies. The lifetime-increasing effects found for NTM and CTM applications are similar in all specifications and to the robust findings in the literature, but the effects of patents for new firm survival differ. Recent EP applications and stocks of NPs have no significant individual effect on survival. Current NP applications and stocks of EP applications significantly reduce the expected lifetime of young firms. These effects only surface after the inclusion of other firm-level variables. In contrast to trade marks, patent activity therefore seems to vary systematically with other firm-level characteristics.

	Est. 2003 or 2006				
Dep. var.: Hazard rate	(1)	(2)	(3)	(4)	(5)
Est. in 2006	1.395***	1.395***	1.395***	1.399***	1.387***
	(−0.00923)	(−0.00924)	(−0.00924)	(−0.00922)	(−0.00933)
Firm-level IPR-variables					
Lag-log of count of national TM registrations	−0.0787**		−0.0774*	−0.101**	−0.100**
	(−0.0397)		(−0.0457)	(−0.0465)	(−0.0465)
Lag-log of count of CTM registrations	−0.130*		−0.200**	−0.198**	−0.196**
	(−0.0676)		(−0.0832)	(−0.0828)	(−0.0828)
Lag-log of count of national patent applications	0.0494		0.087	0.154**	0.154**
	(−0.0453)		(−0.0657)	(−0.0674)	(−0.0674)
Lag-log of count of EP applications	0.0511		−0.0726	−0.0445	−0.0462
	(−0.0556)		(−0.082)	(−0.0825)	(−0.0824)
Lag-log of stock of national TM registrations		−0.0199	−0.00509	0.0157	0.0196
		(−0.0163)	(−0.0187)	(−0.0189)	(−0.0189)
Lag-log of stock of CTM registrations		0.00468	0.0574	0.128***	0.129***
		(−0.031)	(−0.038)	(−0.039)	(−0.039)
Lag-log of stock of national patent applications		−0.00722	−0.0519	−0.0625	−0.0617
		(−0.0331)	(−0.0477)	(−0.0486)	(−0.0486)
Lag-log of stock of EP applications		0.0800*	0.120**	0.235***	0.238***
		(−0.0413)	(−0.0592)	(−0.0596)	(−0.0595)
Firm-level variables					
Firm est. with at least one subsidiary				−1.506***	−1.517***
				(−0.0153)	(−0.0155)
Firm est. as a subsidiary				(−0.0156)	(−0.0157)
				−0.0156	−0.0157
Firm est. owned by foreign parent				(−0.0285)	(−0.0285)
				−0.0285	−0.0285
Firm est. diversified				(−0.00711)	(−0.00711)
				−0.00711	−0.00711
Initial value of total assets				(−0.00523)	(−0.00525)
				−0.00523	−0.00525
(Initial value of total assets)^2				0.0130***	0.0130***
				(−0.000538)	(−0.000539)
Industry-level variables					
Lagged national TM-activity rate					−0.0381***
					(−0.0058)
Lagged CTM-activity rate					0.112***
					(−0.0225)
Lagged National patent-activity rate					0.00932
					(−0.0187)
Lagged EP-activity rate					−0.0392
					(−0.0292)
Initial value mean log of industry capital intensity					0.00371
					(−0.00485)
Initial value logarithmic gross entry rate					0.00804
					(−0.00848)
Lagged real growth rate GDP					0.235***
					(0)
Two-digit industry dummies	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
Subjects	99,026	99,026	99,026	99,026	99,026
Observations	582,596	582,596	582,596	582,596	582,596
Log-Likelihood	−1170661	−1170664	−1170658	−1161185	−1161154
χ^2	46,939	46,931	46,939	58,907	59,044

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4.4.3: Stepwise estimates for a piecewise-constant exponential hazard function
Results from estimating equation (4.1).

It is not clear why NP applications have a similar effect as EP stocks. The average age of a firm filing the first NP is 4.1 years, and the average age of a firm filing the first EP is 4.3 years. The correlation between NP applications and NP stocks is 0.29, and that between EP applications and stocks is 0.27 (table A.2.5 in the appendix). It is unlikely that the stock variables capture the application effects or vice versa.

Jensen, Webster, and Buddelmeyer (2008) find no effect of patent flows or stocks for new firms, but significant lifetime-decreasing effects of patent flows for incumbent firms. In contrast, Helmers and Rogers (2010) find strictly life-time-increasing effects of flows of NP and EP applications for a cohort of UK firms established in 2001. The observation period in the latter study is shorter than in this and the 2008 study. As new patents are associated with a higher probability of exit for incumbent firms and with a lower probability of exit for young firms, the relationship between firm age and the effect of patent applications on firm survival appears to be non-linear.

Larger start-up size, being a parent firm or being foreign-owned decreases the risk of exit, as commonly found in the literature (e.g. Helmers and Rogers 2010). Firms with a very large initial size, however, are exposed to a higher risk of exit, also confirming the non-linearity of the size effect found in previous studies (Evans, 1987; Agarwal and Gort, 2002; Pérez, Llopis, and Llopis, 2004).

Subsidiaries are often found to be at more risk of exit (Caves, 1989), while the findings here suggest the contrary. Harhoff, Stahl, and Woywode (1998) find that subsidiary firms are less likely to exit via insolvency, and these authors also report that insolvencies are much more likely to occur among limited liability firms. The fact that I am only analysing limited liability firms could thus explain the lower risk of exit for subsidiaries. Likewise, diversification is often assumed to pool firm risk and thus to reduce the risk of failure. The findings here suggest that it increases the risk of exit for limited liability firms. In this regard, Harhoff, Stahl, and Woywode (1998) also find that diversification has no significant effect on firm insolvency. Again, the sample composition might explain this deviation from previous studies that use all types of firms.

Column 5 shows the results for the full model. The full model includes firm-level IPR variables in addition to other firm-level and industry-level characteristics. The inclusion of industry-level effects does not affect the coefficients or the significance of the firm-level variables. Only industry-level trade mark activity significantly affects firms' hazard rates. The share of NTM-active firms increases firms' expected lifetime, while the share of CTM-active firms decreases it. Patent activity, mean capital intensity and the gross entry rate appear to have no effect on firm survival in the full sample.

Columns 1 and 2 in table 4.4.4 report results for separate estimations of the 2003 and the 2006 cohorts of new firms. For the 2003 sample, the findings at the firm-level are identical with those in the full sample. At the industry level, more firm entry or a higher average capital intensity reduce the likelihood of survival. This result confirms the commonly accepted view that higher asset requirements make entry more difficult and that higher entry rates are correlated with higher exit rates (Geroski, 1995; Jensen, Webster, and Buddelmeyer, 2008; Helmers and Rogers, 2010).

Individually analysing the 2006 sample reveals significant differences between the two samples. IPR flows no longer significantly affect firm survival, while the effects for the stock variables remain significant at lower precision. The effects of firm-level characteristics also remain unchanged with one exception: diversification reduces the risk of failure for firms created just before the financial crisis. At the industry level, a higher capital intensity also reduces the risk of exit, indicating that these industries were less affected by the financial crisis. Likewise, a higher firm entry rate is also significantly associated with a lower risk of exit. Industries that were less affected by the crisis may have attracted more new firms than others. In this case, the effect of gross entry must not be attributed to increased competition but to new firms'

	Est. 2003	Est. 2006
	(1)	(2)
Dep. var.: Hazard rate		
Firm-level IPR-variables		
Lag-log of count of national TM registrations	-0.103^{*}	-0.0868
	(-0.0602)	(0.0725)
Lag-log of count of CTM registrations	-0.248^{**}	-0.111
	(-0.112)	(0.123)
Lag-log of count of national patent applications	0.187^{**}	0.0963
	(-0.0861)	(0.108)
Lag-log of count of EP applications	-0.0512	-0.0487
	(-0.107)	(0.128)
Lag-log of stock of national TM registrations	0.0104	0.0106
	(-0.023)	(0.0331)
Lag-log of stock of CTM registrations	0.135^{***}	0.109^{*}
	(-0.0492)	(0.0642)
Lag-log of stock of national patent applications	-0.0644	-0.0358
	(-0.062)	(0.0781)
Lag-log of stock of EP applications	0.172^{**}	0.314^{***}
	(-0.0768)	(0.0948)
Firm-level variables		
Firm est. with at least one subsidiary	-1.429^{***}	-1.633^{***}
	(-0.0205)	(0.0235)
Firm est. as a subsidiary	-0.375^{***}	-0.737^{***}
	(-0.0199)	(0.0259)
Firm est. owned by foreign parent	-0.101^{***}	-0.253^{***}
	(-0.0387)	(0.0428)
Firm est. diversified	0.195^{***}	-0.0350^{***}
	(-0.0102)	(0.0104)
Initial value of total assets	-0.101^{***}	-0.140^{***}
	(-0.00727)	(0.00771)
(Initial value of total assets)^2	0.0128^{***}	0.0130^{***}
	(-0.000761)	(0.000778)
Industry-level variables		
Lagged national TM-activity rate	-0.0314^{***}	-0.0442^{***}
	(-0.00787)	(0.00965)
Lagged CTM-activity rate	0.0957^{***}	0.0907^{**}
	(-0.0314)	(0.0370)
Lagged national patent-activity rate	0.000262	-0.0300
	(-0.0244)	(0.0333)
Lagged EP-activity rate	-0.0301	0.0378
	(-0.0377)	(0.0516)
Initial value mean log of industry capital intensity	0.0224^{***}	-0.0792^{***}
	(-0.00623)	(0.00938)
Initial value logarithmic gross entry rate	0.0300^{**}	-0.0290^{**}
	(-0.0117)	(0.0125)
Initial value real growth rate GDP	0.230^{***}	0.238^{***}
	(-0.0117)	(0.00916)
Two-digit industry dummies	Yes	Yes
Region dummies	Yes	Yes
Year dummies	Yes	Yes
Subjects	$45,392$	$53,634$
Observations	$322,823$	$259,773$
Log-Likelihood	$-629,626$	$-495,771$
χ^2	$20,497$	$62,870$

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4.4.4: Estimates by cohorts for a piecewise-constant exponential hazard function

Results from estimating equation (4.1) by cohorts.

self-selection into "safer" industries. The observation that neither capital intensity or gross entry affects firm survival in the full sample is therefore a result of the different effects of these variables in the two individual samples.

The different effects can be explained with the start of the financial crisis, which hit the 2006 cohort of new firms much harder than the 2003 cohort: in all full specifications, the dummy marking the 2006 cohort of new firms indicates a large significant negative effect on survival for these firms: a firm established in 2006 is roughly four times more likely to exit than a firm established in 2003.[33]

Table 4.4.5 summarises the competing risk estimates at the sector level by cohorts (tables A.3.5 and A.3.6 in the appendix to this chapter). The effects of innovation activity within each sector can differ from that across sectors, because these effects are relative to firms operating in the same sector, while the effects in the full analysis reflect effects of innovation relative to all firms. The effects vary considerably across sectors and between the two samples. Some robust patterns emerge nonetheless.

Trade mark and NP applications are associated with significant effects only for firms established in 2003. In particular, only manufacturing firms benefit from NTM activity, and only service firms expose themselves to a higher risk of failure by filing NPs. The effect of EP applications is only significant in electricity, gas and water (EGW) and agriculture sectors and shows no clear pattern.

In contrast, NTM stocks reduce the risk of failure of manufacturing firms established in 2003, but increase it for firms established in 2006. EGW related firms as well as trade firms experience opposite effects. For the majority of firms, CTM stocks lower the expected lifetime. The exceptions are the manufacturing and service firms in the 2003 cohort. The stock of NPs lowers the risk of failure of service and agriculture firms founded in 2003, but increases

[33] The coefficient on the dummy variable indicating the 2006 sample is identical to the log ratio of the hazards of the 2006 sample and of the 2003 sample, respectively.

	All			Manufacturing		Service		Trade		Construction		EGW		ICT & R&D		Agri	
	Pooled	2003	2006	2003	2006	2003	2006	2003	2006	2003	2006	2003	2006	2003	2006	2003	2006
Lag-log of count of national TM registrations	-	-		-													
Lag-log of count of CTM registrations	-	-										-					
Lag-log of count of national patent applications	+	+				+									-		
Lag-log of count of EP applications												+	-			-	
Lag-log of stock of national TM registrations				+	-			-	+		-	-	+				
Lag-log of stock of CTM registrations	+	+	+	-		-	+	+		+		+		+			
Lag-log of stock of national patent applications						-						+	+		+	-	
Lag-log of stock of EP applications	+	+	+		+	+			+		+	-	+			+	
Firm-level variables																	
Firm has at least one subsidiary	-	-	-	-	-	-	-	-	-	-	-		-	-	-		
Firm is a subsidiary	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	+	+
Firm is owned by foreign parent	-	-	-	-	-	+	-	-	-	-	-			-		+	
Firm is diversified	+	+	-	+		+	-	+		+	-	+				+	
Log of total assets	-	-	-			-	-	-	-	-	-	-	-	-			
(Log of total assets)^2	+	+	+	+	+	+	+	+	+	+	+	+	+	+	-	+	
Industry-level variables																	
National TM-activity rate	-	-	-			-		-	-			+	-				-
CTM-activity rate	+	+	+			+	-	+	+			-	+				+
National patent-activity rate					-	-	-		+	+	-		+	-			+
EP-activity rate				-	+		+		-	-	+		-	+			-
Mean log of industry capital intensity		+	-		-	+	-		-	+	+		-	-			+
Logarithmic gross entry rate		+	-		-	+	-										
Real growth rate GDP	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+

Table 4.4.5: Summary of competing risk analysis by sector
+ indicates an increasing effect of the hazard rate, - indicates a decreasing effect of the hazard rate. A “-” therefore indicates lifetime increasing effects.

it in EGW and ICT and R&D industries. With the exception of the 2003 cohort of EGW firms, the stock of EPs increases the risk of failure for firms in most sectors.

At the industry level, the share of NTM-active firms generally lowers the risk of failure, the share of NP-active firms lowers the risk of failure for manufacturing, service and construction firms established in 2006, and the share of CTM-active firms increases the risk of failure for most firms.

On average, IPR-activity thus appears to be associated with a higher probablity to survive. To find out more about the correlation of IPR-activity and the success of a firm, we need to look beyond survival data. In the next section, I analyse whether IPR-activity can also be linked to higher employment growth rates.

4.5 Employment analysis

Table 4.5.1 shows mean logarithmic employment growth rates for different size categories by cohort and IPR-activity. IPR-active firms have higher employment growth rates on average than IPR-inactive firms. Firms in the 2006 cohort grow faster, partly because they started out smaller. For firms in the 2003 cohort, the growth rates seem to increase until firms reach a size of 50-99 employees. Firms larger than that show declining growth rates as they grow larger. This pattern can also be observed for firms in the 2006 cohort, although here the rates increase only until firms reach 20-49 employees. The growth rates therefore clearly refute Gibrat's 'law' (Gibrat, 1931) that growth rates are independent of firm size.

Analysing the growth rates of firms tends to follow Gibrat's methodology. This regresses the growth rate of a factor like employment on the log of the initial value (i.e. the log of employment) and further variables. If the coefficient on the log of employment is negative, larger firms will grow slower than smaller firms. If the coefficient is positive, larger firms will grow faster than smaller firms. Gibrat's 'law' asserts that the coefficient should be zero:

Size by employees	no IP, Est. 2003	Patents only, Est. 2003	TM only, Est. 2003	Both, Est. 2003	no IP, Est. 2006	Patents only, Est. 2006	TM only, Est. 2006	Both, Est. 2006	Total
	Mean logarithmic employment growth rate (Standard deviation) Number of firms								
1-19	5.6%	6.7%	6.9%	6.7%	9.6%	12.8%	12.4%	10.9%	8.2%
	(19.30)	(21.78)	(19.78)	(21.31)	(29.48)	(31.31)	(31.21)	(29.24)	(25.75)
	17793	636	4665	1427	21919	625	5013	1527	53605
20-49	9.5%	5.9%	10.7%	11.9%	14.3%	9.7%	18.7%	18.7%	12.0%
	(21.93)	(13.24)	(19.37)	(25.27)	(30.13)	(22.26)	(30.52)	(37.16)	(25.48)
	1298	59	504	148	861	49	302	79	3300
50-99	9.0%	8.7%	8.0%	10.2%	12.8%	2.7%	13.3%	5.6%	10.0%
	(20.63)	(22.97)	(20.83)	(17.31)	(27.50)	(15.25)	(28.68)	(14.41)	(23.04)
	463	40	179	48	259	10	102	32	1133
100-500	8.9%	11.1%	9.5%	5.6%	10.3%	-1.2%	11.6%	14.5%	9.4%
	(26.52)	(14.52)	(20.62)	(23.49)	(24.65)	(11.78)	(24.78)	(42.41)	(25.35)
	325	19	126	76	224	10	69	33	882
>500	4.7%	-6.0%	2.2%	4.3%	5.7%	3.7%	3.7%	9.5%	4.6%
	(19.43)	(15.17)	(16.76)	(4.18)	(10.65)	(6.92)	(9.92)	(16.84)	(14.89
	79	4	32	12	80	4	22	9	242
Total	6.0%	6.8%	7.3%	7.2%	9.8%	12.1%	12.7%	11.3%	8.5%
	(19.68)	(21.12)	(19.81)	(21.65)	(29.41)	(30.36)	(31.03)	(29.73)	(25.66)
	19958	758	5506	1711	23343	698	5508	1680	59162

Table 4.5.1: Average logarithmic employment growth rates by sector and IPR-type

company growth is independent of company size. There is a large literature on this approach and I follow this here.[34]

The basic equation to be estimated is

$$g^l_{ij,t} = \alpha_{jr,t} + \beta l_{i,t-1} + \gamma \mathbf{IPR}_{i,t-1} + \theta \mathbf{X_{ij,t-1}} + \epsilon_{i,t} \tag{4.1}$$

where α_{jrt} is the time t, industry j and region r specific intercept, $l_{i,t-1}$ is firm $i's$ last period's employment in logs, the vector $\mathbf{IPR_{i,t-1}}$ contains firm $i's$ patent and trade mark flow and stock variables, respectively, and the vector $\mathbf{X_{ij,t-1}}$ contains the firm- and industry-level variables such as size, age, ownership, mean industry capital intensity, the gross entry rate and IPR-activity variables. $\epsilon_{i,t}$ is an i.i.d. firm-idiosyncratic error term with mean zero. As growth rates can vary considerably, I follow standard practice and exclude growth values above the 99th percentile, or below the 1st percentile, of the growth distribution. The summary statistics for the regression samples are shown in the appendix in table A.3.4.

Because the observations of firms not reporting employment are not "missing at random," it is likely that selecting only firms reporting employment introduces a selection bias. The mean comparison tests in table A.3.2 show that the employment sample is slightly but significantly biased towards larger firms. Therefore, I am using the Heckman estimation method to correct for the sample selection bias.

The results of estimating equation (4.1) are presented in table 4.5.2. Column 1 and 2 show simple OLS estimates pooling both cohorts of firms. Columns 2-4 contain results using the Heckman-selection model. The coefficients hardly differ between the ordinary least square (OLS) and the Heckman regressions, indicating that the selection bias is negligible for the question at hand. The results suggest that trade-mark-active firms enjoy a growth premium compared to other firms, and this effect is confined to national trade mark (NTM) flows and stocks. This corresponds to the findings for UK firms

[34]See Sutton (1997), Geroski (1999), or Audretsch et al. (2004) for surveys.

	OLS pooled		Heckman two-step pooled				Heckman two-step 2003	Heckman two-step 2006
Dep. var.: Log employment growth rate								
Firm-level IPR-variables								
Lag-log of count of national patent apps	1.311	1.302	1.450	1.473	2.313	1.302	0.487	1.073
	(1.506)	(1.509)	(1.504)	(1.507)	(1.446)	(1.508)	(1.357)	(3.648)
Lag-log of count of EP apps	−0.0323	−0.0155	0.185	0.176	−0.107	−0.0160	−0.175	0.810
	(−1.539)	(−1.542)	(1.529)	(1.547)	(−1.790)	(−1.540)	(−1.660)	(3.204)
Lag-log of count of national TM regns	5.222***	5.199***	5.259***	5.375***	1.461	5.199***	1.580	9.950***
	(1.439)	(1.440)	(1.440)	(1.440)	(1.101)	(1.439)	(1.343)	(2.809)
Lag-log of count of CTM regns	3.428*	3.425*	3.551*	3.545*	2.292	3.425*	2.991	3.856
	(2.037)	(2.027)	(2.028)	(2.034)	(1.526)	(2.026)	(2.161)	(3.901)
Lag-log of stock of national patent apps	1.035	1.046	1.373	0.971	0.265	1.047	−0.0490	3.414
	(1.035)	(1.034)	(1.041)	(1.049)	(1.091)	(1.033)	(1.030)	(2.484)
Lag-log of stock of EP apps	−3.459***	−3.514***	−3.323**	−3.414**	−1.749	−3.514***	−1.019	−7.706***
	(−1.336)	(−1.337)	(−1.337)	(−1.363)	(−1.331)	(−1.336)	(−1.414)	(−2.896)
Lag-log of stock of national TM regns	1.508***	1.486***	1.414***	1.392***	1.861***	1.487***	1.367***	1.746*
	(0.477)	(0.476)	(0.464)	(0.471)	(0.456)	(0.476)	(0.525)	(0.925)
Lag-log of stock of CTM regns	0.143	0.152	0.144	−0.00706	−0.315	0.152	0.0865	0.791
	(0.921)	(0.920)	(0.916)	(−0.917)	(−0.802)	(0.919)	(0.986)	(1.853)
Firm-level variables								
Lag-log of number of employees	−10.80***	−10.79***	−8.946***	−9.574***	−1.340***	−10.78***	−7.426***	−13.48***
	(−0.365)	(−0.365)	(−0.340)	(−0.351)	(−0.368)	(−0.362)	(−0.573)	(−0.518)
(Lag-log of number of employees)^2	0.816***	0.822***	0.589***	0.688***	0.657***	0.821***	0.494***	1.177***
	(0.0422)	(0.0422)	(0.0377)	(0.0397)	(0.0457)	(0.0421)	(0.0489)	(0.0715)
Log firm age	−10.49***	−10.20***	−10.86***	−10.70***	24.61***	−10.17***	37.88***	36.90**
	(−1.064)	(−1.068)	(−1.057)	(−1.055)	(0.996)	(−1.057)	(11.02)	(17.32)
(Log firm age)^2	0.852**	0.769*	0.854**	0.814**	−15.04***	0.755*	−15.15**	−8.932
	(0.404)	(0.405)	(0.401)	(0.401)	(−0.404)	(0.402)	(−6.704)	(−6.208)
(Lag-log of number of employees)x(Log of age)	2.214***	2.184***	2.380***	2.312***	0.739***	2.183***	1.288***	2.877***
	(0.166)	(0.166)	(0.163)	(0.164)	(0.196)	(0.165)	(0.283)	(0.293)
Firm has at least one subsidiary	−2.126***	−1.899***	−5.481***	−4.684***	−1.861***	−1.899***	−0.966**	−2.722***
	(−0.351)	(−0.350)	(−0.296)	(−0.304)	(−0.379)	(−0.350)	(−0.421)	(−0.574)
Firm is a subsidiary	2.598***	2.594***	1.920***	2.349***	2.439***	2.595***	1.962***	3.194***
	(0.358)	(0.357)	(0.347)	(0.351)	(0.432)	(0.357)	(0.429)	(0.578)
Firm is diversified	1.692***	1.617***	2.332***	2.227***	6.096***	1.621***	0.662**	2.577***
	(0.261)	(0.261)	(0.246)	(0.251)	(0.297)	(0.260)	(0.307)	(0.422)
Industry-level variables								
National TM-activity rate		0.777*				0.777*	0.383	1.216
		(0.419)				(0.419)	(0.416)	(0.752)
CTM-activity rate		−2.321				−2.321	−1.285	−4.072
		(−1.798)				(−1.796)	(−1.503)	(−3.488)
National patent-activity rate		−2.788				−2.788	−0.518	−4.510
		(−1.781)				(−1.779)	(−1.659)	(−3.175)
EP-activity rate		4.448*				4.448*	1.101	7.229*
		(2.500)				(2.498)	(2.513)	(4.269)
Mean log of industry capital intensity		1.171**				1.171**	1.237*	1.696
		(0.591)				(0.591)	(0.730)	(1.064)
Logarithmic gross entry rate		−0.325				−0.325	−0.379	−0.290
		(−0.296)				(−0.296)	(−0.352)	(−0.499)
Real growth rate	−1.688***	2.010***	1.832***	2.006***	1.409***	2.010***	4.443	−0.462***
	(−0.318)	(0.379)	(0.359)	(0.359)	(0.286)	(0.379)	(5.138)	(−0.110)
Constant	34.27***	16.87***	24.35***	27.35***	−35.44***	16.82***	−17.11**	−31.76**
	(2.164)	(3.176)	(1.151)	(1.905)	(−1.741)	(3.172)	(−8.266)	(−13.32)
Sector dummies	*No*	*No*	*No*	*Yes*	*No*	*No*	*No*	*No*
Two-digit industry dummies	*Yes*	*Yes*	*No*	*No*	*Yes*	*Yes*	*Yes*	*Yes*
Region dummies	*Yes*	*Yes*	*No*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year dummies	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
TM vars F-stat	12.4	12.3						
PAT vars F-stat	3.63	3.73						
Industry F-Stat	11.9	7.11						
Region F-Stat	3.71	3.71						
Year F-Stat	6.23	6.69						
Ownership F-Stat	42.6	39						
Age F-Stat	139	135						
Assets F-stat	438	436						
Industry-level F-Stat		5.78						
Log-likelihood	−629,405	−629,373	−790,037	−789,820	−764,764	−789,392	−400,153	−382,294
rho			−0.00602*	−0.00144	1.938***	0.00120	−0.00320	−0.000366
Obs	123,152	123,152	242,998	242,998	242,998	242,998	121,518	121,480

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4.5.2: Employment regressions

in Greenhalgh and Longland (2001) and in Greenhalgh et al. (2011). Firms using European patents (EP), in contrast, grow slower on average.

Firms in industries with higher shares of NTM and EP-active firms also grow faster, while firms in industries with high shares of Community-trade-mark and national-patent-active (CTM-active and NP-active) firms grow slower. Breaking up the full sample into the two cohorts (column 7 and 8) show that only the effects of the shares of trade-mark-active firms are significant.

With regard to firm-level variables, the coefficients on firm size clearly suggest that growth does depend on size. The coefficients on firm size and age are negative and significant, and the coefficients for the respective squared terms are positive and significant, as is common in the literature. Subsidiaries grow faster because some receive support from their parent company. Parent firms and diversified firms appear to grow slower. These firms are often larger firms, and so the coefficients likely capture some of the size effects, too.

4.6 Conclusion

In this chapter I investigated whether innovation related activities by new firms contribute to the probability of successful entry, how survival is affected by knowledge and competitors' innovation related activities, and how these activities are correlated with employment growth. I followed two cohorts of new firms that went through substantially different macroeconomic developments in their first years of existence. Viewing the results in this chapter together with the findings in chapter 3, the following patterns emerge:

Firms using national trade marks (NTM) face a lower risk of exit and grow faster than firms using other or no IPRs. Firms that are active in an industry in which many firms use NTMs also grow faster while being at a lower risk of failure. At the same time, service, construction and ICT industries in which firms register many NTMs have lower entry rates on average. Together this indicates that innovation related activities and the ability to overcome adverse effects from asymmetric information using NTMs increases firms' expected lifetime. Even so, some of this effect might stem from reduced competition, because not all firms can overcome the obstacles posed by asymmetric information if tacit specialised knowledge is prevalent in an industry. Nonetheless, for national trade marks, the pro-competitive effects appear to outweigh the anti-competitive effects.

In contrast, firms using national patents (NP) grow slower on average and expose themselves to a higher risk of failure. Industries in which many firms use NPs have lower entry rates, and the firms in such industries grow at a slower pace. The degree of specialised knowledge required in these industries appears to hamper entry and success for some firms. As regards the direct effect of patents, the literature on industry-life-cycles suggests that product innovation is the more common form of competition at the early stage of an industry, while process innovation becomes the dominating form of competition at later stages. If patents are mainly used to protect inventions that lead to process-innovations, these findings are in line with the industry-life-cycle literature. If, however, patents are mainly used to protect product-innovation related inventions, the findings suggest that it is either the nature of the innovation activity, or the anti-competitive effects of patents, rather than the competitive pressure from new entry that makes survival and growth for NP-active-firms less likely.

Industries in which Community-trade-mark-active (CTM-active) firms have many CTMs attract more entry, but firms grow slower and are more likely to exit. CTMs are consistently associated with performance premiums, which potentially stem from increased export activity. Industries characterised by concentrated and intense CTM use might be highly profitable, which attracts many new firms. Firm exit rates are high, however, so it seems as if these industries are characterised by a competitive fringe and only a few firms that reap high profits. But this circle of successful firms needs not be fixed: firms with large stocks of CTMs are also more likely to exit.

Firms using European patents (EP) are at higher risk of failure than IPR-inactive firms, and industries with many EP-active firms attract more new firms than other industries. These industries therefore appear to be characterised by more promising opportunities for new firms, potentially due to demand from abroad. These new firms then often replace existing firms.

Without further analysis it is not clear whether the higher exit rates are due to barriers to survival (Audretsch, 1995) or due to a dynamic industry composition. Future research could investigate whether the circle of successful firms in industries characterised by intense trade mark and patent use is stable, or whether the high profits for some firms only last until new firms replace them.

The financial crisis had the largest significant effect on firm survival. It clearly affected young firms more in terms of survival prospects and employment than firms that had more time to establish their business. The adverse effect of the financial crisis hit IPR-active and IPR-inactive firms equally hard. It thus reveals the existence of other determinants of young firm survival. The effect of these determinants, which are unobserved in this analysis, is clearly stronger than that of IPR-activity. The GFLIP database and the methodology applied in this chapter can be used to identify these unknown determinants. Candidate variables such as access to finance or proxies for demand can be added to the analysis to test whether they explain the shock, which in this analysis is captured by the 2006-cohort dummy. In addition to informing future entry and survival analyses, this could also enrich studies measuring the indirect effect of the crisis on economic growth through the destruction of young firms.

Postface

At the end of the 80s, Schmalensee (1989) writes "cross-industry studies are out of fashion." Yet, every day we can observe that fashion repeats itself. In the search for statistical regularities in industry dynamics and market structure, cross-industry studies are still fashionable because more and better data become available. The ongoing refinement of methods to analyse 'big data' make not only cross-industry, but also cross-country comparisons at the firm level more valuable. Moreover, the efforts by policy makers worldwide to create a more integrated global market make these analyses ever more important.

I chose to analyse the effect of patents and trade marks on the economy because there seemed to be a bias towards patents in the economic literature on intellectual property. This bias can no longer be justified by data availability, and the results in this thesis clearly show that trade marks are also relevant to economic activity and performance as patents.

It turns out that trade marks are not as neglected in the economic literature as it appeared and as is still often suggested. The empirical economic research of the last decade using trade mark data has vastly contributed to a better understanding of the use of intellectual property by firms, its impact on firm behaviour and thus on the economy as a whole. The results attracted attention by academics and policy makers alike. WIPO dedicated the 2013 World Intellectual Property Report to trade marks in general and brands in particular. Also in 2013, the European Observatory on Infringements of IPRs and the European Patent Office published the first study on the overall contribution of IPR-intensive industries in Europe. A more focussed study on the impact of IPRs on firm performance in Europe will follow this comprehensive investigation in 2015.

The database created for this thesis can be used to repeat the analyses for other countries, eventually culminating in a cross-country comparison that could reveal unknown weaknesses and strengths, or do away with persistent stereotypes, of cross-country differences regarding the role of knowledge and IPRs in entrepreneurial activity. For critics of the institution of intellectual property rights, it will become ever more difficult to ignore its crucial role in economic growth. Even for those that think "[i]ntellectual property has the shelf life of a banana - Bill Gates."

A

Appendix

A.1 Technical notes and definitions

Country income groups

In this thesis I adopt the World Bank classification of 2013 to categorise countries into four groups based on the gross national income per capita.[35] The groups are: low-income countries (per capita income up to USD 1,025), low middle-income countries (per capita income between USD 1,026 and USD 4,125), upper middle-income countries (USD 4,126 to USD 12,745 income per capita) and high-income countries with more than USD 12,745 gross national income per capita.

Firm size

Unless stated otherwise, I use the Eurostat definition of small and medium-sized enterprises:[36] A firm is considered *Micro* with fewer than 10 employees and either less than €2 million turnover or less than €2 million total assets; *small* with fewer than 50 employees and turnover or total assets are less than €10 million; *medium* with fewer than 250 employees and less than €50 million turnover or € 43 million total assets; *large* in all other cases.

The term "product" and the different types of innovation

I follow the OECD Oslo Manual definitions of a product and the different types of innovation: the term *product* covers both, goods and services, and a

[35]http://data.worldbank.org/about/country-classifications, last accessed 27/11/2014

[36]http://ec.europa.eu/enterprise/policies/sme/facts-figures-analysis/sme-definition/index_en.htm, last accessed 27/11/2014

product innovation includes the introduction of new goods and services at least to the firm, as well as significant improvements over existing goods and services. A *process innovation* refers to the introduction of new (or the significant improvement of existing) production or delivery methods. *Marketing innovation* refers to new methods of (or changes to existing) product designs or packaging, product placement, product promotion or pricing. *Organisational innovations* include the introduction of new (or significant changes of existing) business practices, workplace organisation or external relations (OECD and Eurostat, 2005, p. 45-51).

IPR activity

A firm is *patent-active* if during the observation period it either applied for at least one patent or owned for at least one period at least one patent or the depreciated value of it. A firm is *trade-mark-active* if during the observation period it registered at least one trade mark or owned for at least one period one trade mark. A firms falls into the *both IPR-active* category if it is patent and trade mark active.

IPR firm types

I distinguish between four IPR firm types: *IPR-inactive firms*, *patent-only firms*, *trade-mark-only firms* and *both-firms*. A patent-only firm is only patent active, a trade-mark-only firm is only trade mark active, and a "both"-firm is patent and trade mark active.

IPR timing

I refer to the subset of the IPR-active firms that was IPR-active in the first two years after incorporation as *young IPR-active firms*.

A.2 Appendix to Chapter 3

Table A.2.1 shows summary statistics for German firms, 2002-2012. In the left panel are average shares of firms in respective size category. In the right panel are average shares of firms in respective age category. The rows in each panel add up to 100%.

Table A.2.2 summarises the distribution of firm IPR activity. In the left panel are average shares of all firms in respective IPR-activity category. In the right panel areverage shares of firms that were less than two years old on entering the respective IPR-activity category. Rows in each panel add up to 100%. A firm is patent-active if it applied for at least one patent, trade-mark-active if it registered at least one trade mark, and both-active if it applied for or registered at least one patent and one trade mark, respectively.

	Size				Age					*Share*
NACE Rev. 2 division	Micro	Small	Medium	Large	0-1	2-4	5-10	11-24	25+	%
Crop and animal production	0.81	0.16	0.02	0.00	0.11	0.13	0.19	0.42	0.16	0.83
Forestry and logging	1.04	0.10	0.01	0.00	0.20	0.26	0.32	0.29	0.08	1.39
Fishing and aquaculture	0.72	0.08	0.01	0.00	0.09	0.12	0.16	0.34	0.10	0.01
Mining of coal and lignite	0.16	0.00	0.04	0.44	0.00	0.11	0.04	0.35	0.13	0.00
Extraction of crude petroleum and natural gas	0.53	0.02	0.04	0.12	0.12	0.18	0.12	0.18	0.12	0.00
Mining of metal ores	0.16	0.15	0.11	0.05	0.02	0.04	0.03	0.18	0.20	0.00
Other mining and quarrying	0.75	0.20	0.05	0.01	0.04	0.06	0.15	0.30	0.45	0.16
Mining support service activities	0.55	0.20	0.07	0.11	0.21	0.19	0.26	0.18	0.09	0.01
Manufacture of food products	0.77	0.14	0.07	0.02	0.06	0.08	0.14	0.30	0.42	0.88
Manufacture of beverages	0.78	0.15	0.06	0.01	0.06	0.07	0.13	0.26	0.49	0.30
Manufacture of tobacco products	0.77	0.12	0.04	0.07	0.07	0.05	0.10	0.26	0.52	0.03
Manufacture of textiles	0.79	0.14	0.06	0.01	0.07	0.09	0.15	0.31	0.38	0.30
Manufacture of wearing apparel	0.88	0.11	0.05	0.01	0.10	0.11	0.17	0.34	0.33	0.25
Manufacture of leather and related products	0.96	0.12	0.04	0.01	0.07	0.08	0.15	0.53	0.29	0.20
Manufacture of wood and of products	0.81	0.15	0.03	0.01	0.06	0.08	0.15	0.30	0.41	0.51
Manufacture of paper and paper products	0.68	0.16	0.12	0.04	0.05	0.08	0.14	0.31	0.42	0.17
Printing and reproduction of recorded media	0.84	0.12	0.04	0.01	0.06	0.08	0.15	0.34	0.37	0.72
Manufacture of coke and refined petroleum products	0.60	0.16	0.10	0.06	0.09	0.11	0.16	0.23	0.32	0.02
Manufacture of chemicals and chemical products	0.76	0.12	0.09	0.03	0.08	0.10	0.17	0.30	0.35	0.29
Manufacture of basic pharmaceutical products	0.77	0.11	0.07	0.05	0.08	0.11	0.19	0.30	0.32	0.10
Manufacture of rubber and plastic products	0.71	0.17	0.10	0.02	0.05	0.08	0.16	0.33	0.38	0.50
Manufacture of other non	0.80	0.13	0.05	0.01	0.05	0.07	0.16	0.31	0.41	0.54
Manufacture of basic metals	0.70	0.16	0.11	0.04	0.07	0.10	0.19	0.31	0.33	0.23
Manufacture of fabricated metal products	0.76	0.17	0.06	0.01	0.06	0.09	0.17	0.34	0.34	1.91
Manufacture of computer, electronic and optical products	0.79	0.14	0.06	0.02	0.07	0.11	0.22	0.38	0.21	0.75
Manufacture of electrical equipment	0.75	0.15	0.08	0.03	0.06	0.09	0.17	0.37	0.31	0.41
Manufacture of machinery and equipment n.e.c.	0.74	0.15	0.08	0.02	0.07	0.10	0.18	0.33	0.32	1.28
Manufacture of motor vehicles, trailers and semi	0.72	0.14	0.08	0.06	0.07	0.10	0.20	0.35	0.29	0.16
Manufacture of other transport equipment	0.81	0.12	0.05	0.02	0.10	0.14	0.25	0.31	0.20	0.12
Manufacture of furniture	0.78	0.15	0.06	0.01	0.06	0.09	0.17	0.31	0.37	0.25
Other manufacturing	0.86	0.11	0.03	0.01	0.06	0.09	0.17	0.39	0.29	0.89
Repair and installation of machinery and equipment	0.83	0.13	0.03	0.01	0.14	0.15	0.22	0.33	0.17	0.23
Electricity, gas, steam and air conditioning supply	0.94	0.03	0.02	0.01	0.26	0.28	0.28	0.12	0.05	0.98
Water collection, treatment and supply	0.75	0.11	0.10	0.03	0.05	0.09	0.21	0.32	0.32	0.04
Sewerage	0.82	0.15	0.03	0.01	0.08	0.12	0.26	0.39	0.14	0.07
Waste collection, treatment and disposal activities	0.81	0.13	0.05	0.01	0.08	0.12	0.26	0.42	0.12	0.42
Remediation activities, other waste mgmnt services	0.82	0.14	0.04	0.00	0.16	0.18	0.30	0.32	0.04	0.03
Construction of buildings	0.87	0.11	0.02	0.00	0.07	0.11	0.24	0.34	0.24	2.22
Civil engineering	0.71	0.21	0.07	0.01	0.09	0.12	0.21	0.34	0.24	0.49
Specialised construction activities	0.86	0.12	0.01	0.00	0.07	0.11	0.21	0.33	0.28	6.83
Wholesale and retail trade	0.85	0.12	0.02	0.00	0.08	0.11	0.19	0.34	0.29	2.89
Wholesale trade w/o motor vehicles	0.89	0.08	0.02	0.00	0.09	0.12	0.21	0.33	0.25	9.46
Retail trade w/o motor vehicles	0.92	0.07	0.01	0.00	0.08	0.11	0.19	0.30	0.32	9.13
Land transport and transport via pipelines	0.81	0.15	0.04	0.01	0.08	0.11	0.19	0.31	0.30	1.43
Water transport	0.96	0.03	0.01	0.00	0.16	0.23	0.32	0.23	0.06	0.43
Air transport	0.85	0.08	0.03	0.03	0.10	0.15	0.23	0.34	0.16	0.03
Warehousing and support for transportation	0.83	0.12	0.04	0.01	0.12	0.14	0.21	0.30	0.23	1.18
Postal and courier activities	0.85	0.09	0.05	0.02	0.18	0.21	0.30	0.27	0.04	0.12
Accommodation	0.82	0.14	0.03	0.00	0.09	0.13	0.22	0.31	0.26	0.75
Food and beverage service activities	0.88	0.09	0.02	0.00	0.16	0.18	0.25	0.27	0.13	1.24
Publishing activities	0.88	0.07	0.03	0.01	0.09	0.13	0.20	0.32	0.27	0.59
Motion picture, video and TV programme production	0.94	0.05	0.01	0.00	0.15	0.21	0.27	0.26	0.13	2.00
Programming and broadcasting activities	0.83	0.10	0.03	0.01	0.12	0.17	0.25	0.37	0.05	0.08
Telecommunications	0.91	0.06	0.02	0.01	0.24	0.28	0.30	0.16	0.02	0.16
Computer programming and related activities	0.91	0.07	0.02	0.00	0.14	0.20	0.31	0.31	0.04	2.71
Information service activities	0.94	0.05	0.02	0.00	0.23	0.25	0.30	0.17	0.05	0.20
Financial service activities w/o insurance	0.96	0.02	0.01	0.01	0.24	0.21	0.23	0.20	0.12	1.24
Activities auxiliary to financial services	0.96	0.03	0.00	0.00	0.13	0.17	0.25	0.31	0.14	1.68
Real estate activities	0.96	0.02	0.01	0.00	0.12	0.17	0.26	0.27	0.18	8.04
Legal and accounting activities	0.92	0.07	0.01	0.00	0.10	0.14	0.23	0.36	0.17	0.85
Activities of head offices and consultancy activities	0.98	0.01	0.00	0.00	0.13	0.19	0.29	0.25	0.15	13.82
Architectural and engineering activities	0.91	0.07	0.02	0.00	0.11	0.16	0.28	0.36	0.10	2.76
Scientific research and development	0.88	0.08	0.03	0.01	0.14	0.21	0.33	0.26	0.05	0.43
Advertising and market research	0.92	0.07	0.01	0.00	0.11	0.15	0.24	0.36	0.14	1.14
Other professional, scientific and technical activities	0.98	0.01	0.00	0.00	0.16	0.24	0.31	0.18	0.11	2.59
Veterinary activities	0.53	0.11	0.00	0.00	0.09	0.16	0.15	0.19	0.06	0.01
Rental and leasing activities	0.93	0.05	0.01	0.00	0.11	0.15	0.24	0.32	0.19	0.84
Employment activities	0.83	0.07	0.08	0.03	0.19	0.23	0.31	0.24	0.05	0.43
Travel agency, tour operator and related activities	0.93	0.06	0.01	0.00	0.10	0.14	0.23	0.37	0.16	0.63
Security and investigation activities	0.78	0.10	0.09	0.04	0.13	0.16	0.24	0.33	0.13	0.15
Services to buildings and landscape activities	0.83	0.10	0.04	0.02	0.11	0.14	0.22	0.33	0.20	0.98
Office administrative activities	0.94	0.04	0.02	0.01	0.18	0.22	0.29	0.23	0.09	2.20
Public administration and defence	0.87	0.08	0.05	0.02	0.11	0.17	0.29	0.33	0.11	0.13
Education	0.90	0.07	0.03	0.01	0.15	0.19	0.26	0.32	0.08	0.68
Human health activities	0.80	0.07	0.06	0.07	0.16	0.19	0.28	0.26	0.11	0.55
Residential care activities	0.70	0.12	0.14	0.04	0.10	0.16	0.28	0.33	0.13	0.37
Social work activities without accommodation	0.81	0.11	0.06	0.02	0.17	0.21	0.31	0.22	0.08	0.34
Creative, arts and entertainment activities	0.89	0.07	0.02	0.01	0.14	0.18	0.28	0.28	0.11	0.14
Libraries, archives, museums and other cultural activities	0.84	0.09	0.04	0.01	0.11	0.17	0.26	0.28	0.15	0.05
Gambling and betting activities	0.92	0.07	0.01	0.01	0.12	0.13	0.19	0.38	0.17	0.28
Sports activities and Amusement	0.90	0.08	0.01	0.00	0.15	0.19	0.27	0.28	0.10	0.52
Activities of prof and other membership org, trade unions	0.87	0.07	0.03	0.02	0.14	0.17	0.25	0.26	0.18	0.15
Repair of computers and personal equipment	0.90	0.08	0.02	0.00	0.08	0.12	0.24	0.35	0.22	0.20
Other personal service activities	0.93	0.05	0.02	0.00	0.18	0.20	0.26	0.24	0.12	1.88
Activities of households as employers of domestic personnel	0.38	0.02	0.00	0.00	0.02	0.06	0.24	0.08	0.00	0.00
Activities of extraterritorial organisations and bodies	0.30	0.04	0.00	0.03	0.01	0.02	0.16	0.05	0.14	0.00
Total	0.81	0.10	0.04	0.02	0.11	0.14	0.22	0.30	0.20	1.16
Industry level observations	86									

Source: Own calculations based on BvD Amadeus data

Table A.2.1: Size and age distribution across industries

	IPR activity all firms				IPR activity young firms			
NACE Rev. 2 division	National TM	OHIM TM	National Patents	EP Patents	National TM	OHIM TM	National Patents	EP Patents
Crop and animal production	58.3	2.0	32.0	7.7	98.9	0.1	1.0	0.0
Forestry and logging	53.9	1.9	35.2	9.0	93.2	0.1	6.6	0.1
Fishing and aquaculture	42.4	2.2	39.9	15.5	100.0	0.0	0.0	0.0
Mining of coal and lignite	28.9	0.0	0.0	71.1				
Extraction of crude petroleum and natural gas	42.8	0.0	38.4	18.9	100.0	0.0	0.0	0.0
Mining of metal ores	45.6	21.3	12.8	20.3				
Other mining and quarrying	33.8	3.9	42.4	20.0	97.5	0.0	2.1	0.4
Mining support service activities	35.4	5.1	32.2	27.4	100.0	0.0	0.0	0.0
Manufacture of food products	63.7	0.6	30.8	4.9	93.5	0.1	6.3	0.2
Manufacture of beverages	55.3	0.1	41.5	3.1	87.7	0.0	12.1	0.2
Manufacture of tobacco products	56.0	2.0	38.6	3.3	94.4	0.0	5.6	0.0
Manufacture of textiles	63.5	1.2	27.8	7.5	94.0	0.2	5.2	0.6
Manufacture of wearing apparel	63.5	0.6	32.8	3.1	95.0	0.1	4.9	0.1
Manufacture of leather and related products	71.2	0.7	25.4	2.7	98.4	0.0	1.6	0.0
Manufacture of wood and of products	72.1	1.4	21.8	4.7	97.5	0.2	2.1	0.3
Manufacture of paper and paper products	60.7	2.4	26.4	10.5	92.1	1.0	6.7	0.2
Printing and reproduction of recorded media	69.4	1.4	25.1	4.2	96.9	0.2	2.9	0.1
Manufacture of coke and refined petroleum products	45.5	6.7	35.6	12.2	91.4	6.3	0.0	2.3
Manufacture of chemicals and chemical products	47.3	1.6	35.7	15.4	88.8	0.5	8.4	2.4
Manufacture of basic pharmaceutical products	38.9	1.5	41.6	18.0	88.9	0.0	9.0	2.1
Manufacture of rubber and plastic products	57.0	4.8	24.7	13.6	91.7	1.4	5.2	1.7
Manufacture of other non	65.8	1.6	24.7	8.0	94.1	0.4	4.9	0.7
Manufacture of basic metals	65.8	2.9	21.8	9.5	95.3	0.8	2.9	1.1
Manufacture of fabricated metal products	65.4	3.4	22.4	8.7	96.3	0.7	2.3	0.7
Manufacture of computer, electronic and optical products	54.4	4.3	27.0	14.4	91.1	1.4	5.7	1.8
Manufacture of electrical equipment	56.7	4.1	23.8	15.3	93.1	1.7	3.6	1.7
Manufacture of machinery and equipment n.e.c.	55.3	6.7	22.0	16.0	92.0	2.4	3.7	1.9
Manufacture of motor vehicles, trailers and semi	60.0	4.7	20.5	14.8	94.6	0.9	3.2	1.4
Manufacture of other transport equipment	63.4	2.6	24.2	9.8	96.7	0.2	1.9	1.2
Manufacture of furniture	65.3	2.0	23.4	9.2	94.8	0.8	3.8	0.6
Other manufacturing	64.4	1.8	26.0	7.8	92.9	0.6	5.6	0.8
Repair and installation of machinery and equipment	70.5	1.5	23.0	5.0	98.3	0.1	1.5	0.2
Electricity, gas, steam and air conditioning supply	53.5	1.7	35.1	9.7	99.1	0.1	0.7	0.1
Water collection, treatment and supply	49.2	0.7	42.8	7.3	89.5	0.0	8.8	1.8
Sewerage	60.8	1.3	31.3	6.5	97.5	0.0	2.5	0.0
Waste collection, treatment and disposal activities	54.8	1.6	35.4	8.2	97.5	0.1	2.1	0.3
Remediation activities, other waste mgmnt services	56.7	1.2	32.5	9.7	97.0	1.2	1.8	0.0
Construction of buildings	62.2	2.6	27.1	8.1	98.7	0.1	1.1	0.1
Civil engineering	63.5	2.6	26.6	7.3	98.3	0.2	1.5	0.0
Specialised construction activities	61.0	3.2	26.5	9.2	98.5	0.2	1.1	0.1
Wholesale and retail trade	78.6	1.7	15.3	4.4	98.2	0.1	1.6	0.1
Wholesale trade w/o motor vehicles	70.6	2.4	20.7	6.3	95.2	0.4	4.1	0.3
Retail trade w/o motor vehicles	75.7	1.8	17.5	5.0	96.4	0.1	3.3	0.1
Land transport and transport via pipelines	89.9	0.6	7.8	1.7	99.1	0.0	0.9	0.0
Water transport	75.0	1.7	17.4	5.9	99.6	0.0	0.4	0.0
Air transport	80.7	1.2	15.3	2.7	100.0	0.0	0.0	0.0
Warehousing and support for transportation	85.2	0.9	11.5	2.4	98.6	0.0	1.3	0.1
Postal and courier activities	89.8	0.7	8.5	1.1	98.7	0.0	1.2	0.1
Accommodation	87.4	0.6	10.1	2.0	98.6	0.0	1.4	0.0
Food and beverage service activities	86.3	0.7	10.5	2.4	98.3	0.0	1.7	0.0
Publishing activities	57.5	1.5	32.9	8.1	94.0	0.1	5.9	0.1
Motion picture, video and TV programme production	61.9	2.3	27.8	8.0	96.1	0.2	3.6	0.2
Programming and broadcasting activities	51.4	1.8	39.8	6.9	91.0	0.0	8.7	0.3
Telecommunications	55.6	2.2	33.3	9.0	91.8	0.1	7.8	0.3
Computer programming and related activities	54.3	2.7	33.1	9.9	93.3	0.2	6.2	0.3
Information service activities	57.9	1.1	32.9	8.1	92.3	0.0	7.5	0.2
Financial service activities w/o insurance	88.0	0.4	9.9	1.6	98.8	0.0	1.2	0.0
Activities auxiliary to financial services	87.4	0.6	10.3	1.7	98.4	0.0	1.5	0.0
Real estate activities	87.3	0.9	9.4	2.4	99.0	0.0	0.9	0.0
Legal and accounting activities	90.0	0.4	8.0	1.5	98.8	0.0	1.1	0.0
Activities of head offices and consultancy activities	86.4	0.9	10.2	2.5	98.0	0.1	1.9	0.1
Architectural and engineering activities	81.8	2.5	11.8	3.9	96.5	0.8	2.4	0.4
Scientific research and development	36.6	4.1	37.7	21.5	88.7	1.9	6.6	2.8
Advertising and market research	78.7	0.7	18.3	2.3	95.5	0.0	4.4	0.0
Other professional, scientific and technical activities	88.1	0.6	9.2	2.0	97.8	0.1	2.0	0.1
Veterinary activities	80.8	4.1	11.8	3.3	100.0	0.0	0.0	0.0
Rental and leasing activities	88.8	0.7	8.9	1.7	98.4	0.1	1.5	0.0
Employment activities	86.3	0.4	12.1	1.2	97.8	0.0	2.1	0.0
Travel agency, tour operator and related activities	84.9	0.4	13.2	1.5	96.8	0.0	3.2	0.0
Security and investigation activities	89.2	0.2	9.1	1.5	98.6	0.0	1.2	0.2
Services to buildings and landscape activities	88.3	0.6	9.2	1.9	99.2	0.0	0.7	0.0
Office administrative activities	81.9	1.0	14.6	2.5	97.4	0.1	2.4	0.1
Public administration and defence	90.3	0.2	9.2	0.3	98.2	0.0	1.8	0.0
Education	83.8	0.4	13.8	2.0	97.6	0.0	2.3	0.0
Human health activities	84.3	0.5	13.4	1.8	97.7	0.0	2.2	0.1
Residential care activities	87.1	0.5	9.3	3.1	99.5	0.0	0.5	0.0
Social work activities without accommodation	87.4	0.4	10.4	1.7	99.2	0.0	0.8	0.0
Creative, arts and entertainment activities	82.4	0.4	14.8	2.4	97.1	0.0	2.9	0.0
Libraries, archives, museums and other cultural activities	80.5	0.6	16.0	2.8	98.2	0.0	1.8	0.0
Gambling and betting activities	88.6	0.5	9.4	1.5	99.2	0.0	0.8	0.0
Sports activities and Amusement	86.5	0.5	11.4	1.6	97.7	0.0	2.3	0.0
Activities of prof and other membership org, trade unions	85.0	0.4	13.9	0.8	97.5	0.2	2.2	0.0
Repair of computers and personal equipment	90.0	0.6	7.5	1.9	98.7	0.1	1.1	0.0
Other personal service activities	82.7	1.0	13.6	2.7	97.0	0.1	2.7	0.1
Activities of households as employers of domestic personnel	84.8	0.0	15.2	0.0	100.0	0.0	0.0	0.0
Activities of extraterritorial organisations and bodies	70.0	0.0	0.0	30.0	100.0	0.0	0.0	0.0
Total	68.8	1.9	21.5	7.8	96.4	0.3	3.0	0.4
Industry level observations	86							

Source: Own calculations based on BvD Amadeus, DPMA, OHIM and PATSTAT data

Table A.2.2: Patent and trade mark activity for all and young firms across industries

NACE Rev. 2 division	IPR use all IPR users				IPR use young IPR users			
	National TM	OHIM TM	National Patents	EP Patents	National TM	OHIM TM	National Patents	EP Patents
Crop and animal production	0.5	0.1	0.2	0.2	0.1	0.0	0.2	0.3
Forestry and logging	0.3	0.2	0.1	0.1	0.2	0.1	0.0	0.0
Fishing and aquaculture	1.0	0.0	0.1	0.0	0.0	0.0	0.2	0.0
Mining of coal and lignite	1.2	0.0	3.6	0.5	0.0	0.0	0.0	0.0
Extraction of crude petroleum and natural gas	0.3	0.2	0.2	0.1	0.0	0.0	0.0	0.0
Mining of metal ores	1.4	0.5	1.8	2.7	0.0	0.0	0.0	0.0
Other mining and quarrying	0.3	0.2	0.1	0.1	0.2	0.3	0.2	0.1
Mining support service activities	0.2	0.1	0.1	0.0	0.2	0.0	0.0	0.0
Manufacture of food products	3.6	1.8	0.6	1.0	1.3	0.6	0.2	0.2
Manufacture of beverages	5.8	2.0	0.6	0.4	3.5	1.1	0.3	0.2
Manufacture of tobacco products	9.2	1.4	1.9	2.3	1.1	0.4	0.1	0.3
Manufacture of textiles	1.8	1.3	2.3	3.4	0.6	0.6	0.8	1.4
Manufacture of wearing apparel	1.9	1.6	1.4	2.1	0.5	0.5	0.2	0.2
Manufacture of leather and related products	1.3	1.3	0.8	0.7	0.4	0.5	0.3	0.3
Manufacture of wood and of products	0.7	0.7	1.6	1.6	0.3	0.6	1.2	1.1
Manufacture of paper and paper products	1.8	2.4	2.3	2.0	1.3	1.8	0.8	0.8
Printing and reproduction of recorded media	0.6	0.5	2.3	4.7	0.4	0.4	0.2	0.1
Manufacture of coke and refined petroleum products	3.3	1.9	1.4	1.4	1.7	0.4	1.3	1.4
Manufacture of chemicals and chemical products	5.2	4.3	9.6	25.0	2.5	2.0	3.9	5.9
Manufacture of basic pharmaceutical products	19.5	7.7	8.4	32.4	4.7	1.9	1.9	6.3
Manufacture of rubber and plastic products	1.8	1.6	4.1	3.9	1.2	1.0	2.5	2.2
Manufacture of other non	1.9	1.5	3.7	4.0	0.8	0.5	1.3	1.6
Manufacture of basic metals	1.1	1.2	3.3	3.2	0.5	0.6	2.3	2.6
Manufacture of fabricated metal products	0.9	0.9	3.9	3.8	0.4	0.4	1.1	1.2
Manufacture of computer, electronic and optical products	1.9	1.6	8.1	7.1	1.3	1.2	3.5	4.0
Manufacture of electrical equipment	2.2	1.9	11.6	13.3	0.7	0.6	3.9	4.6
Manufacture of machinery and equipment n.e.c.	1.5	1.4	7.0	6.6	0.7	0.8	2.7	2.6
Manufacture of motor vehicles, trailers and semi	5.5	8.5	105.3	82.2	0.9	0.7	7.7	5.9
Manufacture of other transport equipment	1.4	1.4	16.8	18.5	0.6	0.5	3.6	2.2
Manufacture of furniture	2.0	1.3	2.8	2.2	1.1	0.7	0.7	0.4
Other manufacturing	1.6	1.4	2.8	3.1	0.8	0.8	1.8	1.9
Repair and installation of machinery and equipment	0.6	0.6	3.8	4.3	0.3	0.2	1.5	1.2
Electricity, gas, steam and air conditioning supply	0.4	0.1	0.1	0.1	0.1	0.0	0.1	0.0
Water collection, treatment and supply	0.5	0.1	0.4	0.2	0.2	0.3	0.3	0.1
Sewerage	0.3	0.1	0.3	0.1	0.2	0.1	0.3	0.1
Waste collection, treatment and disposal activities	0.3	0.2	0.2	0.2	0.2	0.1	0.1	0.2
Remediation activities, other waste mgmnt services	0.4	0.3	0.3	0.1	1.1	0.3	0.4	0.2
Construction of buildings	0.2	0.1	0.2	0.3	0.1	0.0	0.0	0.0
Civil engineering	0.2	0.1	0.4	0.3	0.1	0.1	0.2	0.1
Specialised construction activities	0.2	0.1	0.3	0.4	0.1	0.1	0.1	0.1
Wholesale and retail trade	0.5	0.3	0.8	0.8	0.3	0.2	0.3	0.4
Wholesale trade w/o motor vehicles	1.6	1.1	1.4	1.7	0.8	0.6	0.5	0.4
Retail trade w/o motor vehicles	0.8	0.6	0.5	0.6	0.5	0.3	0.2	0.2
Land transport and transport via pipelines	0.6	0.3	0.7	1.4	0.4	0.2	0.1	0.1
Water transport	0.9	0.1	0.2	0.5	0.6	0.1	0.0	0.0
Air transport	2.8	4.0	0.3	0.4	0.3	0.2	0.1	0.4
Warehousing and support for transportation	0.7	0.6	0.4	0.5	0.4	0.3	0.1	0.1
Postal and courier activities	3.4	3.7	2.8	7.0	0.8	1.6	0.4	0.2
Accommodation	2.1	0.3	0.3	0.5	0.9	0.2	0.1	0.2
Food and beverage service activities	1.6	0.2	0.1	0.1	0.9	0.1	0.0	0.0
Publishing activities	1.4	0.9	0.1	0.1	0.5	0.6	0.1	0.0
Motion picture, video and TV programme production	0.6	0.4	0.4	0.6	0.4	0.2	0.1	0.1
Programming and broadcasting activities	2.1	2.0	0.2	0.2	1.3	3.7	0.4	0.4
Telecommunications	6.0	5.4	2.5	3.1	0.6	0.6	0.4	0.6
Computer programming and related activities	0.8	0.6	0.3	0.7	0.6	0.5	0.2	0.2
Information service activities	0.7	0.5	0.1	0.1	0.5	0.4	0.0	0.1
Financial service activities w/o insurance	1.2	0.9	1.7	2.6	0.8	0.7	1.2	1.5
Activities auxiliary to financial services	0.8	0.4	0.5	0.9	0.5	0.2	0.1	0.1
Real estate activities	0.7	0.4	1.1	1.8	0.4	0.2	0.2	0.2
Legal and accounting activities	0.5	0.2	0.3	0.6	0.3	0.2	0.0	0.1
Activities of head offices and consultancy activities	1.0	0.8	1.1	1.3	0.7	0.5	0.3	0.3
Architectural and engineering activities	0.9	0.7	2.3	2.4	0.6	0.4	2.2	2.1
Scientific research and development	1.2	1.1	6.6	8.8	0.6	0.7	2.6	3.3
Advertising and market research	1.4	0.8	1.0	1.5	0.8	0.6	0.3	0.1
Other professional, scientific and technical activities	1.2	0.8	3.7	6.1	0.8	0.5	0.8	1.3
Veterinary activities	0.3	0.0	0.2	0.8	0.1	0.0	0.2	1.0
Rental and leasing activities	0.8	0.7	1.3	5.5	0.5	0.5	0.5	0.5
Employment activities	1.2	0.4	0.1	0.1	1.4	0.3	0.1	0.0
Travel agency, tour operator and related activities	1.0	0.6	0.1	0.1	0.5	0.3	0.1	0.0
Security and investigation activities	0.8	0.4	0.3	0.2	0.3	0.1	0.3	0.2
Services to buildings and landscape activities	0.6	0.3	0.4	0.4	0.3	0.1	0.2	0.1
Office administrative activities	1.3	0.9	1.4	2.0	0.8	0.7	0.5	0.8
Public administration and defence	1.2	0.7	0.3	0.1	0.9	1.0	0.3	0.1
Education	0.9	0.5	0.7	1.0	0.6	0.2	0.2	0.1
Human health activities	1.1	0.8	0.5	1.0	0.8	0.3	0.2	0.5
Residential care activities	2.4	0.0	0.1	0.2	2.0	0.0	0.1	0.1
Social work activities without accommodation	0.7	0.2	0.1	0.1	0.4	0.1	0.1	0.0
Creative, arts and entertainment activities	1.6	0.4	0.3	0.2	0.6	0.2	0.2	0.2
Libraries, archives, museums and other cultural activities	1.0	0.6	0.1	0.2	0.3	0.4	0.1	0.2
Gambling and betting activities	0.9	0.6	0.3	0.6	0.3	0.2	0.1	0.1
Sports activities and Amusement	1.1	1.2	0.4	0.5	0.7	0.4	0.1	0.1
Activities of prof and other membership org, trade unions	1.4	0.7	3.0	2.0	1.0	0.6	0.3	0.4
Repair of computers and personal equipment	0.8	0.6	0.5	1.1	0.5	0.4	0.4	0.2
Other personal service activities	1.0	0.6	0.9	1.1	0.6	0.4	0.5	0.7
Activities of households as employers of domestic personnel	1.8	0.0	0.0	0.0	0.9	0.0	0.0	0.0
Undifferentiated products	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Activities of extraterritorial organisations and bodies	3.7	0.8	0.2	0.0	0.0	0.0	0.0	0.0
Total	1.7	1.0	2.9	3.4	0.7	0.5	0.7	0.8
Industry level observations	87							

Source: Own calculations based on BvD Amadeus, DPMA, OHIM and PATSTAT data

Table A.2.3: Average patent and trade mark use for all and young IPR-active firms across industries

Left panel: Average number of registered IPRs by IPR-activity types. Right panel: Average number of registered IPRs by firms that were IPR-active in their first two years after entry.

NACE Rev. 2 division	Gross entry rates Mean	Sd	Min	Max
Crop and animal production	5.5	2.5	1.3	14.1
Forestry and logging	8.3	3.2	1.9	19.3
Fishing and aquaculture	7.0	17.3	0.0	100.0
Mining of coal and lignite	0.0	0.0	0.0	0.0
Extraction of crude petroleum and natural gas	6.8	6.6	0.0	20.0
Mining of metal ores	0.0	0.0	0.0	0.0
Other mining and quarrying	1.7	1.4	0.0	5.6
Mining support service activities	11.3	24.4	0.0	100.0
Manufacture of food products	3.3	1.3	1.4	10.9
Manufacture of beverages	3.4	2.0	0.0	10.4
Manufacture of tobacco products	3.0	4.7	0.0	16.7
Manufacture of textiles	4.0	2.4	1.0	18.1
Manufacture of wearing apparel	4.5	2.9	0.0	17.0
Manufacture of leather and related products	3.8	4.6	0.0	33.5
Manufacture of wood and of products	3.2	1.3	1.0	7.5
Manufacture of paper and paper products	2.7	1.8	0.0	12.2
Printing and reproduction of recorded media	3.1	1.2	0.7	7.3
Manufacture of coke and refined petroleum products	5.0	8.4	0.0	50.0
Manufacture of chemicals and chemical products	4.6	2.1	1.8	13.1
Manufacture of basic pharmaceutical products	4.3	2.5	0.0	12.7
Manufacture of rubber and plastic products	3.0	1.3	1.0	8.6
Manufacture of other non	2.6	1.0	0.9	7.3
Manufacture of basic metals	4.1	1.5	1.3	8.0
Manufacture of fabricated metal products	3.1	0.8	1.8	6.1
Manufacture of computer, electronic and optical products	3.9	1.5	1.3	10.6
Manufacture of electrical equipment	3.3	1.3	0.0	8.9
Manufacture of machinery and equipment n.e.c.	4.2	1.8	2.1	16.6
Manufacture of motor vehicles, trailers and semi	3.2	1.5	0.0	7.9
Manufacture of other transport equipment	4.9	3.0	0.0	14.6
Manufacture of furniture	3.2	1.8	0.0	9.1
Other manufacturing	3.2	0.9	1.7	6.6
Repair and installation of machinery and equipment	7.7	2.2	3.7	16.0
Electricity, gas, steam and air conditioning supply	13.9	3.4	6.9	23.9
Water collection, treatment and supply	2.7	4.1	0.0	20.8
Sewerage	4.1	3.0	0.0	15.5
Waste collection, treatment and disposal activities	4.2	1.4	1.2	9.5
Remediation activities, other waste mgmnt services	7.9	9.9	0.0	60.0
Construction of buildings	3.8	1.0	2.0	7.6
Civil engineering	4.3	1.5	1.2	10.7
Specialised construction activities	3.8	0.8	2.1	7.1
Wholesale and retail trade	4.0	1.0	1.9	8.5
Wholesale trade w/o motor vehicles	4.7	1.0	3.1	9.9
Retail trade w/o motor vehicles	4.1	0.9	2.5	8.3
Land transport and transport via pipelines	4.2	1.3	2.2	9.2
Water transport	4.4	4.8	0.0	21.4
Air transport	3.7	5.0	0.0	29.2
Warehousing and support for transportation	6.3	1.4	3.9	11.7
Postal and courier activities	9.6	4.2	0.0	28.9
Accommodation	4.7	1.2	2.4	8.9
Food and beverage service activities	8.6	1.6	4.8	14.4
Publishing activities	4.7	1.6	1.6	9.8
Motion picture, video and TV programme production	7.0	1.8	1.9	12.7
Programming and broadcasting activities	6.3	6.1	0.0	40.0
Telecommunications	13.0	4.8	0.0	31.2
Computer programming and related activities	7.0	1.2	4.7	11.7
Information service activities	11.9	4.4	0.0	25.0
Financial service activities w/o insurance	13.8	2.9	8.9	29.2
Activities auxiliary to financial services	6.8	1.3	4.2	12.0
Real estate activities	5.6	1.0	3.6	9.1
Legal and accounting activities	5.2	1.2	2.0	8.1
Activities of head offices and consultancy activities	6.7	0.9	4.8	9.5
Architectural and engineering activities	5.4	1.0	3.8	8.1
Scientific research and development	7.1	1.5	3.0	13.4
Advertising and market research	5.8	1.2	2.8	8.9
Other professional, scientific and technical activities	7.3	1.5	3.8	11.9
Veterinary activities	3.3	5.5	0.0	20.8
Rental and leasing activities	5.2	1.5	2.1	10.5
Employment activities	10.0	2.3	5.2	18.9
Travel agency, tour operator and related activities	5.0	1.3	2.1	8.8
Security and investigation activities	7.0	2.8	0.8	15.4
Services to buildings and landscape activities	5.9	1.5	2.9	10.6
Office administrative activities	9.0	1.9	4.8	14.2
Public administration and defence	5.3	3.1	0.0	16.9
Education	7.7	1.8	1.9	11.3
Human health activities	7.9	1.8	4.4	13.0
Residential care activities	5.0	1.5	2.7	8.6
Social work activities without accommodation	9.0	2.8	1.8	25.1
Creative, arts and entertainment activities	7.8	4.9	0.0	40.0
Libraries, archives, museums and other cultural activities	4.7	4.2	0.0	20.0
Gambling and betting activities	6.1	2.2	0.0	13.5
Sports activities and Amusement	7.9	1.4	4.5	13.6
Activities of prof and other membership org, trade unions	6.9	3.9	0.0	25.8
Repair of computers and personal equipment	3.7	1.8	0.0	9.6
Other personal service activities	9.0	2.1	4.3	15.4
Activities of households as employers of domestic personnel	1.0	2.9	0.0	8.3
Activities of extraterritorial organisations and bodies	8.3	14.4	0.0	25.0
Total	5.7	4.4	0.0	100.0
Industry-region level observations	7,352			

Source: Own calculations based on BvD Amadeus, DPMA, OHIM and PATSTAT data

Table A.2.4: Average gross entry rates across industries
Average gross entry rates in percent at the industry level. Gross entry is calculated as the proportion of new firms in a given industry and region. Regions are weighted by their relative size (in terms of number of firms) within an industry.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Logarithmic gross entry rate	1.00													
Log of capital intensity	−0.03 (0.00)	1.00												
National TM-activity rate	−0.07 (0.00)	0.28 (0.00)	1.00											
CTM-activity rate	−0.06 (0.00)	0.24 (0.00)	0.89 (0.00)	1.00										
National patent-activity rate	−0.01 (0.41)	0.06 (0.00)	0.40 (0.00)	0.63 (0.00)	1.00									
EP-activity rate	0.01 (0.18)	0.12 (0.00)	0.52 (0.00)	0.76 (0.00)	0.96 (0.00)	1.00								
National TM stock per firm	−0.12 (0.00)	0.25 (0.00)	0.69 (0.00)	0.63 (0.00)	0.14 (0.00)	0.29 (0.00)	1.00							
CTM stock per firm	−0.10 (0.00)	0.06 (0.00)	0.44 (0.00)	0.51 (0.00)	0.25 (0.00)	0.32 (0.00)	0.69 (0.00)	1.00						
National patent stock per firm	−0.01 (0.34)	−0.09 (0.00)	0.10 (0.00)	0.30 (0.00)	0.47 (0.00)	0.50 (0.00)	0.24 (0.00)	0.63 (0.00)	1.00					
EP stock per firm	0.00 (0.75)	−0.09 (0.00)	0.16 (0.00)	0.36 (0.00)	0.35 (0.00)	0.42 (0.00)	0.29 (0.00)	0.66 (0.00)	0.93 (0.00)	1.00				
National TM apps per firm	−0.01 (0.24)	0.12 (0.00)	0.20 (0.00)	0.15 (0.00)	−0.01 (0.40)	0.05 (0.00)	0.28 (0.00)	0.13 (0.00)	−0.00 (0.77)	0.02 (0.00)	1.00			
EP TM apps per firm	0.01 (0.06)	0.04 (0.00)	0.11 (0.00)	0.12 (0.00)	0.08 (0.00)	0.10 (0.00)	0.11 (0.00)	0.15 (0.00)	0.08 (0.00)	0.10 (0.00)	0.34 (0.00)	1.00		
National patent apps per firm	0.03 (0.00)	0.04 (0.00)	0.04 (0.00)	0.14 (0.00)	0.32 (0.00)	0.31 (0.00)	0.02 (0.00)	0.08 (0.00)	0.29 (0.00)	0.22 (0.00)	0.24 (0.00)	0.29 (0.00)	1.00	
EP apps per firm	0.03 (0.00)	0.05 (0.00)	0.10 (0.00)	0.19 (0.00)	0.28 (0.00)	0.29 (0.00)	0.07 (0.00)	0.14 (0.00)	0.28 (0.00)	0.27 (0.00)	0.24 (0.00)	0.31 (0.00)	0.75 (0.00)	1.00

Note: P-values in parentheses

Table A.2.5: Correlation table

	OLS								
Dep. var.: Deviation from mean of log of gross entry rate	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lag-logarithmic gross entry rate									-0.0177^{**}
									(0.00715)
Industry-region level effects									
Lag-log of turnover	0.00154	0.00373	0.00477	0.00609	0.00296	0.00197	0.0111	0.00720	0.00721
	(0.0103)	(0.0103)	(0.0103)	(0.0103)	(0.0102)	(0.0103)	(0.0100)	(0.0103)	(0.0104)
Lag-log of capital intensity	-0.0312^{***}	-0.0329^{***}	-0.0316^{***}	-0.0326^{***}	-0.0315^{***}	-0.0305^{***}	-0.0275^{***}	-0.0330^{***}	-0.0332^{***}
	(0.0103)	(0.0103)	(0.0103)	(0.0103)	(0.0103)	(0.0103)	(0.00999)	(0.0102)	(0.0103)
Lag-log of national TM apps per firm					-0.0240		-0.0281	-0.0247	-0.0249
					(0.0352)		(0.0352)	(0.0351)	(0.0351)
Lag-log of CTM apps per firm					-0.0108		-0.0103	-0.0106	-0.0107
					(0.0201)		(0.0200)	(0.0202)	(0.0202)
Lag-log of national patent apps per firm						-0.00388	0.00123	0.00286	0.00288
						(0.0157)	(0.0157)	(0.0157)	(0.0158)
Lag-log of EP apps per firm						-0.0148	-0.0167	-0.0147	-0.0151
						(0.0122)	(0.0121)	(0.0122)	(0.0122)
Industry effects:									
Lag-log of national TM stock per firm					-0.477^{***}		-0.226^{**}	-0.146	-0.146
					(0.100)		(0.0965)	(0.119)	(0.120)
Lag-log of CTM stock per firm					0.277^{***}		0.294^{***}	0.384^{***}	0.389^{***}
					(0.0573)		(0.0612)	(0.0626)	(0.0633)
Lag-log of national patent stock per firm						-0.162^{***}	-0.120^{***}	-0.202^{***}	-0.202^{***}
						(0.0402)	(0.0392)	(0.0396)	(0.0398)
Lag-log of EP stock per firm						0.140^{***}	0.0823^{***}	0.108^{***}	0.108^{***}
						(0.0261)	(0.0252)	(0.0255)	(0.0256)
Lagged national TM-activity rate		-0.0117		-0.0146^{*}				-0.0162^{*}	-0.0156^{*}
		(0.00816)		(0.00816)				(0.00832)	(0.00837)
Lagged CTM-activity rate		-0.00991		0.0121				0.00631	0.00553
		(0.0179)		(0.0184)				(0.0186)	(0.0187)
Lagged national patent-activity rate			-0.0916^{***}	-0.0864^{***}				-0.100^{***}	-0.101^{***}
			(0.0223)	(0.0215)				(0.0225)	(0.0227)
Lagged EP-activity rate			0.0904^{***}	0.0950^{***}				0.114^{***}	0.114^{***}
			(0.0284)	(0.0268)				(0.0301)	(0.0303)
Control variables									
Lag-log of age	-0.243	-0.372^{*}	-0.339^{*}	-0.416^{**}	-0.205	-0.252		-0.334^{*}	-0.365^{*}
	(0.187)	(0.203)	(0.196)	(0.206)	(0.193)	(0.190)		(0.202)	(0.205)
(Lag-log of age)^2	0.127^{***}	0.161^{***}	0.152^{***}	0.170^{***}	0.127^{***}	0.134^{***}		0.158^{***}	0.157^{***}
	(0.0351)	(0.0388)	(0.0369)	(0.0391)	(0.0366)	(0.0358)		(0.0385)	(0.0389)
Holding rate	0.888^{***}	0.847^{***}	0.854^{***}	0.851^{***}	0.882^{***}	0.855^{***}	0.911^{***}	0.843^{***}	0.830^{***}
	(0.206)	(0.206)	(0.208)	(0.207)	(0.204)	(0.207)	(0.192)	(0.205)	(0.206)
Real growth rate	0.0118^{***}	0.0154^{***}	0.0143^{***}	0.0162^{***}	0.0276^{***}	0.0196^{***}	0.0162^{***}	0.0289^{***}	0.0288^{***}
	(0.00382)	(0.00382)	(0.00366)	(0.00381)	(0.00483)	(0.00540)	(0.00518)	(0.00566)	(0.00569)
PLC rate	-0.328^{*}								
	(0.172)								
Constant	1.561^{***}	1.783^{***}	1.700^{***}	1.994^{***}	1.469^{***}	1.293^{***}	1.639^{***}	1.976^{***}	2.094^{***}
	(0.305)	(0.322)	(0.289)	(0.330)	(0.285)	(0.264)	(0.0814)	(0.324)	(0.332)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TM vars F-stat					8.8		6.11	9.71	9.74
PAT vars F-stat						7.76	3.31	7.11	7.09
Size F-Stat	4.57	5.06	4.72	5.02	4.73	4.41	4.12	5.28	5.28
Controls F-Stat	16.8	19.7	19.1	20.9	29.1	17.9	19	25.1	24.2
Year F-Stat	26.6	41	44.8	42	33.1	44.8	27.7	35.9	35.5
R^2 within	.0219	.0224	.023	.0232	.023	.0225	.0181	.0252	.0255
Obs	53,127	53,127	53,127	53,127	53,127	53,127	53,129	53,127	53,127

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.2.6: Robustness: Firm entry all sectors, OLS stepwise

Stepwise results from estimating equation (3.2).

	GMM							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. var.: First-differenced log of gross entry rate								
Lag-logarithmic gross entry rate	0.119	−0.0699	0.0657	−0.0819	−0.367*	−0.237	−0.369***	−0.366***
	(0.602)	(0.537)	(0.572)	(0.536)	(0.204)	(0.165)	(0.139)	(0.140)
Industry-region level effects								
Lag-log of turnover	−0.667	0.173	−0.352	0.202	0.0142	−0.357*	−0.187	−0.188
	(0.957)	(0.948)	(0.951)	(0.976)	(0.257)	(0.212)	(0.186)	(0.192)
Lag-log of capital intensity	−2.092*	−1.721*	−1.938*	−1.794*	−1.911***	−0.605	−1.023**	−1.062**
	(1.116)	(0.960)	(1.020)	(0.965)	(0.524)	(0.518)	(0.454)	(0.470)
Lag-log of national TM apps per firm					−0.254		0.0593	−0.0154
					(0.376)		(0.358)	(0.361)
Lag-log of CTM apps per firm					−1.039**		−0.508*	−0.566*
					(0.446)		(0.295)	(0.292)
Lag-log of national patent apps per firm						0.00553	−0.0366	0.0412
						(0.252)	(0.213)	(0.225)
Lag-log of EP apps per firm						−0.344	−0.262	−0.293
						(0.248)	(0.197)	(0.204)
Industry effects:								
Lag-log of national TM stock per firm					−1.092***		−0.924***	−0.372
					(0.254)		(0.251)	(0.237)
Lag-log of CTM stock per firm					0.649***		0.382**	0.535***
					(0.183)		(0.159)	(0.171)
Lag-log of national patent stock per firm						−0.0629	0.0443	0.00957
						(0.0801)	(0.0837)	(0.0837)
Lag-log of EP stock per firm						0.114**	0.0628	0.0617
						(0.0533)	(0.0480)	(0.0488)
Lagged national TM-activity rate		−0.0321		−0.0341				−0.00445
		(0.0360)		(0.0364)				(0.0190)
Lagged CTM-activity rate		−0.0433		−0.0456				−0.0741**
		(0.0559)		(0.0571)				(0.0362)
Lagged national patent-activity rate			−0.0962*	−0.0656				−0.0700**
			(0.0495)	(0.0401)				(0.0310)
Lagged EP-activity rate			0.0500	0.103				0.103**
			(0.0655)	(0.0655)				(0.0485)
Control variables								
Lag-log of age	3.723	2.630	3.328	2.540	1.452	1.823**	1.249*	1.176
	(2.797)	(2.472)	(2.620)	(2.458)	(1.020)	(0.900)	(0.756)	(0.748)
(Lag-log of age)^2	0.0919	0.124	0.116	0.132	0.0964	0.131	0.134	0.157*
	(0.195)	(0.149)	(0.176)	(0.145)	(0.0939)	(0.0995)	(0.0877)	(0.0861)
Holding rate	3.206*	2.161	2.841	2.136	1.908***	1.751***	1.612***	1.552***
	(1.918)	(1.688)	(1.817)	(1.701)	(0.700)	(0.643)	(0.567)	(0.563)
realgrowth_DE	0.283**	0.212**	0.257**	0.215**	0.225***	0.115**	0.154***	0.163***
	(0.113)	(0.103)	(0.105)	(0.103)	(0.0488)	(0.0514)	(0.0495)	(0.0521)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sargan J p-value	.623	.433	.612	.45	.473	.0225	.124	.149
Hansen robust p	.609	.515	.613	.511	.689	.0611	.326	.357
Arellano-Bond AR(1) p	.173	.251	.189	.243	.0127	.0501	.05	.0452
Arellano-Bond AR(2) p	.958	.844	.987	.823	.0465	.129	.0053	.0061
Arellano-Bond AR(3) p	.193	.205	.169	.218	.197	.401	.293	.344
χ^2	816	1,141	959	1,164	1,679	1,617	1,816	1,839
Number of instruments	21	23	23	25	49	49	77	81
Obs	45,744	45,744	45,744	45,744	45,744	45,744	45,744	45,744

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.2.7: Robustness: Firm entry all sectors, GMM stepwise

Stepwise results from estimating equation(3.7).

	GMM							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. var.: First-differenced log of gross entry rate								
Lag-logarithmic gross entry rate	−0.234*	−0.277**	−0.319**	−0.366***	−0.437***	−0.231*	−0.340**	−0.359**
	(0.130)	(0.128)	(0.130)	(0.140)	(0.159)	(0.135)	(0.152)	(0.140)
Industry-region level effects								
Lag-log of turnover	−0.270*	−0.297*	−0.325**	−0.188	0.0649	−0.391**	−0.297	−0.184
	(0.156)	(0.155)	(0.159)	(0.192)	(0.233)	(0.177)	(0.192)	(0.190)
Lag-log of capital intensity	−0.657**	−0.680**	−0.661*	−1.062**	−1.449**	−0.0137	−0.0461	−1.155**
	(0.296)	(0.300)	(0.342)	(0.470)	(0.580)	(0.188)	(0.217)	(0.470)
Lag-log of national TM apps per firm	−0.125	−0.102	0.0522	−0.0154	0.127	0.176	0.0973	−0.0485
	(0.303)	(0.294)	(0.298)	(0.361)	(0.444)	(0.342)	(0.336)	(0.362)
Lag-log of CTM apps per firm	−0.103	−0.109	−0.319	−0.566*	−1.012***	−0.364	−0.424	−0.621**
	(0.194)	(0.199)	(0.247)	(0.292)	(0.374)	(0.305)	(0.305)	(0.282)
Lag-log of national patent apps per firm	−0.0351	−0.0188	−0.0735	0.0412	−0.185	−0.0273	−0.0587	0.106
	(0.145)	(0.144)	(0.170)	(0.225)	(0.345)	(0.188)	(0.202)	(0.222)
Lag-log of EP apps per firm	−0.0722	−0.0955	−0.107	−0.293	−0.182	−0.302*	−0.284	−0.360*
	(0.125)	(0.125)	(0.149)	(0.204)	(0.356)	(0.177)	(0.186)	(0.209)
Industry effects:								
Lag-log of national TM stock per firm	−0.342	−0.332	−0.323	−0.372	−0.406*	−0.275	−0.263	−0.374
	(0.233)	(0.229)	(0.226)	(0.237)	(0.240)	(0.223)	(0.215)	(0.244)
Lag-log of CTM stock per firm	0.463***	0.458***	0.464***	0.535***	0.632***	0.472***	0.420***	0.575***
	(0.136)	(0.136)	(0.143)	(0.171)	(0.175)	(0.140)	(0.143)	(0.173)
Lag-log of national patent stock per firm	−0.0633	−0.0603	−0.0431	0.00957	0.100	−0.0652	−0.0307	0.0121
	(0.0766)	(0.0765)	(0.0772)	(0.0837)	(0.0934)	(0.0803)	(0.0807)	(0.0851)
Lag-log of EP stock per firm	0.0515	0.0494	0.0492	0.0617	0.0399	0.0725*	0.0542	0.0731
	(0.0397)	(0.0394)	(0.0411)	(0.0488)	(0.0663)	(0.0417)	(0.0430)	(0.0502)
Lagged national TM-activity rate	−0.00729	−0.00340	−0.00229	−0.00445	−0.00676	0.00628	0.00534	−0.00482
	(0.0212)	(0.0205)	(0.0200)	(0.0190)	(0.0197)	(0.0214)	(0.0198)	(0.0196)
Lagged CTM-activity rate	−0.0745*	−0.0763*	−0.0762**	−0.0741**	−0.0838**	−0.0855*	−0.0841**	−0.0779**
	(0.0416)	(0.0402)	(0.0384)	(0.0362)	(0.0368)	(0.0449)	(0.0395)	(0.0375)
Lagged national patent-activity rate	−0.0573*	−0.0566*	−0.0568*	−0.0700**	−0.0762**	−0.0681*	−0.0653**	−0.0756**
	(0.0321)	(0.0315)	(0.0309)	(0.0310)	(0.0325)	(0.0371)	(0.0331)	(0.0327)
Lagged EP-activity rate	0.0894*	0.0851*	0.0858*	0.103**	0.119**	0.105*	0.103*	0.113**
	(0.0490)	(0.0480)	(0.0476)	(0.0485)	(0.0500)	(0.0604)	(0.0539)	(0.0513)
Control variables								
Lag-log of age	1.380*	1.247*	1.171	1.176	0.954	1.488**	1.055	1.203
	(0.724)	(0.712)	(0.722)	(0.748)	(0.821)	(0.697)	(0.715)	(0.759)
(Lag-log of age)^2	0.226**	0.219**	0.201**	0.157*	0.138	0.214**	0.199**	0.158*
	(0.110)	(0.106)	(0.101)	(0.0861)	(0.0860)	(0.103)	(0.0849)	(0.0894)
Holding rate	1.570***	1.490***	1.483***	1.552***	1.464**	1.604***	1.389**	1.578***
	(0.584)	(0.570)	(0.558)	(0.563)	(0.589)	(0.572)	(0.557)	(0.566)
realgrowth_DE	0.144***	0.143***	0.136***	0.163***	0.186***	0.0838***	0.0720**	0.173***
	(0.0344)	(0.0345)	(0.0394)	(0.0521)	(0.0609)	(0.0259)	(0.0313)	(0.0520)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sargan J p-value	$1.06e-08$	$7.89e-09$	$2.01e-07$	.149	.483	$1.21e-15$	$5.98e-13$	.115
Hansen robust p	.174	.166	.215	.357	.528	.00144	.00107	.383
Arellano-Bond AR(1) p	.0133	.0209	.0399	.0452	.0346	.0205	.118	.0295
Arellano-Bond AR(2) p	.0645	.0264	.0111	.0061	.00342	.0794	.0235	.00694
Arellano-Bond AR(3) p	.363	.425	.438	.344	.265	.608	.764	.334
χ^2	1,428	1,485	1,578	1,839	1,843	1,697	1,946	1,768
Number of instruments	141	137	117	81	57	102	94	87
Obs	45,744	45,744	45,744	45,744	45,744	45,744	45,744	45,744

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.2.8: Robustness: Firm entry all sectors, GMM

Results from estimating equation (3.7). Same model using different number of instruments.

	GMM							
Dep. var.: First-differenced log of gross entry rate	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lag-logarithmic gross entry rate						−0.369**		
						(0.145)		
Industry-region level effects								
Lag-log of turnover	−0.324*	−0.362**	−0.351**	−0.222	0.0102	−0.325	−0.600*	−0.250
	(0.166)	(0.166)	(0.179)	(0.217)	(0.300)	(0.302)	(0.324)	(0.209)
Lag-log of capital intensity	−0.596*	−0.590*	−0.706*	−1.123*	−1.577*			−0.669
	(0.335)	(0.346)	(0.413)	(0.576)	(0.875)			(0.537)
Lag-log of national TM apps per firm	−0.231	−0.234	−0.106	−0.158	−0.120	−0.261	−0.497	−0.251
	(0.314)	(0.309)	(0.317)	(0.377)	(0.513)	(0.397)	(0.425)	(0.384)
Lag-log of CTM apps per firm	−0.0175	−0.0155	−0.251	−0.463	−0.731	−0.355	−0.388	−0.300
	(0.194)	(0.202)	(0.259)	(0.328)	(0.462)	(0.314)	(0.323)	(0.312)
Lag-log of national patent apps per firm	0.0177	0.0381	0.00737	0.194	0.113	−0.0680	0.128	0.254
	(0.137)	(0.137)	(0.169)	(0.205)	(0.378)	(0.218)	(0.209)	(0.199)
Lag-log of EP apps per firm	−0.121	−0.148	−0.192	−0.456**	−0.492	−0.202	−0.363*	−0.451**
	(0.124)	(0.123)	(0.150)	(0.204)	(0.419)	(0.197)	(0.203)	(0.205)
Industry effects:								
Lag-log of national TM stock per firm	−0.350	−0.344	−0.371	−0.467*	−0.505*	−0.128	−0.138	−0.0959
	(0.242)	(0.243)	(0.244)	(0.265)	(0.290)	(0.230)	(0.267)	(0.241)
Lag-log of CTM stock per firm	0.490***	0.488***	0.532***	0.615***	0.716***	0.318**	0.480***	0.319*
	(0.137)	(0.138)	(0.148)	(0.187)	(0.228)	(0.152)	(0.160)	(0.172)
Lag-log of national patent stock per firm	−0.0966	−0.102	−0.0733	−0.0271	0.0516	−0.0318	−0.104	−0.0177
	(0.0806)	(0.0812)	(0.0855)	(0.0952)	(0.116)	(0.0754)	(0.0778)	(0.0928)
Lag-log of EP stock per firm	0.0763**	0.0791**	0.0870**	0.119**	0.125*	0.0475	0.101**	0.0674
	(0.0386)	(0.0387)	(0.0409)	(0.0481)	(0.0744)	(0.0456)	(0.0459)	(0.0476)
Lagged national TM-activity rate	−0.0258	−0.0246	−0.0275	−0.0308	−0.0345	0.00994	−0.0177	0.00637
	(0.0206)	(0.0206)	(0.0205)	(0.0212)	(0.0223)	(0.0179)	(0.0211)	(0.0157)
Lagged CTM-activity rate	−0.0525	−0.0518	−0.0517	−0.0454	−0.0529	−0.0627*	−0.0374	−0.0102
	(0.0436)	(0.0436)	(0.0431)	(0.0442)	(0.0455)	(0.0344)	(0.0437)	(0.0306)
Lagged national patent-activity rate	−0.0623*	−0.0616*	−0.0658**	−0.0807**	−0.0909**	−0.0353	−0.0488	−0.0109
	(0.0331)	(0.0331)	(0.0334)	(0.0362)	(0.0402)	(0.0288)	(0.0357)	(0.0281)
Lagged EP-activity rate	0.0995**	0.0966*	0.104**	0.119**	0.138**	0.0447	0.0628	0.0182
	(0.0499)	(0.0496)	(0.0504)	(0.0552)	(0.0592)	(0.0425)	(0.0510)	(0.0394)
Control variables								
Lag-log of age	2.247***	2.279***	2.391***	2.635***	2.789***	0.841	2.467***	
	(0.654)	(0.666)	(0.679)	(0.749)	(0.783)	(0.739)	(0.677)	
(Lag-log of age)^2	0.250**	0.246**	0.228*	0.183	0.150	0.250***	0.254**	
	(0.124)	(0.125)	(0.127)	(0.138)	(0.144)	(0.0848)	(0.128)	
Holding rate	2.208***	2.232***	2.293***	2.447***	2.525***	1.249**	2.340***	2.783***
	(0.554)	(0.554)	(0.547)	(0.558)	(0.593)	(0.545)	(0.586)	(0.430)
realgrowth_DE	0.163***	0.163***	0.173***	0.207***	0.244***	0.0207	0.113	0.0572
	(0.0331)	(0.0342)	(0.0404)	(0.0555)	(0.0812)	(0.0662)	(0.0779)	(0.0508)
Lag-log of employment						−0.632	−0.767*	
						(0.412)	(0.433)	
Lag-log of total assets						0.0308	−0.272	
						(0.335)	(0.419)	
(Lag-log total assets)x(Lag-log employment)						0.0568	0.124	
						(0.0727)	(0.0878)	
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sargan J p-value	$7.39e-08$	$7.30e-08$	$2.84e-06$	.0788	.308	.0000369	.00231	.0703
Hansen robust p	.096	.0894	.111	.277	.41	.051	.0912	.383
Arellano-Bond AR(1) p	$2.2e-153$	$4.1e-152$	$1.5e-100$	$2.49e-31$	$4.91e-11$	.0942	$7.3e-112$	$6.45e-96$
Arellano-Bond AR(2) p	.564	.517	.404	.393	.25	.00735	.136	.19
Arellano-Bond AR(3) p	.205	.223	.16	.124	.102	.942	.411	.605
χ^2	1,158	1,160	1,174	1,094	1,022	2,106	1,208	593
Number of instruments	132	128	108	72	48	81	72	70
Obs	45,744	45,744	45,744	45,744	45,744	51,481	51,481	45,746

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.2.9: Robustness: Firm entry all sectors, GMM no lagged dependent variable

Results from estimating equation (3.2) using difference GMM. Same model using different number of instruments.

	OLS								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dep. var.: Deviation from mean of log of gross entry rate									
Lag-logarithmic gross entry rate									−0.0224***
									(0.00680)
Industry-region level effects									
Lag-log of turnover	−0.00691	−0.00319	−0.00680	−0.00212	−0.00739	−0.00881	−0.00824	−0.00366	−0.00341
	(0.00979)	(0.00980)	(0.00976)	(0.00981)	(0.00970)	(0.00978)	(0.00971)	(0.00977)	(0.00984)
Lag-log of capital intensity	−0.0323***	−0.0332***	−0.0334***	−0.0336***	−0.0333***	−0.0310***	−0.0324***	−0.0326***	−0.0330***
	(0.0101)	(0.0101)	(0.0101)	(0.0101)	(0.0101)	(0.0101)	(0.0100)	(0.0100)	(0.0101)
Lag-log of national TM apps per firm					−0.0441		−0.0426	−0.0396	−0.0396
					(0.0360)		(0.0361)	(0.0360)	(0.0360)
Lag-log of CTM apps per firm					−0.00689		−0.00543	−0.00521	−0.00531
					(0.0200)		(0.0200)	(0.0200)	(0.0201)
Lag-log of national patent apps per firm						−0.00807	−0.00643	−0.00342	−0.00334
						(0.0155)	(0.0155)	(0.0156)	(0.0156)
Lag-log of EP apps per firm						−0.00817	−0.00929	−0.00999	−0.0105
						(0.0121)	(0.0121)	(0.0121)	(0.0121)
Lags of industry effects:									
Lag-log of national TM stock per firm (young)					−0.423***		−0.384***	−0.275***	−0.277***
					(0.0743)		(0.0758)	(0.0768)	(0.0775)
Lag-log of CTM stock per firm (young)					0.131***		0.153***	0.154***	0.158***
					(0.0506)		(0.0529)	(0.0543)	(0.0548)
Lag-log of national patent stock per firm (young)						−0.144***	−0.110***	−0.107***	−0.107***
						(0.0363)	(0.0373)	(0.0375)	(0.0378)
Lag-log of EP stock per firm (young)						0.0866***	0.0601**	0.0248	0.0245
						(0.0281)	(0.0285)	(0.0289)	(0.0291)
Lagged national TM-activity rate (young)		0.00426		0.00711				0.00901*	0.00937**
		(0.00470)		(0.00463)				(0.00462)	(0.00466)
Lagged CTM-activity rate (young)		−0.0400***		−0.0479***				−0.0458***	−0.0464***
		(0.00774)		(0.00866)				(0.00894)	(0.00900)
Lagged national patent-activity rate (young)			−0.00936***	−0.0114***				−0.0121***	−0.0124***
			(0.00241)	(0.00227)				(0.00247)	(0.00248)
Lagged EP-activity rate (young)			−0.0128**	0.0149*				0.0157*	0.0155*
			(0.00571)	(0.00783)				(0.00818)	(0.00823)
Lags of control variables									
Lag-log of age	−0.0803	−0.161	−0.0839	−0.178	−0.103	−0.0911	−0.103	−0.180	−0.220
	(0.183)	(0.193)	(0.184)	(0.193)	(0.188)	(0.185)	(0.188)	(0.196)	(0.196)
(Lag-log of age)^2	0.0898**	0.111***	0.0923***	0.115***	0.0985***	0.0950***	0.0993***	0.117***	0.117***
	(0.0357)	(0.0382)	(0.0357)	(0.0382)	(0.0367)	(0.0361)	(0.0368)	(0.0387)	(0.0386)
Holding rate	0.676***	0.639***	0.668***	0.633***	0.714***	0.681***	0.717***	0.687***	0.673***
	(0.198)	(0.196)	(0.197)	(0.196)	(0.197)	(0.198)	(0.197)	(0.198)	(0.198)
realgrowth_DE	0.00757**	0.00979**	0.0118***	0.0100***	0.0110**	0.00361	0.00751	0.00477	0.00448
	(0.00382)	(0.00387)	(0.00371)	(0.00389)	(0.00438)	(0.00451)	(0.00479)	(0.00497)	(0.00499)
PLC rate	−0.237								
	(0.166)								
Constant	1.372***	1.424***	1.329***	1.450***	1.347***	1.180***	1.328***	1.476***	1.628***
	(0.289)	(0.288)	(0.254)	(0.288)	(0.256)	(0.249)	(0.256)	(0.291)	(0.296)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TM vars F-stat					8.76		7.33	4.31	
PAT vars F-stat						4.28	2.53	3.8	3.81
Industry IP F-stat		18.1	8	12.7				10.2	10.4
Size F-Stat	.499	.106	.486	.0469	.58	.812	.719	.141	.12
Controls F-Stat	6.77	7.63	8.95	7.63	8.77	5.2	6.93	6.07	6.05
Year F-Stat									
R^2 within	.0202	.0216	.0205	.022	.0214	.0206	.0217	.0232	.0237
Obs	56,206	56,206	56,206	56,206	56,206	56,206	56,206	56,206	56,206

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.2.10: Robustness: Firm entry all sectors, OLS stepwise young firm IPR

Stepwise results from estimating equation (3.2) accounting only young firms' IPR activity.

	GMM							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. var.: First-differenced log of gross entry rate								
Lag-logarithmic gross entry rate	0.119	−0.0699	0.0657	−0.0819	−0.367*	−0.237	−0.369***	−0.366***
	(0.602)	(0.537)	(0.572)	(0.536)	(0.204)	(0.165)	(0.139)	(0.140)
Industry-region level effects								
Lag-log of turnover	−0.667	0.173	−0.352	0.202	0.0142	−0.357*	−0.187	−0.188
	(0.957)	(0.948)	(0.951)	(0.976)	(0.257)	(0.212)	(0.186)	(0.192)
Lag-log of capital intensity	−2.092*	−1.721*	−1.938*	−1.794*	−1.911***	−0.605	−1.023**	−1.062**
	(1.116)	(0.960)	(1.020)	(0.965)	(0.524)	(0.518)	(0.454)	(0.470)
Lag-log of national TM apps per firm					−0.254		0.0593	−0.0154
					(0.376)		(0.358)	(0.361)
Lag-log of CTM apps per firm					−1.039**		−0.508*	−0.566*
					(0.446)		(0.295)	(0.292)
Lag-log of national patent apps per firm						0.00553	−0.0366	0.0412
						(0.252)	(0.213)	(0.225)
Lag-log of EP apps per firm						−0.344	−0.262	−0.293
						(0.248)	(0.197)	(0.204)
Industry effects:								
Lag-log of national TM stock per firm					−1.092***		−0.924***	−0.372
					(0.254)		(0.251)	(0.237)
Lag-log of CTM stock per firm					0.649***		0.382**	0.535***
					(0.183)		(0.159)	(0.171)
Lag-log of national patent stock per firm						−0.0629	0.0443	0.00957
						(0.0801)	(0.0837)	(0.0837)
Lag-log of EP stock per firm						0.114**	0.0628	0.0617
						(0.0533)	(0.0480)	(0.0488)
Lagged national TM-activity rate		−0.0321		−0.0341				−0.00445
		(0.0360)		(0.0364)				(0.0190)
Lagged CTM-activity rate		−0.0433		−0.0456				−0.0741**
		(0.0559)		(0.0571)				(0.0362)
Lagged national patent-activity rate			−0.0962*	−0.0656				−0.0700**
			(0.0495)	(0.0401)				(0.0310)
Lagged EP-activity rate			0.0500	0.103				0.103**
			(0.0655)	(0.0655)				(0.0485)
Control variables								
Lag-log of age	3.723	2.630	3.328	2.540	1.452	1.823**	1.249*	1.176
	(2.797)	(2.472)	(2.620)	(2.458)	(1.020)	(0.900)	(0.756)	(0.748)
(Lag-log of age)^2	0.0919	0.124	0.116	0.132	0.0964	0.131	0.134	0.157*
	(0.195)	(0.149)	(0.176)	(0.145)	(0.0939)	(0.0995)	(0.0877)	(0.0861)
Holding rate	3.206*	2.161	2.841	2.136	1.908***	1.751***	1.612***	1.552***
	(1.918)	(1.688)	(1.817)	(1.701)	(0.700)	(0.643)	(0.567)	(0.563)
realgrowth_DE	0.283**	0.212**	0.257**	0.215**	0.225***	0.115**	0.154***	0.163***
	(0.113)	(0.103)	(0.105)	(0.103)	(0.0488)	(0.0514)	(0.0495)	(0.0521)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sargan J p-value	.623	.433	.612	.45	.473	.0225	.124	.149
Hansen robust p	.609	.515	.613	.511	.689	.0611	.326	.357
Arellano-Bond AR(1) p	.173	.251	.189	.243	.0127	.0501	.05	.0452
Arellano-Bond AR(2) p	.958	.844	.987	.823	.0465	.129	.0053	.0061
χ^2	816	1,141	959	1,164	1,679	1,617	1,816	1,839
Number of instruments	21	23	23	25	49	49	77	81
Obs	45,744	45,744	45,744	45,744	45,744	45,744	45,744	45,744

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.2.11: Robustness: Firm entry all sectors, GMM stepwise young firm IPR

Stepwise results from estimating equation(3.7) accounting only young firms' IPR activity.

A.3 Appendix to Chapter 4

	Survival (Mean 2003) - (Mean 2006)		Employment (Mean 2003) - (Mean 2006)	
Log of firm assets	0.0826***	(10.26)	0.102***	(8.36)
Log of firm employment	0.285***	(64.91)	0.285***	(58.13)
Log of firm capital intensity	−0.175***	(−17.11)	−0.190***	(−17.73)
National patent-activity rate	0.396***	(58.03)	0.396***	(27.21)
EP-activity rate	0.226***	(50.01)	0.221***	(23.16)
National TM-activity rate	1.075***	(101.86)	0.926***	(44.26)
CTM-activity rate	0.249***	(62.69)	0.232***	(28.68)
Log national patent apps this year	0.00163***	(8.05)	0.00290***	(5.57)
Log national patent stock	0.00269***	(8.34)	0.00989***	(11.41)
Log EP apps this year	0.000918***	(5.77)	0.00196***	(4.54)
Log EP stock	0.00132***	(5.41)	0.00592***	(8.73)
Log national TM apps this year	0.00166***	(8.44)	0.00144**	(3.14)
Log national TM stock	0.0112***	(21.60)	0.0235***	(18.27)
Log CTM apps this year	0.000102	(0.85)	0.000725*	(2.43)
Log CTM stock	0.00110***	(4.20)	0.00597***	(8.83)
Number of firms	−6130	(.)	−2461	(.)
Employment growth in percent			−3.248***	(−14.95)
Observations	681,680		490,816	

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.3.1: T-tests for mean-differences between 2003 and 2006 samples

	2003 (Mean Survival) - (Mean Employment)		2006 (Mean Survival) - (Mean Employment)	
Log of firm assets	−0.249***	(−22.68)	−0.230***	(−23.72)
Log of firm employment	−0.0624***	(−11.97)	−0.0617***	(−15.37)
Log of firm capital intensity	0.00609	(0.56)	−0.00901	(−0.90)
National patent-activity rate	−0.212***	(−16.57)	−0.212***	(−21.68)
EP-activity rate	−0.116***	(−13.86)	−0.121***	(−18.85)
National TM-activity rate	−0.111***	(−6.19)	−0.261***	(−17.41)
CTM-activity rate	−0.0764***	(−10.97)	−0.0934***	(−16.31)
Log national patent apps this year	−0.00371***	(−8.30)	−0.00244***	(−7.26)
Log national patent stock	−0.0120***	(−15.81)	−0.00480***	(−9.06)
Log EP apps this year	−0.00258***	(−6.80)	−0.00154***	(−5.91)
Log EP stock	−0.00720***	(−11.97)	−0.00260***	(−6.56)
Log national TM apps this year	−0.00296***	(−7.57)	−0.00318***	(−10.21)
Log national TM stock	−0.0286***	(−24.97)	−0.0164***	(−20.97)
Log CTM apps this year	−0.00177***	(−7.19)	−0.00115***	(−5.56)
Log CTM stock	−0.00886***	(−15.17)	−0.00400***	(−9.30)
Number of firms	38988	(.)	42657	(.)
Observations	368,243		313,437	

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.3.2: T-tests for mean-differences between survival and employment sample

	Survival 2003			
	$Mean$	Sd	Min	Max
Log of firm assets	2.731521	2.438153	0	14.3121
Log of firm employment	1.76366	1.136366	.6931472	9.472781
Log of firm capital intensity	1.748039	2.104605	0	13.11333
Logarithmic gross entry rate	1.78276	.5147461	0	4.61512
(Log of employment)^2	4.401814	6.382639	.480453	89.73358
(Log firm assets)^2	13.40574	20.22239	0	204.8361
National patent-activity rate	2.44561	3.433044	0	20.02621
EP-activity rate	1.415862	2.243259	0	13.95138
National TM-activity rate	7.785566	4.722885	2.496879	41.37931
CTM-activity rate	2.017788	1.864183	0	18.60068
Log national patent apps this year	.0078534	.1121802	0	4.077538
Log national patent stock	.0245454	.2072602	0	5.331248
Log EP apps this year	.0049996	.0983778	0	4.477337
Log EP stock	.0136497	.1670672	0	5.436164
Log national TM apps this year	.0106357	.1031196	0	4.007333
Log national TM stock	.0776705	.3175438	0	5.267858
Log CTM apps this year	.004685	.0753044	0	3.465736
Log CTM stock	.0215587	.1741365	0	4.828314
(Log national patent stock)^2	.0435589	.5655194	0	28.4222
(Log EP patent stock)^2	.0280975	.5317245	0	29.55188
(Log national TM stock)^2	.1068659	.7061294	0	27.75033
(Log CTM stock)^2	.030788	.3770301	0	23.31261
Number of firms	45,392			
Observations	368,243			

	Survival 2006			
	$Mean$	Sd	Min	Max
Log of firm assets	2.576237	2.587519	0	15.5013
Log of firm employment	1.420237	.988669	.6931472	11.78535
Log of firm capital intensity	1.909993	2.338657	0	13.89974
Logarithmic gross entry rate	1.868533	.5255237	0	4.61512
(Log of employment)^2	2.994531	5.485444	.480453	138.8944
(Log firm assets)^2	13.33219	22.24433	0	240.2904
National patent-activity rate	2.032651	2.924373	.1881615	20.02621
EP-activity rate	1.187044	1.929365	0	13.95138
National TM-activity rate	7.240985	4.402719	2.496879	40.20618
CTM-activity rate	1.822657	1.693235	0	18.60068
Log national patent apps this year	.0058915	.0993295	0	5.043425
Log national patent stock	.0137686	.156207	0	6.188182
Log EP apps this year	.0032793	.0755268	0	4.110874
Log EP stock	.006978	.1135066	0	5.33723
Log national TM apps this year	.0098033	.0931928	0	2.70805
Log national TM stock	.0491976	.2316558	0	3.951244
Log CTM apps this year	.0034096	.0624968	0	2.639057
Log CTM stock	.0126136	.1281006	0	3.89182
(Log national patent stock)^2	.02459	.464426	0	38.2936
(Log EP patent stock)^2	.0129323	.303085	0	28.48602
(Log national TM stock)^2	.0560844	.3883419	0	15.61233
(Log CTM stock)^2	.0165687	.2470547	0	15.14626
Number of firms	53,634			
Observations	313,437			

Table A.3.3: Summary statistics for survival subsamples

	Employment 2003			
	Mean	*Sd*	*Min*	*Max*
Employment growth in percent	6.06279	32.37128	−99.87624	300
Log of firm assets	2.819694	2.443647	0	14.30801
Log of firm employment	1.844229	1.170695	.6931472	9.213037
Log of firm capital intensity	1.752637	2.092632	0	12.81955
Logarithmic gross entry rate	1.752446	.5152004	0	4.61512
(Log of employment)^2	4.771691	6.708844	.480453	84.88004
(Log firm assets)^2	13.92201	20.51287	0	204.7191
National patent-activity rate	2.480698	3.482637	0	20.02621
EP-activity rate	1.432054	2.26757	0	13.95138
National TM-activity rate	7.749479	4.756233	2.496879	41.37931
CTM-activity rate	2.030276	1.889577	0	18.60068
Log national patent apps this year	.0085176	.1174881	0	4.077538
Log national patent stock	.0284317	.2247677	0	5.331248
Log EP apps this year	.0056531	.1055915	0	4.477337
Log EP stock	.0162237	.1844437	0	5.436164
Log national TM apps this year	.0108432	.1046639	0	4.007333
Log national TM stock	.0863017	.3365636	0	5.267858
Log CTM apps this year	.0053069	.0823896	0	3.465736
Log CTM stock	.0251829	.1914253	0	4.828314
(Log national patent stock)^2	.0513282	.6282609	0	28.4222
(Log EP patent stock)^2	.0342822	.6046884	0	29.55188
(Log national TM stock)^2	.1207215	.7639888	0	27.75033
(Log CTM stock)^2	.0372773	.4260704	0	23.31261
Number of firms	27,993			
Observations	272,426			

	Employment 2006			
	Mean	*Sd*	*Min*	*Max*
Employment growth in percent	10.28476	44.06177	−99.9901	500
Log of firm assets	2.706878	2.593622	0	15.5013
Log of firm employment	1.513779	1.040827	.6931472	9.950371
Log of firm capital intensity	1.944446	2.334522	0	13.89974
Logarithmic gross entry rate	1.808218	.5238957	0	4.424847
(Log of employment)^2	3.374833	5.863589	.480453	99.00988
(Log firm assets)^2	14.05397	22.62519	0	240.2904
National patent-activity rate	2.060188	2.993456	.1881615	20.02621
EP-activity rate	1.199033	1.965307	0	13.95138
National TM-activity rate	7.161674	4.430235	2.496879	40.20618
CTM-activity rate	1.825029	1.722311	0	18.60068
Log national patent apps this year	.0063196	.1053843	0	5.043425
Log national patent stock	.0164732	.1726441	0	6.188182
Log EP apps this year	.0040055	.085152	0	4.110874
Log EP stock	.0088055	.1298547	0	5.33723
Log national TM apps this year	.0089287	.089898	0	2.70805
Log national TM stock	.0587842	.2539827	0	3.89182
Log CTM apps this year	.0039883	.0695447	0	2.639057
Log CTM stock	.0156211	.1447416	0	3.89182
(Log national patent stock)^2	.0300769	.5324946	0	38.2936
(Log EP patent stock)^2	.0169395	.3547219	0	28.48602
(Log national TM stock)^2	.0679619	.4300812	0	15.14626
(Log CTM stock)^2	.0211939	.2873011	0	15.14626
Number of firms	31,229			
Observations	218,390			

Table A.3.4: Summary statistics for employment subsamples

Dep. var.: Hazard rate	Manufacturing	Service	Trade	Construction	EGW	ICT & R&D	Agriculture
Est. in 2006							
Lag-log of count of national TM registrations	-0.417^{***}	-0.0695	-0.0977	0.454	0.617	0.166	-0.532
	(0.141)	(0.0965)	(0.138)	(0.313)	(0.714)	(0.143)	(0.389)
Lag-log of count of CTM registrations	0.00792	0.167	-0.195	-0.656	-1.308^{*}	-0.383	0.381
	(0.273)	(0.222)	(0.207)	(0.543)	(0.755)	(0.239)	(1.688)
Lag-log of count of national patent applications	0.151	0.491^{***}	0.0527	0.654	-0.252	-0.230	-0.925
	(0.138)	(0.184)	(0.236)	(0.422)	(0.851)	(0.210)	(2.150)
Lag-log of count of EP applications	0.124	-0.308	0.249	-0.563	5.547^{***}	0.00518	-44.41^{***}
	(0.213)	(0.192)	(0.286)	(0.503)	(1.428)	(0.192)	(1.661)
Lag-log of stock of national TM registrations	0.330^{***}	0.000821	-0.229^{***}	-0.0871	-0.727^{***}	-0.0219	0.229
	(0.0446)	(0.0370)	(0.0536)	(0.103)	(0.232)	(0.0653)	(0.175)
Lag-log of stock of CTM registrations	-0.260^{**}	-0.276^{**}	0.244^{**}	0.964^{***}	2.824^{***}	0.623^{***}	-1.463
	(0.118)	(0.116)	(0.0971)	(0.225)	(0.474)	(0.0920)	(1.023)
Lag-log of stock of national patent applications	0.0598	-0.265^{*}	-0.237	-0.0338	0.892^{*}	0.187	-40.22^{***}
	(0.104)	(0.141)	(0.144)	(0.320)	(0.518)	(0.150)	(1.379)
Lag-log of stock of EP applications	-0.214	0.545^{***}	0.0646	0.204	-39.39^{***}	-0.0567	3.597^{***}
	(0.158)	(0.128)	(0.189)	(0.356)	(1.569)	(0.142)	(0.423)
Firm-level variables							
Firm est. with at least one subsidiary	-0.686^{***}	-1.649^{***}	-0.765^{***}	-0.470^{***}	-0.140	-0.580^{***}	0.109
	(0.0913)	(0.0236)	(0.0614)	(0.0932)	(0.140)	(0.0612)	(0.134)
Firm est. as a subsidiary	-0.530^{***}	-0.376^{***}	-0.397^{***}	-0.602^{***}	-0.368^{***}	-0.597^{***}	0.447^{**}
	(0.0900)	(0.0241)	(0.0595)	(0.111)	(0.124)	(0.0787)	(0.197)
Firm est. owned by foreign parent	-0.669^{***}	0.237^{***}	-0.897^{***}	-1.186^{***}	0.00478	-0.287^{*}	0.574^{*}
	(0.153)	(0.0470)	(0.118)	(0.344)	(0.218)	(0.166)	(0.343)
Firm est. diversified	0.107^{**}	0.183^{***}	0.262^{***}	0.380^{***}	0.590^{***}	0.0597	0.254^{**}
	(0.0423)	(0.0133)	(0.0271)	(0.0329)	(0.0990)	(0.0401)	(0.105)
Intial value of log of total assets	0.0194	-0.0972^{***}	-0.195^{***}	-0.309^{***}	-0.153^{**}	-0.105^{***}	-0.119
	(0.0342)	(0.00973)	(0.0209)	(0.0325)	(0.0627)	(0.0262)	(0.0894)
(Intial value of total assets)^2	0.00861^{*}	0.0128^{***}	0.0367^{***}	0.0261^{***}	0.0342^{***}	0.00848^{***}	0.0282^{**}
	(0.00510)	(0.000955)	(0.00356)	(0.00315)	(0.00909)	(0.00282)	(0.0122)
Industry-level variables							
Lagged national TM-activity rate	0.0472	-0.0375^{***}	-0.132^{**}	0.104	0.601^{***}	0.00837	0.00811
	(0.0297)	(0.00967)	(0.0574)	(0.169)	(0.106)	(0.0260)	(0.0835)
Lagged CTM-activity rate	0.102	0.158^{***}	0.589^{***}	0.107	-2.183^{***}	-0.0689	-0.876
	(0.106)	(0.0412)	(0.221)	(0.533)	(0.629)	(0.0999)	(0.612)
Lagged national patent-activity rate	0.0869	-0.140^{**}	0.0332	7.593^{***}	-0.289	-0.299^{***}	-0.163
	(0.0717)	(0.0708)	(0.153)	(1.487)	(0.531)	(0.0777)	(0.270)
Lagged EP-activity rate	-0.249^{**}	0.0233	-0.326	-13.69^{***}	0.550	0.445^{***}	0.486
	(0.125)	(0.118)	(0.211)	(2.736)	(1.059)	(0.102)	(0.351)
Intial value of mean log of industry capital intensity	-0.0139	0.0405^{***}	-0.0359	0.563^{***}	-0.0848	-0.0671^{***}	0.0780
	(0.0313)	(0.00774)	(0.0372)	(0.0871)	(0.111)	(0.0162)	(0.0620)
Intial value logarithmic gross entry rate	-0.00216	0.0452^{***}	-0.0685	0.0329	0.0752	0.151^{***}	-0.0186
	(0.0282)	(0.0165)	(0.0533)	(0.0525)	(0.0612)	(0.0360)	(0.104)
Lagged real growth rate GDP	0.255^{***}	0.229^{***}	0.229^{***}	0.232^{***}	0.211^{**}	0.196^{***}	0.181^{*}
	(0.0442)	(0.0156)	(0.0277)	(0.0383)	(0.0848)	(0.0444)	(0.0994)
Two-digit industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Subjects	$23,223$	$191,588$	$50,301$	$26,236$	$6,403$	$20,916$	$3,974$
Failures	$3,611$	$28,057$	$8,919$	$4,911$	815	$3,853$	734
Log-Likelihood	$-35,022$	$-330,028$	$-94,245$	$-48,490$	$-6,494$	$-36,873$	$-5,547$
χ^2	$293,927$	$15,613$	$2,753$	$195,128$	$778,124$	$125,510$	$301,608$

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.3.5: Estimates for a piecewise-constant exponential hazard function across sectors for 2003 cohort

Results from estimating equation (4.1).

	Manufacturing	Service	Trade	Construction	EGW	ICT & R&D	Agriculture
Dep. var.: Hazard rate							
Est. in 2006							
Lag-log of count of national TM registrations	−0.167	0.00733	−0.112	−0.00470	0.505	0.0610	−0.256
	(0.230)	(0.106)	(0.145)	(0.700)	(0.364)	(0.188)	(0.757)
Lag-log of count of CTM registrations	0.0778	−0.214	−0.247	2.053	−1.247	0.0418	−0.246
	(0.285)	(0.198)	(0.246)	(1.994)	(.)	(0.242)	(.)
Lag-log of count of national patent applications	0.218	−0.0453	0.294	0.193	−0.109	-0.791^{***}	−1.478
	(0.174)	(0.204)	(0.285)	(0.591)	(0.812)	(0.264)	(.)
Lag-log of count of EP applications	0.0154	0.359	−0.641	−0.880	-0.525^{***}	−0.209	31.45
	(0.180)	(0.247)	(0.490)	(0.717)	(0.184)	(0.369)	(.)
Lag-log of stock of national TM registrations	-0.230^{***}	−0.0710	0.117^{*}	-0.502^{*}	0.416^{**}	−0.115	−0.110
	(0.0773)	(0.0520)	(0.0625)	(0.282)	(0.204)	(0.0941)	(0.579)
Lag-log of stock of CTM registrations	−0.0248	0.289^{***}	0.0650	−2.017	−64.65	0.192	1.621
	(0.132)	(0.110)	(0.125)	(1.504)	(.)	(0.126)	(.)
Lag-log of stock of national patent applications	−0.132	−0.155	−0.287	0.503	1.521^{***}	0.675^{***}	0.554
	(0.140)	(0.139)	(0.209)	(0.380)	(0.441)	(0.173)	(.)
Lag-log of stock of EP applications	0.474^{***}	0.00915	0.643^{**}	1.629^{***}	1.102^{***}	−0.147	−96.56
	(0.150)	(0.197)	(0.281)	(0.612)	(0.248)	(0.245)	(.)
Firm-level variables							
Firm est. with at least one subsidiary	-0.612^{***}	-1.803^{***}	-0.883^{***}	-0.754^{***}	-0.345^{**}	-0.718^{***}	−47.89
	(0.124)	(0.0255)	(0.0846)	(0.138)	(0.145)	(0.107)	(.)
Firm est. as a subsidiary	-0.714^{***}	-0.784^{***}	-0.574^{***}	-0.746^{***}	-0.736^{***}	-0.763^{***}	1.878^{**}
	(0.108)	(0.0304)	(0.0842)	(0.153)	(0.153)	(0.118)	(0.891)
Firm est. owned by foreign parent	-0.848^{***}	-0.123^{**}	-1.383^{***}	-1.537^{***}	−0.268	0.225	−0.906
	(0.203)	(0.0490)	(0.176)	(0.471)	(0.265)	(0.172)	(1.135)
Firm est. diversified	0.0707	-0.0456^{***}	−0.0220	-0.0629^{*}	−0.0554	−0.0230	−0.0126
	(0.0467)	(0.0133)	(0.0256)	(0.0374)	(0.0900)	(0.0439)	(0.299)
Initial value of total assets	0.0540	-0.169^{***}	-0.279^{***}	-0.292^{***}	-0.489^{***}	0.0522	0.184
	(0.0360)	(0.00937)	(0.0270)	(0.0304)	(0.0591)	(0.0390)	(0.183)
(Initial value of total assets)^2	0.0130^{**}	0.0153^{***}	0.0612^{***}	0.0178^{***}	0.0829^{***}	-0.0102^{**}	0.000417
	(0.00520)	(0.000895)	(0.00514)	(0.00334)	(0.0102)	(0.00479)	(0.0245)
Industry-level variables							
Lagged national TM-activity rate	0.0676	−0.0000657	-0.191^{***}	−0.0488	-1.089^{***}	0.0318	-0.848^{***}
	(0.0453)	(0.0156)	(0.0370)	(0.134)	(0.126)	(0.0444)	(0.269)
Lagged CTM-activity rate	−0.0743	-0.169^{**}	0.862^{***}	−0.286	3.880^{***}	−0.0481	2.472^{***}
	(0.123)	(0.0697)	(0.156)	(0.556)	(0.429)	(0.147)	(0.876)
Lagged national patent-activity rate	-0.485^{***}	-0.156^{*}	0.418^{***}	-0.572^{**}	2.257^{***}	0.165	2.029^{***}
	(0.111)	(0.0801)	(0.147)	(0.267)	(0.438)	(0.102)	(0.578)
Lagged EP-activity rate	0.683^{***}	0.324^{**}	-1.220^{***}	1.086^{**}	-4.852^{***}	−0.136	-3.123^{***}
	(0.180)	(0.135)	(0.199)	(0.517)	(0.822)	(0.139)	(1.035)
Initial value mean log of industry capital intensity	-0.258^{***}	-0.0813^{***}	-0.180^{***}	0.106^{*}	-0.748^{***}	0.0677	1.074^{***}
	(0.0560)	(0.0131)	(0.0543)	(0.0564)	(0.183)	(0.0443)	(0.271)
Initial value logarithmic gross entry rate	-0.0582^{*}	-0.0333^{**}	−0.0247	0.0541	−0.0294	−0.00510	0.0949
	(0.0323)	(0.0167)	(0.0626)	(0.0707)	(0.0654)	(0.0437)	(0.118)
Lagged real growth rate GDP	0.254^{***}	0.232^{***}	0.245^{***}	0.251^{***}	0.199^{***}	0.244^{***}	0.266^{*}
	(0.0395)	(0.0114)	(0.0239)	(0.0337)	(0.0586)	(0.0382)	(0.136)
Two-digit industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Subjects	13,032	175,476	33,066	15,342	7,654	13,394	1,678
Failures	2,282	25,759	6,412	2,938	930	2,332	158
Log-Likelihood	−20,781	−300,990	−64,984	−27,310	−7,671	−21,413	−928
χ^2	80,628	12,046	3,016	80,215	5,108	283,020	14,058

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.3.6: Estimates for a piecewise-constant exponential hazard function across sectors for 2006 cohort

Results from estimating equation (4.1).

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Eidesstattliche Versicherung

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