Discussion Paper No. 09-039

Inventions under Siege? The Impact of Technology Competition on Licensing

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Non-technical summary

In recent years, the view on patents as an instrument for firms to appropriate the returns from inventive activities has shifted towards a more explicit consideration of a patent's strategic importance. In fact, firms have increasingly contributed to and been confronted with a patent landscape characterized by numerous but marginal inventions, overlapping claims and multiple patent ownerships for complementary technologies, as well as by patent fences of substitute technologies owned by a single firm or a group of firms. Existing literature suggests that both the fragmentation of ownership and the threat of a firm's patent applications being blocked by other patents lead to increased patenting and in-licensing activity in order to mitigate potential hold-up by opportunistic patentees owning critical patents.

In this paper, we argue that firms facing a high chance of being blocked by technology competitors engage both in in- and out-licensing of technology. This suggests that the blocking threat favors investment in patent licenses rather than in pure in-house research and development (R&D) for some firms while it increases licensing revenues of firms owning blocking patents. The relationship should be particularly pronounced in complex technologies as these exhibit a higher density of patent thickets compared to discrete technologies. We construct a novel measure that captures the threat of being blocked if a firm files an average patent application conditional on its technology portfolio.

Based on a comprehensive dataset of more than 400 manufacturing firms from Germany, our results largely confirm the research hypotheses. Distinguishing the effect of the blocking threat for firms in discrete and complex industries (i.e., product technologies characterized as complex contain a large number of patentable elements while product technologies characterized as discrete consist of relatively few patentable elements), we find that the likelihood of being blocked only affects the licensing activities of firms in complex industries, while there is no effect of blocking on licensing for firms operating in discrete industries. This result is in line with the argument that licensing can mitigate hold-up problems in technology markets. In addition, we take account of the potential feedback effects of licensing on internal R&D investments of the firm and find that these are endogenous.

Das Wichtigste in Kürze

In den vergangenen Jahren sind Patente zunehmend aufgrund ihrer strategischen Bedeutung in Technologiemärkten in den Fokus der Betrachtung gelangt. Tatsächlich haben Unternehmen in immer stärkerem Maße zu einem Umfeld beigetragen, das durch zahlreiche, aber marginale Erfindungen, sich überlagernde Ansprüche und multiple Patenteigentümer für komplementäre Technologien sowie durch „Patentzäune" bei substitutiven Technologien, die von einem einzelnen Unternehmen oder einer Gruppe von Unternehmen gehalten werden, gekennzeichnet ist. Veröffentlichungen zu diesem Thema zeigen, dass sowohl die Fragmentierung der intellektuellen Eigentumsrechte also auch die drohende Blockade der Patentanmeldungen eines Unternehmens durch andere Patente einerseits zu steigenden Patentanmeldungen, andererseits auch zu einer Einlizenzierung von Technologie führen, um Behinderungen durch opportunistisches Verhalten von Eigentümern kritischer Patente zu vermeiden.

In diesem Artikel argumentieren wir, dass Unternehmen Technologie sowohl ein- als auch auslizenzieren, wenn ihr Umfeld von einem intensiven Technologiewettbewerb gekennzeichnet ist. Diese Beziehung sollte bei komplexen Technologien besonders ausgeprägt sein, da diese eine höhere Patentdichte als diskrete Technologien aufweisen. Zu diesem Zweck entwickeln wir ein neues Maß für die Blockadewahrscheinlichkeit einer durchschnittlichen Patentanmeldung eines Unternehmens in Abhängigkeit seines bestehenden Technologieportfolios.

Unsere Ergebnisse auf Grundlage eines Datensatzes von mehr als 400 deutschen Unternehmen im verarbeitenden Gewerbe zeigen, dass Unternehmen tatsächlich Technologie ein- und auslizenzieren, wenn der Technologiewettbewerb hoch ist, d.h. eine hohe Blockadewahrscheinlichkeit von Patentanmeldungen besteht. Beim Vergleich von Firmen in komplexen und diskreten Industriezweigen kommen wir zu dem Schluss, dass die Blockadewahrscheinlichkeit nur die Lizenzierungsaktivitäten von Unternehmen in komplexen Industriezweigen beeinflusst, während sie auf Firmen in diskreten Industriezweigen keine Wirkung hat. Dieses Ergebnis unterstreicht die These, dass Lizenzen dazu beitragen können, „Hold-Up"-Probleme in Technologiemärkten zu lindern. Darüber hinaus beachten wir mögliche Rückkopplungseffekte der Lizenzierungsaktivitäten auf die interne Forschung und Entwicklung (FuE).

Inventions under Siege?

The Impact of Technology Competition on Licensing

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Abstract

In recent years, firms have increasingly contributed to and been confronted with a patent landscape characterized by numerous but marginal inventions, overlapping claims and patent fences. Literature suggests that both the fragmentation of ownership and the threat of a firm's patent applications being blocked by competitors' patents lead to increased patenting and in-licensing activity. In this paper, we investigate the effect of expected blocking on firms' engagement in in- and out-licensing. Based on a sample of more than 400 German manufacturing firms our results show that firms engage in in- and out-licensing if technology competition increases which is in line with the argument that licensing can mitigate hold-up problems in technology markets.

Keywords: Licensing, blocking patents, discrete and complex technologies, technology competition

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Acknowledgements: We thank Dirk Czarnitzki, Georg Licht, Christian Rammer, Cédric Schneider, Tanya Tanayama and the participants of the ZEW brown bag seminar for helpful comments and discussions.

1 Introduction

In recent years, the view on patents and other forms of intellectual property rights (IPR) as instruments for firms to appropriate the returns from inventive activities has shifted towards a more explicit consideration of a patent's strategic importance. In fact, firms have increasingly contributed to and been confronted with a patent landscape characterized by numerous but marginal inventions (Gallini, 2002), overlapping claims and multiple patent ownerships for complementary technologies (Heller and Eisenberg, 1998; Scotchmer, 2004), as well as by patent fences of substitute technologies owned by a single firm or a group of firms (Cohen et al., 2000; Schneider, 2008). As patents grant the holder the right to exclude third parties from using the protected technology, firms may be required, on the one hand, to navigate through 'patent thickets' (Shapiro, 2001) and, on the other hand, to deal with 'blocking patents' threatening the patentability requirements of inventions (Graff et al., 2003; Grimpe and Hussinger, 2008). In response to this development, the filing of patents has increased because a large patent portfolio enhances firms' bargaining power in disputes with rivals (Ziedonis, 2004; von Graevenitz et al., 2008). This may lead to 'overfencing' in technology markets (David, 2001), thereby perpetuating the patent thicket. The surge in patent applications is mainly attributed to firms' efforts to mitigate potential hold-up by opportunistic patentees owning critical or blocking patents (Ziedonis, 2004).

The extent to which these patents with a blocking potential are detrimental to innovation is however ex ante unclear. While blocking patents can deter future inventions or increase the costs of follow-up inventors for inventing around patents significantly, it is in principle possible to mitigate this problem by negotiating a licensing contract on those intellectual property rights. The possibility of licensing has been found to support the functioning of the market for technology (Arora et al., 2001). Yet, recent contributions have emphasized the transaction costs associated with the requisite to license-in intellectual property from a large number of assignees. In this respect, increased transaction costs are the result of 'fragmentation' of patent ownership required to commercialize an invention (Ziedonis, 2004). Some firms would therefore 'under-invest' in research and development (R&D) if it meant having to license technology from multiple owners, while others would substitute in-house R&D investment partly by high licensing expenses (Heller and Eisenberg, 1998). In fact, Cockburn et al. (2008) find that higher fragmentation of technology markets is associated with higher licensing expenditure of the firm, reducing the funds available for technology development. As a result, firms that need to cope with higher fragmentation of the patent landscape have lower market values (Noel and Schankerman, 2006) and new ventures experience delays in the initial round of funding (Cockburn and MacGarvie, 2007).

Fragmentation, however, only captures the concentration of patents across competitors in technology markets. In their decision on the R&D investment and on how to appropriate the returns from an invention, firms need to consider the threat of their own patent applications being blocked by competitor patents in the first place (von Graevenitz et al., 2008). Siebert and von Graevenitz (2008) disentangle the effects of fragmentation and expected blocking. They show that while there is a positive relationship between expected blocking and (ex ante) licensing, fragmentation negatively correlates with the extent of (ex ante) licensing indicating that growing patent thickets undermine licensing as an option to resolve patent thickets. Hence, their results suggest that licensing is an instrument for mitigating patent blocking, which might not work anymore in the presence of patent thickets.

In this paper we follow Siebert and von Graevenitz (2008) by distinguishing between fragmentation and expected blocking and their effect on firm participation in licensing markets. We add to the literature by introducing a different measure that captures the likelihood of being blocked if a firm files an average patent application conditional on its technology portfolio in order to measure expected blocking.[1] Further, it has been largely ignored in the literature so far that fragmentation and blocking put firms with relevant patents in a position to generate income through out-licensing activities or to engage in cross-licensing, i.e. exchanging licenses with other firms. Hence in this paper, we extend previous findings on the effects of technology competition on in-licensing to the effects on out-licensing activities of the firm. Moreover, we draw a distinction between complex and discrete technologies (Cohen et al., 2000). Product technologies characterized as complex contain a large number of patentable elements while product technologies characterized as discrete consist of relatively few patentable elements. These differences should be important when it comes to the threat of being blocked that firms face.

Based on a sample of German manufacturing firms, our results show that expected blocking increases in-licensing of technology as well as out-licensing, suggesting that technology competition spurs cross-licensing activities. The findings are particularly pronounced in

[1] Siebert and von Graevenitz (2008) rely on citation weighted technological similarity between the licensing partners as a measure for expected blocking.

complex technologies as these exhibit a higher density of patent thickets, i.e. are more fragmented, compared to discrete technologies (Cohen et al., 2000). In this respect, we shed new light on firms' decision to make use of the market for technology with respect to inventions that potentially come 'under siege'. Licensing seems to be an effective tool for mitigating hold-up in fragmented industries. Interestingly, our findings stand in contrast to the results by Siebert and von Graevenitz (2008), who conclude that licensing is less effective in industries characterized by a high degree of fragmentation. Hence, our paper contributes to the discussion on how to measure technology competition and the threat of blocking.

The remainder of this paper is organized as follows. Section 2 provides the literature background and details our theoretical framework. Section 3 shows our empirical methods while the results are presented in section 4. We discuss key findings as well as limitations and future research avenues in section 5.

2 Literature Background

Survey evidence for the US and Europe has shown that the protection of intellectual property is often not the most attractive feature of patents although they allow inventors to recoup their R&D investments by granting a temporary monopoly on the invention (Arundel et al., 1995; Cohen et al., 2000). The value of patents is rather determined by their importance as bargaining chips in the market for technologies, e.g. in licensing or M&A negotiations, and by their potential to block the inventions of competitors (Graff et al., 2003; Grimpe and Hussinger, 2008). Although patents facilitate bargaining in technology markets, they are difficult to value, their boundaries are often blurry and difficult to define, and parties owning related, previously patented technologies are often unknown in advance (Merges and Nelson, 1990). This enhances incentives to patent in order to increase the own patent portfolio for a better bargaining position in licensing negotiations and disputes over IPR. In consequence, markets for technology are increasingly characterized by fragmentation, multiple ownership, overlapping claims, patent thickets and patent fences, leaving patenting firms in an opaque and uncertain environment (Ziedonis, 2004).

In this respect, Ziedonis (2004) finds that firms which are confronted with fragmented property rights required to commercialize an innovation will patent more aggressively to reduce the uncertainty of being litigated or to threaten competitors with a reciprocal suit. In fact, the surge in patent applications worldwide over the past two decades has been accompanied by an increase in the number of legal disputes over patent rights (Lanjouw and

Schankerman, 1997). Increasing the rate of patenting indicates firms' endeavor to accumulate a stack of patents available for cross-licensing.

When filing a patent is not a feasible option, licensing opens the way to using the required technology. Nevertheless, several problems arise when IPR are traded at arm's length (Arora et al., 1999; Heller and Eisenberg, 1998; Somaya and Teece, 2000; Graff et al., 2003). First, fragmented technology markets and blurry IPR boundaries lead to diffuse entitlement problems (Heller and Eisenberg, 1998). Second, the difficulty of valuing IPR leads to value allocation problems between the technology owner and the licensee (Graff et al., 2003). Third, the dynamic and uncertain environment of technology markets causes difficulties when setting up and enforcing the contract due to monitoring and metering problems (Ziedonis, 2004). Lastly, there are strategic problems that can arise if IPR are traded at arm's length. For example, rent-dissipation effects can result when technologies are licensed out to other firms, because the licensees become new competitors in product markets (Graff et al., 2003). All the problems associated with arm's-length contracts lead to higher transaction costs which reduces the propensity to engage in licensing. Yet, using a variant of Ziedonis' measure of fragmentation[2] which builds upon the concentration of backward citations in firms' patents among patent holders, Cockburn et al. (2008) show a positive relationship between fragmentation and the extent to which a firm licenses-in technology. In this respect, licensing appears to be an option to resolve holdup problems in fragmented technology markets.

Besides fragmentation, however, firms also need to consider the threat of patent applications being blocked by competitor patents even if patent ownership is concentrated (von Graevenitz et al., 2008; Siebert and von Graevenitz, 2008). Existing patents can block successive patent applications by threatening their novelty requirements (Scotchmer, 1991; Shapiro, 2001; Jaffe and Lerner, 2004; Ziedonis, 2004; Grimpe and Hussinger, 2008). A recent survey of German firms shows that more than 40 percent of patenting firms apply for patents in order to block competitors (Blind et al., 2009). Blind et al. (2009) find particularly striking evidence of "defensive blocking" through patenting. They define this as a forward-looking protection strategy directed at protecting the firm's position in technology markets.

[2] Ziedonis (2004) proposes a Hirschman-Herfindahl type of concentration measure based on backwards citations. Following van Graeventitz et al. (2008), Cockburn et al. (2008) construct the same type of measure but only take a certain type of backward citations into account, namely those that have been identified by the patent examiner at the European Patent Office (EPO) to threaten the novelty or the inventive step made by an invention in question. See section 3.2. for more information.

In this regard, blocking patents can be used to hinder competitors from developing a competing alternative technology (Heeley et al., 2007) or to remove existing patent fences. In fact, von Graevenitz et al. (2008) find for the U.S. semiconductor industry that a firm's patenting activity increases with the density of patent thickets threatening to block its patent applications. Siebert and von Graevenitz (2008), disentangling the effect of blocking and market fragmentation, find that while expected blocking increases the extent of (ex ante) in-licensing there is a negative effect of fragmentation.

Little is known how the threat of being blocked in technology markets affects the out-licensing activities of firms owning relevant IPR. We may expect that firms strive on the one hand to generate income from such activities and on the other hand to engage in cross-licensing (Shapiro, 2001). Moreover, the characteristics of the technology upon which the patent is based should matter considerably. The relationship between the threat of being blocked and licensing should be particularly pronounced in complex technologies as these exhibit a higher density of patent thickets compared to discrete technologies (Cohen et al., 2000). Product technologies characterized as complex exhibit a large number of patentable elements while product technologies characterized as discrete contain relatively few patentable elements. Hence, the number of patents available in a technology area is determined by the existence of these technological opportunities and their facets (von Graevenitz et al., 2008). Complexity arises when several facets within technological opportunities can be patented. As a consequence, a higher number of patentable facets increases the potential number of firms owning patents that refer to the same technological opportunity. Firms will therefore pile up a stack of patents to counter the threat of hold-up. In contrast to complex technologies, discrete technologies refer only to one facet of the technological opportunity that is patentable. The value of each patent will thus be independent from other firms' patents. This implies that, for discrete technologies, there are relatively clear standards to evaluate the patent's validity and protect it against infringement. Complex technologies, on the contrary, are characterized by a less transparent link between patenting and value appropriation as it is unclear whether it will be feasible to defend the IPR itself because of interdependent technologies (Levin et al., 1987; Heeley et al., 2007). As a result, in- and out-licensing should be of minor importance in case of discrete technologies. To sum up, we argue that a higher threat of being blocked in technology markets will trigger both in- and out-licensing activities. We may therefore expect a high correlation of the two activities conditional on a number of firm and technology characteristics, suggesting that they are complements.

3 Empirical methods

3.1 Data

We test our research questions using data from the Mannheim Innovation Panel (MIP), a survey which has been conducted annually by the Centre for European Economic Research (ZEW) on behalf of the German Federal Ministry of Education and Research (BMBF) since 1992. The MIP is the German part of the Community Innovation Survey (CIS) of the European Commission. In 1993, firms were asked about their in- and out-licensing activities in the previous year. This year constitutes a cross-sectional database for our empirical analysis. The firm information was linked to the firms' patent records at the European Patent Office (EPO). Based on firm names and addresses the respondents of the survey were linked to corresponding patent applicants. The link was supported by a computerized text field based search algorithm and every firm-patent applicant match proposed by the program was manually checked.

We restrict the sample to manufacturing firms as patents and hence licensing is supposed to be of a different nature in service industries. Further, only firms that applied for at least one patent at the EPO are taken into account. The latter restriction is necessary because we measure technology competition conditional on the technology fields the firms are active in using their patent portfolio. For innovative firms that never applied for a patent we hence lack the information about the technology fields they are active in.[3] This leaves us with a sample of 483 firms in the manufacturing sector that applied for at least one patent at the EPO. The next section will detail the construction of our measure for technology competition.

3.2 Measuring expected blocking

The measure for expected blocking we propose is based on detailed information of the patent application procedure at the EPO. Each EPO patent application is evaluated by a patent examiner who scrutinizes whether a patent can be granted. The result of this examination is summarized in the so-called "search report". An important information given in the search

[3] Supplementing the technology field information with national patent data bases is not possible for this study as we make explicit use of some detailed information provided only by the EPO (see section 3.2 for details).

report is a list of all documents which are considered as relevant prior art for the patent application in question. Based on the review of prior art a decision is made as to whether a technology is novel enough to get granted patent protection. An interesting feature of the EPO search reports is that references to prior art are classified according to their importance for the patent application in question. Prior art which threatens the novelty requirement of the patent application can thus be distinguished from previous inventions that belong to the state of the art in a particular technology field but do not challenge the novelty of the patent application. References to prior art are marked with an “X” if the invention cannot be considered to be novel or cannot be considered to involve an inventive step when the referenced document alone is taken into consideration. References are marked with a “Y” if the invention cannot be considered to involve an inventive step when the referenced document is combined with one or more other documents of the same category, such a combination being obvious to a person skilled in the art (Harhoff *et al.*, 2005). If a patent has many references classified with X or Y it can still be granted (although this is less likely). This can be the case for patent applications with many claims. X and Y references may only pertain to some claims and the remaining claims can be strong enough to get a (modified) application granted. The information on patent references is taken from the EPO/OECD patent citation database. An earlier version of this database is fully described and analyzed in Webb et al. (2005).

We use the information on prior art in the search report to construct a measure for the intensity of technology competition each firm is likely to face. We build on the fact that a patent application with many X and Y references can be considered a weak patent application with a high likelihood of not being granted. Guellec et al. (2008) provide empirical evidence for the significance of patent citation categories for the identification of blocking patents. Based on an analysis of all EPO patent applications with priority dates between 1990 and 2000 they show that blocking references increase the likelihood of patents not being granted or being withdrawn. We exploit this correlation to create an index for expected blocking. The measure was constructed as follows:

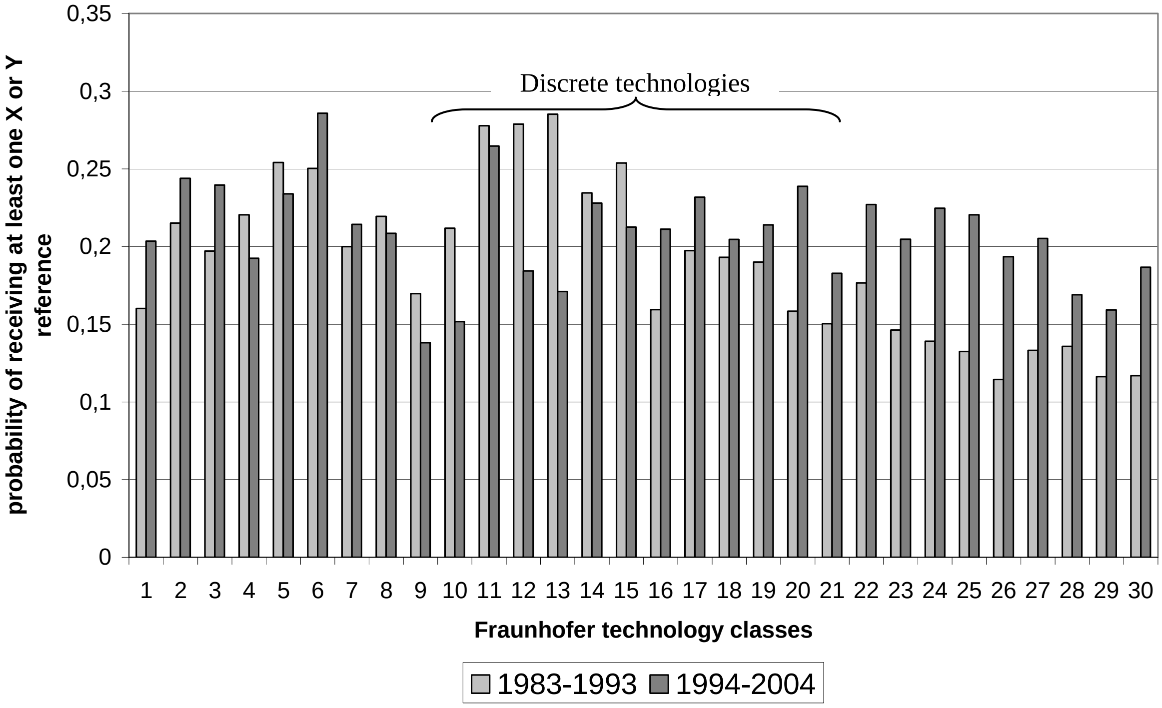
1. In a first step, the probability of receiving at least one blocking (X or Y) reference during the EPO patent examination process is estimated for each of the 30 Fraunhofer technology classes[4] *tech* and per year *t* by using the share of these patent applications:

$$prob_{t,tech} = \frac{\sum patent\ applications\ with\ at\ least\ one\ X\ or\ Y_{t,tech}}{\sum patent\ applications_{t,tech}}. \quad (1)$$

As patent applications are typically associated with more than one technology class we use weights to attribute them to different classes. For instance, in case a patent belongs to two technology classes the patent counts for both with a weight of 0.5. Figure 1 shows the average probability of receiving an X or Y citation per Fraunhofer technology class for two different time windows. It is based on all EPO patent applications since 1983. The graph suggests that there are significant differences over technology classes and over time. For some technology classes, most pronounced for those among 22 to 30, there is a significant increase in the likelihood of being blocked over time. These, but also the classes 1 to 9 where no systematic change can be reported, have been characterized as complex technologies (von Graevenitz et al., 2008) because in these technologies several facets within technological opportunities can be assumed to exist. For the group of discrete technologies, 10 to 21, there is no overall systematic change in either one direction.

[4] The 30 patent technology classes as defined in the OST-INPI/FhG-ISI classification (often referred to as the Fraunhofer classification) is based on a concordance with IPC assignments. For a detailed description see OECD (1994, p.77-78 for the definition). For an overview see Table 5 in the Appendix.

Figure 1: Probability for a patent of receiving at least an X or Y reference across technology fields



2. In the next step the firms' profiles of technological activity are determined based on their previous patent applications. Again, patents belonging to multiple technology classes are attributed to each Fraunhofer technology class with a proportional weight as described above. In order to abstract from the size of the patent portfolio, the percentage of applications in a certain technology class is used instead of the actual numbers of patent applications. The result is a vector describing the importance of each technology field for the firm. For instance, if a firm has in one year one patent attributed to technology classes 1 and 5 and another patent application exclusively belonging to technology class 1 its technology portfolio looks like this: w_n = [(1.5/2);0;0;0;(0.5/2);0;0;0;0;0;…;0]. This vector is constructed for each firm on a yearly base. In order to account for the fact that not every firm has patent applications in each year, the values for w were linearly intrapolated for years without patent applications. It should be noted that 13 percent of the sample firms are active in one technology field only in 1991. However, 79 percent of the sample firms have at least 90 percent of their patents in one technology class. Hence, the patent portfolio weight has eventually little impact on the index.

3. The intensity of technology competition for a firm *i* based on its technology portfolio was then calculated as the sum of the probabilities of receiving at least one X or Y reference weighted by the firm's technological activities:

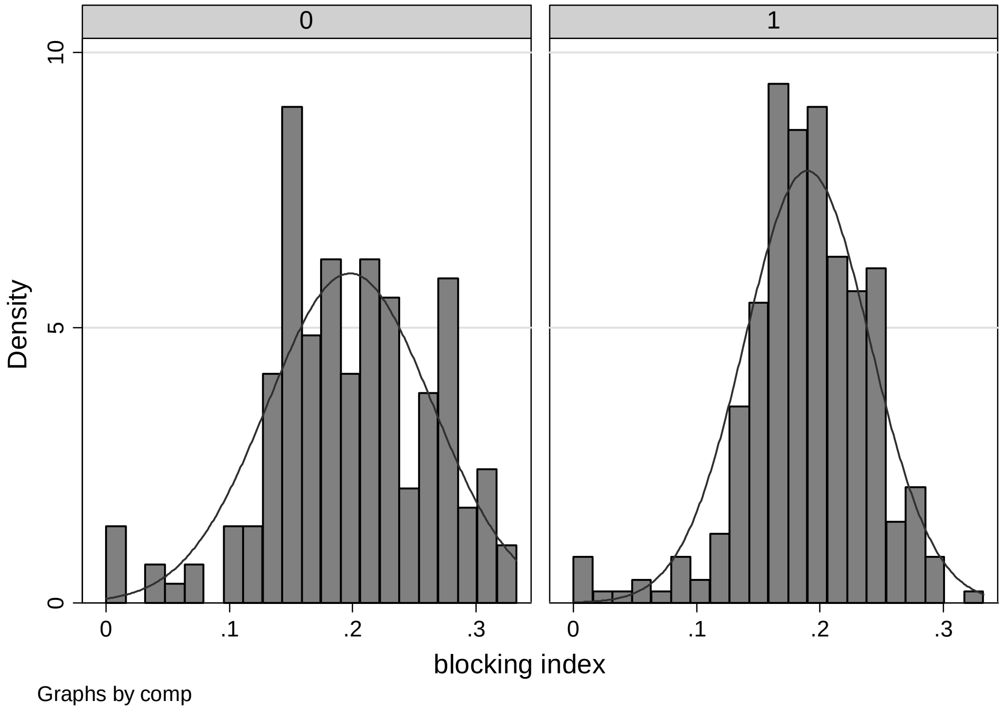
$$index_{i,t} = \sum_{n=tech} prob_{i,t,n} * w_{i,t,n} \qquad (2)$$

This measure is intended to represent the likelihood for an average patent application of being blocked at least once. We therefore call the index 'blocking index'.

Figure 2 shows the density functions of the blocking index for discrete and complex industries. It is based on our sample of 483 patenting firms in German manufacturing. The definition of complex and discrete industries follows Cohen et al. (2000). Discrete industries include chemicals, food, paper, and metals, and the group of complex industries consists of machinery and equipment, electronics, and transportation equipment, i.e. NACE 15-28 and NACE 29-35, respectively. All other manufacturing sectors are defined as complex industries. Figure 2 shows that the likelihood of being blocked with a representative patent is centered around 20 percent for complex and discrete industries. The variance is smaller for complex industries. Only a few firms have a zero probability of being blocked with an average patent application and there are no significant outliers.

Figure 2: Histograms for the blocking index

discrete industries – complex industries

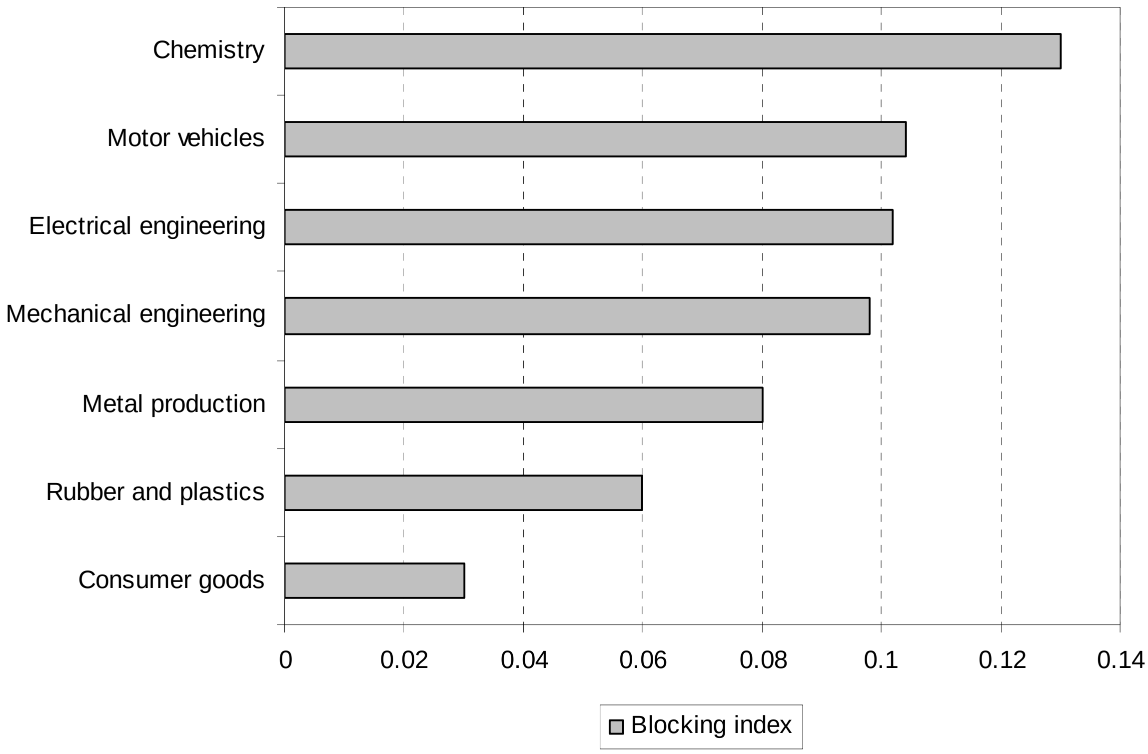


In order to evaluate our measure we compare the blocking index with a survey on motives for patenting at the EPO by Blind et al. (2006). Responses from more than 500 firms revealed that the most important reasons for patenting are defensive blocking and improving the firm's bargaining position on technology markets. Comparing the importance of defensive blocking across industries, Blind et al. (2006) find that the blocking motive is prevalent in all manufacturing industries. However, it is most important in chemical engineering (NACE 24), metal production (NACE 27), mechanical engineering (NACE 29), automotive engineering (NACE 34) and electrical engineering (NACE 30-33), while the blocking motive is less important in consumer goods (NACE 15-19 and 36) as well as rubber and plastics (NACE 25) (see Figure 4 in Blind et al., 2006). If we compare these survey findings with our blocking index we face a very similar pattern. Figure 3 shows the blocking threat across the sample of 1512 firms in German manufacturing.[5] Similar to Blind et al. (2006) we find that

[5] The sample size used for the empirical analysis is smaller as we can only use firm observations that responded to the licensing questions in the survey.

there is not much variation in the blocking probability across these aggregated industries. We however also find that blocking is strongest in chemistry, metal production, mechanical engineering, automotive engineering and electrical engineering, while the blocking motive is least important in consumer goods and rubber and plastics. Hence, our measure for the likelihood of being blocked mirrors the blocking intensity across industries as accessed by patenting firms active in those industries themselves. This gives us further confidence in the measure.

Figure 3: Expected blocking across industries



4 Results

4.1 Descriptive statistics

Table 1 shows descriptive statistics for our sample of patenting firms in German manufacturing. The first column presents means and standard deviations for the variables of interest for the full sample; the second and third columns distinguish between complex and discrete industries.

Table 1: Descriptive Statistics

	Full sample		Complex industries NACE 29-35		Discrete industries NACE 15-28. NACE 36-37	
	mean	std. dev.	mean	std. dev.	mean	std. dev.
In-licensing	0.34	0.48	0.34	0.48	0.34	0.48
Out-licensing	0.42	0.49	0.43	0.50	0.41	0.49
Number of employees	3111	13181	3029	13934	3248	11866
R&D / employment	0.01	0.05	0.01	0.04	0.01	0.07
R&D per NACE2 sector	0.01	0.01	0.01	0.04	0.004	0.004
R&D per NACE2 sector * log(emp)	0.04	0.06	0.04	0.07	0.03	0.04
Patent stock / employment	0.02	0.09	0.01	0.03	0.02	0.14
Blocking index	0.19	0.06	0.19	0.05	0.20	0.07
Export activities	0.94	0.23	0.94	0.22	0.93	0.25
East Germany	0.04	0.20	0.04	0.20	0.04	0.21
Number of observations	483		301		182	

The descriptive statistics reveal some interesting insights. First of all, they show that more than 30 percent of the firms license patents in from third parties and about 40 percent of the firms engage in out-licensing. The percentages do not vary significantly for complex and discrete industries. Both variables are measured as dummy variables indicating whether the firm had used in- and/or out-licensing in 1992. Patenting firms in German manufacturing employ on average about 3,000 people, have an R&D intensity as measured by R&D expenses over employment of about 0.01 and have an average patent stock (PS) per employee of 0.02. The patent stock is defined as follows:

$$PS_t = PS_{t-1}(1-\delta) + patent\ \ applications_t\,, \tag{4}$$

where δ represents the constant knowledge depreciation rate, which is set to 15 percent as is standard in the literature (e.g. Hall, 1990). The patent stock is used with a one year lag to avoid endogeneity problems. Due to the skewness of the patent stock variable it is normalized by employment.

The average probability of being blocked with a representative patent application (given previous patent activities) is 20 percent. Again, there is no significant difference for discrete and complex industries at the unconditional means.

A noteworthy fact presented in Table 1 is that a very small share of about 4 percent of the patenting firms is located in Eastern Germany. This can be explained by the turbulent recent history of Germany. Shortly before the first survey year (referring to 1992), after the fall of the Berlin wall in 1989, Eastern Germany started a transition process from a planned economy into a market economy. Empirical evidence shows significant and relatively persistent differences between Eastern and Western German firms in terms of productivity (Czarnitzki, 2005) and innovativeness (Czarnitzki and Kraft, 2006).

Table 1 shows that there is on average no significant difference between firms in complex and discrete industries, e.g. in terms of labor force, R&D intensity or their patent stock per employee. To further explore the relationships between the variables used in the empirical analysis Table 6 in the Appendix reports the bivariate correlations.

4.2 Multivariate results

In order to analyze the effect of the threat being blocked that a firm faces when filing a patent on the likelihood to be involved in in-licensing and out-licensing we run a series of probability models. Table 2 shows the results. The first columns present the results for two separate probit models for in- and out-licensing and the third and fourth column show the results for a bivariate probit model that allows for correlated error terms of both probit models. In the first part of Table 2 we do not distinguish between the effect of the blocking index for discrete and complex industries. The second part of Table 2 shows the separate effect of the blocking index for complex and discrete industries. In all our models we use firm size as log of employment, R&D intensity (R&D over employment), the patent stock per employer as well as two binary variables controlling for export activities of the firm and firm location in Eastern Germany as control variables. Finally, six industry dummies and a constant are included in our empirical specification.

The first four columns indicate a positive impact of the threat of being blocked on firms' engagement in out-licensing, while there is no significant effect of the blocking index for their in-licensing activities. However, if we distinguish between discrete and complex industries (columns IV-VI) it turns out that there is a strong impact of the blocking index on the threat of in-licensing for firms active in complex industries, while firms in discrete industries are not affected. Focusing on out-licensing activities we find a significant effect of the blocking index for both discrete and complex industries. The effect in the complex industries is however larger in terms of the size of the estimated coefficient and associated with a higher level of statistical significance. Hence, we conclude that the threat of being blocked has a significant impact on firms' involvement in the market for licensing for complex industries, while this effect almost vanishes for firms in discrete industries.

With regard to the control variables Table 2 exhibits a strong correlation between firm size and licensing activities. Large firms typically have better access to capital, which is important for the financing of innovation activities, and they have larger production capabilities, which explains that they are more likely to buy licenses from third parties. Smaller firms turn out to be less involved in the market for licensing. However, we would expect that small and medium-sized firms that often lack the necessary capacity to transform every idea into a new product might benefit substantially from patents and selling licenses as these means allow them to profit from their inventions at least in parts. In order to control for a potential nonlinear effect we included a squared term of firm size as well as a dummy capturing small and medium-sized enterprises in the specifications. There was however no significant evidence for this hypothesis.

Table 2 further exhibits a weak, but negative impact of R&D intensity on the likelihood to engage in out-licensing and no significant effect for firms' in-licensing activities. However, R&D investment is likely to be endogenous with regard to licensing activities. We therefore return to the issue of potential endogeneity of R&D for the licensing decision in the next subsection.

The patent stock of firms is as expected a strong predictor of firms' involvement in markets for licensing. Out-licensing, of course, depends on the ownership of patents. The importance of patents for in-licensing however hints at the importance of cross-licensing and a better position in bargaining negotiations about technologies.

Table 2 further shows that Eastern German firms are less engaged in in- and out-licensing than their Western German counterparts. Many Eastern German firms were founded after re-unification, hence immediately before our survey was conducted. Others were undergoing the transition from state-owned businesses to private corporations. Recent studies have shown that even nowadays Eastern German firms still lack behind in terms of R&D (Czarnitzki, 2005; Czarnitzki and Kraft, 2006).

Finally, the bivariate models presented in columns III and VI show that there is indeed a strong correlation between in- and out-licensing activities of firms. Again, this hints at the importance of cross-licensing activities, i.e. in- and out-licensing can be considered as complementary activities. The empirical specification is very robust against ignoring the possibility of correlated error terms of the in- and out-licensing equation as a comparison of the estimated coefficients of the probit and bivariate probit models show.

As a robustness check we rerun the regressions for the subsample of firms that have one dominant technology sector, i.e. those firms that have at least 90 percent of their patent applications in the year 1991 in one technology class. The results do not change. Further, we add a dummy for complex technologies to our specification to make sure that the result for our main variables is driven by the index itself and not by the industry affiliation alone. The binary variable for complex industries however turns out to be insignificant and the results for the index variables do not change significantly.

Table 2: Probit Models for In- and Out-Licensing

	I	II	III		IV	V	VI	
Model	**probit**	**probit**	**bivariate probit**		**probit**	**probit**	**bivariate probit**	
Dependent variable	**In-licensing**	**Out-licensing**	**In-licensing**	**Out-licensing**	**In-licensing**	**Out-licensing**	**In-licensing**	**Out-licensing**
	coeff. (std. err.)	coeff. (std. err.)	coeff. (std. err.)	coeff. (std. err.)	coeff. (std. err.)	coeff. (std. err.)	coeff. (std. err.)	coeff. (std. err.)
Log(emp.)	0.29***	0.38***	0.28***	0.39***	0.29***	0.38***	0.29***	0.39***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Log(age)	0.02	0.03	0.02	0.03	0.03	0.03	0.03	0.04
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
R&D/emp	-3.73	-5.16*	-3.74	-5.39*	-3.61	-5.15*	-3.60	-5.40*
	(2.72)	(2.78)	(2.75)	(2.92)	(2.65)	(2.77)	(2.68)	(2.91)
Patent stock/ emp.	3.00**	4.38***	2.97**	4.55***	2.88*	4.36***	2.84*	4.54***
	(1.49)	(1.59)	(1.51)	(1.67)	(1.47)	(1.59)	(1.48)	(1.67)
Blocking index	1.86	3.33***	1.87	3.46***				
	(1.17)	(1.23)	(1.17)	(1.21)				
Blocking index *					4.34***	3.71**	4.33***	4.06***
complex techn.					(1.53)	(1.47)	(1.51)	(1.44)
Blocking index *					-0.77	2.86*	-0.88	2.85*
discrete techn.					(1.56)	(1.59)	(1.58)	(1.56)
Exporter	0.55	-0.02	0.60	-0.02	0.59	-0.01	0.64*	-0.00
	(0.38)	(0.33)	(0.39)	(0.33)	(0.38)	(0.33)	(0.39)	(0.33)
East Germany	-0.78*	-0.76*	-0.73*	-0.74*	-0.75*	-0.76*	-0.69	-0.73*
	(0.45)	(0.41)	(0.44)	(0.39)	(0.45)	(0.41)	(0.43)	(0.39)
Industry 2	1.07**	1.27***	1.09**	1.31***	1.13**	1.27***	1.15**	1.32***
	(0.46)	(0.48)	(0.46)	(0.47)	(0.47)	(0.48)	(0.47)	(0.48)
Industry 3	0.17	0.87	0.19	0.89	0.17	0.86	0.20	0.89
	(0.63)	(0.61)	(0.63)	(0.60)	(0.63)	(0.61)	(0.64)	(0.60)
Industry 4	0.78	1.18**	0.79	1.26**	0.70	1.16**	0.71	1.24**
	(0.47)	(0.50)	(0.48)	(0.49)	(0.48)	(0.50)	(0.49)	(0.49)
Industry 5	0.93**	1.41***	0.93**	1.43***	-0.03	1.24**	-0.05	1.20**
	(0.45)	(0.47)	(0.45)	(0.46)	(0.59)	(0.59)	(0.59)	(0.58)
Industry 6	0.83*	1.04**	0.84*	1.07**	-0.23	0.85	-0.24	0.81
	(0.46)	(0.48)	(0.47)	(0.48)	(0.62)	(0.62)	(0.62)	(0.61)
Industry 7	0.57	1.45***	0.60	1.48***	-0.27	1.31**	-0.25	1.29**
	(0.47)	(0.49)	(0.48)	(0.49)	(0.58)	(0.57)	(0.59)	(0.56)
Constant	-4.06***	-4.61***	-4.07***	-4.73***	-3.63***	-4.52***	-3.64***	-4.62***
	(0.68)	(0.68)	(0.69)	(0.68)	(0.71)	(0.71)	(0.71)	(0.70)
ρ			0.42***				0.42***	
			(0.08)				(0.08)	
N	483	483	483		483	483	483	
Log likelihood	-271.19	-267.82	-525.47		-267.60	-267.71	-521.71	
Overall p-value	0.00	0.00	0.00		0.00	0.00	0.00	

***,**,* indicate statistical significance at the 1%, 5%, 10% level

4.3 Endogeneity of R&D

In this subsection we turn to the issue that R&D is likely to be endogenous in the regressions for licensing. As outlined by the theoretical literature, in-licensing might reduce inefficient

R&D investments because firms may have lower incentives to invent around a licensor's patent (Gallini, 1984; Gallini and Winter, 1985). Firms that license their patents out to third parties might, on the one hand, either re-invest the royalties into own R&D or choose to have lower R&D investments due to their head-start over competitors. Firms having a monopoly on a certain technology may (in the short run) have no reason to cannibalize their returns from already existing inventions which would reduce their R&D expenses. Under the assumption that the value of technological knowledge depreciates (e.g., Hall, 1990) and patent protection eventually expires, however, this strategy seems to be feasible only in the short-run. Hence, firms still have incentives to engage in R&D in the presence of licensing. For example, in-licensing firms might want to become independent from their licensors and out-licensing firms might want to sustain their return from licensing in the future. The theoretical literature is ambiguous about the effects of licensing on firms' R&D expenses. According to Gallini and Winter (1985), the overall effect of licensing is expected to be positive when the initial production technologies in a duopoly are close in costs, but negative when the initial costs of R&D are asymmetric. The overall effect of licensing on R&D depends however on many different factors so that the theoretical predictions are quite ambiguous. As a result, we need to take into account that R&D investment is likely to be endogenous with regard to licensing activities.

In order to account for potential endogeneity of R&D we need instrumental variables that correlate with the R&D intensity of the firms, but not with their engagement in the market for technology. As instruments we use the R&D intensity of the industry sectors firms are active in defined on the 2-digit NACE level[6] as well as an interaction of this variable and the log of firm size in terms of employment to increase variation of the instrument across the sample firms. In order to test for endogeneity of R&D in our data and for the relevance and validity of our chosen instruments we run a couple of tests presented in Table 3.

The first set of tests comprises endogeneity tests. We follow Rivers and Vuong (1988) to test whether R&D intensity is indeed endogenous with regard to in- and out-licensing. Technically this test implies a regression of the R&D intensity on the instruments and all other regressors included in the probit specifications I and II in Table 2. In a second step the predicted residuals from this regressions are included in the models I and II (Wooldridge,

[6] As the survey we are using is based on a stratified firm sample we use the survey sampling weights to predict the R&D intensity per industry sector.

2007). The estimated coefficient for the residual is the test statistic for the nullhypothesis of exogeneity of R&D intensity. The first row of Table 3 shows that while we cannot reject exogeneity for in-licensing we can do so for out-licensing. A Rivers and Vuong test applied in the context of a bivariate model in the second step points into the same direction. The third and fourth row show a Wald test for IV probit models for in- and out-licensing and a Durbin-X^2-test for 2SLS models for in- and out-licensing. Both tests suggest the presence of endogeneity of the R&D intensity in the out-licensing model, whereas R&D intensity is exogenous for the in-licensing decision.

Staiger and Stock (1997) emphasize that endogeneity tests as described above can be misleading in case of weak instruments. In case of weak instruments the correlation between the instrument and the endogeneous variable can be artificially high due to the presence of other control variables. Staiger and Stock (1997) suggest evaluating the partial correlation of the instruments and the endogenous variable. As a rule of thumb, they state that the partial F-statistic should exceed the value of 10 to ensure that the instruments are not weak. Table 3 shows that the partial F-statistics for the instruments in both the in- and out-licensing are larger than 30 and highly significant indicating that the instruments have significant additional explanatory power for firms' R&D intensity. Hence, we conclude that weak instruments are not a problem. The second test for weak instruments is based on the minimum eigenvalue statistic following Cragg and Donald (1993) and Stock and Yogo (2005). The nullhypothesis is that instruments are weak. In our case where we only have one endogenous variable the minimum eigenvalue statistic equals the F-statistic. Stock and Yogo (2005) present critical values for this test. Table 3 shows that the minimum eigenvalue statistic exceeds the critical value for the 10% level of statistical significance by far, indicating that we do not face a weak instruments problem.

The final part of Table 3 presents two tests for overidentification. The fact that the number of instruments exceeds the number of endogenous regressors, i.e. the model is overidentified, requires testing whether the instruments are uncorrelated with the error term. Overidentification tests deal with two hypotheses at the same time: first, they test whether the instruments are uncorrelated with the error term and, second, whether the model is incorrectly specified. Table 3 shows that both the Sargan and the Basman test statistic are not significant, indicating that we cannot reject invalidity of our instruments at any convenient level of statistical significance. This result also makes us confident about our model choice.

Table 3: Endogeneity and Relevance Tests

	In-licensing	Out-licensing
Endogeneity tests:		
Rivers & Vuong test-statistic for probit models V, VI, Table 2	0.34	0.06**
(std. err.)	(0.03)	(0.03)
Rivers & Vuong test-statistic for the bivariate probit model VI, Table 2	0.35	0.06**
(std. err.)	(0.03)	(0.03)
Wald-X^2-statistic for IV probit models I, II, Table 2	0.75	4.59**
Durbin-X^2-statistic for 2SLS models III, IV Table 2	0.66	4.01**
Wu-Hausman F-statistic for 2SLS models III, IV Table 2	0.64	3.91**
Relevance tests (for 2SLS models III, IV Table 2):		
F-test for IV significance in the first step	31.37***	
Minimum eigenvalue test: critical value at 10% level of stat. sig. (Stock and Yogo, 2005)	19.93 < min. eigenvalue statistic = 31.37	
Overidentification test (for 2SLS models III, IV Table 2):		
Sragan-X^2-statistic	0.04	0.05
Basman-X^2-statistic	0.04	0.05
Endogenous: R&D intensity		
Instruments: Industry R&D intensity, Industry R&D intensity interacted with log(employment)		
***,**,* indicate statistical significance at the 1%, 5%, 10% level		

As the tests revealed endogeneity of R&D to be an issue for the out-licensing decision we present results for IV probit models and 2SLS estimations in Table 4. Taking endogeneity into account renders the R&D coefficient and most control variables insignificant. Also, the blocking index for discrete industries looses significance. These results support our hypothesis and main finding that the likelihood of being blocked is only of relevance in complex industries.

Table 4: IV probit and 2SLS Estimation for the Out-Licensing Decision

	I	II
Model	**IV probit**	**2SLS**
Dependent variable	**Out-licensing**	**Out-licensing**
	coeff.	coeff.
	(std. err.)	(std. err.)
R&D intensity	6.08	1.94
	(5.50)	(1.78)
Log(employment)	0.34***	0.12***
	(0.06)	(0.01)
Log(age)	0.02	0.01
	(0.04)	(0.02)
Patent stock/employment	-0.92	-0.30
	(2.81)	(0.87)
Blocking index *	2.72*	1.04**
complex technologies	(1.51)	(0.49)
Blocking index *	2.14	0.79
discrete technologies	(1.60)	(0.50)
Exporter	0.32	0.02
	(0.34)	(0.11)
East Germany	-0.64	-0.17
	(0.39)	(0.11)
Industry 2	1.16**	0.35***
	(0.46)	(0.13)
Industry 3	0.83	0.23
	(0.58)	(0.18)
Industry 4	1.11**	0.33**
	(0.47)	(0.14)
Industry 5	1.15**	0.34**
	(0.57)	(0.17)
Industry 6	0.75	0.20
	(0.60)	(0.18)
Industry 7	1.16**	0.34**
	(0.56)	(0.16)
Constant	-4.32***	-0.86***
	(0.71)	(0.19)
N	483.00	483.00
Log likelihood	723.01	
p	0.00	0.00
Endogenous: R&D intensity		
Instruments: Industry R&D intensity, Industry R&D intensity interacted with log(employment)		
***,**,* indicate statistical significance at the 1%, 5%, 10% level		

5 Conclusion and future research

Our research has demonstrated that the threat of being blocked matters considerably for a firm’s participation at the market for technology in terms of in- and out-licensing. The blocking index, describing the threat of a firm’s average patent application to be blocked by a competitor patent, significantly drives the in- and out-licensing behavior of firms. Moreover, when we distinguish between discrete and complex technologies it turns out that both the in- and out-licensing activities are positively affected in complex technologies. In discrete technologies, we do not find consistent evidence for an effect of the blocking index. Taking into account that R&D investments may be endogenous in that there are feedback effects from licensing activity we show that only out-licensing in complex technologies is affected by the blocking index. These findings strongly support our argument that technology licensing can serve as a tool to mitigate hold-up problems. The empirical result that licensing is especially relevant in complex industries only, i.e. industries characterized by a higher degree of technology competition, supports this reasoning.

Our research contributes to the literature in several ways. First, we are able to analyze not only in-licensing but we take account of joint in- and out-licensing activities, extending prior findings by Cockburn et al. (2008) and Siebert and von Graevenitz (2008). Hence, our analysis provides a more complete picture of a firm’s involvement in the market for technology. Second, our blocking index capturing the likelihood to be blocked constitutes a novel measure that can be considered superior to, for example, citation-based measures of technology competition in that these do not yield information in the absence of a citation link between two firms. Another interesting aspect of our study is that the findings stand in contrast to the results by Siebert and von Graevenitz (2008), who conclude that licensing is less effective in industries characterized by a high degree of fragmentation. Hence, our study spurs the discussion about how to measure technology competition and the threat of blocking.

Our research is, however, limited by the data that is available to us. We can only observe whether a firm is engaged in licensing or not. Hence, we miss information on the number of licenses a firm sells or acquires and the nature of the technologies that are licensed, e.g. whether licensed technologies are core to the firm versus non-core technologies. Moreover, we do not have information on the licensing partner and a detailed description of the actual licensing contract. It would be interesting to use a more detailed dataset on licensing in order to exploit the nature of licensing in the context of the threat of blocking and fragmented technology markets.

Appendix

Table 5: Classification of technology areas according to OST-INPI/FhG-ISI

Code	Description Classification
1	Electrical machinery, electrical energy
2	Audiovisual technology
3	Telecommunications
4	Information technology
5	Semiconductors
6	Optics
7	Analysis, measurement, control technology
8	Medical technology
9	Nuclear engineering
10	Organic fine chemistry
11	Macromolecular chemistry, polymers
12	Pharmaceuticals, cosmetics
13	Biotechnology
14	Agriculture, food chemistry
15	Chemical and petrol industry, basic materials chemistry
16	Chemical engineering
17	Surface technology, coating
18	Materials, metallurgy
19	Materials processing, textiles paper
20	Handling, printing
21	Agricultural and food processing, machinery and apparatus
22	Environmental technology
23	Machine tools
24	Engines, pumps and turbines
25	Thermal processes and apparatus
26	Mechanical elements
27	Transport
28	Space technology, weapons
29	Consumer goods and equipments
30	Civil engineering, building, mining

Table 6: Bivariate Correlations

	1.		2.		3.		4.		5.		6.		7.		8.		9.		10.	
1. in-licensing	1.00																			
2. out-licensing	0.39	***	1.00																	
3. log(employment)	0.31	***	0.40	***	1.00															
4. log(age)	0.14	***	0.16	***	0.29	***	1.00													
5. R&D / employment	-0.03		-0.03		-0.19	***	-0.03		1.00											
6. R&D /employment per NACE2 sector	0.09	**	0.13	**	0.15	***	-0.02		0.24	***	1.00									
7. R&D /employment per NACE2 sector interacted with log(employment)	0.14	**	-0.19	***	0.34	***	0.05		0.16	***	0.95	***	1.00							
8. patent stock/ employment	0.002		0.01		-0.28	***	-0.05		0.77	***	0.02	***	-0.05		1.00					
9. Blocking index	0.12	***	0.14	***	0.14	***	0.04		0.08	*	0.18		0.17	***	0.02		1.00			
10. export activities	0.12	***	0.09	*	0.19	***	0.13	***	-0.12	**	0.01		0.04		-0.03		-0.01		1.00	
11. East Germany	-0.11	***	-0.12	**	-0.12	**	-0.32	***	-0.01		-0.01		-0.03		-0.01		0.07		-0.29	***

***,**,* indicate statistical significance at the 1%, 5%, 10% level; n = 1389

Table 7: Industry classification

Abbreviation	Industry	NACE 2-digit code
Industry 1 (reference cat.)	Manufacture of food, tobacco and textiles, clothing, publishing, printing and reproduction of recorded media	15, 16, 17, 18, 19, 21, 22
Industry 2	Manufacture chemicals and plastics	23, 24, 25
Industry 3	Manufacture of other non-metallic mineral products	26
Industry 4	Manufacture of basic metals and fabricated metal products	27, 28
Industry 5	Manufacture of machinery and equipment	29
Industry 6	Manufacture of office machinery, electrical machinery, communication equipment and instruments	30, 31, 32, 33
Industry 7	Manufacture of transport equipment and manufacture n.e.c.	34, 35, 36

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