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Commercializing inventions from public research: Does speed matter?^a

Alexander Schacht^{*}

Abstract

This study addresses the determinants of time-to-licensing, defined as the elapsed time between the disclosure of an invention and the signed licensing contract, and its impact on the commercial success of the licensed inventions from public research. Using a dataset containing detailed information on the licensing activities of the Max Planck Society, I do not find significant evidence that time-to-licensing negatively influences the commercial success of the inventions disclosed between 1980 and 2004. However, separating the effect of the time-to-licensing for the inventions disclosed between 1990 and 2004, I do find a significant negative influence on the likelihood and extent of the commercial success. Thus, the pace of technology transfer has become important because of the rapidly changing business environment and technological obsolescence. Furthermore, inventions from the biomedical section, collaborative inventions with private-sector firms, and inventions that are co-invented with senior scientists require less time to become licensed.

Key words: academic inventions, innovation speed, technology commercialization.

JEL codes: L24, L25, O32

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1. Introduction

Research and development (R&D) and the resultant product and process innovations are an important determinant for a firm's success and competitiveness, thereby enhancing the economic growth and employment in modern economies (Zahra and Nielsen, 2002; OECD, 2003). Due to the rapid changes in economic competitiveness, technologies and consumer preferences, the product life cycles within firms have dramatically shortened and have increased the importance of the rapid development of new products and processes and their implementation into the market (Rosenau, 1988; Kessler and Chakrabarti, 1996).

Aside from a firms' in-house R&D, universities and public research organizations also adopt a particular role as a source of new technologies. According to Smith (1995), along with education, public research institutes promote scientific research and generate new knowledge, which fosters technological progress and new industrial developments. For example, surveyed pharmaceutical industry managers reported that a substantial fraction of the new drugs would not have been developed or would have been delayed without academic research (Mansfield, 1991). Further surveys of industrial R&D executives confirmed the importance of university research for innovation (e.g., Levin et al., 1987; Cohen et al., 2002). Policy makers undertake considerable efforts to increase the linkages between public research institutes and industry. For instance, the Bayh-Dole Act in the U.S. and other similar legislative changes advanced technology transfer as one of the main objectives of public research institutes. Aside from transfer channels such as publications, conferences, consulting, and scientists' migration (Cohen et al., 2002; Agrawal and Henderson, 2002), patenting and licensing has become one of the most common instruments for commercializing scientific inventions (Bozeman, 2000; Shane, 2002).

Licensing inventions from public research institutes enables firms to gain access to new technologies at the point of their discovery, which can result in product or process innovations (George et al., 2002). Not surprisingly, a stream of research investigates the determinants and the effectiveness of university-to-industry technology transfer (e.g., Lee, 1996; Sine et al., 2003; Phan and Siegel, 2006). A further stream examines the nature of technologies (e.g., Jensen and Thursby, 2001; Lowe, 2002; Agrawal, 2006), their commercialization process (e.g., Goldfarb and Henrekson, 2003; Debackere and Veugelers, 2005; Audretsch and Lehmann, 2005) and the role of technology transfer offices within the

transfer process (e.g., Bercovitz et al., 2001; Jensen et al., 2003; Wright et al., 2008; Swamidass and Vulasa, 2009).¹

Moreover, licensing inventions from public research allows firms to skip the process of discovery, which reduces the technological risk and can increase the speed of innovation (Gold, 1987; Markman et al., 2005). The concept of innovation speed is not new and has been applied in a long line of prior studies that are related to product development, market launches, and firm performance (e.g., Kessler and Bierly, 2002; Carbonell and Rodriguez, 2006; Carbonell et al., 2009). However, the relationship between innovation speed and the commercial success of a licensed invention is rather unexplored. Furthermore, evidence for the influence of various determinants on the speed of technology transfer is still scarce. Consistent with the study of Markman et al. (2005), I use time-to-licensing as a proxy for innovation speed, which is defined as the elapsed time between the disclosure of an invention and the signed licensing contract, to investigate these questions.² Analyzing these questions is important because they contribute to theory on innovation speed, clarify the relevance of pace on technology commercialization, and thus can contribute to a more effective university-to-industry technology transfer.

More precisely, this paper aims to analyze how the pace of technology transfer is affected by the differences across technology characteristics, which can be explained by the problems of knowledge transfer for particular inventions (cf. Buenstorf and Geissler, 2012). In addition, the influence of time-to-licensing on both the likelihood and the extent of commercial success is studied. To the best of my knowledge, only the study of Markman et al. (2005) analyzes the determinants of time-to-licensing and its influence on commercial success. Their study is devoted to the institutional determinants of time-to-licensing, while I focus on the invention-specific characteristics. Specifically, inventions are distinguished with regard to the type of technology, i.e., whether an invention belongs to the biomedical section or to the chemistry, physics and technology section. Furthermore, the role of patent protection, collaboration, and inventor seniority is studied. While much is known about the institutional determinants of technology transfer (e.g., Siegel et al., 2004), thus far, the empirical studies have neglected to study the effects of the attributes of technological inventions on the pace of technology transfer.

¹ A detailed literature review on technology transfer and the entrepreneurial role of public research organizations can be found in Rothaermel et al. (2007).

² While Markman et al. (2005) call this ‘commercialization time, the expression ‘time-to-licensing’ appears to be more intuitive and feasible. Nonetheless, the meaning and the definition of both expressions are the same.

To pursue these issues empirically, a dataset is used with detailed information on the licensing activities of the Max Planck Society, Germany's largest non-university public research organization. Whereas the intellectual property rights (IPRs) and the IPR-based commercialization of German universities have both changed with the introduction of the so-called "Arbeitnehmererfindergesetz" (ArbEG) in 2002, the Max Planck Society has been subject to a Bayh-Dole-like legislation since the 1970s. This circumstance provides a rich set of inventions and licensing activities with more than 2,300 inventions and approximately 770 license agreements for the 1980-2004 time period. To identify the time-to-licensing, the dataset includes information on the dates of disclosure and of the license execution. In addition, the dataset contains information on the royalty payments, i.e., whether the invention has been successfully commercialized, as well as on the magnitude of the returns.

The regression results reveal that time-to-licensing does not influence the commercial success of the inventions disclosed between 1980 and 2004. However, after separating the effect of time-to-licensing for the inventions disclosed after 1989, the regression results provide a robust negative influence on the likelihood and the extent of commercial success. Furthermore, the inventions from the biomedical section, the collaborative inventions with private-sector firms, and the participation of senior scientists in the invention development process all require less time to become licensed.

The remainder of the paper is organized as follows: the next section presents the related literature on innovation speed. In section 3, the hypotheses are derived regarding the influence of licensee and technology characteristics on the time-to-licensing and its impact on commercial success. Section 4 provides information about the Max Planck Society, which represents the organizational context of the empirical analysis. Section 5 describes the data and the research design for the empirical analysis, and the results are discussed in section 6. I conclude the analysis and discuss its implications in section 7.

2. Literature review on innovation speed

In firms, there is scarce time for making strategic decisions, especially in frequently changing environments. Rapid decision making and organizational processes have become a crucial resource to gain and sustain competitive advantages (Eisenhardt, 1989; Jones, 1993). Several studies identify a positive relationship between the pace of strategic decision making and firm performance (e.g., Judge and Miller, 1991; Baum and Wally, 2003). Next to quick decision

making, speeding up product development and innovation has become increasingly important and has become the focus of scholarly analysis. In this regard, innovation speed has been identified as one of the primary factors for strategic success, especially for firms that face highly competitive environments, rapid technological change and changing market demands (Nadler and Tushman, 1999).

Research on innovation speed has either addressed the determinants and/or the influence of speed on performance outcomes. The first string of research, which can be separated into the organizational, project and individual levels, examines the different determinants of innovation speed. More precisely, this research includes studies that address the various procedures within organizations that can accelerate innovation speed (e.g., Mansfield, 1988; Cordero, 1991; Ali et al., 1995; Tessarolo, 2007). For instance, Karagozoglu and Brown (1993) identify the different methods and procedures that firms can implement to accelerate their innovation speed using data from 35 high-technology firms. Specifically, the customers' involvement in the testing phase and the use of computer-aided tools in the planning phase have been identified as boosters for innovation speed.

Studies at the individual level discuss the person-specific preferences and perceptions that influence innovation speed (e.g., Rosenau, 1988). For example, the study of Gupta et al. (1992) investigates how R&D, marketing, and manufacturing managers in Germany evaluate three critical variables in the product development process, namely the development schedule, development costs, and product performance. The authors compare the results from Germany and the U.S. and assert that all types of German managers placed the greatest emphasis on the product development schedule, whereas the U.S. managers did not emphasize the product development speed to the same extent.

Project-based studies investigate the determinants of innovation speed associated with various aspects of the product development process (e.g., Millson et al., 1992; McDonough, 1993; Bstieler, 2005). For instance, Cooper and Kleinschmidt (1994) study the determinants of fast-paced product development using 103 new product projects in the chemical industry. They find that cross-functional, dedicated and accountable teams with a strong leadership and top management support positively influence the pace of product development. Likewise, Kessler and Chakrabarti (1999) test the effects of strategic orientation and organizational capability on the speed of 75 new product development projects. They conclude that clear time goals, longer tenure for the team members, and parallel developments increase the speed, whereas product testing decreases the speed.

The second string of research – the benefits of innovation speed – analyzes the impact of innovation speed on outcomes such as development costs, quality or performance. The research results suggest that innovation speed has a substantial positive impact on new product performance (e.g., Lynn et al., 2000; Chen et al., 2005). For example, Carbonell and Rodriguez (2006) study the influence of innovation speed on product performance based on a survey of 178 manufacturing firms. They conclude that innovation speed positively influences new product performance in terms of sales, market share and profitability. Further studies investigate the influence of innovation speed on product quality (e.g., Harter et al., 2000; Lukas and Menon, 2004) and development costs (e.g., Graves, 1989; Murmann, 1994; Langerak et al., 2008). For instance, Kessler and Bierly (2002) find evidence that the innovation speed is positively related to product quality using a sample of 75 new product development projects from 10 U.S. firms. Langerak et al. (2010) analyze the relationship between innovation speed and development costs using survey data from 115 completed product development projects from manufacturing firms. They find a U-shaped relationship between innovation speed and development costs. However, although many studies advertise the benefits of innovation speed on outcome measures (e.g., Rosenthal, 1992; Meyer, 1993), there are other studies that report the opposite effect (e.g., Crawford, 1992; Carmel, 1995).

Because most studies of innovation speed are focused on in-house technological developments and routines, the use of external sources, such as licensing, is somewhat unexplored. In an early study, Gold (1987) discusses the advantages, limitations and risks of using different external sources to accelerate product and process development. Furthermore, Kessler and Chakrabarti (1996) suggest that exploiting external sources can increase the speed of innovation processes. Thus far, very little prior work has studied the relevance of speeding up the technology transfer of inventions from public research organizations. For instance, Dechenaux et al. (2003) study the relationship between patent age, which is defined as the elapsed time from patent issuance to license, and the commercial success or termination of 805 patented technologies from MIT. They observe an inverted and a direct U-shaped relationship for the corresponding hazard rates on the patent age. Llor (2007) investigates the influence of the delay between patent filings and the corresponding transfer agreements on the license revenues of a major public research organization in France and finds no correlation between them. Markman et al. (2005) analyze the determinants of time-to-licensing, defined as the elapsed time between invention disclosure and the signed licensing contract, and its influence on the commercial success of patent-protected technologies from public research institutes. More precisely, they investigate the time-to-licensing for 91 U.S. University

Technology Transfer Offices (UTTOs) and find that the faster UTTOs generate greater returns and have a higher startup formation rate. Moreover, several key determinants of speed, such as UTTO resources, their competency in identifying licensees, and the participation of faculty-inventors in the licensing process, were identified.

The pace by which inventions are transferred to private-sector firms could be important for exploiting the benefits of these novelties to their full extent. Due to rapid technological development and change, it appears reasonable that as the shelf time of the invention increases, its value decreases and therefore its commercial potential (McGrath, 1999; Markman et al., 2005). Moreover, in the meantime, other innovative firms can invent similar technologies that substitute for the existing inventions (Agarwal and Gort, 2001). These substitutes can reduce the value and the returns of the initial disclosed invention. Thus far, insufficient evidence exists as to whether and how the speed of technology transfer influences commercial success. This study contributes to this gap by analyzing the determinants of time-to-licensing and whether time-to-licensing influences the commercial success of licensed inventions with data from the Max Planck Society. In the following, I derive hypotheses regarding the effect of invention-specific determinants on time-to-licensing, as well as the influence of time-to-licensing on commercial success.

3. Hypotheses development

Inventions from public research organizations are one of the major sources of commercially viable innovations. Since the introduction of the Bayh-Dole Act in 1980, which has also been replicated outside of the U.S., public research organizations retain the ownership of publicly funded research results (Lissoni et al., 2008). To organize the protection of the scientists' IPRs and to actively market their inventions, most universities and public research institutes have established technology transfer offices (TTOs). Because technology transfer is a complicated and time-consuming process, TTOs act as agents and primarily support their institutions. This support includes controlling the commercial potential of the disclosed inventions, assessing them for patentability, searching for licensees, conducting negotiations, and monitoring licensees (Siegel et al., 2003a).

Invention-specific determinants

Following the argument of Buenstorf and Geissler (2012), the difficulties in transferring technologies to private-sector firms vary with invention-specific determinants. In this regard, technology characteristics can not only influence the likelihood of successfully concluding licensing agreements (see Buenstorf and Geissler, 2012), but also the pace with which the inventions are transferred to the market. Therefore, in an initial step, I investigate how the technology characteristics influence the speed with which the disclosed inventions are transferred to the market.

Inventions from public research can be differentiated by the technological field in which the invention is generated. More specifically, inventions from public research can be separated into different fields such as biomedical, technical, mechanical, and other sections. It is argued that the technological and commercial potential of inventions can vary across the technological fields, which can influence the likelihood of licensing (Cohen and Levinthal, 1989). In this regard, several studies claim that biomedical inventions have a higher potential for being commercialized and are thus probably more likely to become licensed because of their broad industrial applicability and historical success (Zucker and Darby, 1996; Nerkar and Shane, 2007). Thus, the speed of the technology transfer of biomedical inventions is expected to be higher compared to the non-biomedical inventions, leading to the following hypothesis:

Hypothesis 1: Inventions from the biomedical section require less time to become licensed compared to non-biomedical inventions.

Furthermore, inventions can be separated by assessing the participation of senior scientists in the invention development process. Empirical research reveals a positive correlation between inventive output, such as patenting, and the quality of research of the individual academic scientists (e.g., Breschi et al., 2008; Azoulay et al., 2009). Specifically, senior researchers have a broad knowledge and experience in the field of science and close contacts with private-sector firms. Thus, senior scientists who participate in an invention process signal its outstanding quality and the greater applicability of its technologies, which can influence the likelihood of technology transfer to private sector firms. For instance, Buenstorf and Geissler (2012) find that seniority positively influences the likelihood of licensing across all licensees. Due to the higher reputation of senior scientists, it is expected that their inventions are licensed more quickly to private-sector firms compared to the inventions generated by more junior researchers. Furthermore, the senior scientist can have a

stronger influence on the mediator, i.e., the TTO, which can increase its efforts toward technology transfer. The following is therefore predicted:

Hypothesis 2: Inventions co-invented by senior scientists require less time to become licensed compared to inventions invented by junior researchers.

The ability to appropriate economic returns from innovations is important for inventors and innovators, as well as for the whole economy (Harabi, 1995). Next to secrecy and lead time advantages, patenting is one possible method for protecting inventions and exploiting their returns (Levin et al., 1987; Cohen et al., 2002). Therefore, patented inventions from public research send a strong signal that indicates a verified novelty with a high potential usefulness and uniqueness. This signal is especially important for potential licensees who are interested in inventions that prevent competitors from developing rent-destroying imitations or work-around solutions (Shapiro, 2001). For instance, Buenstorf and Geissler (2012) find that patented inventions are more likely to be licensed than non-patented ones. However, because patent applications require expensive preparations and additional time, the technology transfer of patented inventions, which are complements to lead-time advantages, are expected to take longer compared to non-patented inventions. This conjecture leads to the next testable hypothesis:

Hypothesis 3: Patented inventions require more time to become licensed compared to non-patented inventions.

Negotiations for inventions from public research often include only a limited number of potential licensees and do not necessarily lead to successful agreements for several reasons: the early stage character of academic research (Jensen and Thursby, 2001), the issue of information asymmetry between the inventor and the potential licensee (Shane, 2002), and the problem of complex and non-codified knowledge (Agrawal, 2006). To overcome these problems, firms are often already involved during the early stage development process of inventions through collaborations and other means (Lowe, 2002). Specifically, collaborative research between firms and public research institutes can reduce information asymmetries and increase communication, which can foster the generation of commercially valuable inventions (Siegel et al., 2003b). Moreover, collaborative research has an advantage in that the potential licensee is already determined from the very beginning. Thus, the TTO does not need to

search for a potential licensee, which increases the speed of technology transfer. The following is therefore expected:

Hypothesis 4: Inventions from collaborative research require less time to become licensed to private-sector firms compared to non-collaborative inventions.

The implications of time-to-licensing

The emphasis on an innovation's speed is primarily suited to the rapidly changing business environment, the shrinking window for technological exploitation due to knowledge spillovers, and rapid technological obsolescence (Markman et al., 2005). Theoretically, R&D investments and inventions are related to real options, where the value is inversely related to time, i.e., reducing time-to-licensing increases the value of inventions (McGrath, 1999; Markman et al., 2005). Furthermore, the longer technologies are shelved, the larger the risk that substitutes will emerge (Agarwal and Gort, 2001). In this regard, the commercial potential for these technologies will be lower. At the same time, a faster technology transfer enables firms to gain a competitive advantage when developing and introducing a successful product or process. Thus, with a faster technology transfer, licensees can increase the distance from their competitors, extract more profits, and could develop next generation products due to first-mover advantages (Porter, 1980; Eisenhardt and Martin, 2000).

Certainly, speed can also have an adverse effect on the likelihood and extent of commercial success. One reason for this adverse effect is that a majority of disclosed inventions are at an early stage and the commercialization prospects are less than obvious (Jensen and Thursby, 2001). To better evaluate perspectives, access to information about the inventions and a structured approach with all involved parties is required rather than precipitate action. Nonetheless, consistent with the results of Markman et al. (2005), I hypothesize the following:

Hypothesis 5: Time-to-licensing is negatively related to the likelihood and the extent of commercial success.

4. Empirical context: the Max Planck Society

To analyze the hypotheses developed above, I use detailed data from the Max Planck Society (MPS), Germany's most successful public research organization. The MPS is a German research association that was initially founded in the year 1911 as the Kaiser Wilhelm Society and adopted its current name in 1948. The MPS currently consists of 80 research institutes and three additional research facilities in Germany that perform basic research. The institutes are organized into three sections: (i) the biomedical section; (ii) the chemistry, physics and technology section; and (iii) the humanities and social sciences section.

The MPS is assigned to achieve research excellence, with large research projects that require special equipment or extraordinary expenses. Its primary task is to complement university research by engaging in large-scale, interdisciplinary, or particularly innovative activities in science, (parts of) engineering and the humanities. Approximately 80 percent of the MPS's expenditure is met by public funding from the Federal Government and the German States. The remaining funding stems from donations, member contributions, and a few funded projects. In the period from 2006-2011, the budget of the MPS accounted for 1.3 to 1.4 billion EUR per annum.

Before 2002, the inventions by Max Planck researchers were treated differently from those created by German university researchers. Max Planck researchers, similar to the employees of private-sector firms, are subject to the law on employee inventions, according to which the employees must disclose their inventions to their employer, who is the legal owner of the intellectual property.³ To manage the patent applications and the technology licensing, the MPS established one legally independent technology transfer office, the Max Planck Innovation GmbH (named Garching Innovation GmbH until 1990), which is responsible for the inventions of all of the institutes. Established in 1970, the Max Planck Innovation GmbH is co-located with the Society's central administration in Munich. The patent applications are handled in cooperation with external patent attorneys.⁴ The technologies are marketed to domestic and foreign firms, including spin-offs, which have been actively supported since the early 1990s. Max Planck Innovation GmbH has concluded more than 1,500 license agreements since 1979 (Max Planck Innovation, 2007). The accumulated returns from

³ In contrast, the so-called "professors' privilege" guaranteed the university researchers the retention of their property rights over their research findings. The professors' privilege was abolished in 2002 (see von Proff et al., 2012, for more details).

⁴ Patent applications are applied in case the invention is patentable and even if no licensee has been identified. Thus, the Max Planck Innovation's patenting policy is comparable to that of MIT (cf. Shane, 2002).

technology transfer activities exceeded 200 million EUR, with most of the income resulting from a handful of “blockbuster” inventions. In the case of a successful licensing, the academic inventors receive 30 per cent of all revenues and the Max Planck Institute that employs the researcher receives an additional third. The MPS retains the rest of the revenues for financial purposes.

5. Data description and empirical methods

Data

The present study is based on information provided by Max Planck Innovation GmbH that has been used in earlier works by Buenstorf and Schacht (2011) and Buenstorf and Geissler (2012). The dataset consists of all of the inventions disclosed by Max Planck researchers from the mid-1960s to 2005. Overall 3,012 inventions have been disclosed to the MPS, from which 1,885 resulted in a patent application. Information is available regarding the date of disclosure and the patent application, the institute that the respective invention belongs to, and further invention-specific characteristics such as the involvement of a Max Planck director, as well as whether an invention has been licensed or not. Overall, 864 inventions have been licensed to private-sector firms since the mid-1960s. Because a number of inventions are licensed non-exclusively to a multitude of licensees, there are in total 1,172 license agreements. For each license agreement, the dataset provides additional information on the date of the license agreement and (possibly) its termination, as well as all of the amounts of the payments received based on the license agreement.

To minimize right-censoring problems, the sample is restricted to inventions that were disclosed in 2004 or earlier while using information for payments up to 2007. The data are further restricted to inventions that were disclosed in 1980 or later for two reasons: first, before 1980, Garching Innovation GmbH not only managed the inventions disclosed by Max Planck researchers, but also offered its services to external customers, mostly other public research organizations. Second, the information regarding the pre-1980 inventions is inferior to that for the later inventions. These restrictions lead to a total of 2,376 disclosed inventions, with 773 of them being licensed with 1,047 license agreements.

To analyze the commercial success, the sample size is further reduced by restricting the analysis to the license agreements that provide for royalty payments.⁵ This restriction is necessary because the commercial success of a licensed technology is not directly observable but must be deduced from the incidence of royalty payments. The data includes yearly royalty payments for all individual contracts from conclusion to 2007 or prior termination. In total, 731 contracts provide for royalty payments (with or without additional fixed fees), of which 365 (50 percent) have been successfully commercialized. Table 1 provides an overview of the number of disclosed and licensed inventions from 1980 to 2004, as well as the number of license agreements that provide for royalty payments.

Variables

Three dependent variables are used in the subsequent empirical models: first, a binary variable denotes whether an invention has been licensed. Furthermore, two variables specify the commercial success of the licensed inventions. Specifically, a binary variable is constructed indicating whether the license agreements lead to positive royalty payments. Moreover, because the data includes the yearly payments for all of the individual contracts from conclusion to 2007 or prior termination, the sum of the discounted payments is used as an alternative indicator for commercial success.⁶ Because the accumulated payments for individual license agreements are highly skewed, I employ the natural logarithm to normalize it.

The empirical analysis includes additional information about license agreements, inventions and their licensees. The main variable of interest is *Time-to-licensing*, which measures the elapsed number of days between the disclosure of an invention and the signed licensing contract. To abate concerns regarding non-normality, I employ the natural logarithm of this variable. Figure 1 depicts the logged time-to-licensing for inventions disclosed between 1980 and 2004. A substantial number of license agreements cover multiple inventions that are licensed in the form of a bundle. Lacking more detailed information on the individual inventions covered in these bundles, I treat them as separate observations in the empirical analysis, dividing the royalty payments (if any) equally among the number of bundled inventions. The dummy variable *Bundle* is implemented as a control in the model

⁵ There are several ways in which licensed inventions generate income, including fixed fees and royalty payments. Fixed fees are charged to control for the seriousness of the licensee and include the reimbursement of patent and administrative costs. However, only royalty payments directly reflect the commercial success of the licensed inventions (cf., Agrawal, 2006).

⁶ Royalty payments are discounted to the base year 2000 and are adjusted to the currency “Deutsche Mark”.

specifications. Furthermore, the inventions are classified according to the section of the MPS from which they originate (biomedical section versus chemistry/physics/technology section)⁷ and whether a Max Planck director is among the inventors. The binary variable *Biomed* captures the first distinction. For the latter distinction, the indicator variable *Director involvement* is constructed to identify the inventions by senior researchers.⁸ The year of the invention's disclosure is captured by the integer variable *Disclosure year*, which begins with a zero in 1980. Additionally, the indicator variable *Top 5* is employed for the 5 most active Max Planck institutes with regard to disclosures.

I also employ information about patent applications that are related to licensed inventions. To control for patent applications, the indicator variable *Patent* is employed. For the subset of inventions that are related to patent applications (1,504), further information could be derived from the patent statistics. First, the collaborative inventions are identified on the basis of the patent assignments. The binary variable *Collaboration* identifies inventions that are not (exclusively) related to the Max Planck Society but are (co-) assigned to a private-sector firm.⁹ Furthermore, the integer variable *Patent family size* and a dummy that indicates triadic patent applications in the U.S., the EU and Japan (*Triade*) are employed as proxies for the patent quality.¹⁰

The binary variable *Foreign* classifies the licensees into domestic or foreign according to their postal address. Thereby, the foreign subsidiaries located in Germany are counted as German licensees. Additionally, the indicator variable *Spin-off* divides licensees into spin-offs (i.e., firms started by Max Planck researchers) and external licensees using the Max Planck Innovation's spin-off database. Furthermore, the indicator variable *Repeat licensee* denotes those licensees for which the earlier license agreements with the MPS are found. This variable is motivated by the conjecture that if the later license agreements are related to the earlier ones, their odds of commercialization could be larger due to pre-established contacts and accumulated knowledge. To control for the fields of activity (*Sectoral controls*), licensees are classified into five broad branches employing the standard industrial classification (SIC) numbers. More precisely, I divide the firms into manufacturing, services, and others,

⁷ The humanity section is not taken into account because no inventions are disclosed in this field.

⁸ Directors are the top-level researchers employed at the MPS. Depending on its size, each institute has between two and twelve directors, who can often be considered to be the star scientists (cf. Buenstorf, 2009, for a more detailed account).

⁹ This definition of collaborative inventions is very restrictive (cf. Fontana and Geuna, 2009). However, no better alternative can be provided due to data limitations.

¹⁰ Patent family size is a widely used and accepted measure of patent quality (see Lanjouw et al., 1998; Harhoff et al., 2003).

whereupon the former is split into chemical products, instruments and related products, as well as into other manufacturing products and equipment.

The descriptive statistics and correlations are provided in Tables 2 through 5. More precisely, Table 2 provides the descriptive statistics for all of the disclosed inventions and for the subset of disclosed inventions with patent applications. Table 3 reports the descriptive statistics for the number of licensed inventions providing for royalty payments. Furthermore, Table 4 and 5 report, respectively, the correlation matrixes for all of the disclosed inventions and for the license agreements providing for royalty payments. The highest correlations in both correlation tables show up among the variables *Top 5* and *Biomed*. The correlations for the two independent variables are between 0.3 and 0.5. However, these correlations turn out to be irrelevant in the subsequent analysis. The results are robust to different model specifications, i.e., either excluding the variables or taking them separately into the regression models.

Empirical methods

To analyze the incidence of a licensing event, the appropriate empirical method is a Cox proportional hazard model. The advantage of this model, compared to other models, is that it takes the occurrence of an event, the right censoring, and the elapsed time into account. Time is measured in days, begins with the date of disclosure and ends with the day of the initial license agreement.¹¹ If a disclosed invention is not licensed, it is treated as censored. The following model is specified:

$$h_j(t) = \lim \frac{\Pr\{t \leq T \leq t + \Delta | T \geq t\}}{\Delta t} \quad (1)$$

where $h_j(t)$, the hazard function, is the probability that invention j becomes licensed at time $t + \Delta$, conditional on not having been licensed at time t and Δ being a short interval of time. To account for the influence of covariates, the hazard function is redefined as follows:

$$h_j(t) = h_0(t) \exp(\beta' x_j) \quad (2)$$

¹¹ For a few number of inventions, the date of disclosure or license execution could not be identified. Moreover, in several cases, a licensing agreement is concluded before the disclosure, mainly because of an option to license a nascent technology. These cases are excluded in the subsequent empirical models.

On the left-hand side of equation (2), $h_j(t)$ represents the hazard rate. The baseline hazard function is described by h_0 , whereas x_j indicates the invention-specific covariates.

To study the potential influence of time-to-licensing on the respective outcomes, I subsequently estimate a set of models where the measures of commercial success are regressed on a variety of licensee and technology characteristics.¹² First, a Probit model analyzes the likelihood of commercialization success in which the dependent variable takes the value of 1 if positive royalty payments are realized and zero otherwise. The model is specified as

$$y_{ij}^* = \beta_0 + \beta_1 LicTime_{ij} + L_i \beta_2 + T_j \beta_3 + u_{ij} \quad (3)$$

with

$$y_{ij} = 1 \text{ if } y_{ij}^* > 0$$

$$y_{ij} = 0 \text{ if } y_{ij}^* \leq 0$$

where y_{ij} takes the value of one if firm i successfully commercializes invention j , and y_{ij}^* is an unobserved or a latent variable. $LicTime_{ij}$ represents the elapsed logged number of days between the disclosure of invention j and the signed licensing contract by firm i ; L and T are, respectively, the matrices of licensee- and technology-specific characteristics; and u_{ij} is the error term. Alternatively, Tobit models are employed in which the accumulated royalty payments are used as the dependent variable. The respective model has the following form:

$$y_{ij}^* = \beta_0 + \beta_1 LicTime_{ij} + L_i \beta_2 + T_j \beta_3 + u_{ij} \quad (4)$$

with

$$y_{ij} = \begin{cases} y_{ij}^* & \text{if } y_{ij}^* > 0 \\ 0 & \text{if } y_{ij}^* \leq 0 \end{cases}$$

where y_{ij} takes the values of the latent variable for the positive values and zero otherwise. As in equation (3), the same explanatory variables enter the regression equation. Throughout the

¹² The commercialization of inventions from public research is a two-stage process. In the first step, technologies must be licensed. Because not all inventions are licensed, it is likely that the selection of technologies into licensing is not a random process. Because commercial success is only observable for a subset of licensed inventions, the results might be biased by using such a non-randomly selected sample. However, in the study of Buenstorf and Schacht (2011), the results of the two-stage methodology developed by Heckman (1979) reveal that non-random selection into licensing is not of major concern in the sample analyzing the commercialization of licensed technologies.

analysis, the standard errors are clustered by inventions to control for the occurrence of multiple licensing of the same technology.

6. Results

Speed-related determinants

First, I analyze the determinants that can influence the pace by which inventions are transferred to the market. The results of the Cox proportional hazard models are reported in Table 6.¹³ More precisely, the first two models (Models 1a and 1b) in Table 6 account for all of the inventions and include invention-specific covariates. Specifically, Model 1a includes the indicator variable for the patent application, the director involvement, and the technological section to which the invention belongs. Model 1b additionally controls for the top 5 institutes and the year of disclosure. The last two models (Models 2a and 2b) in Table 6 consider a subset of patented inventions and include the same invention-specific covariates and controls as in Models 1a and 1b. Furthermore, in Model 2b quality measures such as the patent family size and the breadth of the patent protection are implemented as additional controls.

The regression results in Models 1a and 1b (Table 6) identify a strong, significant hazard ratio for biomedical inventions. The hazard ratios (larger than one) suggest that the biomedical inventions that have not been licensed by a certain time have a higher chance of being licensed at the next point in time compared to the inventions from the chemistry-physics-technology section. Thus, the inventions from the biomedical section require less time to become licensed, which is consistent with Hypothesis 1. Models 2a and 2b suggest that the patented biomedical inventions require less time to become licensed compared to the inventions from the chemical-physics-technology section, which confirms Hypothesis 1. These results indicate that the inventions with higher technological and commercial opportunities, such as biomedical inventions, require less time to become licensed. Furthermore, Models 1a and 1b show that inventions that are co-invented by the Max Planck directors are more likely to be licensed at the next point in time compared to the inventions generated by junior researchers. To put it differently, the hazard ratios that are greater than

¹³ Additionally, I employed competing risk models following the method of Lunn and McNeil (1995) to separate the competing events. More precisely, licensing to foreign versus domestic firms and licensing to spin-offs versus external licensees are interpreted as competing events. The results of the invention-specific determinants are similar to the outcomes of the Cox proportional hazard model. These results are available upon request.

one imply that director participation reduces the time until an invention is licensed to private-sector firms, which is consistent with Hypothesis 2. For the subset of patented inventions (Models 2a and 2b), significant hazard ratios confirm this result. Thus, the qualitative and reputational effects appear to influence the pace of technology transfer.

With respect to patent protection, the results in Models 1a and 1b do not support Hypothesis 3, namely that patented inventions require more time to become licensed. Moreover, the results in Models 2a and 2b suggest that collaborative inventions require significantly less time to become licensed compared to non-collaborative inventions, which is consistent with Hypothesis 4. Thus, the collaborations between public research institutes and private firms can not only reduce any information asymmetries but can also reduce the pace by which the inventions are transferred to the market. Finally, two more control variables are noteworthy. First, I find that the inventions from the five most active Max Planck institutes with respect to disclosures require significantly more time to become licensed compared to the disclosed inventions from the other institutes. Second, Model 2b shows that a broad patent protection (Triade) and a larger patent family size promote the speed of technology transfer for an invention. Thus, high-quality technologies are transferred more quickly to private-sector firms than lower quality inventions.

The implications of time-to-licensing

The second part of the analysis covers the impact of time-to-licensing on commercial success. To address this question, two alternative approaches are employed, namely Probit and Tobit models. For each approach, four regression models are estimated employing licensing agreements that provide for royalty payments. Specifically, Models 3a-3d (Table 7) denote Probit regressions using a binary measure for commercial success as the dependent variable, whereas Models 4a-4d (Table 8) denote Tobit regressions employing the logged sum of royalty payments. In Tables 7 and 8, different model specifications are used. More precisely, Models 3a and 4a represent the baseline specification with time-to-licensing as the main variable of interest. In Models 3b and 4b, additional invention-specific controls are implemented, such as whether the invention has been patented, the disclosure year, as well as the section that the invention comes from. Furthermore, Models 3c and 4c include licensee-specific controls, such as the type of firm and the industry section. Finally, in Models 3d and 4d, the complete set of invention- and licensee-specific covariates is integrated.

The results in Table 7 indicate that the logged time-to-licensing does not significantly influence the likelihood of commercial success. Significant marginal effects are obtained for

the patented inventions that are less likely to be commercialized than those for which no patent application is documented (Models 3b and 3d). Thus, licensees appear to obtain a substantial share of licenses for strategic reasons such as “shelving,” which is reflected in the reduced commercialization rates. Furthermore, the time of disclosure indicates that the more recent inventions are less likely to be commercialized than the older ones. This finding could reflect some effects of the right-censored nature of the data. However, this finding could also indicate a reduced average quality of inventions (cf. Buenstorf and Geissler, 2012). Inventions that are licensed as bundles positively influence the likelihood of commercial success. This result could be due to the complementary character of the licensed inventions, which lead more often to commercial success. Finally, the results in Models 3c and 3d suggest that the spin-off licensees are less likely to commercialize the scientific inventions compared to the incumbent firms. To check whether the above findings depend on the choice of the binary measure of commercialization success, a set of Tobit models are additionally estimated (Models 4a-4d in Table 8). Models 4a-4d correspond to the previous model specifications in Table 7. The results in Table 8 are qualitatively very similar to those obtained before. Overall, I do not find any evidence suggesting that the time-to-licensing lowers the likelihood and the extent of commercial success, which contradicts Hypothesis 5.¹⁴

However, the insignificant result of time-to-licensing does not imply that speed is unimportant for certain time spans. It could be that speed has become more important as the economic environment has changed. For instance, Kessler and Chakrabarti (1996) assert that since the 1990s, innovation speed has become one of the most important strategic determinants to create and sustain competitive advantage. To check this conjecture, I replicate the regression models conducted above and include a dummy variable for the inventions disclosed after 1989. Furthermore, I integrate an interaction term that effectively separates the additional effect of time-to-licensing on inventions that were disclosed between 1990 and 2004.¹⁵ Models 5a-5d (Table 9) report the Probit regressions, and Models 6a-6d (Table 10) report the Tobit regressions, including the same set of controls as in the former regression models.

In Models 5a-5d (Table 9), a significant positive correlation is obtained for the inventions that were disclosed between 1990 and 2004. This result suggests that the inventions disclosed after 1989 are more likely to have been commercialized than the

¹⁴ In unreported regression models, I experiment with a quadratic measure of time-to-licensing in both Probit and Tobit models. None of these specifications provide significant results.

¹⁵ A Chow test to find whether the particular date causes a break in the coefficients is significant at the 1 percent level.

inventions disclosed before 1990 in cases where the log time-to-licensing is close to zero. Because the interaction effect is significantly negative, the positive effect of the inventions disclosed after 1989 decreases with the rising log time-to-licensing, which is consistent with the conjecture.¹⁶ Because the interaction effects in the non-linear models can vary for different observations, I employ the method of Norton and Wang (2004) to depict the interaction effect as an example for Model 5d in Table 9. More precisely, Figure 2 shows that the interaction effect in Model 5d is negative for all observations. In terms of the significance of the interaction effect, Figure 3 suggests that the interaction term is significant for all of the predicted probabilities. Furthermore, to check whether the above findings depend on the choice of the binary measure of commercialization success, again a set of Tobit models are estimated (Models 6a-6d in Table 10). The results of these models are qualitatively very similar to those obtained before and confirm the significant negative influence of log time-to-licensing for inventions disclosed after 1989.

The regression results in Tables 9 and 10 could be influenced by unobserved heterogeneity. To control for unobserved heterogeneity across inventions, the regression models are replicated for the inventions that are licensed multiple times, including indicator variables to control for the invention-specific effects. This approach is limited to the subset of inventions that were licensed more than once. In total, 120 inventions have been licensed multiple times, which leads to 272 license agreements.¹⁷ However, this number of license agreements is restricted to the level of commercial success as the dependent variable. In the case of the likelihood to commercialize, the majority of observations are dropped due to a non variation in the binary outcome variable across the licensees of a single invention. Thus, I focus on the extent of commercial success employing Tobit models with invention-specific fixed effects (Table 11). Because fixed effects models rely on a certain amount of within-group variation, I drop the invention-specific controls and include only the licensee controls.

The regression results in Table 11 (Models 7a and 7b) are consistent with the results in Table 10 with respect to the time-to-licensing. Specifically, I find that the inventions disclosed after 1989 generate lower royalty payments with a rising log time-to-licensing, which is consistent with prior results. Thus, after controlling for any unobserved heterogeneity across inventions, I find strong evidence that the time-to-licensing is an important determinant for

¹⁶ To verify this result, I also employed Cox proportional hazard models to investigate the influence of log time-to-licensing on commercial success. Thus, the elapsed time between the initial licensing agreement and the first sale is taken into account. The results are quite similar to the corresponding Probit models with respect to directions and significance levels. The results of these regression models are available upon request.

¹⁷ For two license agreements, no information is available for time-to-licensing. Thus, 270 license agreements are left for robustness checks.

commercial success for the inventions disclosed after 1989. This finding implies that the speed of technology transfer has become a crucial determinant for commercial success due to the rapidly changing business environments and technological obsolescence.

7. Conclusion

The importance of technology transfer from public research as a key source for innovation, and therefore for economic growth and employment in developed countries, has increasingly aroused the interest of policy makers and researchers. In particular, technology transfer through patenting and licensing is seen as a useful tool to encourage innovation. Whereas a multitude of studies investigate the technology transfer of inventions and their commercialization process, only a few works analyze how the speed by which the inventions are transferred to private-sector firms is related to their commercial success.

In this paper, I investigate two questions related to speed. First, I raise the question as to which invention-specific determinants influence the time-to-licensing, which is defined as the elapsed time between the disclosure of the invention and the signed licensing contract. Second, I analyze how the time-to-licensing is related to the likelihood and magnitude of commercial success. The regression results reveal that the inventions from the biomedical section, the collaborative inventions with private-sector firms, and the co-invented inventions with senior scientists (Max Planck directors) require less time to become licensed. According to the influence of time-to-licensing on commercial success, I do not find significant evidence that time-to-licensing negatively influences the commercial success of the inventions disclosed between 1980 and 2004. However, separating the effect of time-to-licensing for the inventions disclosed after 1989, I find a significant negative influence for the time-to-licensing on the likelihood and extent of commercial success. Thus, the regression results partially confirm the findings of Markman et al. (2005) and support the conjecture that the speed of technology transfer has become an important strategic factor since the 1990s (cf., Kessler and Chakrabarti, 1996).

The above analysis is characterized by several limitations. First, the findings of this study cannot be generalized because the analysis covers only one public research organization. However, because the Max Planck Society is one of the most important non-university research organizations worldwide, it takes a key position in Germany's public research landscape. Furthermore, the Max Planck Society is one of the first public research

organizations in Europe to be subject to a Bayh-Dole-like IPR regime. Second, it appears plausible that any unobserved heterogeneity could influence the regression results. Conducting a robustness check to control for unobserved heterogeneity in the licensed inventions does not influence the main finding. However, I cannot conclusively rule out this possibility.

It should be clear that the results of the invention-specific determinants of time-to-licensing should not be taken as a request to interfere in the invention development process. The results provided in this study should be considered by the TTOs, which are responsible for technology transfer and which tend to form the link between public research institutes and private-sector firms. Thus, it appears plausible that improvements in the TTOs' organizational routines and procedures could facilitate the speed of the technology transfer. A more efficient technology transfer has (at least) two advantages. First, from the policy perspective, an efficient technology transfer fosters the effective use of scarce public sources. Second, a more efficient technology transfer could advance the economic and social benefits from basic research. Because the IPR system has recently been adopted by German and other European universities, additional studies are required to better understand the determinants of time-to-licensing and its influence on commercial success.

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Table 1: Disclosed and licensed inventions, 1980-2004

Inventions (patented)	2,376 (1,504)
Licensed inventions (patented)	773 (546)
License agreements (patented)	1,047 (728)
License agreements with royalties (patented)	731 (513)
Commercialized (patented)	365 (218)

Table 2: Descriptive statistics, 1980-2004

	Disclosed inventions				Disclosed inventions with patent application			
	obs	mean	min	max	obs	mean	min	max
Biomed	2197	0.598	0	1	1350	0.586	0	1
Director involvement	2197	0.126	0	1	1350	0.168	0	1
Patent	2197	0.635	0	1				
Disclosure year	2197	14.720	0	24	1350	14.519	0	24
Top 5	2197	0.418	0	1	1350	0.419	0	1
Patent family size					1350	5.354	1	120
Triade					1350	0.245	0	1
Collaboration					1350	0.206	0	1

Table 3: Descriptive statistics, 1980-2004

	License agreements providing for royalties			
	obs	mean	min	max
Commercialization	681	0.504	0	1
Log royalties	681	4.824	0	19.109
Log Time-to-licensing	681	6.525	1.343	9.484
Disclosure year (1980=0)	681	13.419	0	24
Biomed	681	0.775	0	1
Director involvement	681	0.377	0	1
Patent	681	0.706	0	1
Spin-off	681	0.307	0	1
Foreign	681	0.305	0	1
Bundle	681	0.288	0	1
Top 5	681	0.501	0	1
Repeat licensee	681	0.755	0	1

Table 4: Correlations between covariates (licensed inventions), 1980-2004

2197 obs.	Time	Biomed	Patent	Director inv.	Top 5
Disclosure year	1.000				
Biomed	0.072*	1.000			
Patent	0.003	-0.013	1.000		
Director involvement	0.023	0.166*	0.154*	1.000	
Top 5	-0.048	0.340*	-0.001	0.148*	1.000

Note: The asterisk * denotes significance of pairwise correlation at the one percent level.

Table 5: Correlations between covariates (license agreements providing for royalties), 1980-2004

681 obs.	Log t.-t.- licensing	Disc. year	Spin-off	Foreign	Biomed	Patent	Director inv.	Repeat licensee	Bundle	Top 5
Log Time-to- licensing	1.000									
Disclosure year	-0.156*	1.000								
Spin-off	0.028	0.276*	1.000							
Foreign	0.072	-0.028	-0.310*	1.000						
Biomed	0.087	0.166*	0.099*	0.151*	1.000					
Patent	0.389*	0.044	0.184*	-0.062	0.062	1.000				
Director involvement	0.128*	0.111*	0.172*	0.122*	0.201*	0.123*	1.000			
Repeat licensee	0.065	0.036	0.291*	-0.178*	0.127*	0.195*	0.141*	1.000		
Bundle	0.081	-0.003	0.224*	-0.077	-0.015	0.232*	0.154*	0.340*	1.000	
Top 5	0.091	-0.021	0.040	0.095	0.455*	-0.006	0.214*	0.080	0.006	1.000

Note: The asterisk * denotes significance of pairwise correlation at the one percent level.

Table 6: Licensing hazards (Cox proportional hazard model), hazard ratios, 1980-2004

	Model 1a	Model 1b	Model 2a	Model 2b
	All inventions		Patented inventions	
Patent	1.029 (0.095)	1.017 (0.094)		
Biomed	1.495*** (0.129)	1.717*** (0.150)	2.080*** (0.228)	2.041*** (0.224)
Director involvement	5.250*** (0.450)	5.638*** (0.482)	4.858*** (0.481)	4.431*** (0.458)
Top 5		0.696*** (0.054)	0.695*** (0.065)	0.719*** (0.066)
Disclosure year		0.984*** (0.006)	0.994 (0.007)	0.998 (0.008)
Collaboration			1.316** (0.163)	1.229** (0.162)
Patent family size				1.009** (0.004)
Triade				1.274** (0.138)
Observations	2197	2197	1350	1350
(events)	(689)	(689)	(488)	(488)
p>chi ²	0.0000	0.0000	0.0000	0.0000

Robust standard errors in parentheses; *, **, and *** denote significance at the 0.10; 0.05; and 0.01 levels, respectively.

Table 7: Likelihood of commercialization (Probit), marginal effects, 1980-2004

Commercial success = 1	Model 3a	Model 3b	Model 3c	Model 3d
	License agreements providing for royalties			
Log Time-to-licensing	-0.025 (0.019)	-0.011 (0.019)	-0.021 (0.018)	-0.016 (0.019)
Disclosure year		-0.016*** (0.003)		-0.016*** (0.004)
Biomed		-0.038 (0.059)		0.023 (0.063)
Director involvement		-0.022 (0.049)		0.032 (0.049)
Patent		-0.222*** (0.047)		-0.185*** (0.049)
Bundle		0.128*** (0.048)		0.169*** (0.050)
Top 5		0.023 (0.051)		0.009 (0.051)
Spin-off			-0.154*** (0.047)	-0.110** (0.050)
Foreign			-0.014 (0.053)	-0.020 (0.053)
Repeat licensee			0.053 (0.053)	-0.004 (0.056)
Sectoral controls	no	no	yes	yes
Observations (inventions)	681 (531)	681 (531)	681 (531)	681 (531)
Pseudo R ²	0.003	0.072	0.057	0.111

Robust standard errors (clustered by invention) in parentheses; *, **, and *** denote significance at the 0.10; 0.05; and 0.01 levels, respectively.

Table 8: Level of royalty income (Tobit), 1980-2004

Log royalties	Model 4a	Model 4b	Model 4c	Model 4d
		License agreements providing for royalties		
Log Time-to-licensing	-0.271 (0.433)	-0.091 (0.364)	-0.184 (0.371)	-0.189 (0.331)
Disclosure year		-0.348*** (0.064)		-0.336*** (0.065)
Biomed		-0.577 (1.078)		0.220 (1.119)
Director involvement		-1.075 (1.011)		-0.247 (0.944)
Patent		-3.701*** (0.917)		-2.655*** (0.908)
Bundle		2.150** (0.933)		2.581*** (0.924)
Top 5		0.580 (1.036)		0.221 (0.950)
Spin-off			-3.438*** (0.913)	-2.078** (0.902)
Foreign			0.064 (1.107)	0.344 (1.077)
Repeat licensee			1.291 (0.944)	0.425 (0.952)
Sectoral controls	no	no	yes	yes
Constant	3.190 (2.640)	9.272*** (2.304)	3.113 (2.385)	7.860*** (2.313)
Observations (inventions)	681 (531)	681 (531)	681 (531)	681 (531)
Pseudo R ²	0.000	0.024	0.020	0.038

Robust standard errors (clustered by invention) in parentheses; *, **, and *** denote significance at the 0.10; 0.05; and 0.01 levels, respectively.

Table 9: Likelihood of commercialization (Probit), marginal effects, 1980-2004

Commercial success = 1	Model 5a	Model 5b	Model 5c	Model 5d
	License agreements providing for royalties			
Log Time-to-licensing	0.033 (0.029)	0.059** (0.030)	0.044 (0.028)	0.059** (0.028)
1990-2004	0.392* (0.198)	0.407* (0.197)	0.450** (0.183)	0.436** (0.187)
Log time-to-licensing * 1990-2004	-0.102*** (0.037)	-0.102*** (0.037)	-0.109*** (0.036)	-0.106*** (0.036)
Biomed		-0.034 (0.061)		0.028 (0.065)
Director involvement		-0.027 (0.048)		0.030 (0.048)
Patent		-0.204*** (0.046)		-0.172*** (0.048)
Bundle		0.155*** (0.046)		0.191 (0.049)
Top 5		-0.001 (0.050)		-0.017 (0.050)
Spin-off			-0.097** (0.049)	-0.115** (0.049)
Foreign			-0.033 (0.050)	-0.050 (0.050)
Repeat licensee			0.039 (0.053)	-0.004 (0.056)
Sectoral controls	no	no	yes	yes
Observations	681	681	681	681
(inventions)	(531)	(531)	(531)	(531)
Pseudo R ²	0.055	0.082	0.095	0.121

Robust standard errors (clustered by invention) in parentheses; *, **, and *** denote significance at the 0.10; 0.05; and 0.01 levels, respectively.

Table 10: Level of royalty income (Tobit), 1980-2004

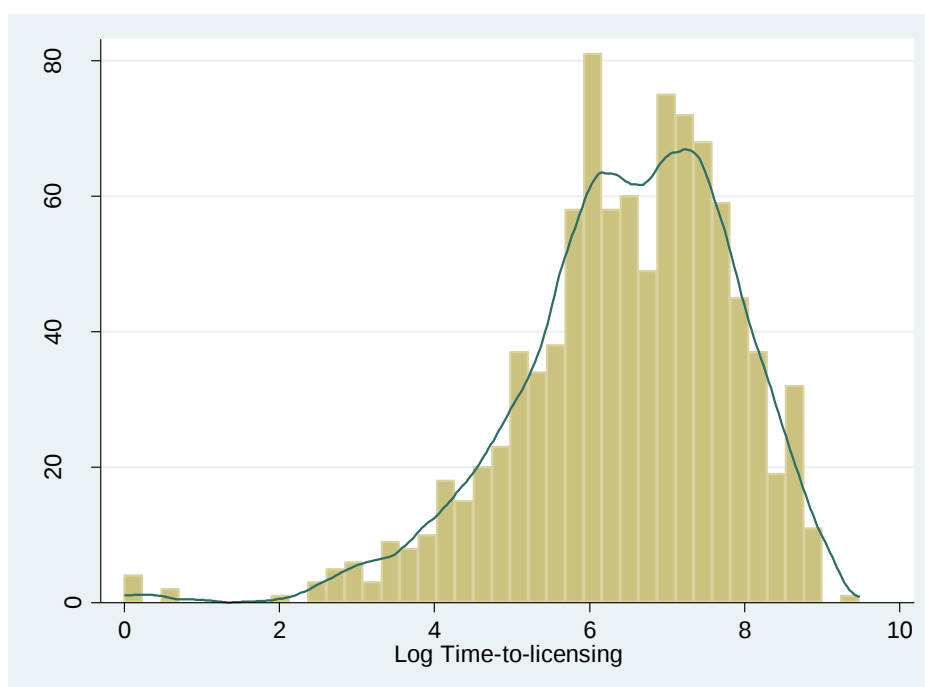
Log royalties	Model 6a	Model 6b	Model 6c	Model 6d
	License agreements providing for royalties			
Log Time-to-licensing	0.913 (0.593)	1.315** (0.591)	1.030** (0.501)	1.257** (0.508)
1990-2004	9.605** (4.488)	9.572** (4.525)	10.285** (4.133)	9.956** (4.200)
Log time-to-licensing * 1990-2004	-2.272*** (0.714)	-2.192*** (0.722)	-2.257*** (0.631)	-2.193*** (0.648)
Biomed		-0.488 (1.105)		0.279 (1.136)
Director involvement		-1.171 (0.932)		-0.229 (0.880)
Patent		-3.220*** (0.909)		-2.339*** (0.870)
Bundle		2.563*** (0.871)		2.908*** (0.889)
Top 5		0.003 (0.951)		-0.354 (0.903)
Spin-off			-1.997** (0.898)	-2.063** (0.901)
Foreign			-0.353 (0.922)	-0.375 (0.960)
Repeat licensee			0.994 (0.895)	0.361 (0.940)
Sectoral controls	no	no	yes	yes
Constant	-0.986 (3.717)	-1.605 (3.825)	-2.198 (3.378)	-2.656 (3.466)
Observations (inventions)	681 (531)	681 (531)	681 (531)	681 (531)
Pseudo R ²	0.021	0.028	0.037	0.042

Robust standard errors (clustered by invention) in parentheses; *, **, and *** denote significance at the 0.10; 0.05; and 0.01 levels, respectively.

Table 11: Level of royalty income (Tobit), 1980-2004 (mult. licenses; invention controls)

Log royalties	Model 7a	Model 7b
	License agreements providing for royalties	
Log Time-to-licensing	1.707*** (0.002)	1.602*** (0.003)
1990-2004	50.024*** (0.027)	53.404*** (0.035)
Log Time-to-licensing * 1990-2004	-3.161*** (0.002)	-3.186*** (0.004)
Bundle		-0.528*** (0.040)
Spin-off		-4.790*** (0.049)
Repeat licensee		0.460*** (0.032)
Sectoral controls	no	yes
Invention-specific effects	yes	yes
Constant	-40.822*** (0.021)	-31.952*** (0.013)
Observations	270	270
(inventions)	(120)	(120)
Pseudo R ²	0.263	0.274

Robust standard errors (clustered by invention) in parentheses; *, **, and *** denote significance at the 0.10; 0.05; and 0.01 levels, respectively.

Figure 1: Time-to-licensing, 1980-2004

Note: The graph pictures a histogram of the number of logged days elapsed between the disclosure of an invention and the signed licensing contract from 1980 through 2004 for licensed inventions. Additionally, a kernel density function is plotted.

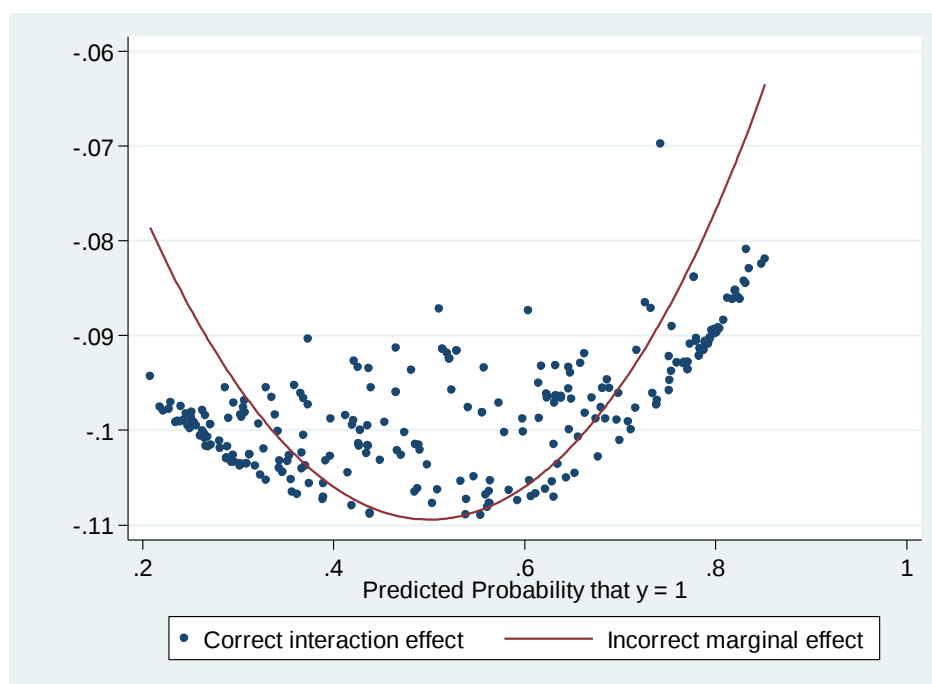
Figure 2: Interaction effects after Probit

Figure 3: Z-Statistics of the interaction effects after Probit

