# *STUDIES ON INFORMAL RESEARCH COLLABORATIONS AND KNOWLEDGE TRANSFER – EMPIRICAL EVIDENCE FROM THE MICRO-LEVEL*

*DEUTSCHER TITEL:*
*STUDIEN ZU INFORMELLEN FORSCHUNGSKOOPERATIONEN UND WISSENSTRANSFER – EMPIRISCHE EVIDENZ VON DER MIKROEBENE*

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*For my parents Gisela and Dietrich*

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## Content

## List of Tables and Figures

### Tables in the text



### Appendix Tables

**Figures**

# 1 German summary – Kurzfassung auf Deutsch

Wissenschaftler und Politiker sind sich heutzutage zunehmend einig, dass das Produktivitätswachstum und der Wohlstand von fortschrittlichen Industrienationen weniger von deren Rohstoffvorräten abhängt, als von deren Fähigkeit, neues, technologisches Wissen zu entwickeln und dieses in marktfähige Produkte zu überführen. Aus diesem Grund haben die Regierungen führender Industrienationen in den letzten Jahrzehnten damit begonnen, Förderprogramme zu implementieren, die die Generierung und Diffusion von neuem technologischem Wissen fördern sollen. So hat beispielsweise die Europäische Union in ihrem siebten Rahmenprogramm beschlossen, zwischen 2007 und 2013 mehr als 53 Milliarden Euro für Forschung und Entwicklung auszugeben (European Communities 2007).

Die Produktion von technologischem Wissen unterscheidet sich von der Produktion materieller Güter. Kogut und Zander (1992) haben gezeigt, dass technologisches Wissen durch die Rekombination von bestehendem Wissen generiert wird und somit einen kumulativen und pfadabhängigen Charakter hat. Durch die Tatsache, dass das technologische Wissen heterogen zwischen den in Forschung und Entwicklung (F&E) aktiven Akteuren (e.g. wissenschaftliche Institutionen, Unternehmen) verteilt ist, sind diese permanent gezwungen, während des Innovationsprozesses externes Wissen zu absorbieren (z.B. Chesbrough 2003, Edquist 2005, Powell and Grodal 2005, Lundvall 2010, Giuliani 2011). Während der erste Ansatz einen Schwerpunkt auf die systemische Natur des Innovationsprozesses legt, betont und untersucht der Innovationsnetzwerk-Ansatz die strukturelle Dynamik des Wissensaustauschs zwischen den Akteuren.

Ein von F&E-aktiven Institutionen oftmals gewählter Weg, um externes Wissen zu akquirieren sind dabei F&E-Kooperationen mit einer oder mehreren externen Institutionen. Empirische Analysen, die einen solchen Wissenstransfer zwischen Einrichtungen im Rahmen des Innovationsprozesses untersuchen, basieren ihre Untersuchungen dabei zumeist auf Daten zu formalen F&E-Kooperationen. Formale Kooperationsvereinbarungen sind solche Kooperationen, die in irgendeiner Weise formalisiert sind (z.B. auf Verträge aufbauen).

Die Motive, Mechanismen und Konsequenzen des formalen Wissenstransfers sind im Vergleich zu denen des informalen Wissenstransfers empirisch weit umfassender erforscht. Bönte und Keilbach (2005) argumentieren, dass informaler Wissenstransfer, dadurch dass er keinen Formalien unterliegt, im Vergleich zu formellem Wissens- und Technologietransfer schwerer zu definieren und messen ist und dass aus diesem Grund vergleichsweise wenig empirische Studien zu informalem Wissenstransfer im Innovationsprozess existieren.

Dabei haben großangelegte empirische Untersuchungen auf institutioneller Ebene gezeigt, dass formale Kooperationsaktivitäten oft nur einen Bruchteil der eigentlichen Wissenstransferaktivitäten der forschenden Institutionen reflektieren, da ein großer Teil des Wissensaustauschs zwischen F&E-aktiven Institutionen auf einem informellen Weg geschieht (z.B. Link und Bauer 1989, Bönte und Keilbach 2005). Die existierenden empirische Studien zeigen auf, dass dieser informelle Wissens- und Technologietransfer dabei eine besonders hohe Bedeutung für den Wissensaustausch zwischen Industrie und Wissenschaft und für den Wissensaustausch innerhalb von wissensbasierten Industrien hat (z.B. Meyer-Kramer und Schmoch 1998, Prevezer 2001, Owen-Smith und Powell 2004, Salavisa et al. 2012).

Zum anderen wird aktuell die Thematik des informalen Wissenstransfer von Wissenschaftlern in Zusammenhang mit „Brain Drain“-Debatten und Debatten über die wirtschaftlichen Nutzungsrechte von Erfindungen, die mit öffentlichen Mitteln unterstützt worden sind, in vielen Ländern diskutiert (z.B. Nguyen 2006, Link et al. 2007).

Darüber hinaus existieren in der ökonomischen Theorie unterschiedliche Ansichten bezüglich der Konsequenzen informaler Wissenstransferaktivitäten von Unternehmen. Während Arbeiten aus der ressourcenbasierten Ökonomie nahe legen, dass der informelle Abfluss von Wissen an Konkurrenten die Wettbewerbsfähigkeit von Unternehmen mindert (z.B. Liebeskind 1996, Brown und Duguid 2001), zeigen beispielsweise die Arbeiten von Hippel (1987) und Schrader (1991), dass der informelle Wissensabfluss in Unternehmen oftmals nicht unkontrolliert geschieht, sondern dass eher ein Handel mit informellen Wissensabflüssen und Wissenszuflüssen zwischen konkurrierenden Unternehmen besteht.

Diese Arbeit beinhaltet – neben einem theoretischen Teil – vier empirische Kapitel, die neue Evidenz auf Mikroebene zu der Thematik der informellen Wissensflüsse im Innovationsprozess beinhalten.

Der erste empirische Teil der Arbeit analysiert, inwieweit individuelle und fakultätsbezogene Faktoren die Entscheidung eines Wissenschaftlers beeinflussen, an informellen Wissenstransfer zu Unternehmen zu partizipieren. Wir zeigen auf Basis einer Befragung von deutschen Wissenschaftlern, dass die Entscheidung eines Forschers, sich in informellen Wissenstransfer zu engagieren, sowohl von fakultätsbezogenen Faktoren (z.B. Forschergruppengröße) als auch von individuellen Charakteristika des Wissenschaftlers (z.B. Geschlecht, Stellung in der Fakultät) abhängt. Die meisten Ergebnisse unserer Studie sind dabei in Einklang mit den Ergebnissen einer Studie von Link et al. (2007), die US-Wissenschaftler an Universitäten zu ihrem Engagement in informellen Wissens- und Technologietransfer befragt haben. Im Unterschied zu Link et al. (2007) zeigen wir für unsere deutschen Wissenschaftlerdaten, dass die Anzahl der Patente eines Wissenschaftlers einen positiven Einfluss auf die Entscheidung des Wissenschaftlers hat, an informellem Wissenstransfer teilzunehmen.

Der zweite empirische Teil der Arbeit basiert ebenfalls auf einer Befragung deutscher Wissenschaftler und zeigt, inwieweit internationale Mobilität von Wissenschaftlern deren Wahrscheinlichkeit beeinflusst, sich in informellen und formellen Wissens- und Technologietransfer an Unternehmen in ihrem Heimatland und/oder in ihrem Gastland zu engagieren. Wir zeigen, dass die Dauer eines Forschungsaufenthaltes einen positiven Einfluss auf die Wahrscheinlichkeit des Wissenschaftlers hat, sowohl Wissen in das Gastland als auch in das Heimatland zu transferieren. Die Häufigkeit von Forschungsaufenthalten dahingegen scheint nur eine positive Auswirkung auf die Wahrscheinlichkeit eines Forschers zu haben, Wissenstransfer zu der Industrie im Heimatland zu betreiben. Unsere Ergebnisse zeigen zumindest für Deutschland, dass internationale Mobilität von Wissenschaftlern also nicht wie oftmals befürchtet zu einem Wissensabfluss, sondern eher zu einem Wissensgewinn führt.

Während die ersten beiden empirischen Kapitel Faktoren analysieren, die kritisch für die Initiierung von informellem Wissenstransfer sind, untersuchen die anderen beiden empirischen Teile der Arbeit zwei Phänomene, die hauptsächlich als Konsequenz von informellem Wissenstransfer auftreten: Wissensflüsse von Unternehmen zu wissenschaftlichen Einrichtungen und geteilte Eigentumsrechte von Erfindungen.

Der dritte empirische Teil der Arbeit untersucht Wissensflüsse von Unternehmen zu wissenschaftlichen Einrichtungen in der biotechnologischen Industrie. Wissensflüsse in diese Richtung sind bisher relativ unerforscht geblieben. Auf der Basis von Patentdaten identifizieren wir Wissensflüsse anhand von Patentzitationen und vergleichen die Zitationswahrscheinlichkeit der Patente, zwischen denen Wissensflüsse bestehen, zu selektierten Kontrollpatentpaaren. Wir zeigen, dass nicht nur institutionsspezifische Merkmale, wie beispielsweise das Kollaborations- und Patentprofil oder die geographische Lokation von den Patent anmeldenden Institutionen, sondern auch inventionsbezogene Faktoren, wie etwa der approximierte ökonomische Wert, die wissenschaftliche Komplexität oder die technologische Spezifität einer Erfindung einen Einfluss auf die Zitationswahrscheinlichkeit haben.

Der letzte empirische Teil der Arbeit beschäftigt sich mit Innovationen mit geteilten Eigentumsrechten. Solche Innovationen entstehen häufig aus informalen F&E-Kooperationen, da hier die Eigentumsrechte an einer möglichen Invention a priori nicht geklärt sind. Genauer untersucht der letzte empirische Teil der Arbeit die Motivation von Unternehmen, gemeinsam ein Patent anzumelden. Gegeben dem legalen und organisatorischen Aufwand, der mit gemeinschaftlichen Patentanmeldungen einhergeht, haben Unternehmen normaler Weise einen starken Anreiz, gemeinsame Patentanmeldungen zu verhindern. Wir testen wiederum auf der Basis von Patentdaten aus der Biotechnologie die Hypothese, dass die Entscheidung von Unternehmen, gemeinsam ein Patent anzumelden, von dem zukünftigen, erwarteten ökonomischen Nutzen des Patents abhängt. Wir zeigen als Beitrag zur Methodenentwicklung, dass sich nichtparametrische Matchingverfahren dazu eignen, kausale Inferenz auf Patentebene zu testen.

Basierend auf den Erkenntnissen aus den empirischen Teilen, können wir folgende, übergreifende Schlussfolgerungen ableiten: Wir finden in unseren Studien starke Evidenz dafür, dass Wissen kontinuierlich – sei es aufgrund regulärer Forschungstätigkeiten oder aufgrund von Mobilität von Wissenschaftlern – aus wissenschaftlichen Einrichtungen abfließt. Offensichtlich befinden sich deutsche, wissenschaftliche Einrichtungen immer noch in einem Lernprozess, wie sie die Nutzungsanreize von eigenen Technologietransfermechanismen steigern können.

Auf der anderen Seite haben wir gezeigt, dass Unternehmen von diesen informellen Wissensflüssen aus der Wissenschaft (z.B. durch die Mobilität von Wissenschaftlern) profitieren. Von daher schlussfolgern wir, dass die Politik es nicht zwangsläufig als oberste Priorität sehen sollte, den Wissensabfluss aus der Wissenschaft gänzlich zu verhindern, sondern eher Rahmenbedingungen zu schaffen, damit die inländische Industrie und Wissenschaft stärker von diesen informellen Wissensflüssen profitieren kann. Dieses gilt insbesondere in wissensbasierte Industrien wie die biotechnologische Industrie, wo die Grenze zwischen industrieller und wissenschaftlicher Forschung stark aufgeweicht ist. Wissenschaftliche Einrichtungen und Unternehmen müssen ihrerseits sicherstellen, dass sie die Kapazitäten und Expertise aufweisen, um in zunehmend offeneren Innovationsprozessen zu partizipieren und von informellen Wissenszuflüssen zu profitieren.

# 2 Introduction

*"Coming together is a beginning, staying together is progress, and working together is success." - Henry Ford*

Nowadays economic scholars widely agree that the productivity growth and wealth of developed countries depend far more on a country's ability to generate new technological knowledge and to transfer it into marketable inventions, than on its natural resources (David and Foray 2002). Peter Drucker (2001) has introduced the term "knowledge society" to describe this starting transformation process of societies in developed countries, where knowledge is regarded to be the most important resource in the future.

Politics around the world have started to support and foster this transformation process, well knowing that due to the scarcity of natural resources, the successful generation of new knowledge will sustain the economic competitiveness of countries.

In the European Union, this political rethinking started with the Lisbon strategy in 2000, where the EU member countries agreed to the strategy "*to become the most competitive and dynamic knowledge-based economy in the world capable of sustainable economic growth with more and better jobs and greater social cohesion"* (Lisbon European Council 23 and 24 March 2000, Presidency conclusions[1])). One primary goal of the Lisbon strategy was to overcome the so called "European paradox". The "European paradox" describes the paradox that the EU has excellent researchers who produce valuable scientific work, while the commercialization of the research outputs lags behind considerably compared to other developed countries, i.e. the US (e.g. Dosi et al. 2006, European Commission 2011). As a consequence, the production of technological and scientific knowledge has moved in the focus of EU politics.

The launch of the 6$^{th}$ and 7$^{th}$ EU framework programmes aimed at implementing the Lisbon strategy and overcoming the "European paradox" by introducing new research programmes

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[1] The whole speech can be assessed at http://www.europarl.europa.eu/summits/lis1_en.htm , last date of assessment: July 26$^{th}$, 2012)

and bundling together existing research programmes that had the goal to promote the production and commercialization of new technological knowledge (European Communities 2007). With the implementation of the 7th Framework Program, the EU member countries agreed to contribute more than 53 billion Euros to research for the years 2007-2013 (European Communities 2007).

The production of knowledge is however different from the production of tangible assets. First, knowledge is produced by the recombination of already existing knowledge (Kogut and Zander 1992) and has therefore a cumulative and path dependent character (Dosi 1982). There are two types of knowledge, explicit knowledge that can be codified and easily transferred between actors and implicit/tacit knowledge that is not codified and therefore not easily transferrable (Polanyi 1966, Grant 1996, Liebeskind 1996). It has been shown that the generation of new technological knowledge is mostly achieved by the interaction of both, explicit and implicit knowledge (Nonaka et al. 2000).

In order to be able to successfully combine these different sources of explicit and implicit knowledge that are needed for the development of new knowledge, actors in an economic system are permanently forced to acquire additional external knowledge, which is especially true in those industries where the technological development is rapid and science based (e.g. Gambardella 1995, Niosi 2003). Moreover, Gerybadze and Reger (1999) have shown that the globalization of R&D and the resulting increasing number of transnational collaborations require a change in the management of innovation. In the end, the degree to which the actors are able to acquire external knowledge depends mainly on their absorptive capacities (Cohen and Levinthal 1990) and the “tacit dimension” (Polanyi 1983) of the external knowledge.

To put an emphasis on the meaning of knowledge acquisition and knowledge production in the innovation process, Chesbrough (2003) has introduced the concept of the “open innovation”. The concept moves away from the strategy of closed innovation to an innovation strategy where the innovation process is characterized by “the use of purposive inflows and outflows of knowledge to accelerate internal innovation, and to expand the markets for external use of innovation, respectively” (Chesbrough et al. 2006, p. 1).

Different theoretical approaches have been developed within the last couple of decades to more formally capture this interactive nature of the knowledge production process. Maybe the most popular approach is thereby the Innovation System (IS) approach that can be applied to describe the dynamic interplay of several institutional actors on a national, regional, local, industrial, or technology level in the process of knowledge generation and transfer (e.g. Edquist 2005, Fagerberg 2005, Lundvall 2010). Another approach, closely related to the innovation systems approach is the innovation network approach that uses social network based methods to describe the structural dynamics of knowledge transfer and generation between actors in an innovation network (e.g. Powell and Grodal 2005, Giuliani 2011).

In practice, one commonly used way for firms to access and transfer external knowledge that is tacit to a certain degree and to create new knowledge is to engage in research collaborations. The rationale behind cooperative research is rather simple: By linking together different actors with different knowledge bases, it is likely that cross-stimulation effects for the exchange and generation of knowledge are achieved.

Depending on the scope of the research, those collaborations can link together firms in a vertical way (e.g. Arora and Gambardella 1990, Pisano 1990, Baum et al. 2000) or in a horizontal way (e.g. Gulati 1998, Khanna et al. 1989, Silverman and Baum 2002). Frequently research collaborations are found between firms and scientific institutions such as universities or research institutes (Hagedoorn et al. 2000). The main purpose of these industry-science collaborations for firms is usually to acquire scientific knowledge, to integrate this knowledge in the knowledge base of the firm and to generate potentially marketable output.

In order to foster this knowledge exchange and knowledge creation process that is characteristic for R&D collaborations, the EU government and national governments have started to dedicate more and more money of the overall research funds to collaborative research projects (European Communities 2007).

The benefits of those vertical, horizontal or industry-science funded and not-funded research collaborations for the development of a competitive knowledge base and for a research productivity increase of the collaborating firms have been widely discussed in numerous empirical studies (e.g. Kogut and Zander 1992, Powell et al. 1996, Powell 1998, Ahuja 2000, Tödtling et al. 2009, Aschhoff and Schmidt 2008). Besides studies regarding the firm level, the positive effect of collaboration for the productivity of scientists has also been stressed by several works (e.g. Lee and Bozeman 2005, Defazio et al. 2009).

The vast majority of these empirical studies that analyze the formation motives and evaluate the benefits of R&D collaborations base their analyses thereby on formal research collaborations. Formal research collaborations are those research collaborations that are build on some kind of formalized agreements (e.g. contracts). Data on formalized R&D agreements have the advantage that they usually contain comprehensive information on the duration of cooperative projects, on the type of partners involved, and are widely available.

In contrast to this, the existing empirical literature that contributes empirical evidence on the formation incentives and benefits of informal R&D collaborations (R&D collaborations that are not formalized by e.g. a contract) is rather scarce.

This fact is puzzling however for several reasons:

First, several large scale innovation surveys on the cooperative behaviour of firms have revealed that firms which engage in R&D, usually show a wide and deep network of informal R&D collaborations (i.e. collaborations that are not formalized by legal agreements) besides formal R&D cooperation agreements (e.g. Link and Bauer 1989, Kleinknecht 1989, Santarelli and Sterlacchini 1990, Bönte and Keilbach 2005). Especially for science based industries, like the biotechnological industry, these informal R&D ties of firms with other firms and/or scientists are supposed to play a crucial role for the competitiveness of firms and the overall development of the industry (e.g. Kreiner and Schultz 1993, Audretsch and Stephan 1996, Zucker et al. 1999, Prevezer 2001, Owen-Smith and Powell 2004, Salavisa et al. 2012). In addition to that, several studies have outlined that informal transfer mechanisms seem to generally play also an important role for the exchange of knowledge between scientific institutions and firms (Meyer-Kramer and Schmoch 1998, Thursby and Thursby 2000, Cohen et al. 2002, Murray 2004).

Second, informal knowledge exchange activities of scientists have been widely discussed in developed as well as in emerging countries in the context of a brain drain due to mobility of scientists (Adams 1968, Mountford 1997, Nguyen 2006, Regets 2007, OECD 2007), and in the context of changes in the legislation for the intellectual property rights of inventions that have been funded with public money (Link et al. 2007).

Third, there are contradicting works regarding the consequences of informal knowledge transfer of firms. While the resource based view literature suggests that knowledge which is informally leaking out of firm boundaries could lower the competitive advantage of the firms (Wernerfelt 1984, Liebeskind 1996, Brown and Duguid 2001), other works have suggested that firms in turn could also benefit from informal knowledge that flows in their boundaries (von Hippel 1987, Schrader 1991).

The empirical assessment of the preconditions that favour the initiation, the handling, and the consequences of these informal R&D collaborations however is extremely difficult, since informal R&D ties are difficult to measure (Bönte and Keilbach 2005). The existing empirical evidence on these topics is mostly limited to studies on firm level (e.g. Schrader 1991, Kreiner and Schultz 1993, Owen-Smith and Powell 2004, Bönte and Keilbach 2005, Salavisa et al. 2012). Only very few empirical studies provide empirical evidence on informal knowledge transfer based on micro-level data (e.g. Link et al. 2007, Markman et al. 2008). In order to understand the rationales and motives of actors that underlie informal knowledge transfer however, more micro level evidence is required.

Within recent years and as a consequence of changes of the intellectual property rights on inventions that were financed with federal money in some countries (e.g. Bayh-Dole Act of 1980 in the US, modification of the Arbeitnehmer-Erfindungsgesetz 2002 in Germany), some empirical evidence on the motives of scientists to engage in informal knowledge transfer has been provided by Link et al. (2007) and Markman et al. (2008). The empirical findings by Link et al. (2007) and Markman et al. (2008) however are both based on samples of US scientists, so that a generalization of their findings to European countries remains a challenge.

While the motives of scientists to engage in informal technology transfer have at least found some attention in the empirical literature, less micro-level evidence exists on the characteristics of knowledge that is informally transferred within industry or between science and industry or on the consequences of informal knowledge transfer.

In this thesis, we provide four empirical studies, in which two empirical studies analyze the factors that initiate informal knowledge transfer from science to industry on the basis of a dataset that stems from a comprehensive survey of German scientists. The other two empirical parts of this thesis are based on biotechnology patent data from the European Patent Office (EPO) and deal with two phenomena that mostly arise from informal knowledge transfer: The flow from knowledge from industry to science and shared intellectual property rights on patents. The patent data analyses is restricted to the biotechnology industry, because several studies have highlighted the importance of patents for this industry and thus patents are a good proxy for information for knowledge generation and knowledge flows for this industry (e.g. Mazzoleni and Nelson 1998, Schankerman 1998, Arora et al. 2008). Besides, by accessing the additional information that lies in patent data (e.g. information about patent applicants, citation information), important knowledge related characteristics of the patented invention can be investigated.

The thesis is structured as follows:

The *third chapter* briefly describes and summarizes some existing theoretical and empirical evidence on knowledge dynamics in the innovation process. First, it is shown how the acquisition, utilization, and production of knowledge differ from that of tangible goods, whereby a put a focus on the tacit dimension of knowledge, since the degree of tacitness of knowledge has an important impact on its transferability (chapter 3.1). Next, two theoretical concepts that are widely used to display the knowledge interactions between institutional actors in an innovation process are described: The notion of innovation systems and the theoretical framework of innovation networks (chapter 3.2). Chapter 3.3 outlines basic theoretical and empirical evidence on knowledge flows in innovation networks that mostly stem from social network methodology. Chapter 3.4 summarizes the main theoretical concepts and existing empirical evidence, why actors in the innovation process engage in informal R&D linkages.

The *fourth chapter* provides short summaries and information on the publication status of the following four empirical sections, which represent the centrepiece of the work.

The *fifth chapter* is the first empirical chapter and analyzes technology transfer[2] from universities to industry. While there is a vast amount of literature that empirically assesses university-industry transfer via the analysis of patents and/or publications, comparatively little is known on the mechanisms that support these science-industry interactions on the individual level. Based on a sample of more than 800 German university scientists we determine individual and faculty based factors that support informal knowledge transfer activities of scientists and compare our results to existing empirical evidence from a US study.

The *sixth chapter* provides further empirical insights into informal and formal science-industry knowledge transfer activities of scientists. While the fourth chapter examines career related and faculty related factors that are critical for the engagement of scientists in informal knowledge transfer, we focus in the fifth chapter on the question how international mobility of scientists (both from university and public scientific institutes) is related to their knowledge and technology transfer activities to industry in both, their host and their home countries. The chapter thus provides an important contribution to the highly debated question whether the international mobility of scientists leads to an economically undesirable brain drain for the home countries of the scientists, or to a beneficial brain circulation for both countries.

In the *seventh chapter*, we empirically derive factors that influence the probability of industry to science knowledge flows in the biotechnological industry. While most empirical studies that analyze knowledge flows between science and industry concentrate on those knowledge flows with the direction from science to industry, knowledge transfer from industry to science has widely been neglected. From the sparse, existing empirical evidence however it is known, that industry to science knowledge transfer happens mostly in an

[2] In the following we will use the terms knowledge transfer and technology transfer synonymously.

informal way. We proxy knowledge flows and knowledge flow directions on the basis of patent citations and estimate weighted, bivariate probit models on the factors that influence the citation probabilities of industry applied patents by other industry applied patents and by patents that have been applied for by scientific institutions.

The *eighth chapter* empirically examines industry patent applications with shared intellectual property rights in the biotechnology industry. The existing literature on this topic has shown that shared intellectual property rights on patents mostly result from informal R&D collaborations, since informal R&D collaborations are not bound to any legal contracts and thus cause not clarified ownership on inventions. This not settled ownership of inventions can have the consequence that the participated collaborators either find an informal agreement on the ownership on the invention or the ownership of the invention is shared, as it is the case of patent applications with multiple patent applicants. Shared ownerships on patents however are associated with complex legal issues so that firms have an incentive to avoid these shared intellectual property rights. Following this argumentation line, we hypothesize that joint patent applications are associated with a higher economic potential compared to patents with a single ownership. We empirically test this hypothesis by applying a nonparametric matching procedure.

The *ninth chapter* contains the main conclusion in which the findings of the empirical parts are summarized and the gain of knowledge of this thesis is outlined. Further, implications for policy and further research are provided.

The remaining chapters provide supplementary material of the thesis.

# 3 Theory: Knowledge dynamics in the innovation process

## 3.1 Acquisition and utilization vs. production of technological knowledge

Although all of the empirical chapters contain theoretical subchapters, this chapter will outline and summarize the broader economic theories that are the basis for this work.

The ability of firms to *acquire* and *utilize* external technological knowledge[3] has long been recognized to be crucial for their success and for the overall economic development of a nation. The theoretical foundations for this assumption can be traced back to the beginnings of the endogenous growth theory. Arrow (1962a) developed a 'learning by doing' model in which the firms operate with constant returns of scale and knowledge itself is a productive factor but is assumed to be constant by the firms. If a single firm raises its capital stock however, this investment increases the knowledge level of the whole economy. Therefore the whole economy shows increasing returns (Levhari 1966)[4]. Romer (1986, 1989) presented a modified model of the learning by doing model of Arrow. In the Romer model, new knowledge is regarded to be the key factor of long term growth and is produced by an investment in research and technology (R&D). Thereby it is important to note, that investments in R&D show diminishing returns, and that the firms which invest in R&D cannot fully appropriate the returns since the newly generated knowledge leaks out of the firms and increases the knowledge base and production possibilities of other firms. And whilst investments in R&D show increasing returns, the use of new knowledge leads to increasing returns in production. In a later work Romer (1990) separated knowledge into a rival and non-rival technological component. Thus the technological component of knowledge shows a public good character, i.e. the use by one firm does not exclude the use by other firms. Since Romer's models implies that newly generated knowledge cannot be fully appropriated

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[3] Sahal (1981) and Bozeman (2000) emphasise that there is no clear distinction between knowledge transfer and technology transfer, since technology is always based on knowledge and this knowledge is always transferred in the moment when a technology is transferred between two organisations, such as a public research organisation and a firm. We will use the terms technology and knowledge synonymously throughout the whole thesis

[4] For an overview on endogenous growth models see Shaw (1992).

by the knowledge producer, but leaks out of the firm boundaries and is at the same time a valuable asset for other firms, the models provide a theoretical fundament for the existence of knowledge spillovers in an economy[5]. These knowledge spillovers can be absorbed or appropriated by other firms, depending on their absorptive capacities (Cohen and Levinthal 1990), and the nature of knowledge itself. There are several dimensions how the nature of knowledge can be characterized. Knowledge can be created by basic or applied research, can be scientifically or/and technically complex or simple, and can be created by disciplinary or interdisciplinary research (for an overview see Brennenraedts et al. 2006). Moreover, technological knowledge is characterized by a cumulative and path dependent nature (Dosi 1988) and the production of new technological knowledge is characterized by a high degree of uncertainty (Nelson and Winter 1977, 1982).

Although the mentioned dimensions of the nature of knowledge might facilitate or complicate the exchange of knowledge between organizations, the "tacit dimension" (Polanyi 1966) of knowledge is regarded to play the most important role when it comes to the question how knowledge can be transferred between actors. Tacit knowledge refers to knowledge that is not codified and thus implicit to the owner, and is thus regarded to be a key factor for the comparative and strategic advantages of organizations (e.g. Winter 1987, Cowan and Foray 1997, Balconi 2002). The strict binary division of knowledge into tacit and non-tacit knowledge has been challenged by several works however (Johnson et al. 2002, Nightingale 2003, Garcia-Muina et al. 2009). Johnson et al. (2002) point out that knowledge can seldom be fully codified without losing important information of the knowledge and thus conclude that most of the codified knowledge has a underlying, but not codified share of tacit knowledge. At the same time, Nonaka and Takeuchi (1995) show on the basis of their proposed SECI (Socialization, Externalization, Combination, Internalization) model how codified knowledge can be turned into tacit knowledge and vice versa due to interactive social dynamics. Thus the tacit character of knowledge is not fixed but is likely to change over time.

[5] Another theoretical model of the endogenous growth theory that is often cited concerning theoretical explanations of knowledge spillovers is presented by Grossman and Helpman (1991).

There are several ways how both, tacit and codified knowledge can be transferred by organizations. Strait forward ways for organizations to broaden their knowledge base include e.g. the reading of scientific articles, the hiring of external professionals, and the further qualification of the own employees. Besides, R&D collaborations between organizations are considered to be one of the most important and effective transfer mechanisms of external knowledge that is tacit to some degree (e.g. Cassiman and Veugelers 2002). The meaning of R&D collaborations as a knowledge transfer mechanism has gained in importance due to the fact that the technological knowledge base of most industries changes rapidly and knowledge is widely and diversely distributed among organizations (von Hayek 1945). Thus organizations are forced to exchange knowledge to create valuable new combinations of existing and new technological knowledge (Nahapiet & Ghoshal 1998). As a consequence R&D cannot be seen as a static process that takes place isolated from outside surroundings, but instead rather as an interactive process of learning of various actors (Lundvall 1988, Chesbrough et al. 2006). The innovation system approach and the innovation network approach are two popular theoretical concepts, which have been introduced in innovation economics with the aim to capture the interactive nature of the innovation process.

### 3.2 On innovation systems and innovation networks

Within the last years the innovation systems approach that puts an emphasis on this "systemic nature of innovation" (Fagerberg 2005, p. 4) has been the dominant institution based theory to describe the innovation process. The innovation systems approach basically builds on two main assumptions: First, knowledge is considered to be the most important resource in modern economy and second, knowledge can only be gained through interactive learning that takes place in a socially embedded process which is shaped by various actors (Lundvall 2010). Edquist (2005) defines an innovation system as "all important economic, social, political, organizational, institutional, and other factors that influence the development, diffusion, and use of innovation" (Edquist 2005, p. 182).

Because of the broad theoretical concept that underlies the innovation system approach, extensive work has been undertaken by various scholars to develop more specific concepts of innovation systems.

Analyses of innovation systems on the national level (National innovation systems) take into account the existence of national states and the resulting differences regarding socio-cultural issues and national policy measures (i.e. Lundvall 1992, Carlsson 1995, Edquist 1997, Lundvall 2010). Although it is evident that the growing internationalization of organizations and the rise of supranational organizations like the EU soften the meaning of national borders, several studies have emphasized the persistent importance of national institutional settings and politics for the process of innovation (Archibugi and Michie 1997, Carlsson 2006, Lundvall 2010).

The examination of innovation systems at the regional sector (Regional innovation systems) accounts for clustered structures, regional governance and regional institutional settings, as well as influences from the overlying national innovation system(s) (i.e. Cooke et al. 1997, Swan et al. 1998, Cooke 2002). Some even finer definitions of the regional character of IS are provided by Fischer et al. (2001) referring to urban innovation systems or Breschi and Lissoni (2001) who introduced the term of local innovation systems.

Sectoral innovation and production systems touch theoretically upon the innovation systems literature, introducing important contributions that have been made by the industry life cycles literature (i.e. Utterback 1994, Audretsch 1995, Klepper 1996), and propose that sectoral boundaries are linked to other related industries via a dynamic process. Malerba (2002) defines a sectoral system of innovation and production as “the set of new and established products for specific uses and the set of agents carrying out market and non-market interactions for the creation, production and sale of those products” (Malerba 2002, p. 249).

The technological innovation systems approach (i.e. Carlsson and Stankiewicz 1995, Carlsson and Jacobsson 1997, Carlsson et al. 2002) applies a system approach to innovation. Systems consist of components, relationships and attributes and considers technology as a knowledge field, a product/an artifact or a group of related products (Carlsson 2002). An important difference of the technological systems approach compared to the other innovation systems approaches is that it focuses on generic technologies, wich are not bound to a single industry or sector but can have applications in various industries.

It becomes obvious, that all innovation systems approaches overlap and are interrelated to some degree. As Cantner and Meder (2008) put it:

“Looking […] on actors engaged in cooperative invention and innovation it is obvious that they at the same time belong to several of the innovation systems mentioned. [In example a] [...] firm takes part in the national innovation systems, as it belongs to a technological innovation systems comprising several [...]firms, to a sectoral system [...], to a regional system related to the location of the firm including some surroundings, and finally also to the urban system of the city of location.” (Cantner and Meder 2008, pp. 2-3).

More recently, the innovation network approach has attracted the attention of the scientists in the field of innovation economics. Innovation networks can be seen as a result of the interactive processes of learning in an IS and describe the sum of shorter and more persistent R&D collaborations that surround an organization in the innovation process (Ahuja 2000, Powell and Grodal 2005, Tödling et al. 2009).

The advantages of innovation networks in contrast to institutional co-operation arrangements are thereby, that “they permit the informal exchange of unique and idiosyncratic assets such as knowledge and know-how [...] Second, they are a relatively loose and rapid way to put individuals or organizations in contact, even when they are not formally connected to each other.” (Giuliani 2011, p. 156). Innovation networks can thus be seen as a commonly used way, how institutional actors or individuals establish informal R&D linkages with other institutions.

### 3.3 Basic theoretical concepts and empirical evidence on knowledge flows in innovation networks

The theory on innovation networks has most of its origins from the social network theory. Freeman (2004, p.2) defines social network analysis as “[…] the structural approach that is based on the study of interaction among social actors […] “.

Several sociological works have analyzed determinants that shape the social networks of individuals. Examples include the influence of childrearing (Munch et al. 1997), the influence of the marital status (Hurlbert and Acock 1990) or gender specific differences (Moore 1990) that effect the composition and dynamics of personal social networks.

Within the last couple of decades the field of economic sociology has shaped two theories that are especially important for the application of social network theory in economics: The concept of embeddedness and the theory on social capital.

Granovetter (1985) has argued in his seminal work that most economic behaviour is shaped (so called "embedded") by social networks. Coleman (1988) picks up Granovetters idea of embeddedness and states:

"Granovetter's idea of embeddedness may be seen as an attempt to introduce into the analysis of economic systems social organization and social relations not merely as a structure that springs into place to fulfill an economic function, but as a structure with history and continuity that give it an independent effect on the functioning of economic systems" (Coleman 1988, p. 97).

This notion of Coleman is particularly important since it works out that the embeddedness in networks can be understood as a perpetual influence that affects the behaviour of actors in an economic system.

Regarding the concept on social capital, Coleman (1988), Burt (1992) as well as Tsai and Ghoshal (1998) have pointed out that not only the existence and structure of interpersonal relationships is crucial for the social development of individuals, but that individuals are likely to benefit from the underlying resources of their social relationships.

The theoretical concepts of embeddedness and social capital have subsequently been applied to the phenomena of inter organizational interaction in the innovation

Powell and Grodal (2005) point out that in industries where the scientific progress advances rapidly in different technological fields, innovation networks play the most central role. This is due to the fact that under those circumstances usually no single institution is able to gather all necessary knowledge from all technological fields to create an innovation at the edge of the scientific progress. Pyka et al. (2007) along with Powell et al. (2005) show that especially in knowledge based industries, the existence of innovation networks is a persistent phenomenon and in most cases the innovation networks themselves become the locus of innovation.

Empirical studies have confirmed a positive relationship between the degree of embeddedness in an innovation network and innovation performance mostly in knowledge based industries like the biotechnology industry (e.g. Powell et al. 1999, Baum et al. 2000, Pyka et al. 2007) and the semi-conducter industry (Stuart 2000).

The positive impact of firms being embedded in an innovation network and the innovative performance of the firms has also been revealed in a couple of more diverse industries like the banking sector (Zaheer and Bell 2005) or the chemical industry (Ahuja 2000).

Furthermore, several works have started to detangle the concepts of embeddedness and social capital and have provided important empirical evidence on single aspects like, i.e. the composition of innovation networks, the position of single actors in innovation networks[6] and the density of innovation networks. While there are many other works that have produced empirical evidence on the topic of innovation networks, we will concentrate on the mentioned three topics to provide a basic understanding of the innovation network theory.

*The composition of innovation networks and the position in an innovation network/centrality*

Reagens and Zuckerman (2001) have empirically analyzed the network composition of 224 R&D teams and find that high network heterogeneity is associated with an enlarged learning opportunity and increases the productivity of the R&D networks. Becker and Dietz (2004) follow the line and show empirically for a set of German firms, that the involvement in more heterogeneous innovation networks enhances the research productivity of the firms. Phene et al. (2006) and Quinrana-Garcia and Benavides-Velasco (2008) show empirically for the

[6] Refer i.e. to Borgatti et al. (2009) for an overview on the basic concepts on direct ties, indirect ties and redundant ties.

biotechnology industry on the basis of patent data the importance of combination of diversified knowledge for the creation of innovations. Phelps (2010) shows for the telecommunications industry, that technological complementarily of a firm's research network partners is significantly positive related to the firms' explorative innovation.

Powell and Smith-Doerr (1994), Powell et al. (1999), Tsai (2001), and Powell et al. (2005) among others have empirically shown that there is a positive impact of central innovation network position on the innovative performance of economic actors. Tsai (2001) points out that a central position of an actor in an innovation network enhances its possibility to draw the desired knowledge out of the network. Gnyawali and Madhavan (2001) argue in line that central firms better informed and are more likely to create new beneficial collaborations. Gnyawali and Madhavan (2001) argue however at the same time that there is a possible trade off associated with central positions, due to the fact that a central position in a network demands to cope with more information. Noteboom et al. (2006) use firm level panel data on alliance formation and patenting activities and show empirically the existence of an inverse U-shaped relationship between centrality and exploration activities of the firms.

*Strong ties vs. Weak ties and the density of an innovation network*

An ongoing debate in the literature of innovation networks is the meaning of the presence of strong and weak ties of an actor for its innovative output. The density of an innovation network is thereby determined by the relative strength of the ties that belong to the network.

Granovetter defines the strength of a tie as "a (probably linear) combination of the amount of time, the emotional intensity, the intimacy (mutual confiding), and the reciprocal services which characterize the tie" (Granovetter 1973, p. 1361). In his work Granovetter (1973) has proposed the "strength of weak ties" thesis which states that weak ties are often more useful for sourcing new knowledge since weak ties can build a bridge between otherwise disconnected groups. A network that exists only of strong ties on the contrary is regarded to be less efficient for the acquisition of new knowledge since all members of the network have a close relationship and thus a similar knowledge base and as a consequence a large part of the exchanged knowledge will be redundant.

The empirical evidence regarding the strength of ties and the consequences for knowledge diffusion and new knowledge acquisition is contradicting. A number of empirical studies have shown that strong ties tend to build trust among the actors in a network and can facilitate the transfer of more complex and tacit new knowledge (e.g. Uzzi 1997, Hansen 1999) while weak ties are supposed to play an important role for the transfer of non-tacit new knowledge (Hansen 1999)[7].

### 3.4 Why do firms and scientists engage in informal R&D linkages? Theoretical concepts and empirical evidence on informal R&D ties and knowledge transfer

In this work, an informal R&D linkage of an organization/individual is defined as any kind of knowledge exchange with another organization and/or individual that is not bound to any kind of formal and/or legal agreement (see i.e. von Hippel 1987, Schrader 1991, Van Aken and Weggeman 2000).

From industry specific studies, case studies, and interviews (e.g. von Hippel 1987, Schrader 1991, Freeman 1991, Kreiner and Schultz 1993, Powell et al. 1996) it is known that innovating organizations tend to have a large network of informal ties, which they use for knowledge transfer and knowledge acquisition. This is simply explainable by the fact that the individual informal networks of the employees sum up and interact at the organization level. Thus "behind every formal network, giving it the breath of life, are usually various informal networks" (Freeman 2001, p. 503) and Powell et al. (1996) argue in line: "beneath most formal ties, then lies a sea of informal relations" (Powell et al. 1996, p. 120).

While there are various studies that examine the characteristics of formal R&D agreements (e.g. Kogut 1988, Kamien et al., 1992, Cassiman and Veugelers 2002, Goyal 2007), the theoretical and empirical evidence on the characteristics of informal R&D agreements and

[7] For an overview see i.e. McFadyen et al. (2009).

the resulting knowledge transfer is rare.  Bönte and Keilbach (2005) state that the relative lack of empirical and theoretical evidence on informal R&D ties can be explained by the difficulties to define and measure informal R&D agreements.

However, although the overall share of works on informal R&D collaborations is comparably small, those empirical and theoretical works that exist date back to the late 1960s.

In an early work, Allen and Cohen (1969) have analyzed the information gathering behaviour of US engineers and show that the engineers in their sample prefer to rely on their informal network for information gathering instead of the use of codified information sources (such as literature). In a later study – based on the analysis of SMEs in eight different industries and three different countries – Allen et al. (1983) have worked out that technological knowledge in all considered industries and countries flows mainly via informal networks between SMEs and that only a small share of technological knowledge is transferred via “formal mechanisms” (Allen et al. 1983, p.199).

At the same time a different “Allen”, Robert C. Allen (1983) points out that many inventions are not solely discovered by single institutional actors like firms, individuals or public research institutions – or consortia of them. Instead he suggests that networks of institutions create inventions – so called “collective inventions” (Allen 1983, p.1). Thereby Allen (1983) states that the “essential precondition for collective invention is the free exchange of information about new techniques and plant designs among firms in an industry” (Allen 1983, p.2).

Von Hippel (1987) has examined the flows of knowledge in informal networks in the US steel mini-mill industry. Contrary to Allen’s (1983) idea of “collective invention”, von Hippel (1987) proposes that knowledge is not freely exchanged between firms in informal networks but instead technological knowledge is traded between employees of competing and non-competing firms. Von Hippel (1987) shows thereby on the theoretical basis of a prisoner’s dilemma model, that this information trading is likely to be beneficial for the firms. Schrader (1991) has provided more evidence to this hypothesis by analyzing a sample of nearly 300 managers from the US steel and mini-mill industry. He finds strong evidence from the data that the employees indeed trade information, that the managers are aware of it, and that this “informal know-how trading” (von Hippel 1987, p.291) among the employees indeed results in a better economic performance of the firms.

Around the same time, a few large scale studies on the R&D cooperative behaviour of firms provided evidence that informal R&D linkages among firms are not necessarily specific to single industries or technologies, but rather a more widely spread phenomena. Link and Bauer (1989) have examined the collaborative R&D activities of a large sample of U.S. manufacturing firms and have shown that about 90% of the reported R&D partnerships of the firms were of an informal nature. Moreover, the works of Kleinknecht (1989) and Santarelli and Sterlacchini (1990), both based on surveys among manufacturing firms in Europe, find evidence that informal R&D partnerships are especially characteristic for small and medium sized enterprises (SMEs).

Bönte and Keilbach (2005) examined innovating firms in Germany and show that the informal cooperations of these firms occur more frequently and are more valuable for the knowledge acquisition process of the firms.

In addition to these more general findings, several empirical studies show that informal R&D co-operations play a key role for the acquisition of external knowledge especially in knowledge-based industries and for the exchange of knowledge between scientific institutions and firms.

Kreiner and Schultz (1993) show that informal R&D collaborations have driven the network evolution of Danish biotech firms. Prevezer (2001) emphasizes the importance of the existence of informal networks of biotech firms for the early development of the US biotechnology industry. In line, Owen-Smith and Powell (2004) show that the size and depth of informal networks of biotechnology firms in the Boston biotechnology cluster has eased their access to external knowledge. Salavisa et al. (2012) have investigated innovation networks of Portuguese biotechnology firms and show that the informal knowledge networks of the biotechnology firms are denser and show more strong ties compared to the formal knowledge networks of the firms. The authors argue that knowledge networks with strong ties are characterized with a higher level of trust and can thus enhance the access to complementary assets which are needed for innovation (Salavisa et al. 2012).

Regarding the role of informal R&D agreements for the knowledge exchange between firms and scientific institutions, Meyer-Kramer and Schmoch (1998) have surveyed professors at German universities and find that the Professors rate informal contacts with firms as important as formal R&D collaboration agreements with firms. Thursby and Thursby (2000) have investigated industry licensing executives and come to the result that informal contacts between firm employees and university employees are the most important mechanism for firms to acquire university knowledge, next to publications and conferences. Cohen et al. (2002) conducted a survey among firm R&D laboratories and show in line with Thursby and Thursby (2001) that for many industries, informal interaction with scientific institutions is an as important way to acquire university knowledge as the screening of papers/patents or the visit of conferences. Thereby, Cohen et al. (2002) confirm that informal interaction between universities and firms are most important for knowledge intensive sectors. Murray (2004) has analyzed the interplay of biotechnology firms and academic inventors and demonstrates how valuable the underlying social scientific network of these academic inventors is for the competitiveness of the firms. Salavisa et al. (2012) show for high tech industries that the presence of universities in informal innovation networks of firms plays a central role in bridging knowledge between the firms.

Moreover, the topic of informal knowledge transfer from science to industry has gained special interest, since the US and subsequently other countries have granted universities the ownership of inventions that were developed with federal research funds, in order to foster the knowledge transfer between science and industry (Thursby and Thursby 2003). Ever since, works have started to analyze the knowledge transfer behaviour of university scientists and the efficiency of these technology transfer-mechanisms that were introduced at universities as a consequence of the changes in legislation (e.g. Bozeman 2000, van Looy et al. 2011). In this context, some interview based studies have shown that university scientists often share their knowledge and inventions with industry via informal knowledge transfer mechanisms next to the existing formal transfer mechanisms (e.g. Siegel et al. 2003, Siegel et al. 2004, Markman et al. 2008). Yet, little is known on the individual and faculty related factors that provoke scientists to engage in informal knowledge transfer. Link et al. (2007) have analyzed a sample of US scientists and have shown that the propensity of scientists to engage in informal knowledge transfer is affected by the incentive structures (share of royalty, tenure) of the faculty for technology transfer activities of the scientists.

In sum, we have outlined that several empirical studies suggest that informal R&D partnerships play an important role for the collaborative activities of individuals and/or firms for the innovation process. Although existing empirical findings thereby suggest that informal knowledge exchange is generally not restricted to certain industries or technologies, it seems to be an especially important tool to absorb knowledge in science based industries.

The following four empirical sessions provide micro level evidence on both, formation factors and consequences of informal R&D collaborations.

# 4 Short abstracts and publication status of the empirical parts

***Chapter 4: Informal University Technology Transfer: A comparison between the United States and Germany***

Published with slight changes as:

Grimpe, C. and H. Fier (2010), Informal university technology transfer: a comparison between the United States and Germany, *The Journal of Technology Transfer* **35(6)**, 637-650. DOI 10.1007/s10961-009-9140-4 (with kind permission to reuse article from Springer Science+Business Media B.V.)

Existing literature has confined university technology transfer almost exclusively to formal mechanisms, like patents, licenses or royalty agreements. Relatively little is known about informal technology transfer that is based upon interactions between university scientists and industry personnel. Moreover, most studies are limited to the United States, where the Bay-Dole-Act has shaped the institutional environment since 1980. In this paper, we provide a comparative study between the United States and Germany where the equivalent of the Bay-Dole-Act has come into force only in 2002. Based on a sample of more than 800 university scientists, our results show similar relationships for the United States and Germany. Faculty quality which is however based on patent applications rather than publications serves as a major predictor for informal technology transfer activities. Hence, unless universities change their incentives (e.g., patenting as one criterion for promotion and tenure) knowledge will continue to flow out the backdoor.

***Chapter 5: International Scientist Mobility and the Locus of Knowledge and Technology Transfer***

Published with slight changes as:

Edler, J., Fier, H. and C. Grimpe (2011), International scientist mobility and the locus of knowledge and technology transfer, *Research Policy* **40(6)**, 791-805.

http://dx.doi.org/10.1016/j.respol.2011.03.003 (with kind permission to reuse article from Elsevier Limited)

Despite the growing interest of scholars and policymakers to better understand the determinants for researchers in public science to transfer knowledge and technology to firms, little is known how temporary international mobility of scientists affects both their propensity to engage in formal and informal knowledge and technology transfer (KTT) as well as the locus of such transfer. Based on a sample of more than 950 German academics from science and engineering faculties, we investigate how the duration and the frequency of scientists' visits at research institutions outside their home country affect KTT activities. We find that most mobile scientists engage in KTT to firms both in the host and in their home country, suggesting that KTT activities to firms abroad do not substitute or crowd out, but complement KTT to firms in the home country. We further find that the longer research visits abroad are, the higher the likelihood that scientists engage in KTT to firms, again both in the host and the home country. However, the more frequently scientists visit institutions abroad, the more likely they are to engage in KTT to firms only in their home country. Our results therefore provide evidence for the benefits of "brain circulation". The article contributes to the growing strand of literature on scientist mobility and on the determinants of industry-science linkages at the individual level.

***Chapter 6: Against the one-way-street: Analyzing knowledge transfer from industry to science***

Published with slight changes as:

Fier, H. and A. Pyka (2011), Against the one-way-street: Analyzing knowledge transfer from industry to science, *The Journal of Technology Transfer* (Online First).
DOI 10.1007/s10961-011-9226-7 (with kind permission to reuse article from Springer Science+Business Media B.V.)

Knowledge transfer from industry to science happens mainly informally and has so far been neglected by empirical studies. This work aims at contributing to this issue by analyzing differences in the factors that influence the probability of knowledge transfer within industry and from industry to science in the biotechnology sector. In order to model these knowledge flows we conduct a citation analysis on the basis of patent data. We then estimate a weighted bivariate probit model on the citation probability of industry and science on the basis of a combined sample of citing and cited patent pairs and an equal number of control patent pairs. The empirical results suggest that there are considerable differences in the citation probability. Cultural closeness for instance has a positive effect on the citation probability from industry to industry while the citation probability of scientific institutions is not affected by cultural distance.

***Chapter 7: Is it worth all the trouble? An assessment of the economic value of firm patent applications with shared intellectual property rights in the biotechnology industry***

Published with slight changes as:

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DOI 10.1007/978-1-4614-6102-9_8 (with kind permission to reuse article from Springer Science+Business Media B.V.)

Shared intellectual property rights on patents are often the result of informal collaboration and are connected with complex legal issues and therefore organizations (e.g. firms) that apply for patents have a strong incentive to avoid co-ownership on their patents. In contrast to this the share of EPO firm patent applications with a joint ownership has increased in the biotechnology industry during the last two decades as it has been observed in other industries. From this the question has to be forced, whether joint patent applications are associated with a higher economic potential compared to the patents with no joint ownership so that firms are willing to cope with the legal issues that are associated with shared intellectual property rights on patents. We measure the economic value of a patent by the number of subsequent citations it has received and empirically address this question by the application of a nonparametric matching approach on patent level. We show that there indeed exists a positive causal relationship between the decision of a firm to jointly apply for a patent and the future economic value that is associated with the regarded patent.

# 5 Informal University Technology Transfer: A Comparison Between the United States and Germany

## 5.1 Introduction

Knowledge produced in the public sector has frequently been shown to be an important ingredient of economic growth and technological change (Jaffe 1989, Adams 1990, Link and Siegel 2007). In this respect, patterns of evidence for university technology transfer focus on the institutions (e.g. technology transfer offices), the agents involved in technology commercialization, academic spin-offs, university-industry cooperative research centers or science parks and incubators (Bozeman 2000, Aerts et al. 2007, Rothaermel et al. 2007). Most of the existing research puts emphasis on formal university technology transfer mechanisms (i.e. those that embody or directly lead to a legal instrument like a patent, license or royalty agreement (Bozeman 2000, Feldman et al. 2002, Thursby and Thursby 2002, Siegel and Phan 2005). Few authors have investigated informal university technology transfer mechanisms (e.g. Link et al. 2007). Informal technology transfer focuses primarily on interactions of the agents involved (i.e. on university scientists and industry personnel) where property rights are of secondary importance.[8] Link et al. (2007) conceive informal technology transfer as a mechanism through which technology knowledge flows between the agents, for example by technical assistance or consulting. While formal technology transfer mechanisms frequently aim at transferring a research result like a patent or a license to use a technology, informal mechanisms do not, and there is usually no expectation that they will. In this sense, formal technology transfer is seen as a mechanism to allocate property rights whereas informal technology transfer is much more about informal communication processes. Examples could be contacts between academics and industry personnel at conferences, joint publications, academic consulting, or other informal contacts, talks and meetings.

[8] In the following, we will use the term ‘university scientist’ as shorthand for scientists employed at universities or other public research institutes.

However, Siegel et al. (2003) and Thursby et al. (2007) find that many university scientists in the United States do not disclose their inventions to their university although prescribed by law. And even if university inventions are publicly disclosed some firms will try to approach scientists and arrange to work with them directly (Hall et al. 2003). Hence, informal technology transfer seems to be a dominant mode of collaboration. Link et al. (2007) find that 52 percent of the scientists they addressed through the Research Value Mapping Program Survey of Academic Researchers had some kind of working relationship with industry personnel. Formal and informal technology transfer cannot always be easily isolated from each other as collaborative research or consulting could comprise patents being transferred from university to industry. In fact, existing literature suggests that formal and informal technology transfer may go well together (Siegel et al. 2003, Link et al., 2007) in that informal contacts improve the quality of a formal relationship or that formal contracts are accompanied by an informal relation of mutual exchange on technology-related aspects. Grimpe and Hussinger (2008) find that both channels are complementary (i.e. using one channel of collaboration if the other one is in place has a higher incremental impact on the innovation performance of firms than using one of the two channels more intense in isolation). It is therefore not surprising that formal and informal technology transfer may occur simultaneously (Perkmann and Walsh 2007) and that firms have an interest to make use of both.

Taking these findings together suggests that university administrators will have an interest to better understand the determinants of informal technology transfer given their objective to create revenues for the university. In the United States, the commercialization of technology developed by university scientists had been spurred by the enactment of the Bayh-Dole Act in 1980. In other countries like Germany, an equivalent to the Bayh-Dole Act only came into force 20 years later in 2002. The scientists' right to commercialize inventions privately before 2002 is still reflected by a rather low number of German university patents (Czarnitzki et al. 2007, Czarnitzki et al. 2008) and few licensing agreements (Grimpe and Hussinger 2008) compared to the United States. Hence, the purpose of this paper is to shed light on the effects that institutional differences might have on the choice of scientists to transfer technology informally. We present comparative findings for Germany by using the approach of Link et al. (2007). Moreover, we extend their previous findings by focusing on two neglected factors more explicitly: the scientist's individual productivity as well as the research environment in which the informal technology transfer takes place. Using a comprehensive sample of more than 800 German university scientists, we explore the determinants of informal technology transfer and derive implications for university administrators and policy makers.

The remainder of the paper is organized as follows: The next section first provides a brief review of the literature on university technology transfer. We then describe the results of the pioneering study on informal technology transfer in the United States (Link et al. 2007) and outline what might be expected in the German context. Section 3 explains our empirical methods before the subsequent section will show the results. We conclude the paper with a brief summary statement.

## 5.2 Literature background and theoretical considerations

Literature has identified two major sources of motivation for university scientists: The first has been described as recognition within the academic community. Recognition can most prominently be achieved through publications, patent applications, presentations and the awarding of research grants. As tenure decisions and promotions are primarily a function of recognition in its various forms, untenured faculty members will have strong incentives to pursue these objectives. Second, faculty members may also be motivated by the opportunity to acquire additional resources, resulting either in personal financial gain or in funding available for a build-up of physical and human capital at the scientist's institution (Link et al. 2007). Analyzing the effectiveness of university technology transfer offices (TTOs) which were created mainly as a consequence of the Bayh-Dole Act assigning the rights on faculty inventions to the university, Siegel et al. (2003) and Siegel et al. (2004) find, however, that these TTOs provide little incentives for faculty involvement. In other words, university TTOs loose opportunities for technology commercialization due to a perceived unfavorable royalty distribution to the scientist. In fact, simply increasing the returns to faculty members seems to make the commercialization process more effective (Friedman and Silberman 2003, Lach and Schankerman 2004, Link and Siegel 2005). However, significant difficulties in negotiating and transacting with the TTO remain (Link and Siegel 2005) which suggests that university scientists may have strong incentives to informally transfer their research results instead of choosing the route through the TTO.

Link et al. (2007) have been the first to shed further light on the decision of academics to engage in informal technology transfer. Their results for the United States are based on the Research Value Mapping Program Survey of Academic Researchers for which a sample of university scientists and engineers with a Ph.D. at the 150 Carnegie Extensive Doctoral/Research Universities during the time period spring 2004 to spring 2005 was collected. Link et al. (2007) distinguish between three mechanism through which informal technology transfer may occur: commercializing technology through direct collaboration with industry personnel, joint publication with industry personnel, and serving as a formally paid consultant to an industrial firm. They link these choices to a number of variables depicting faculty characteristics, including gender, tenure/years with tenure, age, and the percent of time spent on grants-related research. While gender serves as a control variable, the tenure variables are intended to measure faculty quality in terms of received recognition and research success. These measures are based on the argument that tenure serves as a signal and that more credentialed faculty will also be in higher demand by industry (Murray 2004). Age is included to disentangle the effects from tenure as a signal of faculty quality and the time necessary to build up relationships with industry. The percent of time allocated to grants-related research serves as another proxy for human capital as the awarding of grants involves a review process by an external organization, and only the most promising grant applications will presumably be likely to pass this hurdle. Finally, academic disciplines control for different technological and hence transfer opportunities.

Their results show that 52 percent of the scientists had some kind of working relationship with industry personnel, including most prominently consulting (18 percent), joint commercialization of technology (15.8 percent) and joint publication activities (14.6 percent). Regarding their faculty quality indicators they show that tenured academics are more likely than untenured academics to engage in all three informal technology transfer activities. Consistent with this finding, the number of years with tenure as an alternative measure increases the propensity for informal technology transfer. Moreover, they observe the same effect for the percentage of time spent on grants-related research. Regarding the gender, male faculty members are found to be more likely to transfer technology informally than female faculty members. Although Link et al. (2007) control for disciplinary effects, they argue that gender effects might also be explained by disciplinary selection in that women are typically less represented in disciplines most active in technology transfer. Regarding the scientist's age, they find that younger academics are more likely to engage in joint commercialization of technology. There is no effect on the other two forms of informal technology transfer. In sum, the results by Link et al. (2007) provide first insights into the decision of academics to engage in informal technology transfer. There are, however, a number of reasons which suggest that results on the propensity to engage in informal technology transfer could be different in different institutional contexts. In the following, we will thus provide arguments that point to the differences between the United States and Germany with a possible influence on the academic's choice for engaging in informal technology transfer.

Differences can, first of all, be attributed to the existence of the Bayh-Dole-Act in the United States since 1980. In Germany, the 'professor's privilege' ('Hochschullehrer-Privileg') was in place until 2002. Based on Article 5 of the German constitution, which focuses on the freedom of science and research, the professor's privilege entitled academics in Germany to use their scientific results for private commercialization even if the underlying research was carried out at and financed by the university or other public sources (Kilger and Bartenbach 2002). In fact, the professors' right to commercialize inventions privately before that year is reflected by a low number of German university patents (Czarnitzki et al. 2007, Czarnitzki et al. 2008). Moreover, university licensing which is receiving much attention in the literature on industry-science links is used by relatively few German firms (Grimpe and Hussinger 2008). Instead, consulting and informal collaboration have been shown to be substantial. Although several years have passed since the abolishment of the professor's privilege in Germany, we can expect these patterns to persist, particularly because most German universities are still in the process to set up an effective technology transfer infrastructure. As a consequence, university scientists in Germany, and especially highly credentialed faculty members, should be more likely to engage in informal technology transfer than their U.S. counterparts.

Second, differences between the United States and Germany could arise from different work contracts. While U.S. faculty members receive their pay typically only for nine months of the year, German academics are paid for twelve months. The missing three months could in turn motivate U.S. faculty to seek other income opportunities and to engage in informal technology transfer. Moreover, U.S. faculty might be under higher pressure than their German colleagues to acquire research money to support ongoing projects and junior staff.

Third, we may assume that the specific German orientation towards excellence in engineering plays a role for the informal technology transfer behavior. Several German universities have a long-standing tradition and reputation in the field of engineering. Engineering research is organized in large research groups, with multi-million research funding and close collaboration with industry. Moreover, engineers in Germany are typically member of the German engineers association ('VDI – Verein Deutscher Ingenieure'). Both the bonds through their alma mater and the network provided by the engineering association should therefore facilitate informal technology transfer activities. As a result, we should be able to observe strong positive effects particularly from scientists in engineering disciplines.

Besides the alleged differences between the United States and Germany, our research also aims at extending the findings of Link et al. (2007) by focusing more in detail on the faculty quality dimension as well as on the scientist's research environment. While the faculty quality indicators used by Link et al. (2007) are presumably correlated with individual productivity, they do not account for the different facets of productivity upon which tenure and grant award decisions are typically based. We have outlined above that academic prestige serves as a signal to potential commercialization partners in industry. Prestige can in turn be built up through publications or patents. Recent studies for the United States and Germany show that publications and university patenting are positively linked (e.g., Agrawal and Henderson 2002, Stephan et al. 2006, Czarnitzki et al. 2009). As a consequence, we will include direct measures of the publication and patenting activities of scientists and relate them to their informal technology transfer behavior. More specifically, we expect positive effects from publications on the decision to jointly publish with industry personnel and from patents on the informal commercialization of technology. Regarding consulting, we expect positive effects from both publications and patenting.

Besides research productivity, tenure and the awarding of grants, there is another aspect of faculty quality that has been neglected so far (i.e. whether the scientist is a research group leader). Obviously, leading a research group should be associated with some academic prestige developed through publications or patents. Moreover, being a research group leader should lead to a multitude of contacts with industry personnel at various occasions. Assuming that the group leader's recognition increases with group size, there should be an incentive to engage in informal technology transfer and acquire research money to support the group. Effects should be particularly pronounced for the decision to commercialize technology and to serve as a paid consultant as these forms of technology transfer could serve as a mechanism to raise funding.

As a final extension to the model by Link et al. (2007) we suggest that the scientist's research environment matters for the decision to transfer technology informally. In this context, Etzkowitz (2003) has put forward the notion of research groups as 'quasi-firms' in entrepreneurial universities. Provided that research funding is awarded on a competitive basis, research groups will presumably exhibit firm-like qualities. In the following, we will focus on one aspect of the research environment which is the size of the peer group at the scientist's institution. On the one hand, the more people are working on similar topics the more internal opportunities for collaboration arise. On the other hand, competitive pressure for research money will also be higher which is why we expect academics to be more likely to engage in informal technology transfer.

### 5.3 Data and econometric model

The data used in our empirical analysis stem from a survey among German scientists which was carried out on behalf of the German Federal Ministry of Education and Research. The aim of the survey, which was part of an evaluation project of the 6th European Union Research Framework Program, was to get an overview of university scientists' efforts to acquire research grants from various sources. Data were collected in 2008 using an online survey instrument. On the one hand, contacting respondents via e-mail involves the risk of not reaching a considerable number of persons due to outdated or misspelled e-mail addresses. On the other hand, e-mails have the advantage to be independent from space (i.e. the e-mail will reach the scientist although she or he might be away from the home office). Two major data sources were used for the sampling procedure. In a first step, the population of scientists employed at German universities was derived from the 'Hochschullehrerverzeichnis' from the year 2006. The 'Hochschullehrerverzeichnis' is a database containing the names, degrees and contact information of the academic personnel holding a PhD and being employed at German universities.[9] In a second step, scientists at government-funded public research institutes were identified via an internet search of the institutes' websites. These research institutes belong to one of the four large German science organizations: Max Planck Society, Fraunhofer Society, Leibniz Association and Helmholtz Association. In total, 20,519 scientists with available e-mail addresses were identified. For 4,250 scientists, delivery of the message failed because of a wrong e-mail address. We obtained 2,797 responses, a response rate on the net sample of 17.2 percent which can be regarded as satisfactory for such a large-scale online survey. Due to missing values for some variables the actual number of observations available for analysis is, however, lower.

The measures of informal technology transfer and the explanatory variables are based on faculty responses. To achieve comparability, we used exactly the same questions as in the Research Value Mapping Program Survey of Academic Researchers (Link et al. 2007). For our dependent variables relating to alternative mechanisms of informal technology transfer, scientists were asked to respond to these statements in the survey:

*During the past 12 months:*

[9] This excludes the so-called 'universities of applied sciences' whose major task is teaching and not research.

- *I worked directly with industry personnel in an effort to transfer or commercialize technology or applied research.*

- *I co-authored a paper with industry personnel that has been published in a journal or refereed proceedings.*

- *I served as a formal paid consultant to an industrial firm.*

We estimate several probit models and regress the three choices to transfer technology informally on different sets of explanatory variables. The first set is intended to exactly replicate the analysis by Link et al. (2007) for Germany, thus including faculty characteristics like gender (males=1, 0 otherwise), tenure (tenured=1, 0 otherwise), age (in logs)[10], pre-eminence of the faculty member, as measured by the percent of time spent on grants-related research, and dummies for the scientific disciplines (social sciences and humanities, life sciences, other natural sciences, engineering sciences, with social sciences and humanities being the reference case). As an alternative specification, we include a scientist's number of years with tenure (in logs), leaving tenure and age out of the model due to high correlation.

The second set of variables is our extension to the model used by Link et al. (2007). The survey of German scientists provides more in-depth information about the scientist's productivity and the institutional environment in which the research activities are carried out. Scientists were asked whether they are leading a research group (leader=1, 0 otherwise) and how many publications in refereed journals and patent applications they were able to achieve in the period from 2002 to 2006 (each entered in logs). To control for the research environment and, more specifically for the size of the peer group, scientists were asked how many colleagues they have at their institution working on similar research topics (in logs).

[10] For all variables which enter the regression in logs, a value of 0 was replaced by 0.1 to prevent missing values due to the log transformation.

## 5.4 Results

*Descriptive statistics*

The descriptive statistics (**Fehler! Verweisquelle konnte nicht gefunden werden.**) show that almost half of the surveyed scientists worked together with industry personnel in an effort to commercialize technology. Slightly more than 20 percent of the scientists exhibit at least one joint publication with industry personnel. Around 17 percent of the scientists served as a formally paid consultant to a firm. Regarding the faculty characteristics we find that the majority of the surveyed scientists are male (86 percent) with an average age 49 years. A high share of the scientists in our sample is tenured (83 percent) and on average the scientists have been tenured since 12 years. Further, the surveyed researchers spent about one third of the time on grants-related research. Regarding the scientific disciplines, our sample is rather evenly split between the four categories.

**Table 1: Descriptive statistics (Chapter 4)**

| Variable | Obs. | Mean | Std. Dev. | Min. | Max. |
|---|---|---|---|---|---|
| Commercialize technology | 945 | 0.438 | 0.496 | 0 | 1 |
| Joint publication | 938 | 0.230 | 0.421 | 0 | 1 |
| Consulting | 925 | 0.172 | 0.377 | 0 | 1 |
| Gender | 943 | 0.856 | 0.351 | 0 | 1 |
| Tenure | 926 | 0.828 | 0.377 | 0 | 1 |
| Percent time spent on grants-related research | 880 | 32.378 | 22.867 | 0 | 100 |
| Age | 948 | 49.283 | 8.371 | 28 | 70 |
| Years with tenure | 745 | 11.913 | 8.391 | 1 | 43 |
| Social sciences and humanities | 929 | 0.212 | 0.409 | 0 | 1 |
| Life sciences | 929 | 0.284 | 0.451 | 0 | 1 |
| Other natural sciences | 929 | 0.302 | 0.460 | 0 | 1 |
| Engineering sciences | 929 | 0.201 | 0.401 | 0 | 1 |
| Research group leader | 928 | 0.706 | 0.456 | 0 | 1 |
| No of publications | 948 | 20.638 | 26.440 | 0 | 200 |
| No of patent applications | 948 | 0.714 | 1.927 | 0 | 24 |
| Size of the peer group at the scientist's institution | 948 | 30.324 | 76.077 | 0 | 1000 |

Sample restricted to scientists with non-missing values for at least one informal technology transfer channel.

If we compare the descriptive statistics for the sample of German scientists with the descriptive statistics of the sample used by Link et al. (2007) we can observe considerable differences. Apparently, German scientists are more active in commercializing technology than their U.S. colleagues but somewhat less active in joint publication and consulting activities. At the same time the U.S. sample is more balanced regarding the gender of the scientists compared to the sample of the German scientists which results from gender stratification. The descriptive statistics for the additional variables which were not available in the U.S. sample show that about 70 percent of the scientists in our sample stated that they were research group leaders at the time when the survey was conducted. The productivity variables reveal that the surveyed scientists published around 20 articles in refereed journals within a five year period and on average applied for 0.7 patents during the years 2002 to 2006. Finally the variable that controls for the size of the peer group shows that on average the size of the peer group at the scientist's institution is about 30 scientists.

*Probit regressions*

Table 2 presents the results of probit regression models. For each of the three dependent variables four different model specifications are estimated. Models (1) and (2) for each dependent variable show the results of the basic model following the empirical approach of Link et al. (2007). In Model (1) we include the tenure dummy and age while the years with tenure are omitted due to high correlation with age. Model (2) substitutes age by years with tenure. Models (3) and (4) show the same specification as (1) and (2) but they are extended by the additional variables on productivity and research environment discussed before.

Regarding gender, Link et al. (2007) find that male academics are more likely to engage in informal technology transfer, specifically in the commercialization of technology and consulting activities. We are able to confirm this finding for the German data. It is particularly pronounced for consulting activities where the coefficient is highly significant. Moreover, we can largely confirm the positive effects from tenure on the likelihood to engage in technology commercialization and joint publication. Model (2) however shows that the number of years with tenure does not have any effect on informal technology transfer which is in stark contrast to the findings by Link et al. (2007). Similarly, age turns out to have no effect at all which is in concordance with the findings from the United States. We can again confirm the U.S. findings regarding the share of time spent on grants-related research. In both datasets, the effect is positive and significant for all three forms of informal technology transfer. To sum up, our findings for the German scientists largely confirm the results obtained by Link et al. (2007). Apart from differences in the descriptive statistics regarding the actual engagement in the three forms of informal technology transfer, the relationships between the assumed driving factors are similar, despite the institutional differences between the United States and Germany.

While in the U.S. study discipline effects were held constant and results weighted by discipline sampling proportions, the models using the German dataset include dummy variables to capture discipline effects.[11] This enables us to consider disciplinary effects more explicitly. Generally speaking, all three included disciplines are more likely to engage in informal technology transfer compared to the reference group of social sciences and humanities which is anything but surprising. Particularly engineering scientists are very likely to engage in all three forms of informal technology transfer, suggesting that there are indeed strong informal ties between academics and industry personnel, for example through the German engineers association. There is no effect on consulting for other natural scientists.

Turning to the extension of the baseline models, we find several interesting effects. Apparently, being a research group leader matters considerably for technology commercialization and consulting but not for joint publication. This finding confirms our theoretical reasoning that research group leaders have a higher incentive to acquire research money in order to finance their group. In this light, joint publication activities seem

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[11] The reason for this is that sampling proportions by field could not be taken into account as – due to the inclusion of government-funded research institutes – the population of scientists in Germany with regard to the field is not fully transparent. In Germany, a significant share of the engineering related research activities are performed by the Fraunhofer institutes in comparison to universities. The same applies to life sciences research which is to a significant extent performed at Max Planck institutes.

inappropriate. Moreover, research group leaders are often caught in administrative business and therefore often do not find the time to conduct research and publish the results. Our measure for the research environment (i.e. the size of the peer group) turns out to be marginally positively related to technology commercialization and negatively to consulting. We expected a positive sign throughout due to the argument that research funding is awarded on a competitive basis and the size of the peer group should positively influence the level of competition for funds. We may speculate that the negative sign for consulting hints at a different kind of peer pressure not to engage too intensively in activities that do not primarily benefit the university or research institute but rather the private remuneration.

Finally, focusing on the research productivity indicators publications and patent applications we find that the number of publications is not important at all for the decision to engage in any form of informal technology transfer. Instead, patent applications have a consistently positive and significant effect. Obviously, scientists succeed in signalling their quality to industry not by publications which would rather contribute to academic merits but by patents. Firms seem to acknowledge the practice-oriented work of the scientists that may be immediately integrated into the firm's knowledge base. In this respect, our results are in contrast to previous findings for the biotechnology industry showing that university "star" scientists, measured in terms of publication activity, are attractive partners for firm scientists to collaborate with (e.g., Zucker and Darby 1996, Zucker et al. 2002). Hence, this argument seems to hold true only in the specific disciplinary setting of biotechnology while it disappears when scientists from various disciplines are considered.

Comparing the baseline models (1) and (2) with our extended models (3) and (4) shows that the positive tenure effect as a proxy for faculty quality observed both in the U.S. and German data is partly taken over by the patent and research group leader variables. Faculty quality hence seems to be a multifaceted construct on which the added variables were able to shed some more light.

**Table 2: Probit results (Chapter 4)**

| | Commercialize technology | | | | Joint publication | | | | Consulting | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** | **(1)** | **(2)** | **(3)** | **(4)** | **(1)** | **(2)** | **(3)** | **(4)** |
| Gender | 0.231* | 0.203 | 0.155 | 0.146 | 0.298* | 0.222 | 0.213 | 0.135 | 0.632*** | 0.782*** | 0.647*** | 0.819*** |
| | (0.137) | (0.162) | (0.144) | (0.171) | (0.170) | (0.195) | (0.177) | (0.203) | (0.194) | (0.245) | (0.200) | (0.254) |
| Tenure | 0.349** | | 0.214 | | 0.394** | | 0.299* | | 0.087 | | -0.027 | |
| | (0.144) | | (0.155) | | (0.168) | | (0.177) | | (0.171) | | (0.179) | |
| Years with tenure (in logs) | | -0.02 | | -0.013 | | 0.001 | | 0.021 | | 0.047 | | 0.076 |
| | | (0.065) | | (0.068) | | (0.071) | | (0.074) | | (0.077) | | (0.080) |
| Percent time grants-related | 0.005** | 0.005* | 0.005** | 0.004 | 0.005** | 0.006** | 0.005* | 0.006* | 0.004 | 0.005 | 0.004* | 0.006* |
| research | (0.002) | (0.003) | (0.002) | (0.003) | (0.002) | (0.003) | (0.002) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| Age (in logs) | 0.038 | | -0.018 | | 0.217 | | 0.098 | | 0.379 | | 0.266 | |
| | (0.310) | | (0.332) | | (0.337) | | (0.353) | | (0.358) | | (0.367) | |
| Life sciences | 0.472*** | 0.474*** | 0.211 | 0.211 | 0.389** | 0.483** | 0.128 | 0.227 | 0.469*** | 0.558*** | 0.406** | 0.499** |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (0.135) | (0.153) | (0.152) | (0.171) | (0.169) | (0.195) | (0.187) | (0.215) | (0.162) | (0.187) | (0.178) | (0.207) |
| Other natural sciences | 0.287** | 0.233 | 0.147 | 0.074 | 0.514*** | 0.597*** | 0.360** | 0.451** | -0.13 | -0.131 | -0.143 | -0.134 |
| | (0.133) | (0.148) | (0.146) | (0.162) | (0.163) | (0.186) | (0.177) | (0.202) | (0.172) | (0.193) | (0.183) | (0.210) |
| Engineering sciences | 1.365*** | 1.372*** | 1.007*** | 1.009*** | 1.123*** | 1.253*** | 0.897*** | 1.060*** | 0.585*** | 0.611*** | 0.478*** | 0.549*** |
| | (0.155) | (0.169) | (0.164) | (0.179) | (0.172) | (0.193) | (0.184) | (0.205) | (0.171) | (0.191) | (0.182) | (0.204) |
| Research group leader | | | 0.415*** | 0.378*** | | | 0.138 | 0.203 | | | 0.403*** | 0.440*** |
| | | | (0.118) | (0.133) | | | (0.131) | (0.149) | | | (0.145) | (0.170) |
| Size of the peer group at the | | | 0.048 | 0.066* | | | -0.045 | -0.049 | | | -0.093** | -0.134*** |
| scientist’s institution (in logs) | | | (0.036) | (0.040) | | | (0.040) | (0.044) | | | (0.043) | (0.048) |
| No of publications (in logs) | | | -0.096** | -0.069 | | | 0.069 | 0.076 | | | -0.036 | 0.004 |
| | | | (0.043) | (0.047) | | | (0.047) | (0.050) | | | (0.049) | (0.054) |
| No of patent applications | | | 0.795*** | 0.733*** | | | 0.521*** | 0.488*** | | | 0.304*** | 0.274*** |
| (in logs) | | | (0.101) | (0.108) | | | (0.084) | (0.090) | | | (0.087) | (0.094) |
| Constant | -1.443 | -0.863*** | -1.239 | -1.091*** | -2.903** | -1.719*** | -2.454* | -1.926*** | -3.428** | -2.168*** | -2.975** | -2.400*** |
| | (1.162) | (0.235) | (1.250) | (0.271) | (1.269) | (0.291) | (1.333) | (0.323) | (1.357) | (0.341) | (1.397) | (0.381) |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Pseudo R2 | 0.115 | 0.114 | 0.195 | 0.188 | 0.095 | 0.095 | 0.149 | 0.153 | 0.069 | 0.077 | 0.104 | 0.118 |
| N | 835 | 668 | 821 | 657 | 828 | 661 | 814 | 650 | 821 | 655 | 808 | 645 |
| LR Chi2 | 131.399 | 104.918 | 219.089 | 170.786 | 84.423 | 70.369 | 129.368 | 110.718 | 52.072 | 47.992 | 77.657 | 72.903 |
| P-value | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

* p<0.10, ** p<0.05, *** p<0.01; Social sciences and humanities serve as reference group. Robust standard errors in parentheses.

## 5.5 Conclusion

The purpose of this paper was to shed light on the effects that institutional differences have on the choice of scientists to transfer technology informally. Our comparison of results for the United States and for Germany reveals similar behavior of faculty. Focusing in more detail on the research productivity of faculty in terms of publications and patents our results show that particularly university scientists with a track record of patent applications are an attractive partner for firm scientists in joint informal technology transfer activities.

The lesson learned from our research is simple; faculty, like all economic agents, respond to incentives and until universities change their incentives (e.g., patenting as one criterion for promotion and tenure) knowledge will continue to flow out the backdoor.

# 6 International Scientist Mobility and the Locus of Knowledge and Technology Transfer

## 6.1 Introduction

It has almost become conventional wisdom that knowledge originating from universities and public research centres is a crucial constituent of technological change and economic growth (e.g. Jaffe 1989, Adams 1990, Mansfield 1991, Salter and Martin 2001). In fact, knowledge and technology transfer (KTT) from academia to industry has attracted considerable attention in the literature with a focus on the scientists involved, the research institutions, the agents in technology commercialisation (e.g. transfer offices), or on the modes of transfer, such as formal and informal KTT (e.g. Schmoch et al. 2000, Siegel and Phan 2005, Link et al. 2007, Rothaermel et al. 2007). Yet, despite the growing interest of scholars and policymakers in science, technology and innovation (STI) policy to better understand the factors motivating scientists[12] to transfer knowledge and technology to firms, little is known how temporary international mobility[13] of these scientists affects both the propensity to engage in KTT as well as the locus of such transfer.

This question is important for at least two reasons. First, international mobility of researchers in public science has increasingly become an integral part of academic careers (Edler 2007, Ackers and Gill 2008, Cox and Verbeek 2008), and understanding the effects that mobility has on collaboration with industry can be assumed to yield insights for policy making. Second, international scientist mobility is implicitly associated with a discourse on "brain drain", affecting the technological capabilities through an absence of skilled workers

[12] In the following, we will use the term "scientist" as short-hand for scientists employed at universities and other public research institutes and centres in the field of science and engineering.

[13] Mobility, obviously, is a complex term. In this paper, we focus on *inter*-national yet *intra*-sectoral mobility, i.e. mobility within academia. Thus, we are not concerned with moves from public research into firms, but with cross-border moves of university scientists.

and thus eventually the competitiveness of the home countries of mobile scientists in academia (Adams 1968, Mountford 1997). Moreover, temporary mobility might lead to permanent migration of scientists. In this respect, policy makers in all countries – not only in developing or emerging economies – are concerned that research activities of mobile scientists result in KTT to firms predominantly in the host country, although the scientist's research was substantially funded by the home country (OECD 2002, Nguyen 2006, OECD 2007). Despite the vivid discussion of potential negative effects of international scientist mobility on the scientist's home country, however, a more recent approach has coined the term "brain circulation" to put emphasis on the benefits for both home and host country from scientists' international mobility (Regets 2007).

Hence, in this paper we aim at shedding light on the relationship between international scientist mobility and scientists' KTT activities by analysing the role of both the duration of a research visit outside the scientist's home country and the frequency of such visits. In a first step, we identify the factors that motivate scientists in academia to become internationally mobile. We define scientist mobility[14] as research visits at a host institution outside the scientist's home country that take longer than one month. Shorter activities, which for example would also include the attendance of international conferences, can be assumed to impact KTT activities differently than being embedded as a visiting researcher at a host institution. Moreover, we do not consider permanent moves to another country which imply that the scientist does not have an immediate intention to return to the home country. In a second step, we focus on the scientist's decision to engage in KTT and on the locus of such activities.

Our theoretical reasoning is guided by the scientific and technical human capital approach (e.g. Bozeman et al. 2001, Bozeman and Corley 2004, Boardman 2009, Ponomariov and Boardman 2010). Scientific and technical human capital has been described as "the sum of an individual researcher's professional network ties, technical knowledge and skills, and

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[14] We use the more general term mobility in contrast to other authors like Ackers and Gill (2008) who use the terms mobility and migration synonymously.

resources broadly defined" (Bozeman et al. 2001, 636). Consequently, international mobility can be characterised as a way to augment the scientist's professional network and the resources available, thus increasing the scientist's scientific and technical human capital. We suggest in this paper that scientific and technical human capital plays a key role in the transmission of scientific knowledge from academia to industry as it influences the ability and inclination of individual scientists to engage in KTT activities.

The empirical part of our paper is based on a random sample of more than 950 public scientists in Germany. We estimate Heckman selection models to account for the fact that not all scientists have international research experience. The paper further explores how KTT activities to home and host country firms relate to each other, i.e. we investigate whether KTT to host country firms substitutes or crowds out KTT to firms in the home country, or whether the two are complementary and mutually reinforcing. In this respect, we contribute to the literature in a number of ways. For the first time, we provide a direct link between international mobility and the KTT activities of scientists. While the effects of permanent migration have been studied in more detail, little is known about temporary mobility. Insights on this can be assumed to sharpen our understanding of the determinants of scientists' engagement in KTT activities and to inform STI policy making. Moreover, our data on mobile and non-mobile scientists allow for an investigation of the factors that encourage or discourage scientists to become internationally mobile. From a theoretical perspective, we conceptualise mobility as a driver of scientific and technical human capital which has been frequently shown to impact on scientific productivity.

The paper is organised as follows. The next section gives a brief review of the literature on scientist mobility and KTT activities and links the two in order to specify our hypotheses. Section 3 provides an overview of our empirical methods, before section 4 will show the empirical results. The paper concludes by outlining the implications of our findings for science and technology policy and by identifying further research opportunities at the intersection of scientist mobility and KTT activities.

## 6.2 Literature background

*Mobility of scientists*

The discourse on the causes and effects of mobility of academics and highly skilled workers has frequently been associated with concerns about a potential brain drain. As a consequence, mobility has been framed in a context of loss and possible negative effects. This discussion goes back at least to Adams (1968) and has been coined in the context of development policy, analysing the scale, scope and consequences of the movement of scientific and economic elites from developing and emerging countries to a richer nation (Adams 1968, Mountford 1997, for an overview see Nguyen 2006). However, while the discourse has long been focused on developing countries, initially the brain drain discussion was led in the United Kingdom in the 1950s and 1960s, when a loss of highly skilled workers and scientists to the United States had become apparent (Cervantes and Guellec 2002). In the 1990s, the economic consequences of scientist and highly skilled worker mobility came back on the agenda of OECD countries (Salt 1997, OECD 2002, Schiff 2005, Hunter et al. 2009). Recognising the importance of a sufficient pool of scientists and highly skilled workers, even in advanced countries worries about brain drain have re-emerged and been counteracted by policy schemes to retain the scientific elites. Indeed, the phenomenon of scientist mobility has been discussed in most OECD countries as a potential risk to the economy of the sending country.[15] For example, the United Kingdom and the United States have intensified their efforts to re-attract or retain scientific elites at the end of the 1990s and beginning of the 2000s (Cervantes and Guellec 2002).

However, the risk discourse around international mobility of scientists has not prevented a strong increase of international scientist mobility (Casey et al. 2001, OECD 2002). Part of this mobility is migration, i.e. the move to another country in order to stay there for an indefinite time, and part is temporary. Although European governments in particular have been worried about a potential brain drain to the United States, existing data show that actual migration, i.e. the emigration of scientists, is rather limited (Cervantes and Guellec 2002, Robinson et al. 2007). In contrast, temporary mobility has become more important in recent

[15] For the developing countries – which are not within the scope of our paper – this is obvious, although some views in the 1990s have claimed that the benefit for the sending country might be higher than the costs, which is – at least – a highly contested conclusion (Fiani 2003).

years, as scientists – and particularly PhD students and Post-Docs – gain experience abroad to come back and exploit the knowledge gained in their home country. Thus, the term brain circulation was coined in order to signal the potential gain stemming from temporary mobility, as such circulation implies linkages between national science and innovation systems (Saxenian 2002).

The overall allocation of benefits from scientist mobility is, however, not entirely clear. Several authors find that higher mobility in terms of brain circulation not only leads to a better career development of individual scientists,[16] but also contributes to the overall production and exchange of knowledge and subsequently potentially increases welfare (e.g., Thorn and Holm-Nielsen 2006, Edler 2007, Cox and Verbeek 2008). Freeman (2010) presents data on the mobility of scientists, highly skilled workers, students and graduates (see also de Grip et al. 2010), together with shifts in global talent production towards Asia. He argues that mobility creates benefits with respect to the speed and breadth of knowledge production as well as regarding the global transfer of knowledge. At the same time, these benefits are accompanied by challenges for advanced Western countries in their competition with emerging economies like China or India (Freeman 2010).

Scientist mobility is therefore said to enrich careers, create networks, support a better international flow of knowledge, better job matches through global job search and greater ability of employers to find rare or unique skill sets (Regets 2007). All this allegedly leads to some form of cognitive integration in scientific fields across borders, facilitating complementarities in knowledge production. Regets (2007), in compiling international country-level data on mobile scientists with a focus on the US, claims not only an overall net benefit for the global economy and the receiving (host) countries, but also for the sending country. For the host country, Regets (2007) suggests increased incentives for natives to seek higher skills leading to an increase in domestic economic returns to human capital investments, increased knowledge flows and collaboration as well as increased ties to foreign research institutions, export opportunities for technology, remittances, and other

[16] Cox and Verbeek (2008) have shown that the impact on scientists is not always and automatically positive.

support from "diaspora networks". Interestingly, and most important for our concern in this paper, Regets (2007) envisions very similar effects for the sending countries, thus making a strong argument for circulation and bi-directional benefits. However, these largely positive net effects of mobility for the receiving countries are not unambiguously supported in the literature. Both Bekhradnia and Sastry (2005) and Ackers and Gill (2008) argue that a high level of inward mobility may lead to dependencies on foreign in-flow that is unstable and hard to sustain – combined with the risk of mobile researchers returning to their home countries, "taking their skills with them" (HEFCE 2006, 44).

While brain drain remains an issue on the political agenda of some countries, the recent discourse has been about circulation and the requirement to enable and foster short and medium term stays. A major rationale behind those circulation programmes has been the insight that becoming part of global networks and collaborating with other scientists abroad enhances the capabilities and productivity of mobile scientists (Edler 2007, Defazio et al. 2009). Scientists realise a whole range of positive individual benefits, and by doing so they create positive net effects in the country in which they are originally based and to which they return or keep up linkages. Therefore, European countries have intensified efforts to govern brain circulation in order to increase their benefits from scientist mobility (e.g., Thorn and Holm-Nielsen 2006). Moreover, the insights on the benefits of scientist mobility have led to a "mobility strategy for the European Research Area (ERA)" in which mobility – with a focus on circulation – is seen as a major pillar for the creation of a single European market in science.[17]

In sum, apparently the fear of brain drain in some OECD countries has made way for more hope for brain circulation and related economic benefits. One increasingly recognised issue is the potential benefit for home countries of temporarily mobile scientists through an increased "knowledge flow across borders" (Regets 2007). There is however a severe shortage of empirical knowledge about the modes, scale and scope of effects of circulation of public scientists for the innovation system of both receiving and sending countries. We do

[17] For a summary see COM (2005).

not know to what extent mobile scientists do engage in KTT and where they mainly do it, either in the receiving or the sending country. Moreover, we know little about the factors that determine why scientists engage in KTT and, equally important, what drives them to become internationally mobile in the first place. Our paper is intended to fill this specific gap. It does not claim to discuss the broader consequences of migration or mobility, but instead focuses on one specific aspect in-depth using a novel dataset. In the following section we will review the existing evidence on causes and effects of KTT activities from academia to industry, which subsequently will be linked with the discussion of scientist mobility in order to derive our hypotheses.

*Knowledge and technology transfer from academia to industry*

There is wide agreement today that collaboration between science and industry plays a crucial role for the innovative capabilities of firms as well as for the overall economic development of a country (e.g. Hall et al. 2003, Link and Scott 2005). With the rise of the "mode 2 concept" (Gibbons et al. 1994) which posits a close interaction between scientific and industrial actors in the production of knowledge, KTT activities between academia and industry have gained further importance. Minbaeva et al. (2003) define knowledge transfer as a multi-stage process which involves the identification of relevant knowledge, the actual transfer of knowledge, as well as its final use by the receiving organisational unit. However, since the subject of knowledge transfer cuts across a variety of academic fields and application contexts, there is no common definition of the term across the disciplines, and the definition depends on how knowledge itself is defined (Bozeman 2000, Cummings and Teng 2003). Moreover, Sahal (1981) and Bozeman (2000) emphasise that there is no clear distinction between knowledge transfer and technology transfer, since technology is always based on knowledge and this knowledge is always transferred in the moment when a technology is transferred between two organisations, such as a public research organisation and a firm.

There are numerous modes of KTT, both formal and informal. Formal KTT usually involves a legal instrument like a patent, license, or royalty agreement (Bozeman 2000, Feldman et al. 2002, Thursby and Thursby 2002). In contrast to this, informal KTT refers either to the absorption of knowledge codified in specific research outputs or to interactions between public scientists and industry personnel. In this sense, knowledge could flow for example by technical assistance or consulting (Grimpe and Fier 2010), within collaborative research (Link et al. 2007) or through a temporary or permanent move from public research to industry (COM 2006). We use the term KTT in a broad understanding that refers to knowledge embodied in technological artefacts, codified and non-codified knowledge, as well as knowledge that is co-produced in various forms, e.g. in collaborative projects.

From the perspective of an industrial firm, interaction with public science is attractive for several reasons. Firms tend to “underinvest” in the production of new knowledge and technology through research and development (R&D) as the results achieved may be relevant for other companies and may thus spill over to competitors (Arrow 1962b). Further, knowledge production incurs high costs, as knowledge often involves complex and dynamic processes which firms cannot cope with internally (Dasgupta and David 1994, Crespi et al. 2006). Firms therefore strive to get access to complementary resources in universities and public research organisations and to explore new technological opportunities (Jacobsson 2002, Santor and Chakrabarti 2002, Adams 2006, Broström 2010). Firms also need access to the public scientists themselves in order to hire scientific personnel and thus to keep up their absorptive capacity for future KTT activities (Hall et al. 2003), as knowledge sought through external experts is often complementary to firms’ technological core (Song et al. 2003). Within the last few years, several studies have evaluated the links between science and industry with a view to firm success, typically finding that firms’ ability to innovate is positively influenced by industry-science interaction (Arvanitis et al. 2008, Broström 2010). Further exemplary evidence includes Belderbos et al. (2004) who examine industry-science interactions on the basis of a large scale innovation survey, concluding that interactions between firms and universities or research institutes significantly increase the firm’s sales with innovative products. A study of German companies found that firms sourcing knowledge from universities are more likely to innovate (Edler 2003).

While the generally positive effects of KTT on firm performance provide an explanation for why firms seek to collaborate with academics, existing literature has also shed light on what drives individual scientists to collaborate with firms and engage in KTT activities. This literature has developed within connected but slightly different conceptual lenses. A first lens is the *resource*-based view (e.g. van Rijnsover et al. 2007), which – in line with the original concept developed for firms (e.g. Barney 1991) – posits that individuals are enabled to collaborate by the resources at their disposal. They seek collaboration to enhance these resources and thus improve their personal competitive advantage vis-à-vis other researchers. A *second* approach to look at individual determinants of KTT is to understand the *organisational context*, i.e. the characteristics of organisations that encourage, enable or constraint scientists in their KTT efforts (e.g., Meyer-Krahmer and Schmoch 1998, Siegel et al. 2003, Siegel et al. 2004, Ponomariov and Boardman 2010). A third and related approach is the *scientific and technical human capital approach*, which refers to scientific and technical human capital as "individual endowments", tacit and craft knowledge as well as social contacts and networks (e.g., Bozeman et al. 2001, Bozeman and Corley 2004, Boardman 2009, Ponomariov and Boardman 2010). All approaches have in common that they focus on how various characteristics of individuals and their organisational environment influence their ability and inclination to engage with firms and transfer knowledge.

With respect to resource-driven considerations, scientists seek access to complementary knowledge, expertise and resources just like firms do (Katz and Martin 1997, Melin 2000, Thorsteinsdottir 2000, Beaver 2001). Link et al. (2007) examined knowledge transfer between academia and industry on the basis of a survey among university scientists. Their results suggest that university researchers rank collaboration with industry as very important because it allows them to benefit from the transferred knowledge and the use of equipment. Siegel et al. (2004) find that many researchers benefit from collaboration and knowledge transfer to industry due to the use of advanced equipment and laboratories at the firms' premises. Meyer-Krahmer and Schmoch (1998) investigated the importance of different types of interaction with industry. The interviewed scientists rated those interaction types with industry as more important that involved a bidirectional exchange of knowledge with industry, thus pointing towards the importance of both receiving and transferring knowledge. Moreover, scientists seek to collaborate with industry in order to get access to research grants as they have become a major source of university research funding (Beaver 2001, Hall et al. 2003, Bozeman and Corley 2004).

A second approach focuses on the meaning of the organisational environment. It has been shown that KTT differs depending on the mission and institutional context of public scientists. Broadly speaking, there is a substantial difference between university-affiliated scientists and those affiliated with institutionally funded basic research institutes on the one hand and scientists at public research institutes that are mission-oriented or that are set up to link science with industry on the other hand. For Germany, Schmoch et al. (2000) and Heinze and Kuhlmann (2008) have demonstrated that researchers at universities and Max Planck institutes, which are – by and large – more oriented towards basic research and publications as major indicator of excellence, tend to be less active in collaboration with firms than scientists from Fraunhofer institutes whose mission is application oriented and that need to acquire industry funding. This result has been confirmed by Ponomariov (2008) for universities, finding a negative correlation between scientific quality of university units and their propensity to collaborate with firms. Moreover, Ponomariov (2008) finds that the presence of industry near or on campus increases KTT activities.

Similarly, Siegel et al. (2004) show that a considerable number of scientists rate the reward systems for KTT at the research institutions as insufficient, thus obstructing a higher level of transfer activities. In fact, several papers have highlighted the importance of an appropriately designed reward system at the research institutions to stimulate the scientists' engagement in KTT. In this context, Friedman and Silberman (2003), Lach and Schankerman (2004) and Link and Scott (2005) find a positive relationship between royalty payments and the scientists' propensity to engage in KTT activities. Jensen et al. (2001), Owen-Smith and Powell (2001), and Thursby and Kemp (2002) highlight the critical role of intellectual property rights, such as patents, for KTT. They find that the faculty's awareness of commercialisation opportunities and an active involvement in the process of commercialisation of scientific discoveries positively influence the patenting behaviour of scientists. Patents, in turn, create opportunities to enter the "market for technology" and facilitate the exchange of knowledge assets (Arora et al. 2001). Finally, there is also clear evidence that scientists in different scientific fields have different collaboration behaviours (Meyer-Krahmer and Schmoch 1998, Schmoch et al. 2000, Heinze and Kuhlmann 2008).

Finally, the third approach, the scientific and technical human capital approach, puts emphasis on individual-level research capacity. It combines the first two lenses, but is slightly broader in discussing determinants of individual research capacity. Belkhodja and Landry (2007) show that a number of factors driving the scientist's scientific and technical human capital like the career age, productivity, hierarchical position as well as previous successful collaboration relate positively to the scale of collaboration with firms. Furthermore, scientists who are well connected, i.e. who occupy a central position in professional networks, collaborate significantly more. Boardman (2009) as well as Ponomariov and Boardman (2010) suggest that scientists affiliated with a university research centre may augment their scientific and technical human capital and, in this respect, their ability to conduct research together with industry and to publish the results. The underlying mechanism for this is the notion that social capital creates human capital. Joining a research centre implies interaction with other centre participants as well as access to centre resources. As a result, a scientist's centre-enhanced research capacity will facilitate industry-science interaction and KTT activities.

This review has demonstrated that scientists may engage in KTT for a variety of reasons. Although the three theoretical lenses presented – and particularly the resource-based view and the scientific and technical human capital approach – are interconnected, the following section will primarily draw from the scientific and technical human capital approach. This approach combines important perspectives of the other two approaches. However, it focuses on the influence that the *broader* environment and a whole range of factors related to the individual – such as career pathways, social position in networks (social capital) – have on the actor's resources and their application and hence on their behaviour. In short, a change in the broader environment or in those key factors can trigger a change in behaviour. For our study, this perspective best helps us to delineate the effects that international mobility of scientists – a feature of scientists' career paths that has become increasingly important – will likely have on engaging in KTT activities with firms both in the home and the host country.

*Linking KTT with international mobility of scientists*

Both KTT activities and scientist mobility have been characterised as increasingly important phenomena, and both promise benefits at the individual *and* systemic level. In this respect, it becomes imperative to explain the mechanism through which international mobility might have an impact on scientists' KTT activities. As indicated before, our theoretical reasoning will be guided by the scientific and technical human capital approach which has been applied in a number of recent studies investigating industry-science collaboration (e.g., Bozeman and Corley 2004, Boardman 2009, Ponomariov and Boardman 2010). The scientific and technical human capital approach is particularly appropriate because of its emphasis on individual-level research capacity which can be affected – inter alia – by professional relationships and network ties. Our starting assumption is that international mobility might serve as a prominent way to increase an individual's embeddedness in professional – academic and non-academic – networks which translates into higher scientific and technical human capital. Our overarching research hypothesis is therefore that international mobility of scientists increases the propensity that these scientists will engage in KTT activities to firms.

As our starting point, we identify two major dimensions of mobility that may have an influence on KTT activities of mobile scientists: the duration of a focal research visit to a host country institution, as well as the scientist's more general international orientation in her or his academic career, which we define as the frequency of research visits relative to the scientist's career age. Proponents of the scientific and technical human capital approach have argued that "social capital begets human capital" (Ponomariov and Boardman 2010, 616). Mobile scientists are exposed to collaborators and probably resources they did not have access to before. In this respect, scientists increase their research capacity, i.e. their human capital, some of which might be the result of further training and development. Moreover, by making formal and informal connections, scientists also expand their social capital that eventually might increase their ability to facilitate the transfer of knowledge and technology to firms (Ponomariov and Boardman 2010).

The duration of a research visit outside the scientist's home country may thus impact the scientific and technical human capital because longer research visits abroad result in more intensive experiences and stronger embeddedness in the foreign context. Such visits create opportunities for more intensive interaction and knowledge exchange or co-production of knowledge. While these arguments suggest that longer research visits abroad predominantly benefit KTT activities to firms in the host country, we might also expect positive effects of a longer visit for KTT activities to firms in the home country. The reason is that industry in the home country will typically have a higher interest in collaborating with a scientist with a higher scientific and technical human capital gained through international exposure. This opens the opportunity for firms to acquire more distant knowledge and technology with a high degree of novelty and uniqueness from the firm's point of view. Hence, our first hypothesis can be stated as:

*Hypothesis 1a (H1a): The longer the research visit to an institution outside the scientist's home country takes, the higher the likelihood that the scientist will engage in KTT activities to firms in the home country.*

*Hypothesis 1b (H1b): The longer the research visit to an institution outside the scientist's home country takes, the higher the likelihood that the scientist will engage in KTT activities to firms in the host country.*

Second, the frequency of research visits abroad might have an important role to play as it reflects a form of the scientist's international orientation. Frequent research activities abroad may, for example, lead to a higher number of contacts, the build up of reputation and, therefore, also to a more diverse and broad potential for interactions. As before, a high frequency of visits also suggests that the scientist may become well embedded into the scientific context of the host country. This should particularly be true due to the cumulative effects of repeat visits as these are likely to better facilitate building up social capital. Moreover, we can assume that scientists with a high international orientation are generally more open-minded, which might also help in terms of establishing contacts with industry. As a consequence, a higher frequency of research visits abroad should facilitate KTT activities to firms both in the host and the home country.

*Hypothesis 2a (H2a): The higher the frequency of research visits to institutions outside the scientist's home country, the higher the likelihood that the scientist will engage in KTT activities to firms in the home country.*

*Hypothesis 2b (H2b): The higher the frequency of research visits to institutions outside the scientist's home country, the higher the likelihood that the scientist will engage in KTT activities to firms in the host country.*

Finally, it is of particular interest for policy makers to explore the relationship between KTT activities to firms in the host and the home country. If there was a positive correlation between KTT of a mobile scientist to firms in the host country and the home country, then international scientist mobility would have direct positive effects for firms in the home country, as well. Mobile and transfer-active scientists would constitute a natural transfer mechanism of relevant knowledge and technology to industry, regardless of national borders. In turn, the more mobile and transfer-active scientists a country had, the more attractive it would become as a location for international firms. In addition, a higher number of transfer active and mobile scientists would contribute to a more efficient and effective linking of complementary knowledge globally. Reflecting the brain drain discourse, there is an obvious imbalance between the growing need to foster mobility and KTT on the one hand, and concerns about a sufficient return of knowledge to the home country on the other hand. Both the scientific and technical human capital approach and the resource-based view would suggest that scientists prefer those transfer activities that promise a gain in knowledge for them as well, i.e. they seek reciprocal partnerships with firms, in order to expand their research capacities and human capital. If that is true, international KTT activities promise to yield positive effects on the scientists and thus will also benefit the innovation system of the scientist's home country. Moreover, scientists with collaborative experience can be assumed to be both more open to and more attractive for industrial partners as they understand the application-oriented interest of firms and know how to manage relationships with firms (Grimpe and Fier 2010). If there are no confidentiality agreements between a scientist and a particular firm in place, scientists are therefore likely to seek further collaboration opportunities in order to acquire funding and to commercialise their knowledge and technology. As a result, our third hypothesis reads:

*Hypothesis 3 (H3): There is a positive correlation between KTT activities to firms in the host and the home country.*

In the following section we will outline our research methods used to test our hypotheses before we present the results.

## 6.3 Research methods

*Data*

The data used in our empirical analysis originate from a survey among German scientists carried out on behalf of the German Federal Ministry of Education and Research (Edler 2007). The aim of the survey, which was part of a large-scale project on the internationalisation of German publicly financed research and science, was to depict the willingness, the motives and the actual extent of international mobility of scientists in Germany. Data were collected in 2006 using an online survey instrument.

An online survey is a particularly useful instrument in our case because it allowed us to reach those scientists who were temporarily absent from their home office, i.e. who were on a visit, in a quick and efficient way. In this respect, it can be regarded as superior compared to a survey administered via mail. Moreover, it enabled us to reach a large number of scientists who provided detailed information about their mobility pattern. While in-depth case studies with a selected group of scientists could have generated even more detailed information, they would have precluded further statistical analyses which allow us to draw conclusions based on a large number of observations and controlling for several individual and institutional factors. In any case, the information is self-reported, which could raise concerns with respect to response accuracy. However, we believe that the advantages of such an online survey outweigh the drawbacks (for a discussion see Bertrand and Mullainathan 2001).

Two major data sources were used for the sampling procedure. In a first step, the population of scientists holding a PhD and employed at German universities was derived from the "Hochschullehrerverzeichnis" of the year 2005. The "Hochschullehrerverzeichnis" is a database containing the names, degrees and contact information of the academic personnel employed at German universities.[18] In a second step, scientists at (partly) government-funded public research institutes were identified via an internet search of the institutes' websites. These research institutes belong to the four large German science organisations: Max Planck Society, Fraunhofer Society, Leibniz Association and Helmholtz Association. In total, around 20,000 scientists from 113 German universities and 231 research institutes were identified with their e-mail addresses and invited to participate in our survey. Questionnaires of 1,509 respondents were retained; the overall response rate was 15.8 percent, which can be regarded as satisfactory for such a large-scale online survey.[19] For the analysis, we limited the sample to those scientific disciplines where a transfer of technological knowledge to firms is potentially relevant – i.e. in agricultural and environmental sciences; biology and chemistry; physics, mathematics and computer sciences; engineering sciences; medicine, psychology – thus excluding social sciences and humanities. Excluding cases with missing values leaves 958 observations available for analysis.

*Variables and measures*

Dependent variable

To qualify the KTT activities of scientists, the respondents were asked to indicate whether their *most recent* research activity outside of Germany resulted in a *transfer of technological knowledge or expertise* to a firm in Germany and/or in the host country. We chose the most recent visit as the focal visit of our analysis for several reasons. First of all, it could be argued that the most recent visit was actually not relevant at all. However, letting a scientist choose which visit to report from would probably heavily bias the results as scientists might only choose those visits where KTT occurred. Defining the most relevant visit creates additional problems as scientists might have a different understanding of what they consider as relevant. Second, we can assume that scientists are better able to recall their experiences

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[18] This excludes the so-called "universities of applied sciences" whose major task is teaching and not research.

[19] The response rate reflects the fact that many scientists could not be reached due to an outdated or misspelled e-mail address.

when reporting from the most recent visit compared to a visit that had taken place been a longer time ago. We hence obtain two dummy variables. However, only 54 percent of all scientists in our sample have international research experience. Whether KTT as a result of such activities occurred or not is therefore not observable for scientists lacking this experience. We will address this issue methodologically by estimating selection models (see the model section for details).

Explanatory variables

In order to capture the international mobility of scientists, we use two survey variables: the *duration* of the focal research visit, i.e. the scientist's most recent visit abroad, and the scientist's more general *international orientation* which we associate with the frequency of international visits.

International research activities can be limited in duration or indeterminate. The latter case might for example apply to German scientists with a regular working contract at an institution abroad. We therefore use four dummy variables for visits lasting between 1 to 3 months (short-term), 4 to 12 months (medium-term), longer than 12 months (long-term) and for research activities of indeterminate duration but at least for 12 months. The dummy for short-term activities is used as the reference category in all regressions. It could be argued that the choice for the length of each category is somewhat arbitrary. However, we believe that a distinction between short-term, medium-term, long-term and research activities of indeterminate length abroad makes sense as they are also associated with different levels of effort for the scientist and corresponding administrative requirements. In this sense, short-term stays of up to 3 months are relatively easy to realise as temporary accommodation and office space would be rather easy to find. Moreover, it may not be necessary to apply for a visa and deal with other bureaucratic issues. The U.S. Visa Waiver Program, for example, allows German citizens to stay for up to three months in the United States without a visa, as long as they do not take up employment. All these efforts can be assumed to increase with medium-term stays that take up to one year. If a research activity is planned that takes even longer, scientists will probably seek some form of permanent residency with consequences for private and administrative aspects of their lives. Hence, although such a four-level conceptualisation of duration is necessarily somewhat arbitrary, we believe that it represents a pragmatic approach to capture the scientist's mobility choice.

Our measure for the general international orientation of the scientist is defined as the number of research visits abroad that took longer than 1 month, divided by the scientist's career age. The career age is defined as the number of years that have passed since the scientist received her or his PhD. For obvious reasons, the career age is closely connected to the scientist's opportunities to engage in research activities abroad. Hence, we use the career age to control for these age effects. The international orientation therefore shows the importance of research visits abroad during the scientist's career.

Besides duration and frequency, we control for the destination of the scientist's research visit. In the questionnaire, scientists were asked to indicate the host country of their international research activities. These were grouped into three groups and we include dummy variables for Western Europe and North America. The rest of the world serves as the reference category.[20]

We have argued that the scientist's propensity to engage in KTT activities not only depends on mobility but also on other personal characteristics of the scientist. Therefore, we include several variables to control for the individual level effects. We measure the scientist's productivity by including dummy variables for her or his publication activities (i.e. 0 to 3, 4 to 6, and more than 6 articles in refereed journals) and for having applied for a patent. These variables refer to the three years prior to the survey. We account for the age of the scientist by including the career age in linear and squared form to control for potential non-linearity. Moreover, we include dummy variables for the gender, whether the scientist is employed at a university or at one of the institutes belonging to the large German science organisations (i.e., Fraunhofer Society, Max Planck Society, Helmholtz Association, and Leibniz Association

[20] As the descriptive statistics will show, 85 percent of the scientists indicated North America and Western Europe as their destination. Despite a strong (politically motivated) interest in mobility to Asia and particularly China, it would thus not make sense to include separate dummy variables due to the low number of observations.

and other institutes, with the Leibniz and other institutes serving as reference group), and whether the scientist received a grant for the international research visit.

Further, we measure the enabling and pull factors of international research activities with two dummy variables. The first variable indicates enabling conditions. We asked whether the scientist perceived the available funding opportunities for international research activities to be sufficient. The second variable is the perceived importance of the research environment abroad relative to the home environment. We use two variables on the number of research groups or research institutions within Germany and outside of Germany which the scientist indicated to be important for her or his research (none, 1 to 4, 5 to 10, more than 10). When the number of important research groups abroad is higher than the number of domestic research groups, then the new variable takes on the value of 1, if it is lower or the same, the value is 0. Finally, we include discipline dummies (environmental sciences; biology, chemistry, pharmacy; engineering sciences; medicine, psychology), with physics, mathematics, computer sciences serving as a reference category in all estimations.

### 6.4 Estimation model

Our dependent variables, the transfer of knowledge and technology to firms in Germany or in the scientist's host country as a result of an international research visit, are only observable if scientists have international research experiences. All other scientists would consequently not be able to engage in such KTT. The sample is therefore censored, which implies that we have to use a two-stage selection model. Estimating a simple regression model using only data on scientists with international research experience (i.e. whether the scientist had been abroad for at least a month in her or his career at all) would generate inconsistent estimates (Heckman 1979). Including international experience as an exogenous variable would ignore the endogeneity between the KTT behaviour and international experience. We address this issue by estimating probit models with selection correction. The models consist of estimating two equations. In the first stage, the selection equation stage, the probability for having international research experience at all is estimated. In the second stage, the regression of interest, the determinants of the KTT activities to firms in the host and the home country are investigated. The two stage selection model assumes that there is a potential correlation between the error terms of the two equations (see Greene 1993 for a discussion). If that correlation is nonzero, estimates will be inconsistent unless accounted for through the selection model.

The Heckman selection model requires that at least one factor be identified that influences the selection (i.e. international experience), but not the dependent variable of the second stage regression model (i.e. KTT). We argue that the two variables portrayed as enabling and pull factors for international research activities fulfil this criterion. International research activities require funding, which will typically not be provided by the host institution. Therefore, scientists may apply for specific international grants or other grants. Moreover, research abroad only makes sense if there are opportunities to learn from and to collaborate with partners who work in similar fields and who provide an added value over domestic partners (pull). This does not imply that scientists will not go abroad if there are more potential domestic collaboration partners even though there are some research groups abroad which are highly important. However, we argue that a higher relative importance of international partners should at least result in a preference for international over domestic partners and thus increase the likelihood that international research activities occur. At the same time, both enabling and pull factors should not have any effect on the knowledge transfer behaviour of scientists. We test this assumption empirically by including the enabling and pull factors in both the first and second stage regression of a probit model with selection. As predicted, both variables have a positive and significant effect on the international experience and no significant effect on the KTT activities. Our estimation model can therefore be considered as valid.

In the second step of our estimation we employ a seemingly unrelated bivariate probit model. The model reflects our choice of two dummy variables as dependent variables: KTT to firms in the host and the home country. As outlined above, we are not only interested in the relation between the independent and the dependent variables, but also in the *relation between the two dependent variables*. We have argued that the two variables have a complementary relationship, i.e. KTT to firms in the host country does not substitute for knowledge transfer to firms in the home country and vice-versa. Instead, a complementary relationship would indicate that both directions of knowledge transfer occur at the same time. The bivariate probit model provides an indirect test for complementarity. The idea is to test for a positive correlation between the two practices conditional on a vector of covariates *X* (Athey and Stern 1998, Cassiman and Veugelers 2006). If the resulting correlation coefficient *rho* is positive and significant we can assume that both practices are complements rather than substitutes.

## 6.5 Results

*Basic characteristics of scientist mobility and KTT*

**Fehler! Verweisquelle konnte nicht gefunden werden.** shows the descriptive statistics of the dependent as well as our main explanatory and control variables. Correlation tables for the variables in the first and second stage of the selection models can be found in the appendix (Tables A2,A3). There is no indication for collinearity in our data as evidenced by the low values of the variance inflation factors (VIF) and condition numbers (Belsley et al. 1980).

**Table 3: Descriptive statistics (Chapter 5)**

| Variable | Obs. | Mean | Std. Dev. | Min. | Max. |
|---|---|---|---|---|---|
| Transfer to firms in Germany (d) | 514 | 0.163 | 0.370 | 0 | 1 |
| Transfer to firms in the host country (d) | 509 | 0.169 | 0.375 | 0 | 1 |
| Short-term stay (1 to 3 months) (d) | 514 | 0.461 | 0.499 | 0 | 1 |
| Medium-term stay (4 to 12 months) (d) | 514 | 0.138 | 0.345 | 0 | 1 |
| Long-term stay (> 12 months) (d) | 514 | 0.171 | 0.377 | 0 | 1 |
| Stay of indeterminate length (d) | 514 | 0.230 | 0.421 | 0 | 1 |
| International orientation (ratio) | 514 | 0.290 | 0.246 | 0 | 1.111 |
| Grant received for the focal research visit (d) | 514 | 0.796 | 0.404 | 0 | 1 |
| Host country in Western Europe (d) | 514 | 0.259 | 0.438 | 0 | 1 |
| Host country in North America (d) | 514 | 0.591 | 0.492 | 0 | 1 |
| International experience of at least one month (d) | 958 | 0.537 | 0.499 | 0 | 1 |
| Career age (years) | 958 | 15.437 | 10.283 | 0 | 41 |
| Gender (d, 1=female) | 958 | 0.148 | 0.356 | 0 | 1 |
| Employed at a university (d) | 958 | 0.467 | 0.499 | 0 | 1 |
| Employed at Fraunhofer institute (d) | 958 | 0.068 | 0.252 | 0 | 1 |
| Employed at Max Planck institute (d) | 958 | 0.134 | 0.340 | 0 | 1 |
| Employed at Helmholtz institute (d) | 958 | 0.244 | 0.430 | 0 | 1 |
| Employed at Leibniz or other institute (d) | 958 | 0.129 | 0.336 | 0 | 1 |

| | | | | | |
|---|---|---|---|---|---|
| Patent application in last 3 years (d) | 958 | 0.310 | 0.463 | 0 | 1 |
| No. of publications in last 3 years 0-3 (d) | 958 | 0.267 | 0.443 | 0 | 1 |
| No. of publications in last 3 years 4-6 (d) | 958 | 0.237 | 0.425 | 0 | 1 |
| No. of publications in last 3 years >6 (d) | 958 | 0.486 | 0.500 | 0 | 1 |
| Environmental sciences (d) | 958 | 0.144 | 0.351 | 0 | 1 |
| Biology, chemistry, pharmacy (d) | 958 | 0.290 | 0.454 | 0 | 1 |
| Physics, mathematics, computer science (d) | 958 | 0.310 | 0.463 | 0 | 1 |
| Engineering sciences (d) | 958 | 0.119 | 0.324 | 0 | 1 |
| Medicine, psychology (d) | 958 | 0.137 | 0.344 | 0 | 1 |
| Satisfied with availability of funding for intern. mobility (d) | 958 | 0.211 | 0.408 | 0 | 1 |
| Rel. imp. of research groups abroad higher than at home (d) | 958 | 0.693 | 0.461 | 0 | 1 |

(d): dummy variable

The descriptive statistics show that slightly more than half of the scientists in our sample do have international experience and can be used in the second stage of the selection model. The statistics further show that two dependent variables on the KTT behaviour are almost equally distributed. About one out of five scientists transferred knowledge and technology to firms in Germany during the focal research visit abroad. Slightly more scientists have engaged in KTT to firms abroad, i.e. in their (former) host countries.

Regarding the explanatory variables, our main focus is on the mobility variables. It turns out that, based on the information about their last research visit abroad, the majority of German academics go abroad for a rather short period of 1 to 3 months. Medium-term stays are somewhat less common (14 percent) than long-term stays (17 percent). Moreover, 23 percent of the scientists indicated their research activity abroad to be of indeterminate length. The international orientation, expressed by the ratio of the number of research visits and the career age, shows that on average scientists go abroad for at least one month about every fourth year. Most of the scientists chose North America as the destination for their international research activities and the vast majority received a grant for these activities.

The second group of explanatory variables reflects personal and professional characteristics of the scientists in our sample. On average, the scientists have been active after their PhD for 15 years (career age), and 15 percent of the scientists in the sample are female. Moreover, the descriptive statistics show that the sample is almost equally balanced regarding the locus of employment of the scientists (universities vs. non-universitary, i.e. public research institutes). Regarding the scientific productivity during the three years prior to the survey, it turns out that around 30 percent of the scientists had applied for at least one patent and most of the scientists had published more than 6 papers in refereed journals. With respect to the scientific discipline, about every third scientist in our sample is working in the fields of physics, mathematics or computer science. These disciplines are followed by biology, chemistry, pharmacy (29 percent), environmental sciences (14 percent), medicine, psychology (14 percent), and engineering sciences (12 percent).

The last two explanatory variables work as exclusion restrictions in the selection models, i.e. they are expected to determine the decision to be internationally mobile at all but they should be irrelevant for the decision to transfer knowledge and technology. Only 21 percent of the academics stated to be satisfied with the available funding opportunities for international research activities. The second exclusion restriction reflects the scientists' assessment of the importance of research groups abroad. Almost 70 percent of the scientists indicated the importance of foreign research groups to be higher than domestic research groups for their own research activities.

*International mobility as the determinant of KTT activities*

**Fehler! Verweisquelle konnte nicht gefunden werden.** shows the results from our probit selection models for the scientists' decision to move abroad (first stage of the model) and to engage in KTT activities either to firms in Germany or in the host country (second stage of the model). In the following, we will first discuss the results from the first stage before we move on to the second stage. We can see from the *rho* coefficient in the lower part of **Fehler! Verweisquelle konnte nicht gefunden werden.** that there is a significant correlation between the error terms of the two equations for the second model (KTT to firms in the host country). This indicates that a selection model is in fact required to yield consistent estimates results.

The enabling and pull factors – *availability of funding* and *relative importance of scientists abroad* – which serve as exclusion restrictions turn out to be significant in the two first stage equations and they have the expected sign. The propensity to move abroad for a period of at least one month increases when scientists are satisfied with the availability of funding for such activities and when they realise that research groups or institutions abroad are relatively more important than in the home country.

Concerning the other explanatory variables of the decision to go abroad, our findings indicate that neither the career age nor the gender have an effect. The organisational context however, matters.. University scientists appear to be much more likely to go abroad compared to scientists at Fraunhofer or Helmholtz institutes. A reason for this is that many scientists at Fraunhofer and Helmholtz institutes are more likely to have permanent contracts, and they focus more on application-driven research, often in close collaboration with industry. Thus, they have lower pressure (or incentives) and less opportunities to become a visiting researcher abroad.

Moreover, our results reveal a link between going abroad and being highly productive in terms of publication output. Scientists with more than 6 publications achieved during a three-year period prior to the survey (the reference group) are significantly more likely to go abroad than those with lower publication output. There are indications for a virtuous circle: highly credentialed scientists are more attractive as collaboration partners and thus more likely to be invited to or engaged in international research activities. At the same time, these excellence-driven research visits increase the likelihood for subsequent high level publications with international colleagues. In contrast, and in line with our observations of non-university staff, application-oriented research productivity (indicated in our survey by having previously applied for a patent) is not linked to mobility.

Regarding the scientific disciplines, scientists in environmental sciences, engineering sciences and medicine or psychology have a lower propensity to move abroad than the reference group which are scientists in physics, mathematics and computer science.

**Table 4: Probit models with selection – determinants of the decision to go abroad (first stage) and to engage in KTT to firms (second stage) (Chapter 5)**

| | Decision to go abroad | KTT to firms in Germany | Decision to go abroad | KTT to firms in host country |
|---|---|---|---|---|
| Medium-term stay (4 to 12 months) (d) | | -0.306 | | -0.207 |
| | | (0.247) | | (0.197) |
| Long-term stay (>12 months) (d) | | 0.620*** | | 0.497** |
| | | (0.228) | | (0.214) |
| Stay of indeterminate length (d) | | 0.214 | | 0.542** |
| | | (0.254) | | (0.234) |
| International orientation (ratio) | | 0.547* | | 0.156 |
| | | (0.325) | | (0.235) |
| Grant received (d) | | 0.081 | | -0.09 |
| | | (0.185) | | (0.131) |
| Host country in Western Europe (d) | | -0.202 | | -0.434** |
| | | (0.235) | | (0.212) |
| Host country in North America (d) | | -0.298 | | -0.403** |
| | | (0.220) | | (0.186) |

| | Decision to go abroad | KTT to firms in Germany | Decision to go abroad | KTT to firms in host country |
|---|---|---|---|---|
| Career age (years) | -0.004 | -0.027 | -0.005 | 0.031 |
| | (0.017) | (0.033) | (0.017) | (0.026) |
| Career age (years, squared) | 0.000 | 0.001 | 0.000 | -0.001 |
| | (0.000) | (0.001) | (0.000) | (0.001) |
| Gender (d, 1=female) | -0.024 | 0.016 | -0.003 | -0.01 |
| | (0.127) | (0.227) | (0.126) | (0.174) |
| Employed at university (d) | 0.512*** | 0.034 | 0.470*** | -0.344** |
| | (0.120) | (0.274) | (0.119) | (0.163) |
| Employed at Fraunhofer institute (d) | -0.582*** | 1.050*** | -0.650*** | 0.917*** |
| | (0.206) | (0.356) | (0.207) | (0.298) |
| Employed at Max Planck institute (d) | -0.121 | -0.312 | -0.178 | -0.035 |
| | (0.158) | (0.295) | (0.160) | (0.224) |
| Employed at Helmholtz institute (d) | -0.440*** | 0.059 | -0.461*** | 0.295 |
| | (0.134) | (0.286) | (0.133) | (0.202) |
| Patent application (d) | -0.057 | 0.587*** | -0.071 | 0.310** |
| | (0.103) | (0.164) | (0.103) | (0.144) |
| No. of publications in last 3 years 0- | -0.639*** | 0.332 | -0.661*** | 0.437** |

| | Decision to go abroad | KTT to firms in Germany | Decision to go abroad | KTT to firms in host country |
|---|---|---|---|---|
| 3 (d) | | | | |
| | (0.112) | (0.294) | (0.112) | (0.198) |
| No. of publications in last 3 years 4-6 (d) | -0.257** | 0.148 | -0.257** | 0.168 |
| | (0.112) | (0.197) | (0.112) | (0.149) |
| Environmental sciences (d) | -0.361** | -0.218 | -0.389*** | 0.168 |
| | (0.144) | (0.281) | (0.144) | (0.203) |
| Biology, chemistry, pharmacy (d) | -0.190 | -0.263 | -0.216* | 0.025 |
| | (0.118) | (0.217) | (0.119) | (0.166) |
| Engineering sciences (d) | -0.781*** | 0.716** | -0.767*** | 0.796*** |
| | (0.158) | (0.353) | (0.157) | (0.220) |
| Medicine, psychology (d) | -0.768*** | 0.307 | -0.779*** | 0.374 |
| | (0.145) | (0.336) | (0.145) | (0.252) |
| Availability of funding (d) | 0.203* | | 0.176* | |
| | (0.109) | | (0.102) | |
| Relative importance of scientists abroad (d) | 0.259*** | | 0.265*** | |
| | (0.100) | | (0.090) | |
| Constant | 0.384* | -1.260** | 0.440** | -0.646 |

| | Decision to go abroad | KTT to firms in Germany | Decision to go abroad | KTT to firms in host country |
|---|---|---|---|---|
| | (0.223) | (0.610) | (0.220) | (0.446) |
| Rho | -0.254 | | -0.804* | |
| | (0.541) | | (0.204) | |
| N (uncensored observations) | 958 (514) | | 953 (509) | |
| Wald Chi2 | 67.186 | | 88.099 | |
| P-value | 0.000 | | 0.000 | |

(d): dummy variable; standard errors in parentheses.

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

Short-term stays (1 to 3 months) and physics, mathematics, computer sciences serve as reference groups.

In the second stage, which explains the determinants of KTT activities, we find differentiated results for KTT to firms in the home and the host country. First of all, long-term visits beyond 12 months increase the likelihood that scientists engage in KTT activities to firms in general, both in the home and the host country, in comparison to short-term visits, our reference category. In contrast to this, medium-term stays do not show a significant effect. With respect to stays of indeterminate length, our results indicate a positive effect only for KTT activities to firms in the host country. By and large, these findings provide support for hypothesis 1a and hypothesis 1b. Apparently, scientists need to be embedded into the host country's research environment for a year or more to fully realise the benefits from higher social capital and to generate the opportunities that result in a transfer of knowledge and technology. What is more striking, however, is that this not only holds true for the transfer to firms in the host country but also relates back to firms in the home country. A longer visit abroad is therefore beneficial to the innovation system of the scientist's home country and not detrimental as the discourse on brain drain might suggest. There is an additional benefit for the host country if the scientist's stay is indeterminate in length but this does not imply that there is a negative effect on KTT activities to firms in the home country. Hence, longer research visits apparently lead to the creation of additional scientific and technical human capital that facilitates collaboration with firms both in the host and the home country.

This finding is further supported when we look at the general international orientation of the scientists (defined as the number of visits abroad divided by the scientist's career age). Here we find a positive and significant effect for KTT to firms in Germany, while there is no significant effect for a transfer to firms in the host country. This finding supports hypothesis 2a but rejects hypothesis 2b. Higher international orientation apparently leads to an increased attractiveness of the scientist for firms back in the home country (reputation, relevance), and it can be interpreted as an instrument for the creation of an international network that facilitates KTT opportunities. In short, frequent international mobility is conducive to KTT only in the home country. In contrast, for KTT to firms abroad it is not frequent international mobility but only the duration of the visits abroad which makes a difference. This confirms the need for embedding and building up trust as a precondition for KTT abroad.

We find no effect of the scientist's host country in the decision for KTT to firms in the home country. However, our results show strong negative effects in the decision for KTT to firms in the host country if the host country was in Western Europe or North America compared to the rest of the world. It seems that there is a split between the knowledge and excellence driven mobility to the U.S. and some advanced European countries that implies less proximity to application and industry on the one hand and more pull from other countries with a greater need for input to industrial R&D from outside the country on the other hand. For those countries and the firms within them, mobility of scientists is one means to increase knowledge inflow into the country.

With respect to the other explanatory variables for the decision to engage in KTT, we find that grants supporting the international research activity do not have an effect, nor do the career age or gender play a role. Being employed at a university and having a high publication activity actually decrease the likelihood of KTT to firms in the host country, while there is no significant effect for KTT to firms in Germany. In other words, highly credentialed scientists with high academic output are less likely to transfer knowledge and technology to foreign firms. For those scientists, mobility is not linked to transfer activities abroad. In contrast, patents have a strong positive influence on the KTT activity in both models. The decisive connection between patent applications of scientists and their KTT activity, as pointed out by Schmoch et al. (2000) and Owen-Smith and Powell (2001), can thus be confirmed. This finding also indicates that scientific and technical human capital is characterised by a build up of skills and knowledge amenable to industrial application. Correspondingly, scientists at Fraunhofer institutes, which are by mission application and transfer oriented, are more likely to transfer knowledge and technology as opposed to their colleagues at universities (Heinze and Kuhlmann 2008). Strikingly, the effect on KTT is highest for scientists at Fraunhofer institutes despite their low mobility. This combination of low mobility and high KTT activity contrasts sharply with university scientists who exhibit high mobility but low propensity for KTT and with scientists at Helmholtz institutes who exhibit both low mobility and a low propensity for KTT. Again, the organisational context appears to moderate the extent to which scientific and technical human capital can be developed. Differences also emerge with respect to the scientific disciplines. We find that engineers are much more likely to transfer knowledge and technology than scientists from any other field to firms in the home and host country. In fact, there is a strong tradition of industry-science collaboration in engineering sciences in Germany (Grimpe and Fier 2010).

Finally, **Fehler! Verweisquelle konnte nicht gefunden werden.** shows the results from the bivariate probit model for the relationship between KTT activities to firms in Germany and, at the same time, to firms in the host country, i.e. between our two dependent variables. In this model we can only use the data on scientists who actually reported international experience, which explains the smaller sample size. It turns out that the *rho* correlation coefficient – conditional on the vector of covariates $X$ – is highly significant with a value of 0.858. Apparently, there is no trade-off between both transfer directions, but rather a mutually reinforcing, i.e. complementary, relationship. Scientists who transfer technology to firms in Germany do so also to firms in the host country. Transfer effects are thus distributed broadly and there is no clear home or host country advantage. Consequently, hypothesis 3 receives full support. As a caveat, our data do not allow us to investigate scientist behaviour over time, i.e. whether scientists started engaging in KTT activities in the host country and continued in the home country.

**Table 5: Bivariate probit model – determinants of the decision to engage in KTT to firms (Chapter 5)**

| | KTT to firms in Germany | KTT to firms in host country |
|---|---|---|
| Medium-term stay (4 to 12 months) (d) | -0.232 | -0.245 |
| | (0.258) | (0.270) |
| Long-term stay (>12 months) (d) | 0.692*** | 0.725*** |
| | (0.228) | (0.220) |
| Stay of indeterminate length (d) | 0.347 | 0.674*** |
| | (0.266) | (0.255) |
| International orientation (ratio) | 0.690* | 0.162 |
| | (0.355) | (0.343) |
| Grant received (d) | 0.039 | -0.117 |
| | (0.195) | (0.184) |
| Host country in Western Europe (d) | -0.073 | -0.594** |
| | (0.252) | (0.235) |
| Host country in North America (d) | -0.124 | -0.578*** |
| | (0.235) | (0.216) |
| Career age (years) | -0.003 | 0.055 |
| | (0.034) | (0.034) |
| Career age (years, squared) | 0.001 | -0.001 |
| | (0.001) | (0.001) |

| | | |
|---|---|---|
| Gender (d, 1=female) | 0.032 | -0.071 |
| | (0.241) | (0.238) |
| Employed at university (d) | 0.121 | -0.069 |
| | (0.209) | (0.198) |
| Employed at Fraunhofer institute (d) | 1.149*** | 0.895** |
| | (0.372) | (0.353) |
| Employed at Max Planck institute (d) | -0.309 | -0.081 |
| | (0.311) | (0.278) |
| Employed at Helmholtz institute (d) | 0.038 | 0.033 |
| | (0.252) | (0.243) |
| Patent application (d) | 0.537*** | 0.403** |
| | (0.170) | (0.167) |
| No. of publications in last 3 years 0-3 (d) | 0.175 | 0.094 |
| | (0.208) | (0.204) |
| No. of publications in last 3 years 4-6 (d) | 0.081 | 0.053 |
| | (0.189) | (0.185) |
| Environmental sciences (d) | -0.195 | 0.031 |
| | (0.254) | (0.239) |
| Biology, chemistry, pharmacy (d) | -0.366* | -0.098 |

| | | |
|---|---|---|
| | (0.206) | (0.191) |
| Engineering sciences (d) | 0.694*** | 0.477* |
| | (0.269) | (0.273) |
| Medicine, psychology (d) | 0.223 | -0.236 |
| | (0.251) | (0.277) |
| Constant | -1.824*** | -1.386*** |
| | (0.542) | (0.513) |
| rho | 0.858*** | |
| N | 488 | |
| Wald Chi2 | 688.49 | |
| P-value | 0.000 | |

(d): dummy variable; standard errors in parentheses.

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

Short-term stays (1 to 3 months) and physics, mathematics, computer sciences serve as reference groups.

### 6.6 Conclusion

Using a survey of more than 950 German scientists from universities and public research centres, this paper for the first time links the determinants and patterns of international mobility of scientists with their engagement in KTT activities. The findings confirm most of our hypotheses, qualify others, and bring to the fore a set of results that need deeper and more comparative research.

A first set of findings concerns the mobility patterns and conditions for mobility in general as a pre-condition for international KTT. More than 50 percent of the scientists have been abroad for at least a month during their career. We have found that mobile researchers are more productive in terms of publications. In this respect, mobility can be characterised as a consequence of as well as a catalyst for excellence. Moreover, in order to be mobile, 80 percent of the scientists indicated that their focal research visit had been funded at least partially through grants. At the same time, only one fifth of all scientists are satisfied with the support they can get for international mobility. The results further show that the existence of strong and important research groups abroad is an important pull factor for mobility. Given that excellence and relevance in scientific knowledge production are spreading across the globe with the emergence of new scientific strongholds, the opportunities and needs for international mobility can be assumed to increase accordingly.

Our analysis has produced a set of new insights as to the relationship between mobility and KTT. First of all, scientists who transfer knowledge and technology do so, generally speaking, both at home and abroad. In other words, there is a complementary relationship between both activities (confirming H3). This is important as knowledge accumulates continuously through KTT and subsequent KTT encompasses the knowledge of earlier transfers. Transferring knowledge abroad while being mobile thus does not diminish the activities and effects of subsequent transfers but rather increases them.

Second, the *duration* of research visits has a positive impact on the propensity to transfer knowledge and technology in the host country *and* in the home country (confirming H1a and H1b). While the simple transfer of artefacts or licenses can be achieved through short contacts, transferring complex and maybe even tacit technological knowledge requires more intensive contact over time. Third, and potentially more important, the *more frequently* scientists are internationally mobile during their career, the more they engage in KTT activities to firms in their *home* country (confirming H2a), while frequency does not have implications for the likelihood to engage in KTT in the host country (rejecting H2b). Hence, it apparently pays off for a country if its scientists are frequently abroad. Generally speaking, mobility can thus be characterised as a driver for the scientific and technical human capital that facilitates collaboration with industry. Fourth, the direction of mobility makes a difference for KTT *abroad* but not at home. Mobile German scientists are more inclined to engage in KTT to firms outside North America and Western Europe, while for KTT back home it is not important in which country the scientists had been.

Finally, the institutional context matters considerably in that it appears to interact with the creation of scientific and technical human capital. University scientists are much more likely to be mobile but less inclined to transfer knowledge and technology internationally than scientists from public research institutes. In this regard, we find that scientists at Fraunhofer institutes typically engage in KTT despite their low mobility which is in sharp contrast to university scientists who have a higher likelihood to go abroad but are less inclined to engage in KTT. Scientists at Helmholtz institutes also contrast sharply with Fraunhofer and university scientists as they exhibit a low likelihood both to go abroad and to engage in KTT.

Our findings contribute to the literature in several ways. We provide for the first time empirical evidence for the effects that international mobility has on KTT activities of academics. In this respect, we extend existing literature that has so far predominantly focused on permanent migration (e.g., Regets, 2007). Moreover, based on empirical evidence our research provides insights into the factors that, on the one hand, drive scientists to go abroad and, on the other hand, determine whether and where scientists engage in KTT. Form a theoretical perspective, we extend the application of the scientific and technical human capital approach by identifying mobility as a means to increase both the scientist's human *and* social capital that result from being embedded in an international network.

While these findings provide interesting insights, it is important to acknowledge the limitations of our research. Mobility is a multi-faceted construct while our approach only considers the most recent research visit that a scientist reports. In this regard, we do not account for the individual "history" of a scientist's research visits, for example repeat visits to the same host country institution. Moreover, we know little about the specific circumstances of the focal visit like the scientist's motivation and objectives. Our findings are also limited to the extent that KTT activities are measured using a dummy variable that does not account for the different modes or types of knowledge to be transferred. Consequently, these limitations have to be considered when it comes to the implications for STI policy.

As for policy and framework conditions, the main – and simplest – message is that international mobility needs to be enabled and actively supported as it is positively linked to excellence and KTT; it is beneficial in terms of enhancing scientific and technical human capital of scientists and their propensity to transfer knowledge. From the perspective of the *home* country, support mechanisms for outward mobility particularly pay off if they allow scientists to gain experience abroad, to broaden networks and to frequently establish ties internationally. This would call for enabling frequent research visits with the opportunity to return to the home country, for example through secondments that allow scientists to stay linked to their home organisation. Moreover, the findings indicate that the potential threats from a brain drain are limited, even if the scientists opt for a long-term research activity abroad. In this respect, supporting scientists at public non-university research institutes, who tend to be less mobile than university scientists, would be most effective. This is obviously most beneficial in systems with a large non-university public research sector. In Germany, for example, there has long been a discussion as to how sensible it is to support mobility of such non-university scientists that are often more application and industry oriented (Edler 2007). The findings in this study provide evidence for the benefits of outward mobility also for this particular group of scientists.

In order to benefit from *inward* mobility, it is most beneficial for the *host* country if scientists stay for a considerable time period. Embedding into the host country system takes time. KTT within a foreign innovation system typically does not take place on a short-term basis but requires the build-up of trust, networks and mutual recognition. From the perspective of the host countries of foreign scientists, this has important implications. Attracting foreign scientists should be linked to specific collaborative projects, as this increases the likelihood that firms in the host country benefit from KTT. In other words, *brain gain* in public science should be turned into *brain embedding* through direct and close collaboration if the local industry is intended to benefit. Further, policies should encourage “shuttle” mobility. Rather than supporting a one-off part time attraction, they should enable (repeated) circulation as this tends to increase the likelihood of mutual transfer (Ackers and Gill 2008). In fact, in

Europe STI policy at all levels has already been quite eager to provide framework conditions that allow public scientists to engage in international research activities and in KTT.[21] The motivation to promote KTT and scientist mobility is similar: while the individual and social benefit of both is high, transaction costs impede a full realisation of the benefits. A re-examination of the effectiveness of these policy instruments and their interplay in the light of our findings seems therefore warranted.

Our findings indicate that international mobility is part of an opening process of public science that benefits the home economy in many ways and thus does *not* pose a threat but an opportunity. Mobility can be supported for the benefit of the scientist, her or his scientific and organisational environment and the national innovation system. However, to develop more appropriate framework conditions and support mechanism, future research should particularly try to develop a more nuanced understanding of both the scientists' mobility patterns and the different ways knowledge and technology transfer could occur. Moreover, we restricted our understanding of mobility to intra-sectoral mobility and neglected inter-sectoral mobility. The latter refers to mobility from public research to industry-funded research and has been shown to be an effective mechanism to transfer both codified and tacit knowledge (OECD 2002). It is obvious that these two types of mobility could be better linked, e.g. by analysing the scale and scope of cross-border mobility from the public research system into firms. If we want to understand the contribution of public research to the globalisation of KTT activities, this gap needs to be closed.

[21] European science and technology policy is characterised by an abundance of measures and initiatives to promote KTT, cooperation and mobility. Two European sources may suffice to illustrate this claim: first, the European Trendchart Database (www.proinno-europe.eu) that gives an overview of all science and technology policy initiatives within the EU countries; second, the ERAWATCH database that collects and analyses science and technology policy across Europe (http://cordis.europa.eu/erawatch/).

# 7 Against the one-way-street: Analyzing knowledge transfer from industry to science

## 7.1 Introduction

The expansion of higher education has led not only to the fact that many people nowadays have acquired substantial knowledge about recent scientific discoveries and research topics but has also resulted in a continuously increasing number of jobs with scientific orientation and methods (Gibbons 1994). In science based industries like the biotechnology industry, Science and Knowledge have even become the most important production inputs. However, knowledge differs from scarce production factors as it can be "sticky" (von Hippel 1994) which means that knowledge is sometimes so specialized that it can not be easily transferred from one actor to another. In order to capture these preconditions different economic concepts have been introduced within the last two decades which seem to be more suitable for explaining technological changes in science based industries when compared to neoclassical concepts of scarce resourse allocation. Almost all new economic concepts place knowledge in the middle of their analysis and describe innovative processes as a result of interactions between organizations that permanently produce and absorb knowledge. The concept of innovation systems focuses on the flow of technology between various actors like firms, universities and the government and analyses these technology flows on a regional, national or supranational level (Lundvall 1992, Nelson 1993). Etzkowitz and Leydesdorff (1997) describe a triple helix of university-industry-government relations – in contrast to the national innovation systems approach - which is a reorganizational component across institutions and national boundaries. One of the most recent concepts in the theory of firm puts its main focus on the participation in external networks of organization. The idea of "open innovation" was first introduced by Henry Chesbrough (2003), who conducted a number of company based case studies and came to the conclusion that organizations (i.e. firms) have to open themselves up to external networks in order to gain new knowledge.

This external knowledge can then be combined with already existing firm knowledge and capacities to successfully contest innovative activities[22].

On the basis of the introduced economic concepts it becomes obvious that knowledge should not only flow from universities or other public research institutions to firms but also vice versa. However the empirical literature on technology transfer in science based industries has mostly dealt with the question, how firms can profit from research results of scientific institutions. Narin et al. (1997) investigated the citation linkages between U.S. patents and scientific papers and showed that over 70% of the industrial patents cite papers originating in public science. McMillan et al. (2000) confirmed these results again on the basis of citation patterns and revealed that especially the carrying out of basic research by public research institutions is critical for the successful development of the biotechnology industry in the US. Firms in the biotechnological industry are not solely transferring knowledge from research institutions but are actively conducting their own research. Gittelman and Kogut (2003) have analyzed a sample of 116 US biotech firms in the time period between 1988 and 1995 and showed that the total publication rate of the firms almost doubled in that time span.

Given the fact that biotechnology firms themselves are valuable knowledge producers the question has to be asked whether this generated knowledge is also of value for scientific research institutions. With our paper we aim to contribute empirical evidence to this research gap in the literature by analyzing differences in the factors that influence the occurrence of knowledge flows within industry as well as from industry to science in the biotechnology sector.

The knowledge flows are thereby modeled via a backward patent citation analysis on the basis of EPO patent data. As a result we are able to identify cited and citing patent pairs. We then use a quasi-experimental design which has been first introduced by Jaffe et al. (1993). This quasi-experimental framework compares the identified citing and cited patents with a

[22] A brief overview of economic concepts that put knowledge central to their perspective can be found in Dogson et al. (2006), pp. 334-335.

matched sample of control patents. On the basis of this combined sample we estimate a weighted bivariate probit model on the citation probability of science and industry.

The structure of the paper is as follows. In the second section we provide a short overview on the characteristics of the biotech industry and of the importance of patent protection in this industry. The third section discusses whether there is a rationale for technology transfer from industry to science. The fourth section reviews the empirical literature on patent based studies of knowledge flows. The subsequent three sections contain the empirical part of the paper. First the data and methodology are presented (fifth section) and then the variables and descriptive statistics are shown (sixth section). The estimation strategy and the results are presented in the seventh section. Section eight closes with a conclusion.

## 7.2 Characteristics of the biotech industry and patent protection

Like other science based industries the biotechnology industry differs from existing non-science based industries in its pattern and dynamics of technological change. Pavitt (1984) analyses sectoral patterns of technical change by classifying firms according to three dimensions. According to this taxonomy *supplier dominated* firms are characterized by weak R&D and engineering capabilities and their main technology lies in cutting costs through embodied technical change. Thus supplier dominated firms apply rarely for patents. *Production intensive* firms instead exploit scale economies of production and therefore aim at realizing performance increasing product and process innovations. Product innovations are often protected by patents while process innovations are kept secret. In contrast to the first two groups *science based* firms depend on the progress of the relevant sciences and their main technology stems from R&D activities of the firms in the sector. Innovations are protected through patents, lead-time advantage and secrecy. However science based industries are not a homogeneous group but include mature industries as well as young industries, and also the R&D intensity varies widely within the science based industries.

Within the science based industries the biotech industry is considered to be a rather young industry which is characterized by an extraordinary high R&D intensity (Niosi 2000). The invention of the recombinant DNA technique by Cohen, Boyer and Berg at beginning of the 1970's is often considered to be the starting point for the so called modern biotechnology.

Zucker and Darby (1996) were among the first who analyzed the success factors for the formation of the biotechnology industry. In their work they emphasized the role of individual star scientists as a knowledge source for biotech firms. Today the biotechnology industry in developed countries is characterized by a considerable high fraction of small and medium sized firms which are highly R&D intensive and attract a large amount of money from public subsidiary programs and venture capital agencies (Fuchs 2003). Furthermore biotechnology firms are increasingly engaged in scientific publications. Gittelman and Kogut (2003) have analyzed a sample of 116 US biotech firms in the time period between 1988 and 1995. They show that the total publication rate of the firms almost doubled in this period.

With the rise of the modern biotechnological industry and the growing awareness of the broad potentials of this industry the question of how to protect intellectual property of biotechnological inventions moves in the centre of interest. At the beginning of the 1980s the existing patent protection laws in the US and other countries were not designed for the protection of biotechnological inventions. With a broadened definition of patentable subject matters due to a change of the patent protection law in the US in 1992 and subsequent changes of patent protection laws in other countries it becomes possible to protect biological active substances including single molecules and proteins (Ko 1992). With these institutional modifications, today patents create a basis for trading inventions. Consequently patents are of major importance in biotechnology not only in the protection of marketable inventions and thus as a positive signal for venture capital firms but also for discoveries that are not marketable at the first glance but feature great value for future research (Mazzoleni and Nelson 1998).

## 7.3 Knowledge interactions in the biotechnology industry – is there a rationale for knowledge transfer from industry to science?

Today, knowledge is considered to be an indispensable factor for economic growth. Arrow was the first who stressed the importance of knowledge for economic growth. In his *learning-by-doing* model, Arrow assumes that new knowledge is created depending of the level of new investments. In turn the technologies accessible for firms depend on the economy wide knowledge stock. This Arrowian view suggests that technological knowledge has the non-excludable and non-rival character of a public good and can be transferred and appropriated with rather low efforts and costs (Arrow 1962b, Arrow 1969).

This rather traditional approach to the nature of technological knowledge has been challenged by the Neo-Schumpeterian approach in recent years. In the view of Neo-Schumpeterians technological knowledge is considered to be a quasi-public good, which means that the character of technological knowledge bears higher levels of appropriability and excludability compared to the Arrowian view (Rosenberg 1994, Antonelli 1999). Moreover the production of technological knowledge is considered to be path-dependent and cumulative and can have a local character. This Neo-Schumpeterian view of technological knowledge implies that “knowledge is the result of complex processes of creation of new information building upon the mix of competences acquired by means of learning processes, the socialisation of experience, the recombination of available information and formal R&D activities” (Antonelli 1999, p. 245). The innovation system approach confirms this view and emphasizes the importance of interactions between industry and science for a successful innovation process due to its increasing complexity (Lundvall 1992, Nelson 1993, Nelson and Rosenberg 1993). Moreover, a number of studies have examined the relationship between the technological complexity (measured by the R&D intensity) of industries and the number of R&D alliances and they have found a positive correlation between these two factors (e.g. Freeman 1991, Hagedoorn 1995).

Related to their science based nature, problems of appropriability and excludability of technological knowledge are even more severe in the modern biotechnological industry (Arora and Gambardella 1990). In order to succeed in the biotechnology industry firms must permanently keep close contact to the moving technological frontier and must create valuable technological knowledge on their own (Gambardella 1995, Niosi 2003). Thus, the ability of firms to draw knowledge from scientific institutions or other firms is regarded to be an important factor for their success (Kenney 1986, Prevezer 2001, Niosi 2003, Powell et al. 1996). Several studies have shown that geographical closeness between firms and research institutions in biotechnology can facilitate this knowledge transfer from science to industry (Zucker et al. 1994, Audretsch and Stephan 1996, Zucker and Darby 1998, Powell et al.

1999). Also the role of individual scientists for the prosperity of firms in biotechnology has been highlighted (Zucker and Darby 1996).

Besides the critical role of knowledge flows from science to industry also knowledge interactions between firms in biotechnology have been recognized to be crucial for the industrial development. Pyka and Saviotti (2005) analyze research networks in the biotechnology industry and conclude that a coexistence of large diversified firms and small dedicated biotech firms is crucial for industrial development. For small firms a co-operation with large pharmaceutical or chemical firms can result in the gain of more market relevant knowledge in the form of the use of advanced production capabilities, better market access due to a better distribution infrastructure and experience in conducting clinical trials (Pisano 1990, Baum et al. 2000). In turn large firms in the biotech sector seek to co-operate with small/medium sized research intensive firms in order to acquire marketable knowledge and to spread risks (Arora and Gambardella 1990).

Whilst these two directions of knowledge flows namely from science to industry and within industry have been fairly well analyzed, there is a lack of evidence regarding knowledge flows from industry to science. The main reason for the negligence of research on knowledge transfer from industry to science is the threat of a negative influence of technology transfer upon the norms of open science (Merton 1973). In traditional sectors like manufacturing, universities and public research institutes are still considered to be the most important producers of valuable scientific research (Gibbons et al. 1994).

In the biotechnology industry however, things look different. Due to the mentioned science base of the industry, firms themselves next to public research organizations have accumulated a large stock of technological knowledge. This creation of technological knowledge within firms has been accelerated by venture capital firms with the aim of realizing returns due to groundbreaking inventions as well as public subsidy programs with the objective of not falling behind the industrial development compared to other countries. As a result, there is a considerable amount of valuable technological knowledge in the biotechnology industry that has not been transferred by research institutions in the first place but has been created within the firms. Pisano (1990) conducted an empirical analysis among US firms and found that firms in biotechnology rely more often only on technological knowledge which has been created in-house especially in those areas where the firms have accumulated in-house R&D.

Thus the question arises whether public research organizations in the field of biotechnology are willing and able to participate in the knowledge that has been produced by firms. The existing literature on this topic is rare and there are no specific studies for the biotechnology industry. Meyer-Krahmer and Schmoch (1998) have conducted a survey among professors from universities or public research institutions in science based fields and asked them to rate the importance of different interaction types with industry. As a result the interviewed professors rated those interaction types with industry higher where a bidirectional exchange of knowledge with industry occurs. Link et al. (2007) have examined knowledge transfer between industry and science on the basis of a survey among individual scientists. Their results suggest that university researchers rank collaboration with industry as very important and state that they benefit from the transferred knowledge and the use of improved equipment. Kaufman and Tödtling (2001) emphasize the importance of a bidirectional knowledge exchange between industry and science in innovation co-operations. It becomes obvious that knowledge transfer from industry to science has not been completely neglected in previous studies but it is mostly mentioned as a by-product from science to industry knowledge flows. This study aims at contributing more empirical evidence to the topic of industry to science knowledge flows in the biotechnology industry.

## 7.4 Review on patent based studies of knowledge flows

Patent data have been extensively used to shed light on the innovation process. Patent documents provide information about the technology of an invention as well as detailed information about the inventor and assignee of the invention. For example patent counts have been frequently used as an indicator of innovation activity. However, patent data should be handled with some caution. Griliches has surveyed in his seminal work the pitfalls that may arise when using patent statistics as innovation indicators but concludes that "Nothing else even comes close in the quantity of available data, accessibility, and the potential industrial, organizational, and technological detail" (Griliches 1990, p. 1702).

The idea to use patent data as an indicator for knowledge flows can be traced back to Schmookler (1966) and Scherer (1982). Schmookler among others brought up the discussion, that the economic benefits of firms due to R&D could not be solely reduced to their own R&D activities, but also to the embodiment of technological knowledge through intermediate products produced by other sectors. Scherer (1982) took up Schmooklers idea and developed a complex “interindustry technology flows” matrix which traces back the knowledge of R&D performing industries to industries that purchased the products of the R&D performing industries. In subsequent work Scherer relied on a data set that contains over 15.000 US patents that were individually examined to determine the original industry of the patent and the industries for which the use of the patent was anticipated and linked them to the R&D outlay of corporations. The linked R&D outlays were then distributed through a “technology flows” matrix. The estimation results indeed revealed the critical role of embodied technological knowledge for firms’ productivity growth (Scherer 1982, Griliches and Lichtenberg 1984).

More recent work that use patent citations to trace knowledge flows mostly deal with the question whether knowledge flows are technologically bounded, geographically concentrated and what industry specific differences exist (e.g. Jaffe et al. 1993, Jaffe and Trajtenberg 1996, Porter 2000a, Maurseth and Verspagen 2002).

Stolpe (2002) modeled the citation probability among patents in the liquid crystal display technology and revealed that technological closeness has a significant positive influence on the citation probability. However Stolpe (2002) did not make a distinction between the institutional types of the assignees of the citing patents. Hu and Jaffe (2003) have worked out the positive effect of technological closeness for the citation probability in a cross country comparison. Besides the technological closeness also the technological generality of the cited patent may have an influence on the citation probability. Trajtenberg et al. (1992) have shown that university research outcomes are more basic and harder to appropriate than research outcomes of industry.

The hypothesis that knowledge flows might be geographically bounded has been heavily analyzed and discussed within the last years. Firms that have the same cultural background are more likely to exchange knowledge than firms with different cultural backgrounds. Mowery et al. (1996) have shown that more knowledge exchange takes place in alliances with partners in the same country. Empirical evidence is less clear regarding geographical closeness. Jaffe et al. (1993) were the first who found direct evidence that knowledge spillovers as measured by patent citations are indeed locally concentrated. Although the quasi-experimental design that was used by Jaffe et al. (1993) was challenged afterwards (Thompson and Fox-Kean 2005, Thompson 2006), the empirical evidence could not be disproved. Although doubts remain from the theoretical perspective (Breschi and Lissoni 2001) it is supposed that geographical closeness has a positive impact on the citation probability.

A few recent studies have analyzed knowledge flows in the biotechnological sector on the basis of patent data. McMillan et al. (2000) have worked out the importance of public science for the development of the US biotechnology industry on the basis of patent data. The authors conclude that especially small biotech firms depend on the basic knowledge that is created by public research organizations. Gittelman (2006) has examined the differences in the public-private knowledge flows between the US and France on the basis of patent citations. In line Zucker and Darby (1998) emphasize the importance of individual scientific careers for interactions between firms and public research organizations. Moreover they point out that technological performance, as measured by the number of granted patents, depends on a heterogeneous setting of organizations and interactions.

## 7.5 Data and methodology

*Patent citation analysis and data*

The study is based on patent application data from the European Patent office (EPO)[23] which cover the years between 1978 and 2003. The patent data include information about the name(s) and country(ies) of origin of the inventor(s) as well as the assignee(s), the declared

[23] For a comprehensive overview on the application and examination process at the EPO see Michel and Bettels (2001).

IPC classes as well as application and grant dates. Moreover a patent document contains references to other patents, so called citations. In EPO patent data, these citations have mainly the legal function to specify the knowledge that justifies a claim for novelty and are mostly added by the patent examiners instead of the inventors. Alcácar and Gittelman (2006) find that examiners played a significant role in identifying prior art, adding 63% of citations on the average patent, and all citations on 40% of patents granted. This might be due to two reasons. Either the inventors are not aware of the patents that have been added by the examiners (Criscuolo and Verspagen 2008) or the inventors have strategically omitted citations (Alcácar and Gittelman 2006). Nevertheless, since we focus on a rather small technological field the actors should not have problems identifying prior art (Maurseth and Verspagen 2002). Regarding strategic omission of prior art the patent examiners and the application process of the EPO plays an important role. In the patent application process, the applicant receives a detailed search report, conducted by the patent examiners, which discloses essential prior art on which the examiner would mainly base his grant decision. After obtaining the search report, the applicant must decide whether he wants to pursue the application process or not. Thus the risk that prior art remains undetected is minimized by the work of the patent examiner.

In a first step we identify on the basis of the OECD compendium of patent statistics (OECD 2008) all relevant international patent classification (IPC) classes concerning biotechnology. Following this classification scheme all records where at least one of the relevant IPC classes was listed in the application are kept for further analysis. Subsequently all applicants in the data files are assigned by hand to the following categories: firms, universities, public research institutions, individuals, others. Our data cover 72427 patents that have been applied for in the mentioned time period. We use the application date of the patent application as the relevant time point for our analysis as it is common in most scientific works that deal with patent analysis.

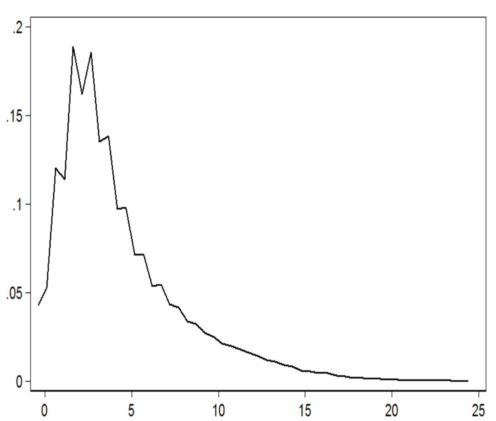
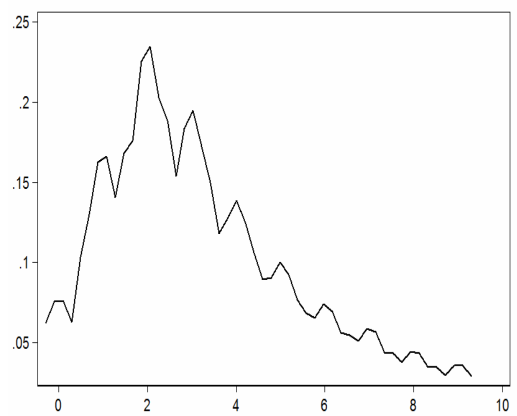
The aim of the study is to analyze the differences in the factors that influence the probability of knowledge transfer within industry and from industry to science in the biotechnology sector. In order to model these knowledge flows we conduct a backward patent citation analysis: for each patent in the sample all citations which have been made by timely subsequent patents in the sample are identified. For the whole sample we identify 10184 patents that have received a citation and we identified 24662 cited and citing patent pairs since one patent can receive multiple citations. In a next step all patent pairs where the cited patent and citing patent showed the same application name, so called self citations were excluded from the sample since they solely reflect in-house knowledge flows. 19753 patent pairs remain for further analysis.

*Restriction of the sample and truncation*

Since the analysis concentrates on a comparison of the knowledge flows from industry to science and within industry only those patent pairs were kept, where at least one firm was among the applicants of the cited patent and at least one firm and/or one research institution was among the applicants of the citing patent. We find 15100 patent pairs where the cited patent shows an industrial applicant and the citing patent shows an applicant from industry and/or science. However due to the fact that in many countries scientists had or still have the privilege to assign patents under their own name, the share of scientific applicants of the citing patents is likely to be underrepresented.

The application of a patent citation approach necessitates considering one difficulty, because the patent that has been filed first in the sample has a much larger time frame to be cited compared to the patent that has been filed more recently in the sample. This problem of truncation has been heavily analyzed in empirical studies. Caballero and Jaffe (1993) and Jaffe and Trajtenberg (1999) estimated the shape of the citation lag distribution via a parametric function and Hall et al. (2001a) used non-linear functions to approximate the shape via estimation. Stolpe (2002) states in his work that in the ideal case citation studies should be based on patents that have been filed at exactly the same point in time so that the problem of temporal influences on the citation frequency can be neglected. However in the same breath he accounts for the fact that patent data are flow data and that they are thus only measurable over time. In his study he sets a time limit of three years for the selection of the patents that are later referred to via citation analysis. Almeida (1996) deals with the problem of truncation by including the citation lag in his latter estimation. Gittelman (2006) includes not only the citation lag but also the square of the citation lag in her regression and moreover limits the time span where the cited patents are identified. Figure 1 shows the distribution of the citation lag by means of a Kernel density estimation. The cited patents receive most of their citations in the second and third year after their publication date. 10 percent of the citations have been made more than 9 years after the EPO publication date of the cited patent. We drop all citations that show a citation gap of more than 9 years and keep 13796 patent pairs for further analysis. The distribution of the citation lag for these 13796 patent pairs is also shown in Figure 1. The percentiles of the citation lag distribution for the unrestricted and restricted sample is shown in appendix table A4. By following the approach of Gittelman (2006) and including not only the citation lag but also the squared citation lag in the following estimation we consider that there are rather few patents with a very short or very long citation lag.

**Figure 1: Distribution of the citation lag (Chapter 6)**

| Distribution of the citation lag for the whole sample (15100 observations) | Distribution of the citation lag after excluding observations with a citation lag of more than 9 years (13796 observations) |
|---|---|
| <br>x-axis: density, y-axis: citation lag in years | <br>x-axis: density, y-axis: citation lag in years |

The exclusion of citations with a citation lag of more than 9 years however does not adequately adjust for the possible bias of our estimation results due to truncation at the right tail of our sample, since more recent application years of the cited patents still have a greater chance of being cited.

Since we have a long panel from 1978-2003 we are able to control for this possible truncation bias by comparing the estimation results for a number of different time spans from which we select the cited patents. Therefore we look at the distribution of the citation lag in our sample and run the estimations for the following time spans for which we select the cited patents: 1978-2002 (10% percentile), 1978-2000 (50% percentile), and 1978-1996 (90% percentile).

*Construction of a control sample*

Because we want to analyze differences in the factors that influence the citation probability we need to include reference values to the sample of identified cited and citing patent pairs in order to maintain interpretable results. For this purpose we follow an experimental design which was first introduced by Jaffe et al. (1993) and later used by several other studies (e.g. Almeida and Kogut 1999, Stolpe 2002). Within this experimental framework, a non-cited patent that shows the same first three digit international patent classification (IPC) class and the same EPO application date as the cited patent is randomly searched for each citing patent within the original sample. However it is important to note that the fact that a patent is chosen to be a control patent for a specific citing patent does not mean that it can not have received citations in an earlier or later point of time. Due to the construction of the control sample our sample size doubles and we have a total of 27592 observations in our sample.

Due to the construction of the control sample we are able to model an unconditional probability for the factors influencing the citation probability. The conditional probability for the influencing factors is given when an actual citation has occurred. Thus the hypothesis that can be tested is whether a statistically significant difference between the conditional and unconditional probabilities exists when examining the citation probability[24].

[24] The two probabilities are related. Bayes rule states that P(Citation I Influencing factor)/P(Citation)=P(Influencing factor/Citation)/P(Influencing factor).

## 7.6 Variables and descriptive statistics

The dependent variables in our estimation *INDIND* and *INDSCI* are binary variables indicating whether a patent that has been applied for by industry has received a citation by a patent that was applied for by either industry *(INDIND*) and/or scientific institution(s) (*INDSCI*).

Building upon the previous discussion a set of independent variables is included in the estimation that is likely to have an influence on the citation probability.

To begin with we include a variable to proxy the technological closeness of the patent pair. *TECHCL* is a dummy variable indicating whether the two patents in a patent pair show the same 6-digit IPC class. Since we look at industry research outcomes as possible appropriable targets we assume that their technological character might be less basic. Nevertheless things might turn out to be different for two reasons. On the one hand, we look at a science intensive industry where a large part of industrial actors are involved in basic research. On the other hand, we only consider knowledge flows from industry to industry and industry to science. However, we assume that a high technological generality[25] implies a more basic technological character of the invention of the cited patent. Therefore, we expect that it is positively related with the citation probability from industry to science. Furthermore, we assume that a more specific technological character of a technological invention is positively related with the citation probability within industry. While previous works that measured the technological specialization of patents on the basis of IPC-classes often used the Herfindahl-index, van Zeebroeck et al. (2006) have compared different technological concentration measures on the basis of EPO patents. They come to the result, that the Gini-Coefficient[26] in line with the C20-measure is the most reliable measures for technological concentration. Moreover they recommend at least a 4-digit aggregation level of the IPC-classes used. Consequently, our study relies on the Gini-Coefficient for the identified

[25] Generality is also referred to as basicness. See i.e. Stolpe (2002).

[26] The Gini Coefficient is a statistical measure for relative concentration. It relies on the concept of the Lorenz Curve. The Gini Coefficient takes on values between zero and one, whereas the value one corresponds to perfect inequality.

biotechnology related IPC classes of the citing patents aggregated to the 6-digit level as a measure for technological specialization. We specify

*generality =1- Gini coefficient*

as a proxy for the technological generality of the cited invention. In those cases where the Gini-Coefficient is calculated on the basis of only one IPC-class the measure for generality is replaced with zero. However, since the Gini-Coefficient reduces complex data to one parameter, there is the danger that valuable information from the used data is neglected. In this case, the Gini-Coefficient does not account for the number of different IPC classes of the citing patents, although this is obviously valuable information when approximating the technological generality of an invention. In order to account for this shortcoming we include an interaction term between the measure of technological generality and the total number of different IPC-classes of the citing patents (*INTGINI*) in the regression instead of the plain measure of technological generality.

The variable *CULCL* indicates the cultural closeness of the patent pairs. *CULCL* is a dummy variable and measures whether the two patents in the patent pairs have the same assignee countries.

Besides that we include a dummy variable reflecting whether the cited or cited control patent has been assigned by both, industry and science (*COMMON_CITED*). It is important to note that the variable *COMMON_CITED* is a rough indicator for joint research, since firms and research institutions can of course conduct joint research without being jointly listed as assignees in a particular patent application. However, a joint assignment of the common research might signal that the protected invention has a major value for both the scientific and the industrial progress.

Additionally, we include variables that reflect the overall patenting activity in the biotechnology field of the assignee(s) of the cited or cited control patent (*NOPATS_CITED*) and the patenting activity of the applicant(s) of the citing patent (*NOPATS_CITING*). *NOPATS_CITED* and *NOPATS_CITING* are continuous variables and contain the cumulated number of patents that the assigning institution(s) have applied for up to the EPO date of the considered patent in the particular patent pair. It is expected that a high patenting activity of the assignee(s) of the citing patent (*NOPATS_CITING*) is positively related to the citation probability, especially regarding scientific institutions as assignees. This assumption is owed to the work of Owen-Smith and Powell (2001) who revealed that scientific institutions which patent have a higher propensity to engage in technology transfer. More precisely they analyzed the propensity of scientific research institutions transferring knowledge to other firms or research institutions. However we assume that scientific institutions that patent might also show a higher probability to draw knowledge from patents that have been applied for by firms. These scientific institutions might be better informed about the patented inventions of firms due to a review of existing inventions during the application process.

We also include a proxy for the economic value (*ECVALUE*) of the cited respectively cited control patent. *ECVALUE* contains the whole number of subsequent citations that a cited patent has received on the basis of our original sample. Harhoff et al. (1999) obtained value estimates of inventions filed in patents due to a survey of the patent owners. They found a significant positive relationship between the private value estimate of the invention of the filed patent and the number of subsequent citations of this specific patent. Hall et al. (2001b) have confirmed this positive relationship. In their work they compare different measures that are likely to influence the market value of firms and conclude that a citation weighted patent stock is more highly correlated with the market value than the plain patent stock. Since we expect firms to be profit oriented we expect that they transfer knowledge from the economically most valuable inventions.

We also control for the country of residence of the assignees at the time point of their patent application. Since we have a large number of applicant countries in our sample we decide to include dummies for the countries that account for most of the patent applications in our sample[27]. As a consequence the included country dummies have to be interpreted in relation to all other countries that are not captured via the country dummies. For example

[27] A table showing the distribution of the assignee's country of residence is shown in the appendix table A5. See also the OECD Biotechnology statistics (OECD 2006) for a more general overview on the patenting activities of different countries at the EPO.

the variable *US_CITED* contains the information whether at least one of the assignees of the cited or cited control patent was located in the United States during the patent application process and *US_CITING* contains the same information for the assignee of the citing patent. Analogous we created dummy variables for Japan (*JP_CITED, JP_CITING*), Germany (*GER_CITED, GER_CITING*), Switzerland (*CH_CITED, CH_CITING*), France (*FR_CITED, FR_CITING*), Great Britain (*GB_CITED, GB_CITING*) and the Netherlands (*NL_CITED, NL_CITING*).

As already discussed we include two variables to control for the citation lag. *YEAR_DIFF* and *YEAR_DIFFSQ* are continuous variables which reflect the time lag between the cited or cited control patent and citing patents and the controls, measured by years. We further include dummies for the application year (*YEAR1-YEAR23*) of the cited and cited control patent to control for intertemporal differences in the patenting activity.

*Descriptive statistics*

Table 6 shows the descriptive statistics of the combined sample. The descriptive statistics for the single samples (cited and citing patent pairs and control patent pairs) is shown in appendix table A6. Due to the construction of the sample the control patent pairs account for exactly half of the data. It can be seen that knowledge flows from industry to science are rare but indeed happen. About 10% of the actually cited and citing patent pairs received citations by public scientific institutions (*INDSCI*). Some few patents have received citations from patents were both firms and scientific research institutions are among the applicants.

**Table 6: Descriptive statistics (Chapter 6)**

| | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| *INDSCI* | 0,053 | 0,225 | 0 | 1 |
| *INDIND* | 0,454 | 0,498 | 0 | 1 |
| *TECHCL* | 0,413 | 0,492 | 0 | 1 |
| *CULCL* | 0,286 | 0,452 | 0 | 1 |
| *INTGINI* | 0,121 | 0,235 | 0 | 2,443 |
| *COMMON_CITED* | 0,014 | 0,118 | 0 | 1 |
| *ECVALUE* | 3,831 | 4,645 | 1 | 64 |

| | | | | |
|---|---|---|---|---|
| *NOPATS_CITED* | 68,933 | 100,789 | 1 | 622 |
| *NOPATS_CITING* | 59,678 | 89,857 | 2 | 582 |
| *YEAR_DIFF* | 3,368 | 2,302 | 0 | 9 |
| *DE_CITED* | 0,112 | 0,316 | 0 | 1 |
| *US_CITED* | 0,419 | 0,493 | 0 | 1 |
| *JP_CITED* | 0,204 | 0,403 | 0 | 1 |
| *CH_CITED* | 0,043 | 0,203 | 0 | 1 |
| *FR_CITED* | 0,030 | 0,171 | 0 | 1 |
| *GB_CITED* | 0,063 | 0,242 | 0 | 1 |
| *NL_CITED* | 0,029 | 0,167 | 0 | 1 |
| *DE_CITING* | 0,122 | 0,328 | 0 | 1 |
| *US_CITING* | 0,408 | 0,492 | 0 | 1 |
| *JP_CITING* | 0,207 | 0,405 | 0 | 1 |
| *CH_CITING* | 0,046 | 0,208 | 0 | 1 |
| *FR_CITING* | 0,042 | 0,200 | 0 | 1 |
| *GB_CITING* | 0,040 | 0,196 | 0 | 1 |
| *NL_CITING* | 0,040 | 0,196 | 0 | 1 |
| *27592 observations* | | | | |

With respect to the technological closeness (*TECHCL*), we find that about 41 % of the examined patent pairs show the same 6 digit IPC class. Technological closeness can thus be observed more often than cultural closeness (*CULCL*). Only about 29 % of the patent pairs show the same assignee country.

Only a small number of patents in our sample have been jointly applied for by science and industry. The variable *COMMON_CITED* indicates that only between 1.5 % of the inventions in our sample have assignees from both industry and science. The actual number of joint patent applications between industry and science in the relevant time span is higher since in many countries scientists had and still have the privilege to freely realize the economic benefits of their inventions[28]. Accordingly, one has to bear in mind that *COMMON_CITED* can only be interpreted as a rough indicator for joint research between science and industry. The variable which reflects the economic value of the patented invention shows that on average a cited or cited control patent receives citations from almost 4 other subsequent patents. Regarding the overall patenting activity in the biotechnology field of the assignee(s) of the patent pairs we find that the assignees of the cited patents (*NOPATS_CITED*) have applied for more patents than the assignees of the citing patents (*NOPATS_CITING*). Finally, the descriptive statistics show that most of the patents in our sample have been assigned by firms or research institutions from the United States (*US_CITED, US_CITING*).

### 7.7 Estimation Strategy & Results

The focus of this paper is to investigate differences in the citation probability from industry to industry and from industry to science. Thus our two dependent variables in the estimation indicate whether a patent that has been assigned to industry has either received a citation by a scientific institution (*INDSCI*) or by a firm (*INDIND*).

We report the correlations among the variables in the appendix table A7.

In order to get a first hint on differences between the citation probability of industry and science, we conducted t-tests for continuous variables and for dummy variables in a two sample test of proportions. The results can be found in the appendix table A8. However the t-tests and tests of proportions just indicate whether there is a significant difference in the mean or proportional values of the variables but cannot provide information about the size of these effects. Therefore a discrete probability model is applied.

It is reasonable to assume that a patented invention can receive patents from both, industry and science. Thus the citation behavior of industry and science might not be independent of each other. In order to capture the citation behavior of industry and science properly we estimate a bivariate probit model instead of estimating the two equations separately. The

[28] I.e. in Germany this privilege was not changed until 2002.

bivariate probit model estimates two equations for binary dependent variables simultaneously and allows the error terms to be correlated. Thus by applying a bivariate probit model we aim to enhance the usage of the complete underlying information of our variables. The econometric specification of our model is as follows:

$$INDSCI^{*} = \beta_1 X + \epsilon_1$$

$$INDIND^{*} = \beta_2 X + \epsilon_2$$

$$COV(\epsilon_1, \epsilon_2 \mid X) = \rho$$

where $INDSCI^{*}$ is the latent propensity for an industry patent to receive a patent citation from science, $INDIND^{*}$ is the latent propensity for an industry patent to receive a patent citation from industry, and $X$ is the vector containing the outlined independent variables.

Because we restrict our sample to cited and citing patent pairs and their controls we apply sample weights to the regression to avoid bias from a probability based sample. The sample weights show the probability that a patent pair was chosen from our initial sample that contains the information of all EPO patents between 1978-2003. Thus for patent pairs where the citing patent shows a more recent application date, the probability for a cited patent to be chosen from all possible prior patents is higher compared to citing patents with an earlier application date. Additionally, the probability that a cited and citing patent pair was chosen from the sample is lower than the probability that a control patent pair was chosen from the sample. In the weighted bivariate regression the sample weights are included as inverts such that patent pairs with a lower probability to be chosen are weighted higher for the estimation in relation to those patent pairs with a higher sample inclusion probability.

Table 7 shows the estimation results of the weighted bivariate probit model. In order to account for a possible bias of the regression results due to shifts in the citation lags we limit the years from which we select the cited patents to 1978-2000 (according to the 50% percentile of the citation lag distribution). We will later discuss how differently chosen time spans will affect our estimation results.

For the interpretation of the regression results, it is important to notice that we depict only a very small fraction of the real knowledge transfer activities of the firms and research institutions in our sample. We can only interpret the knowledge transfer activities which we find on the basis of patent citations in our sample.

Technological closeness (*TECHCL*) of the two patents in a patent pair has a significant positive effect on the probability to be cited from industry however not from science. Thus the findings of Stolpe (2002) and Hu and Jaffe (2003) are confirmed regarding only inter-industry knowledge flows. Our results show that scientific institutions in contrast tend to transfer knowledge from firms that is complementary to their own knowledge.

Cultural closeness (*CULCL*) has a positive significant effect on the citation probability of industry but does not seem to play a role for the citation probability of scientific institutions. A possible explanation is that the knowledge flow is highly related to the persons involved in the research process such that spillovers among firms are facilitated from cultural proximity (i.e. Porter 2000b, Mowery et al. 1996). In contrast, researchers from scientific institutions are forced to conduct a thorough search for prior art and related works when writing for academic publications. Therefore they are less likely to be affected by cultural distance.

The interaction term (*INTGINI*) that reflects the technological generality of the cited or cited control invention suggests that firms are more likely to cite industrial inventions with a less broad technological character. While we find a negative relationship between an increasing technological generality of the possible cited invention and the citation probability of industry we do not find a significant relationship between technological generality and the citation probability of scientific institutions.

The indicator for joint research *COMMON_CITED* shows a highly significant positive effect on the citation probability from industry to science. As pointed out previously the indicator for common research is rather blurry since we expect that more firms have conducted common research with science on the patented invention with the difference that these scientific institutions were not listed as applicants in the patents applications. Still a joint patent application between science and industry obviously signals the scientific relevance of the invention to other research institutions and thus increases the probability of a scientific citation. We observe an opposed effect of the joint research dummy for the citation probability of industry. Patent applications that stem from joint research activities between industry and science seem to protect more basic knowledge which is less compatible to the research activities of most firms.

**Table 7: Results of the weighted bivariate probit model (Chapter 6)**

| | Industry to science (INDSCI) | | | Industry to industry (INDIND) | | |
|---|---|---|---|---|---|---|
| | Coef. | Std.Err. | | Coef. | Std.Err. | |
| *TECHCL* | -0,148 | 0,042 | *** | 0,553 | 0,034 | *** |
| *INTGINI* | 0,068 | 0,077 | | -0,527 | 0,059 | *** |
| *CULCL* | -0,065 | 0,049 | | 0,310 | 0,040 | *** |
| *ECVALUE* | 0,020 | 0,010 | * | 0,031 | 0,009 | *** |
| *ECVALUESQ* | -0,0004 | 0,000 | ** | -0,0002 | 0,000 | |
| *NOPATS_CITED* | 0,0001 | 0,000 | | 0,001 | 0,000 | *** |
| *NOPATS_CITING* | -0,006 | 0,000 | *** | 0,002 | 0,000 | *** |
| *COMMON_CITED* | 0,722 | 0,125 | *** | -0,568 | 0,106 | *** |
| *YEAR_DIFF* | 0,015 | 0,029 | | 0,004 | 0,023 | |
| *YEAR_DIFFSQ* | -0,003 | 0,003 | * | 0,003 | 0,003 | |
| *DE_CITED*[a] | -0,072 | 0,096 | | -0,178 | 0,077 | |
| *US_CITED*[a] | 0,109 | 0,083 | | -0,233 | 0,067 | *** |
| *JP_CITED*[a] | -0,017 | 0,079 | | -0,090 | 0,065 | |
| *CH_CITED*[a] | 0,381 | 0,119 | *** | -0,268 | 0,094 | *** |
| *FR_CITED*[a] | -0,191 | 0,129 | | 0,064 | 0,106 | |
| *GB_CITED*[a] | -0,114 | 0,111 | | 0,086 | 0,093 | |
| *NL_CITED*[a] | 0,088 | 0,120 | | 0,003 | 0,099 | |
| *DE_CITING*[a] | 0,157 | 0,083 | * | 0,177 | 0,072 | ** |
| *US_CITING*[a] | 0,181 | 0,064 | *** | -0,122 | 0,056 | ** |
| *JP_CITING*[a] | -0,266 | 0,076 | *** | 0,267 | 0,063 | *** |
| *CH_CITING*[a] | -0,457 | 0,125 | *** | 0,279 | 0,084 | *** |
| *FR_CITING*[a] | 0,313 | 0,109 | *** | -0,036 | 0,102 | |
| *GB_CITING*[a] | -0,196 | 0,106 | * | 0,197 | 0,083 | ** |
| *NL_CITING*[a] | 0,112 | 0,120 | | -0,022 | 0,105 | |

| | | | | | | |
|---|---|---|---|---|---|---|
| *CONS* | -0,705 | 0,145 | *** | 0,343 | 0,127 | *** |
| *ATRHO* | -1,262 | 0,036 | *** | | | |
| *RHO* | -0,851 | 0,010 | | | | |

*Wald test of rho=0: chi2(1) = 1221,43 Prob > chi2 = 0,000*

*27352 Observations*

Note: *** ,**, * indicate a significance level of 1%, 5%, 10%, cited patens were selected for the years 1978-2000 (50% percentile of citation lag distribution), Year dummies are included, *29508 observations.*[a] *interpretation in reference to other countries.*

The economic value (*ECVALUE*) of the patented invention expressed by the total number of received subsequent citations also shows a contrary effect on the citation probability of industry and science. We find a strong linear positive effect of the economic value of a patented invention and its citation probability from industry. Firms that are active in biotechnology are obviously successful in filtering out inventions with a great economic potential. We find a rather weak inversed u-shaped relationship between the economic value of a patented invention and the citation probability of science. A possible explanation for this weak relationship between the economic value of an invention and the citation probability of science could be the mentioned fact that many inventions that are protected by patents are not marketable at a first glance. Thus, they do not bear a high economic value but are characterized by a considerable value for further scientific research (Mazzoleni and Nelson 1998).

We find that the patenting experience of the applicant firm of the cited patent (*NOPATS_CITED*) has only a positive effect on the citation probability of industry. Firms that show a high patenting activity seem to conduct more applied research. In contrast to this finding an increase in the accumulated number of patents of the citing (*NOPATS_CITING*) research institutions bears a significant negative probability for the research institution to cite industry patents. This finding is opposed to our assumption that research institutions that have a high number of accumulated patents might show a higher probability to transfer knowledge from industry patents. Obviously research institutions in the biotechnology sector are screening the knowledge that has been created by firms on a regular basis, especially when they are not frequently patenting. On the contrary assignee firms of the citing patents that show a high patenting activity are more likely to cite patents from other firms. Thus the mentioned necessity for biotechnology firms to acquire external knowledge from other firms to keep up with the technological frontier even when they are actively involved in own research is confirmed by this result.

The included country dummies show opposed effects on the citation probability of industry and science. However the following results have to be interpreted with caution due to differing privileges in the economic usage of inventions of scientists in different countries. Patents that have been assigned by Swiss firms (*CH_CITED*) show a greater probability of being cited by scientific research institutions compared to those patents that are assigned in other countries. Since large pharmaceutical firms are located in Switzerland we assume that especially knowledge that is related to biotechnological drug development is interesting for research institutions. Besides this, we do not find any geographical effects regarding the assigne's country of residence of the cited patent for the citation probability of science. Thus the results confirm that cultural proximity obviously plays a minor role for the knowledge transfer from industry to science. Further our results show that the citation probability by science increases when the research institutions are located in France (*FR_CITING*), the US (*US_CITING*) and to a smaller extend in Germany (*DE_CITING*). Thus the results suggest that especially French and US research institutions compared to research institutions from other countries are more actively involved in screening and transferring knowledge that has been produced by industry. Given the strong international competitiveness of the US biotechnology industry we speculate that this "reverse knowledge transfer" might play a role for its successful development. Some support for this thesis can be found in the historical development of the US scientific research system. Feller (1990) states that with the begin of the 1970s universities in the US increasingly dedicated themselves to conducting socially useful research which was partly due to government induced research programs in nuclear and information technology research during the Cold War. And David (1994) points out that US policies at the same time realized the importance of new technology and started to view universities more under global competitive aspects. Research institutions that are located in Japan (*JP_CITING*), Switzerland (*CH_CITING*) or Great Britain (*GB_CITING*) show a lower probability to engage in knowledge transfer from industry. Especially the result for Switzerland is interesting. It seems that Swiss companies produce valuable new biotechnological related output which is absorbed by various international research institutions whereas Swiss research institutions are not able to profit from the knowledge that is produced by the companies in their home country in relation to the reference countries. Regarding knowledge transfer from industry to industry our results suggest that patents that are hold by Swiss firms (*CH_CITED*) and US firms (*US_CITED*) in relation to the other reference countries show a lower probability to receive a citation by other firms. In turn when we look on the nationalities of the citing patent firms we see that firms from Germany (*DE_CITING*), Switzerland (*CH_CITING*), Japan (*JP_CITING*) and Great Britain (GB_CITING) show a higher probability to cite an industry patent compared to our reference countries. Our finding that US firms are less actively involved in inter-industry knowledge transfer has to be interpreted with a lot of caution. Given the findings of Narin et al. (1997) and McMillan et al. (2000) who emphasize the importance of the strong ties between US biotechnology firms and research institutions we carefully assume that either US firms are indeed more actively involved in transferring knowledge from research institutions than from other firms or that *within-knowledge-transfer* between US firms is mostly informal.

*Robustness check for truncation*

We conduct a robustness check on our model with respect to the mentioned possible bias of our estimation results due to shifts in the citation lags. Therefore we adjust the years from which we select the cited patents by looking at the percentiles of the citation lag distribution. We first look at the 10% percentile of the citation lag distribution which indicates that the cited patents are collected until the year 2002. The estimation results of the model which covers the application years of the cited patent from1978-2002 are displayed in the Appendix table A9. Next we run the model for the 90% percentile of the citation lag distribution which means that we drop all cited patents that have been issued after 1996 (Appendix table A10). Due to the fact that we excluded citations with a citation lag of more than 9 years this model mostly adjusts for a possible bias due to truncation, however many observations are lost when we ran the model for this limited time span. We see that the regression results remain very stable when we compare the three estimated models. We detect slight shifts in the significance levels of *ECVALUE* which implies that patents that are applied for later in the sample seem to receive more citations. Moreover some rather slight changes in the significance levels for some country dummies can be observed. From this we conclude that our estimation results are not strongly biased from truncation.

### 7.8 Conclusion

Existing theoretical approaches which aim to capture the dynamics of knowledge creation in science based industries suggest that knowledge that is created on one organizational level flows in all directions. A vast literature exists that describes the potential benefits of knowledge flows from scientific research institutions to biotechnology firms. The other direction, namely knowledge flows from industry to science has been mostly neglected by empirical studies. This paper contributes towards this topic by empirically investigating two questions: Are there knowledge flows from industry to science and how can we find them? And if there are those knowledge flows how do they differ from inter-industry knowledge flows? To answer the first question we conduct a patent citation analysis on the basis of EPO patent data. We look at patent applications of firms that have received citations of industry and/or science. Knowledge flows from industry to science exist but are rare. Only about 10% of the patent pairs in our sample received citations by public scientific institutions.

In order to investigate differences in the knowledge flows from industry to industry and from industry to science we estimate a weighted bivariate probit model on the citation probability of industry and science on the basis of a combined sample of citing and cited patent pairs and an equal number of control patent pairs. The empirical results show that there are considerable differences in the citation probability. The nature of these newly created knowledge has an impact on the citation probability of science and industry. Technological relatedness has a positive effect on the citation probability of industry while research institutions are more likely to transfer knowledge which is complementary to their own knowledge. We further find that knowledge with a more specialized technological character is more likely absorbed by firms. Cultural closeness has a positive effect on the citation probability from industry to industry while the citation probability of scientific institutions is not affected by cultural distance. Since knowledge flows are highly related to the persons involved in the research process we assume that cultural proximity might facilitate spillovers among firms. Researchers from scientific institutions in contrast are forced to screen prior art and related works when they write for academic publications and are thus less likely to be affected by cultural distance. The economic value has only a strong positive effect on the citation probability of industry but effects the citation probability of science to a smaller extent. This might be explained by the fact that many inventions in the biotechnology sector that are protected by patents obviously seem to be not profitable at a first glance but feature great value for further scientific research. Co-operation between firms and research institutions on a patent application seems to have a signal effect for other research institutions regarding the potential usefulness for one's own research and thus results in a higher citation rate from science.

Our results suggest that knowledge transfer in the biotechnology industries indeed is not a one-way street between universities and other public research institutions and firms but works in both directions. This result qualifies present-day biotechnology industries as science-based industries par excellence as the division of labor in research activities between firms and public research organizations blurs the ancestral boundaries between applied and basic research. The results implicate for politics that also our investigated direction of knowledge flow namely from industry to science should be taken into account, i.e. when industry science collaboration programs are evaluated.

Our results show that US research institutions are obviously very active in absorbing new knowledge that is created by industry. From the literature it is well described that a strong scientific biotechnological knowledge base and resulting strong ties between biotechnological firms and research institutions has a positive influence on the economic competitiveness of a country's biotechnological industry (Narin et al. 1997, McMillan et al. 2000). This finding can be considered to be one piece in the mosaic of explaining the economic and innovative strength of the biotechnology industry in the US. Research institutions in other countries should be encouraged to participate in this "reverse technology transfer", for instance via an increased number of international conferences where both, scientists from industry and academia meet.

It is important to notice that our study has severe limitations. Most important, our study captures only a very small part of the knowledge transfer activities within industry and between industry and science. We only depict the knowledge transfer that is formalized in patent applications. Next scientists in many countries had or still have the privilege to assign patents under their own name thus the share of scientific applicants is likely to be underrepresented. Additionally, a lot of patent citations are added by the examiners at the EPO patent office. These added patent citations do not necessarily reflect knowledge flows but often simply reflect the effort of the patent examiner to detect prior art. Our estimation results are to some extent biased because of this fact. Finally, some of our dependent variables are rather imperfect proxies to capture characteristics of the patents and applicants so the interpretation of these dependent variables has to be done with a lot of caution.

Despite these limitations we believe that this paper discloses an important topic. Further research has to be done to better understand the mechanisms that stand behind knowledge transfer from science to industry. One possible strategy could be to conduct surveys among researchers that are actively involved in biotechnological research and are employed at public research institutions to better understand the value of industrially produced knowledge for public scientific research activities.

# 8 Is it worth all the trouble? An assessment of the economic value of firm patent applications with shared intellectual property rights in the biotechnology industry

## 8.1 Introduction

The biotechnology industry as other science based industry is characterized by rapid advances in scientific research so firms are steadily urged to absorb external knowledge to keep pace with the speed of knowledge accumulation in the industry (Arora and Gambardella 1990, Henderson et al. 1998). As a result firms in the biotechnology industry frequently collaborate on R&D to profit from complementary knowledge and resources of their collaboration partners (Gulati 1998).

Inter-firm collaboration on R&D however always urges the participating firms to find agreements on the intellectual property rights of possible jointly generated inventions. Usually firms that collaborate on R&D find ex ante or ex post agreements on the intellectual property rights of their common generated inventions and try to avoid shared intellectual property rights on inventions (Luoma et al. 2010). This is mostly due to the fact that shared intellectual property rights on inventions are associated with the need of complex legal agreements between the collaborating firms and none of the collaborating firms can fully appropriate the monopoly rent on the invention (Haagedorn 2003).

Despite this, Narin and Hicks (2001) have shown that the share of joint patent applications at the *United States Patent and Trademark Office* (USPTO) has increased over time and the highest shares of jointly owned patents can be observed in knowledge intensive industries like the biotechnology industry. We show in line that the share of joint patent applications of firms in the field of biotechnology has increased at the European Patent Office (EPO).

Given these contradicting findings what are the motives and factors associated with joint patent applications of firms in the biotechnology industry? The existing empirical evidence on this topic is rare. A few empirical studies have shown that previous joint patenting experience increases the likelihood of firms to apply a joint patent application (Haagedorn et al. 2003, Kim and Song 2007). Khoury and Pleggenkuhle-Miles (2011) in line with Kim and

Song (2007) show that firms in the biotechnology industry which have jointly applied for patents with other firms develop broader and more diverse research capabilities compared to firms that avoid joint patenting.

Within this study we aim to contribute new empirical evidence on the causal relationship of the decision of firms to jointly apply for a patent on an invention and the economic value associated with the invention. Given the uncertainty associated with inventions in the biotechnology industry (Mazzoleni and Nelson 1998) we assume that firms which collaborate on R&D insist to maintain intellectual property rights on their jointly generated inventions since they could assume that these inventions are associated with a high future economic value which could not be properly assessed during the invention stage.

We investigate this research question by applying a nonparametric matching procedure. We use patent data and show that the decision of firms to jointly apply a patent is driven by the future economic value associated with the patent.

The remainder of the paper is organized as follows. In section 2 we give an overview on the motives of inter-firm R&D collaboration in the biotechnology industry. Section 3 describes the importance of patens as an intellectual property rights protection mechanism and section 4 addresses some theoretical topics associated with shared intellectual property rights on patents. Section 5 is on existing empirical evidence on the motives and factors associated with joint patent applications of firms in the biotechnology industry and works out our research hypothesis. Section 6 provides a description of the empirical implementation of our hypothesis, gives an overview on the used data and variables, and shows the descriptive statistics of our sample. Section 7 shows the results of our nonparametric matching approach and section 8 closes with a conclusion.

*Theoretical part*

## 8.2 R&D collaboration motives of firms in the biotechnology industry – A system of innovation approach

It has long been recognized that innovation is not a static process that takes place isolated from the outside surroundings. Instead, various economic studies have shown that innovation should rather be seen as an interactive process of learning that is shaped by various institutions and afflicted by a high degree of uncertainty (Nelson and Winter 1977, 1982; Lundvall 1988). In the economic literature, the innovation systems (IS) approach has been a dominant theory during the last two decades in order to capture these interactive processes of learning that will eventually yield innovations. The IS approach is basically build on two main assumptions. First, knowledge is considered to be the most important resource in modern economy and second, knowledge can only be gained through interactive learning that takes place in a socially embedded process which is shaped by various institutions (Lundvall 2010). There are various definitions of IS. One of the broadest definitions defines an IS as "all important economic, social, political, organizational, institutional, and other factors that influence the development, diffusion, and use of innovation" (Edquist 2005, p. 182).

The biotechnology industry like other science based industries is a good example for the application of the IS approach.

First of all, knowledge is the main production factor and characterized by rapid advances and moreover a wide dispersion of the sources that produce knowledge can be observed (Powell and Owen-Smith 1998). In order to not fall behind competitors and state-of-the art research, biotech firms are urged to steadily review and absorb this newly generated knowledge (Arora and Gambardella 1990, Henderson et al. 1998). R&D activities in the biotechnology sector are often characterized by a high degree of financial uncertainty, R&D and technologic uncertainty, regulatory uncertainty and market uncertainty.

Moreover, biotech R&D activities are often time consuming and expensive[29] (Teece et al. 1997). Because of this, interactive learning plays a crucial role for knowledge acquisition.

Powell et al. (1996) depict that informal R&D collaboration plays an important role in the biotechnology industry since firms heavily rely on their informal networks. Pyka and Saviotti (2005) investigate the permanent nature of R&D collaborations in the biopharmaceutical

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[29] for example the development of new drugs

industry and thus provide evidence that permanent R&D networks contribute to the survival of dedicated biotech firms next to large diversified pharmaceutical firms.

The motives of firms in the biotechnology industry, to engage in inter-firm research collaborations are different, depending mainly on their size and background.

Horizontal alliances between firms in the biotech sector link firms of the same size to each other. These alliances have the preliminary goal to achieve explanatory targets by either linking together firms with complementary assets or additional similarities (Gulati 1998). Thereby horizontal alliances are often more difficult to manage due to overlapping competencies even if the participating firms are no direct competitors (Doz et al. 1989, Khanna et al. 1998, Silverman and Baum 2002). Vertical alliances of firms in the biotech sector are often found among small and medium sized biotech firms and large pharmaceutical and chemical firms. Thereby the small and medium sized firms in the biotech sector are often former spinoffs from universities or other research institutions or at least have academic founders and thus employ some of the brightest scientists (Fisher et al. 1996). They keep close contact to scientific institutions and often undertake the first step in transferring basic research results in marketable products. However, these small and medium sized biotech firms have rather week financial resources and a lack of distributional infrastructure. Thus for small and medium sized biotech firms such alliances with large firms have been identified to be important for their successful product development as well as for a faster market access and enhanced marketing and distribution mechanisms (Arora and Gambardella 1990, Pisano 1990, Baum et al. 2000). In turn due to large diversity of research activities in biotechnology, large pharmaceutical and chemical firms are permanently facing the threat to fall behind new research technologies. Thus large firms in the biotech sector permanently have an incentive to get access to complementary technological knowledge which is produced by small and medium sized biotech firms (Arora and Gambardella 1990, Baum et al. 2000).

## 8.3 The meaning of patents for intellectual property rights protection in the biotechnology industry

Prior to the 1980s, international patent protection laws did not allow the protection of living organisms or biologically active substances like single molecules or proteins. As the biotechnology industry emerged and the economic value of biotechnological inventions became more obvious, international patent laws were adjusted and changed to satisfy the needs of intellectual property rights protection for biotechnological inventions.

One breakthrough in the changes of international patent laws was in 1980 when the US Supreme Court ruled that the genetic modification of a bacterium was patentable (Willison and McLeod 2002). Another major change of the patent protection law in the US was made in 1992 when it became possible to protect single molecules and proteins (Ko 1992). In the following years patent protection laws in other countries and in the EU were accordingly adjusted to allow the protection of biologically active substances (Leskien 1998).

Several works have shown the importance of patents for the intellectual property rights protection in the biotechnological industry. Cohen et al. (2000) have conducted a large scale survey on 1,478 R&D laboratories in the US in 1994 and show that patents in the biotechnology industry are the most important mechanism to protect intellectual property rights. Schankerman (1998) comes to a similar result by outlining that firms in the biotechnology industry are more willing to pay renewal fees on their patents compared to other industries. Arora et al. (2008) presented a measure, so called “patent premium” that relates the return of a patented invention to an unpatented invention and show that the patent premium is only positive for a few knowledge intensive industries including the biotechnology industry.

## 8.4 Shared intellectual property rights on patents

Shared intellectual property rights on patents occur when two or more assignees are found on one single patent application. This implies that the intellectual property rights are indeed shared between the applicants listed in the joint patent application and as a consequence the applicants that apply for a joint patent[30] have to find several agreements on how i.e. the patent rent should be divided or how acquisition offers of the joint patent should be handled. Thus joint patent applications have to be viewed differently from cross licensing agreements or patent infringement agreements where ex-post or ex-ante agreements between patent holders are negotiated to balance the expected license return losses and gains of the involved actors (Hagedoorn 2003).

The consequences of joint patenting are evidently more far-reaching compared to cross licensing agreements and infringement agreements and usually organizations that are actively conducting research try to avoid a sharing of intellectual property rights on their inventions (Marchese 1999, Luoma et al. 2010).

Shared intellectual property rights on patents usually occur as a result of collaboration and can thus be viewed as a special result of collaborative activity. Hagedoorn (2003) has interviewed US firms in his work which are actively involved in joint patenting and comes to the result that joint patenting mostly results from informal R&D collaboration and small sized R&D projects were the contributions of the involved partners to the realized invention can't be properly separated.  Hicks and Narin (2001) who have studied the patterns of joint patenting on the basis of USPTO patent data reveal that the share of joint patent applications has increased between the early 1980s and 1999 and patents with multiple applicants are mostly concentrated in highly knowledge intensive sectors like biotechnology, pharmacy and medical equipment. In line Hagedoorn (2003) shows again on the basis of USPTO patent data – using slightly different technology classifications – that the highest proportion of firm owned patents with shared intellectual property rights can be found in knowledge intensive sectors like chemicals and pharmaceuticals (including biotechnology) or information technology where patents generally play an important role for knowledge protection.

[30] We use the term „joint patent“ synonymously with the term “patents with shared intellectual property rights” throughout the whole paper.

## 8.5 Empirical evidence on the rationale of joint firm patents in the biotechnology industry

With regard to recent studies and the related literature, a core question occurs in context to firm's patenting strategies: Is there any reason why patents with shared intellectual property rights could be more valuable than patents with a single ownership? Patents with shared intellectual property rights create a lot of administrative and legal work to the jointly assigning firms. So then why do firms assign patents with a shared ownership and why has the share of joint patents increased in knowledge intensive industries as it has been outlined by Hicks and Narin (2001)? Hagedoorn (2003, p.1044) puts it this way: "Theoretically it is rather difficult to understand why, given the legal status of joint patents, companies would share their patents with other companies [...]".

Recently some few empirical studies have started to investigate motives and factors associated with joint patenting of firms. The existing empirical evidence on this topic is rare though.

Hagedoorn et al. (2003) have constructed a sample of firms and have empirically investigated the relationship between inter-firm collaboration experience and the number of joint patent applications. They show that the number of jointly owned patents of the firms does not seem to depend on the general collaboration experience of the firms but rather exclusively on the firm's experience with joint patenting itself. They conclude that firms who have experienced joint patenting might have established some inner organizational experience and guidelines about how joint patent applications can be handled.

Kim and Song (2007) use joint patents as a productivity measure of inter-firm R&D alliances in the pharmaceutical industry and show that joint patents that result from inter-firm R&D alliances have a non linear (inverted U-shaped) relationship with the developing technological base of the collaborating firms. Moreover they find that joint patenting between alliance partners seems to occur more often when the alliance partners had previous ties with each other.

Some recent work of Khoury and Pleggenkuhle-Miles (2011) relates the experience of biotechnology firms on joint patenting to their evolution of research capabilities. They use a sample based on over 250 biotechnology firms and show that firms which engage in joint patenting develop a broader research capability base compared to those firms that tend to avoid joint patent activities.

Besides the positive effects of prior collaboration experience on the likelihood of joint patenting of firms and the outlined positive effects of joint patenting of firms on the development of their research capabilities however less empirical evidence exists on further motives why firms in knowledge intensive sectors like the biotechnological sector increasingly engage in joint patents.

One alternative explanation to the question why firms file patent applications jointly could be that inventions that are patented jointly are associated with an assumingly high but at the time of the invention unknown expected economic value such that the collaboration partners hesitate to allocate the expected patent rents to a single collaboration partner and fail to find an a priori agreement on the ownership of the patent. One work that could underpin this hypothesis is the paper of Mazzoleni and Nelson (1998) in which the authors state that biotechnology patents are often not marketable at the first glance but might have great economic potential in the future. Given this uniqueness surrounded with patents from knowledge intensive industries like the biotechnology industry  our major hypotheses is: firms that have created an invention out of joint research have an incentive to maintain their shares on the intellectual property rights of the invention since they regard the joint invention as economically valuable but are not able to properly assess its real economic value and thus might fear to lose patent rents associated with the jointly created invention. We assess this hypothesis via a nonparametric matching approach on the basis of EPO patent data.

*Empirical part*

## 8.6 Empirical implementation, data, variables, and descriptive statistics

*Empirical implementation – Propensity score matching*

The aim of our study is to investigate whether joint patent applications of firms are associated with a higher economical value compared to patent applications of firms with a single ownership.

The fact whether a patent is jointly applied or not is the result of a selection bias, since firms that jointly apply for a patent have actively agreed to share intellectual property rights on their invention. This selection bias has the consequence that jointly applied patents will differ from patents with a single ownership in a set of important characteristics.

Several econometric approaches have been developed to correct for the presence of a possible selection bias including differences in differences methods, selection models, instrumental variable estimation, and nonparametric matching procedures (for an overview on recent developments see  Imbens and Wooldridge 2009). Nonparametric matching procedures have been primarily introduced for the evaluation of active labor market policies (e.g. Heckman et al. 1999, Lechner 2002a, Lechner 2002b, Blundell et al. 2004,). In innovation economics the nonparametric matching methods have mostly been used for the evaluation of public research funding (i.e. Busom 2000, Czarnitzki et al. 2004, Czarnitzki et al. 2011). In both application fields the participation in a public measure (i.e. the participation in a labor market program or the receipt of public funding) is called treatment and is compared to a matched group of nonparticipants. In our case the treatment is a jointly applied patent. With the nonparametric matching approach the patent value for the group of jointly applied patents can be compared to a simulated counterfactual situation that assesses the patent value for the group of jointly applied patents if they had not been jointly applied. The matching estimator simulates the counterfactual situation on the basis of a constructed control group of patents with single ownerships were each jointly applied patent is matched to a patent with single ownership that shows the same set of characteristics as the jointly applied patent. The matching method thus balances the group of treated observations to the group of untreated observations on a set of characteristics and attributes remaining differences in the outcome (in our case the patent value) to the treatment effect.  The *average treatment effect of treatment on the treated (ATT)* can be illustrated by the following equation:

$$ATT = E(Y_T|S = 1) - E((Y_C|S = 1)$$

$Y_T$ is the outcome variable (the patent value) and $S$ refers to the treatment with S=1 being the group of jointly applied patents and S=0 being the group of patents with a single ownership. The patent value for the group of jointly applied patents, $E(Y_T|S = 1)$, is directly observable. $Y_C$ reflects the potential patent value that would have been realized if the group of jointly applied patents had not been jointly applied. $E((Y_C|S = 1)$ thus describes the outlined counterfactual situation (the patent value for the group of jointly applied patents if they had not been jointly applied) which is not directly observable and has to be simulated.

We apply a modified propensity matching procedure as it has been proposed by Lechner (1998). The "plain" propensity matching procedure as it has been suggested by Rosenbaum and Rubin (1983) reduces the number of variables that determines the treatment status to a single variable in the matching function, namely the propensity scores which are prior estimated from a probit model on the binary treatment indicator variable. Lechner (1998) suggested a modification which allows the inclusion of several additional variables in the matching function. We construct the control sample by applying the nearest neighbor approach with replacement based on the Mahalanobis distance which includes several variables next to the propensity scores which were prior estimated on the basis of a probit model on the treatment indicator variable (joint patent applications vs. patents with a single ownership). A comprehensive overview on the single steps in the nonparametric matching procedure applied can e.g. be found in Czarnitzki et al. (2004).

*Data*

Our Study is based on EPO patent application data. We have a full coverage of the data for the years between 1984 and 2003[31]. The information of the patent data include the name(s) and country(ies) of origin of the inventor(s) as well as of the assignee(s), citations to other patents and/or citations to other documents (non-patent citations), information about the

[31] We like to thank the European Patent Office and the Centre of European Economic Research (ZEW) in providing the biotech patent data.

declared IPC classes as well as its application and grant dates. We use the IPC classes that have been identified to be relevant for biotechnology on the basis of the OECD patent compendium (2008) to identify all patent applications that contain at least one IPC class that is related to biotechnology. 66,936 patents remain for our further analysis.

On the basis of the identified patents we conduct a citation analysis and identify all subsequent citations that a biotechnology related patent has received by other biotechnology related patents in our sample.

Further we assigned all patent applications to the following classes: firms, research institutions, individuals and others. We limit our analysis to all patents that are signed by either one or multiple firms and keep 46,083 patents for our further investigation. It is important to note that we solely concentrate on all patent applications that have been jointly applied for by firms, so we drop for our matching approach all patent applications where for e.g. a university is listed as an applicant next to a firm applicant. We drop those joint patents with mixed classes of assignees since we would not be able to find proper control observations for those patents.

Next we restrict our analysis to the five countries that have assigned most of the patent applications in our sample namely the US, Germany, Japan, Great Britain and France. We chose to restrict our data to only those countries with the highest patenting activity to ensure that we can find proper control patents for our matching approach. The restriction to those five countries implies a loss of 8955 observations.

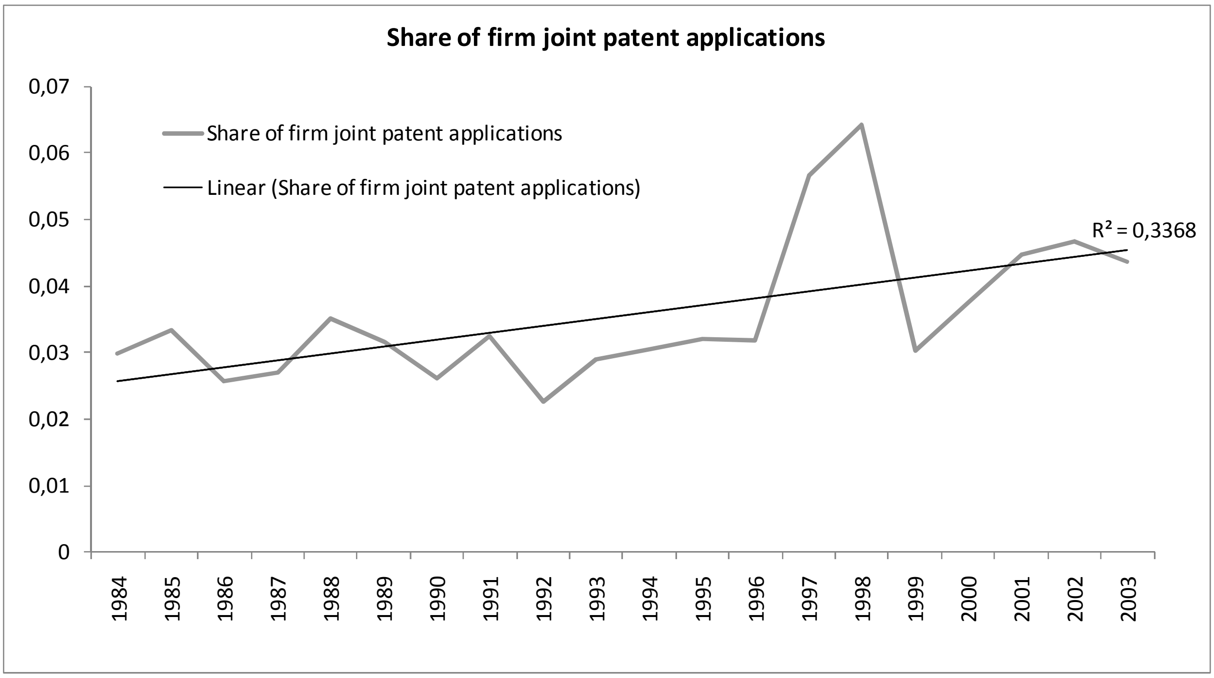
For our further analysis we keep 37128 patent applications.

*Variables*

We create a dummy variable (*JOINT*) which indicates whether a patent application has been jointly filed by two or more firms (*JOINT=1*) or not (*JOINT=0*). As it has been outlined before *JOINT* is our treatment indicator variable.

Figure 2 shows the share of joint patent applications of firms in relation to the application years. We can see that the share of joint patent applications of firms in our sample has increased from about 3% in 1984 to about 4.5% in 2003. Also the linear trend line suggests that there is a positive trend on the occurrence of joint patent applications. Our findings thus confirm the outlined findings of Hicks and Narin (2001) and Haagedorn (2003).

**Figure 2: Share of firm joint patent applications for the application years 1984-2003 (Chapter 7)**




We aim to relate the treatment effect of joint patent applications to the value of a patented invention. We therefore have to measure the value of the patent applications in our sample. One popular and straight forward way to proxy the economic value of a patent is the number of subsequent citations it has received (Harhoff et al. 1999, Hall et al. 2001b)[32]. The use of patent citations in an economic analysis where patents with different application years are jointly analyzed yields the problem of truncation though since a patent that has been filed earlier in the sample has a greater probability to receive more patent citations compared to a patent that has been filed more recently. This truncation issue has been heavily analyzed and several methods have been proposed to ease this bias (Caballero and Jaffe 1993, Jaffe and Trajetenberg 1999, Hall et al. 2001a). By applying a nonparametric matching approach on the patent data however, we suggest that the truncation bias can be

[32] Other methods to proxy the economic value of patents have been suggested, for an overview regarding the biotechnological industry see Albino et al. (2009).

accounted for by simply including the patent application years in the matching function. Given that the number of control patents is large enough the matching method will then search for each treated patent a control patent with exactly the same application year. As a result the group with joint patent applications should not differ from the group of patents with single ownership regarding their patent application year frequency distributions.

Our outcome variable *CITATIONS* reflects the number of citations a patent has received from the other subsequent patents in our sample.

Next we describe a set of variables that are likely to influence the decision of a firm to jointly apply for a patent or not. Those variables are important to estimate the propensity scores that are included in the matching function and can further be included in the matching function directly.

As described before the studies of Hagedoorn et al. (2003) and Kim and Song (2007) suggest that there is a positive effect of prior joint patenting experience of firms on the likelihood of firms to apply for a joint patent. We consider the application date of the patents in our sample and create a dummy variable (*PRIOR*) that indicates whether the applicant or one of the applicants of a patent has filed a joint patent with another firm previously to the considered patent application.

Next we include a measure that reflects the overall patenting rate of the applicants and to some extend at least proxies the firm size of the applicants. Generally one would expect a positive relationship between firm size and the number of patent applications on one hand because of differing R&D capacities and on the other hand because of differing financial assets to enforce patent rights (Schettino and Sterlacchini 2009). The relationship between firm size and the number of patent applications in the biotechnological industry is not clear though. Rothaermel and Thursby (2007) examine a sample of biotechnology firms for the years 1980-2000 and find a positive impact of firm size on the number of generated biotech patents for the years 1980-1990 however they do not find that this positive relationship holds for the years 1990-2000. *LNMEANANZPAT* is a continuous variable and contains the cumulative number of patent applications that the firm has applied for up to the application year of the considered patent application. In the case of joint patents we take the mean value of the cumulative patent application counts of the firms. Due to the fact that the distribution of the mean cumulative number of patent applications is heavily screwed we include the logarithmic value in our further analysis.

Next we include a variable that controls for the scientific complexity surrounded by the patented invention. We measure the scientific complexity of a patented invention by the total number of non patent references cited in the patent application of the patent (*NONPATCIT*). So called non patent citations have been recently used as proxies for science-industry linkages at the invention level (e.g. Cassiman et al. 2008, Lo 2010). In addition to this van Zeebroeck and van Pottelsberghe (2011) show that the number of non patent citations in the search report of a patent can be used to depict the scientific complexity of a patented invention. We hypothesize that if a patented invention is scientifically complex the firms might be more urged to get access to external knowledge and thus might have a higher probability to collaborate with a firm on this invention which as a consequence could lead to shared intellectual property rights on this invention.

Other control variables:

- Application years: As lined out before we control for the application years (*YEAR1984-YEAR2003*). On the one hand because we aim to control for the truncation bias of the citations and on the other hand because we observed a positive linear trend on the share of joint patent applications in our sample (Figure 2)
- First-digit-IPC-classes: We control for the first digit IPC class listed as the first IPC class in the patent application of a patent to control for possible differences of the likelihood of joint patent applications due to different technological fields (*IPC1-IPC8*).
- Country dummies: We control for the country of origin of the first applicant listed in the patent application since historical and cultural differences of countries could affect the probability of a firm to jointly apply for a patent (*US, GB, DE, FR, JP*).

*Descriptive statistics*

Table 8 shows the descriptive statistics for our full sample.

**Table 8: Descriptive statistics of the full sample (Chapter 7)**

| | Jointly applied patents (1426 observations) | | Patents with single ownership (35702 observations) | | Two sided t-test on equality of means |
|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | |
| *PRIOR* | 0,661 | 0,474 | 0,362 | 0,481 | *** |
| *LNMEANANZPAT* | 3,613 | 1,749 | 2,973 | 1,795 | *** |
| *NONPATCIT* | 2,187 | 4,189 | 1,869 | 3,426 | *** |
| *IPC1* | 0,090 | 0,286 | 0,090 | 0,286 | |
| *IPC2* | 0,013 | 0,115 | 0,011 | 0,103 | |
| *IPC3* | 0,770 | 0,421 | 0,771 | 0,420 | |
| *IPC4* | 0,004 | 0,065 | 0,001 | 0,025 | *** |
| *IPC5* | 0,000 | 0,000 | 0,000 | 0,009 | |
| *IPC6* | 0,000 | 0,000 | 0,000 | 0,012 | |
| *IPC7* | 0,123 | 0,328 | 0,127 | 0,333 | |
| *IPC8* | 0,000 | 0,000 | 0,001 | 0,023 | |
| *US* | 0,429 | 0,495 | 0,559 | 0,496 | *** |
| *JP* | 0,227 | 0,419 | 0,172 | 0,377 | *** |
| *FR* | 0,028 | 0,165 | 0,046 | 0,208 | *** |
| *GB* | 0,195 | 0,396 | 0,079 | 0,269 | *** |
| *DE* | 0,121 | 0,327 | 0,145 | 0,352 | ** |
| *YEAR1* | 0,013 | 0,115 | 0,019 | 0,137 | |
| *YEAR2* | 0,018 | 0,134 | 0,022 | 0,146 | |
| *YEAR3* | 0,016 | 0,126 | 0,024 | 0,155 | ** |
| *YEAR4* | 0,018 | 0,134 | 0,028 | 0,166 | ** |
| *YEAR5* | 0,028 | 0,165 | 0,032 | 0,177 | |
| *YEAR6* | 0,028 | 0,165 | 0,035 | 0,185 | |
| *YEAR7* | 0,025 | 0,157 | 0,039 | 0,193 | *** |
| *YEAR8* | 0,034 | 0,180 | 0,038 | 0,190 | |
| *YEAR9* | 0,020 | 0,139 | 0,039 | 0,193 | *** |
| *YEAR10* | 0,028 | 0,165 | 0,035 | 0,183 | |
| *YEAR11* | 0,034 | 0,180 | 0,039 | 0,194 | |
| *YEAR12* | 0,035 | 0,184 | 0,043 | 0,203 | |
| *YEAR13* | 0,041 | 0,198 | 0,048 | 0,213 | |
| *YEAR14* | 0,086 | 0,281 | 0,055 | 0,227 | *** |
| *YEAR15* | 0,118 | 0,322 | 0,069 | 0,253 | *** |
| *YEAR16* | 0,063 | 0,243 | 0,082 | 0,274 | ** |
| *YEAR17* | 0,083 | 0,277 | 0,089 | 0,284 | |
| *YEAR18* | 0,114 | 0,317 | 0,095 | 0,293 | ** |

| | | | | | |
|---|---|---|---|---|---|
| *YEAR19* | 0,116 | 0,320 | 0,089 | 0,285 | *** |
| *YEAR20* | 0,082 | 0,275 | 0,081 | 0,272 | |
| *CITATIONS* | 0,380 | 1,112 | 0,384 | 1,336 | |
| *37128 observations* | | | | | |

The two sided t-tests on the equality of means for the two groups show that applicants of joint patents show a higher previous experience with joint patent applications (*PRIOR*) and show a higher previous patenting rate (*LNMEANANZPAT*). Moreover inventions that are patented jointly are of a more complex scientific nature when compared to patents with no shared intellectual property rights (*NONPATCIT*). Besides also the countries of origin of the applicants are significantly different among the two groups. A higher proportion of Japanese applicants (*JP*) and applicants from Great Britain (*GB*) can be found in the group of jointly applied patents compared to the group of patents with a single ownership. It is important to notice that the t-test shows no significant difference between the two groups for our outcome variable (*CITATIONS*). In fact, patents with a single ownership receive slightly more patent citations compared to patents with a joint ownership. As we described above however our data are biased due to selection and we account for this bias in the following section by applying a nonparametric matching model

### 8.7 Results from the nonparametric matching procedure

First we estimate a probit model on the application of a joint patent (*JOINT*).The probit model (Table 9)shows that prior joint patenting experience (*PRIOR*) and the scientific complexity of the patented invention has a highly significant impact on the probability of firms to jointly apply for a patent. Moreover the country dummies and a Wald test on the joint significance of the application years is highly significant. Regarding the IPC classes we find three IPC (IPC5, IPC6, IPC8) classes that only occur in the group of patents with a single ownership. Those three IPC classes are dropped for the probit estimation and for this reason we lose 27 observations.

**Table 9: Probit estimation on the application of a joint patent (Chapter 7)**

| JOINT | Coef. | Std. Err. | |
|---|---|---|---|
| *PRIOR* | 0.541 | 0.034 | *** |
| *LNMEANANZPAT* | 0.004 | 0.010 | |
| *NONPATCIT* | 0.011 | 0.003 | *** |
| IPC1[a] | -0.138 | 0.121 | |
| IPC3[a] | -0.209 | 0.114 | |
| IPC4[a] | 1.024 | 0.292 | *** |
| IPC7[a] | -0.157 | 0.119 | |
| US[b] | -0.608 | 0.039 | *** |
| JP[b] | -0.386 | 0.043 | *** |
| FR[b] | -0.538 | 0.076 | *** |
| DE[b] | -0.532 | 0.049 | *** |
| Constant term | -1.307 | 0.154 | *** |
| Test on the joint significance of year dummies | | $\chi(19)=81.01$ | *** |
| Pseudo $R^2$ | | 0.071 | |
| Log Likelihood | | -5614.977 | |
| # observations | | 37101 | |

Note: 19 year dummies included in the regression, Year1 serves as reference year; [a]IPC2 serves as reference class; IPC5, IPC6, IPC8 dropped since they are only found in the group of patent applications with single ownership and 27 observations are dropped; [b]Great Britain serves as reference class

Next we use the control sample to find a control patent application from the group of patent applications with a single ownership for each treated patent application. We apply the nearest neighbor approach with replacement based on the Mahalanobis distance. Next to the estimated propensity scores from the described probit estimation we include all independent variables of our probit estimation in the Mahalanobis metric restriction. Due to the fact that we have more than 35,000 possible control patent applications for just 1,426 treated patent applications, we believe that we can apply this really stringent approach to find proper control observations.

Table 10 shows the detailed matching results of our approach. It is important to note that we do not lose any observation due to the failure of common support.

**Table 10: Matching results based on 37,101 observations (Chapter 7)**

| Variable | | Mean | | P-value of two sided t-test on mean equality |
|---|---|---|---|---|
| | | joint patent applicaton | patent with single ownership | |
| PROPENSITY SCORE | Unmatched | 0,069 | 0,037 | 0,000 |
| | Matched | 0,069 | 0,067 | 0,283 |
| PRIOR | Unmatched | 0,661 | 0,362 | 0,000 |
| | Matched | 0,661 | 0,644 | 0,346 |
| LNMEANANZPAT | Unmatched | 3,613 | 2,974 | 0,000 |
| | Matched | 3,613 | 3,538 | 0,243 |
| NONPATCIT | Unmatched | 2,187 | 1,870 | 0,001 |
| | Matched | 2,187 | 2,014 | 0,259 |
| US | Unmatched | 0,429 | 0,559 | 0,000 |
| | Matched | 0,429 | 0,435 | 0,734 |
| JP | Unmatched | 0,227 | 0,172 | 0,000 |
| | Matched | 0,227 | 0,223 | 0,823 |
| GB | Unmatched | 0,195 | 0,079 | 0,000 |
| | Matched | 0,195 | 0,194 | 0,925 |
| FR | Unmatched | 0,028 | 0,045 | 0,002 |
| | Matched | 0,028 | 0,027 | 0,909 |
| DE | Unmatched | 0,121 | 0,145 | 0,013 |
| | Matched | 0,121 | 0,121 | 0,954 |
| IPC1 | Unmatched | 0,090 | 0,090 | 0,988 |
| | Matched | 0,090 | 0,088 | 0,895 |
| IPC2 | Unmatched | 0,013 | 0,011 | 0,366 |
| | Matched | 0,013 | 0,013 | 1,000 |
| IPC3 | Unmatched | 0,770 | 0,771 | 0,894 |
| | Matched | 0,770 | 0,771 | 0,929 |
| IPC4 | Unmatched | 0,004 | 0,001 | 0,000 |

| | | | | |
|---|---|---|---|---|
| | Matched | 0,004 | 0,004 | 1,000 |
| IPC7 | Unmatched | 0,123 | 0,127 | 0,599 |
| | Matched | 0,123 | 0,123 | 1,000 |
| CITATIONS | Unmatched | 0,380 | 0,384 | 0,910 |
| | Matched | 0,380 | 0,292 | 0,021 |

Note: 20 Year dummies are not reported, they are not significant after the matching however. The full matching results are reported in appendix table A1

The means and corresponding t-tests show that none of the employed covariates differ after the matching. Appendix table A11 displays the full matching results including the matching results for the single application years. Concerning the correction of the truncation bias of our outcome variable *CITATIONS* due to different application years we observe that the truncation bias for the application years is almost completely ruled out by the matching procedure. The p-values of the two sided t-test on mean equality for the application years show a range of 0.924-1.000. Also the Propensity score (PROPENSITY SCORE) shows no significant difference after the matching.

We do observe however a mean difference in our outcome variable *CITATIONS* which can be attributed to the treatment. Table 11 shows the average treatment effect on the treated with bootstrapped standard errors. On average a patent application that has been jointly applied would have received significantly less patent citations if it had not been jointly applied. We can see that this difference amounts to approximately 0.09 patent citations that the jointly applied patent would have received less if it had not been jointly applied. From these findings we assume that there is a causal relationship between the economic value of a patented invention and the decision of firms to share intellectual property rights on this invention

**Table 11: Average treatment effect on the treated (ATT) (Chapter 7)**

| Variable | Sample | Treated | Controls | Difference | Standard errors |
|---|---|---|---|---|---|
| CITATIONS | Unmatched | 0.3801 | 0.3841 | -0.0041 | 0.0359 |
| | ATT | 0.3801 | 0.2917 | 0.0884 | 0.0431* |

* bootstrapped standard errors

## 8.8 Conclusion

In this paper we contribute new empirical evidence on the rationale of firms to jointly apply for patents. Existing empirical evidence suggests that previous joint patenting experience has a positive impact on the likelihood of firms to apply for joint patents. Moreover a positive impact of prior joint patenting experience on the development of a firm's research capabilities has been outlined for the biotechnology industry.

We hypothesize that the decision of a firm to jointly apply for a patent is driven by the future economic value of the jointly applied invention. Given the uncertain true economic potential associated with inventions from knowledge intensive industries like the biotechnology industry, we assume that firms which have jointly generated an invention insist to maintain the intellectual property rights on their invention if they suppose that their jointly generated invention could feature great economic potential in the future which cannot be properly assessed during the invention stage. In this case the collaborating firms will fail to find a priori agreement on the allocation of the intellectual property rights on their inventions and will thus share the intellectual property rights.

We test this hypothesis via a nonparametric matching approach on EPO patent data. We show that a causal relationship exists on the decision of firms to jointly apply for a patent and the economic value of the patented invention for the biotechnology industry. We find that patents with shared intellectual property rights would have significantly received fewer citations if they had not been jointly applied.

Our approach has some severe shortcomings though. First of all it is unlikely that we included all relevant covariates that determine the decision of a firm to jointly apply for a patent in our probit estimates. Although we applied very stringent restrictions to the construction of our control sample it is still likely that patents with a joint ownership differ from patents with a single ownership in important characteristics. We also totally neglected the financing background of the firms in our sample. Kortum and Lerner (2000) show for US manufacturing industries that that there is a positive relationship between the venture capital activities and the patenting rate in an industry. Assuming that venture capital financed firms might have a greater probability to apply for a patent compared to not venture-backed firms it would be important to control for the financing background of the firms in our sample.

Despite these shortcomings however we believe that our paper contributes new evidence on the rationale of firms to jointly apply for patents in the biotechnology industry. Moreover we show that the nonparametric matching approach can be a powerful method to determine causal relationships not only on firm level but also on patent level.

Further research has to be done however to reveal more factors that are associated with the firm’s decision to jointly apply for patents. One attempt could be to control for the financing background of the applicant firms.

# 9 Main Conclusion

In this thesis, we have contributed micro-level empirical evidence on the initiation and consequences of informal R&D linkages.

In the first empirical part of this thesis we have worked out how individual and faculty related factors affect the decision of scientists to engage in informal knowledge transfer to firms. The decision of a scientist to engage in informal knowledge transfer means at the same time that to a certain extend knowledge flows out back door of the universities. We have shown that both, individual and faculty related factors of scientists influence their probability to engage in informal knowledge transfer and that these factors do not seem to differ at a great extend for German scientists compared to US scientists. In contrast to the existing empirical literature (e.g. Zucker and Darby 1996, Zucker et al. 2002) that is mostly restricted to the field of life sciences, we have shown at least for the German sample that the patent record of a scientist seems to be more important in signaling research quality to industry than the publication record when a wider spectrum of scientific fields is considered. Obviously firms seem to acknowledge the practice-oriented work of the scientists that may immediately flow into the firm’s knowledge base.

Besides incentive and career related factors we have shown in the context of the second empirical chapter that international mobility of scientists has not only a positive impact on the scientific productivity but also a positive impact on the likelihood to engage in knowledge and technology transfer in both, their host and their home countries. We have hypothesized that the transfer of knowledge to industry in both, the home and the host countries, might be an important way for scientists to become more visible and to build up a international reputation. More specifically we have outlined that the duration of a research visit has a positive impact on the likelihood of scientists to transfer knowledge and technology to both, their home and their host countries, while the frequency of research visits abroad seems to only be positively related to the knowledge and technology transfer activities of scientists to their home countries. Based on our findings, international mobility of scientists can therefore be seen as a driver for the scientific and technical human capital that facilitates collaboration with industry and enhances the propensity of scientists to engage in the transfer of knowledge. We have shown on the basis of the German scientists sample that – at least for timely limited and repetitive stays of researchers abroad – international mobility of scientists does not seem to lead to a brain drain but rather to a brain gain for home countries of the scientists.

While the first two empirical parts of this thesis have analyzed factors that are critical for the initiation of informal knowledge and technology transfer, the remaining two empirical chapters have investigated two phenomena that mainly occur in the context of informal R&D collaborations: Knowledge flows from industry to science and shared intellectual property rights on inventions.

Whereas the vast majority of studies that have analyzed knowledge flows in the biotechnology industry have focused on knowledge flows within industry or from research institutions to firms, the opposite flow direction, namely from industry to science has remained mainly unexplored. Using EPO patent data, we have identified knowledge flows from industry to science and within industry on the basis of patent citations and have compared the retrieved pairs of citing and cited patents to matched control patent pairs to depict differences in the citation probabilities. We have shown that not only institution related factors like the patent portfolio, the collaboration profile, and the location of the citing and cited patent applicants but also invention/patent related characteristics like the scientific complexity, the estimated economic value, or the degree of technological specialization of a patented invention have an impact on the citation probabilities. While we show that technological relatedness of a patented invention with the patent portfolio of a firm or research institution for instance has a positive effect on the citation probability of industry, research institutions are more likely to transfer knowledge which is complementary to their own knowledge.

The last empirical part of this thesis has analyzed the rationale of firms to jointly apply for patents. From the literature it is well described that patents with shared intellectual property rights mainly result from informal R&D collaborations and are most characteristic for science based industries. Given the legal and organizational effort associated with patents with shared intellectual property rights, collaborating firms usually have a strong incentive to avoid joint patent application. Despite this different empirical studies have observed that the number of joint patent applications in several industries has increased within the last decades. Still, less is known on the factors that drive the decision of firms to share intellectual property rights on an invention instead of differently agreeing on intellectual property rights. We have tested the hypothesis that the decision of firms to jointly apply for patents depends on the expected, future economic value of the jointly developed inventions on the basis of EPO biotechnology patent data.

We have revealed for our data that patents with shared intellectual property rights would have received significantly fewer citations if they had not been jointly applied. Besides the gain of knowledge with regards to content we have introduced nonparametric matching approaches as an adequate tool to address causal inference of research questions related to micro level patent data.

Although every empirical study has severe shortcomings which we described, we contributed valuable, new empirical evidence to the topic of informal R&D agreements.

On the basis of our empirical findings we are able to deduct some policy recommendations. First of all – recalling our findings of the empirical sections which are based on the surveys of university researchers – we have found strong evidence in our studies that knowledge continuously leaks out of university and research institution boundaries via informal technology transfer channels, despite changed legislation and the efforts of German universities to profit from the knowledge themselves. Obviously, German universities and research institutions are still in a learning process to increase the efficiency and usage of newly generated technology transfer mechanisms (e.g. technology transfer offices). We have shown that the decision of researchers to engage in informal technology transfer is almost purely incentive driven. Thus, next to the development and implementation of more efficient technology transfer mechanisms at German research institutions, also stronger incentives (e.g. enhanced research funds) for scientists to commercialize their findings and inventions via research institutions transfer channels should be provided. One rather extreme way to tackle this problem – at least in more applied scientific fields – would be to integrate commercialization of knowledge activities in the tenure track programs of scientists.

However there are two sides of the same coin: While research institutions on the one hand may lose future turnovers from their generated knowledge due to informal knowledge transfer activities of their scientists at least to some degree, we have outlined on the other hand, how important these informal science-industry knowledge flows are for the competitive advantage of firms, especially for firms in science based industries. Given this tradeoff, national policy makers should not have the ultimate incentive to prevent informal knowledge flows from science to industry, but rather to ensure, that national industries can benefit from these knowledge resources.

A highly discussed topic in the context of the “European Paradox” has been the assumption of EU representatives that the EU might looses valuable scientific knowledge to competing nations like the US due to international mobility of European scientists (e.g. Van der Wende 2007).

In this context, a rather intuitive, but from our view wrong way would thereby to give more incentives to the scientists to remain in their home countries. First of all, international research stays of scientists are nowadays an inherent part of the academic career and are necessary for the scientists in order to acquire complementary scientific knowledge. In addition to that, we have found evidence on the basis of our German sample that international mobility of scientists does not seem to lead to a brain drain, but rather to a brain circulation where the industries of both, the host and the home countries can profit. In fact, we have shown that at least for more short term, repetitive research stays, the firms of the home countries of the scientists tend to benefit even more compared to foreign firms, in terms of the extend of transferred knowledge.

The activities of national politics to foster and support international mobility of scientists (e.g. providing more funds for research stays abroad), should thus be generally broadened, and specifically extended in the way that they allow and foster repetitive stays of scientists.

In the context of the last two empirical chapters we have outlined, how informal knowledge agreements can be identified and analysed on the basis of patent data. Although the caveats of using patent data to depict knowledge flows and knowledge collaborations are well described in the economic literature, we believe that we have empirically addressed two important phenomena that arise in the context of informal R&D collaborations between institutions. As a bottom line, the findings of our last two empirical chapters implicate that the R&D activities of firms – at least in the biotechnology industry – seem to be in first line an interactive and open process, as it has been described by the open innovation paradigm of Chesbrough (2003). Knowledge seems to circulate between the institutional actors in the biotechnology industry, and the line between industrial and scientific research is blurry to not existing. As a consequence, research institutions are only a provider of scientific knowledge for industrial research, but are actively transferring knowledge themselves (Gibbons 1994). We have revealed that US research institutions, compared to research institutions of our developed countries are obviously very active in absorbing new knowledge that is created by industry. Given the competitive advantage of the US biotechnology industry, we have interpreted this finding as yet another building block that determines the economic competitiveness of a country's biotechnology sector. While it is generally known that US research institutions interact closer with industry, compared to European research institutions (e.g. European Commission 2011), we believe that our empirical findings contribute a more detailed understanding on the characteristics of the knowledge sourcing process of research institutions and are therefore valuable for the "European paradoxon" discussion.

Given this, we propose that scientists in Europe should be encouraged to consider not only the results of local/national industrial research, but also research activities from firms abroad as a valuable knowledge asset. In line with our previous findings this could mean that scientists should be encouraged to actively get in contact with research active firms, when they conduct research stays abroad.

Besides, we have shown that the participation of firms in an open innovation process requires a rethinking of existing managerial routines. In this context, we have analyzed the phenomenon of patents with shared intellectual property rights, since they are frequently regarded to result from informal research collaborations. Although patents with shared intellectual property rights certainly remain an organizational and strategic challenge for firms, we have found empirical evidence that firms seem to develop organizational routines to cope with those patents.

We therefore believe, that firms should be supported and encouraged to build up organizational and strategic capabilities in order to cope with the challenges, which arise from the increasing openness of the innovation process.

Several tasks remain for further research. Although we have contributed new empirical evidence, the topic of informal technology transfer still needs to be further explored, given its assumed importance in the era of the open innovation paradigm (Chesbrough 2003). Moreover we have shown that research on informal technology transfer can contribute important aspects in the discussion of the "European Paradox".

The availability of data that are sufficient for analyzing informal knowledge transfer activities of firms or for investigating the role of informal knowledge transfer for single innovation projects however remains a problem. Since informal knowledge flows and activities are traceable in patent data and other innovation project level data sets to only to a very limited extend, large scale micro level innovation surveys are needed to further explore the characteristics that surround informal R&D collaboration activities in the innovation process.

# 10 References


Ackers, L. and B. Gill (2008), *Moving People and Knowledge. Scientific Mobility in an Enlarging European Union*, Cheltenham.

Adams, J.D. (1990), Fundamental Stocks of Knowledge and Productivity Growth*, Journal of Political Economy* **98**, 673-702.

Adams, J.D. (2006), Learning, Internal Research, and Spillovers, *Economics of Innovation and New Technology* **15**, 5-36.

Adams, W. (1968), Introduction, in: Adams, W. (ed.), *The Brain Drain*, New York.

Aerts, K., Matthyssens, P. and K. Vandenbempt (2007), Critical Role and Screening Practices of European Business Incubators, *Technovation* **27**, 254-267.

Agrawal, A. and R. Henderson (2002), Putting Patents in Context: Exploring Knowledge Transfer from Mit, *Management Science* **48(1)**, 44-60.

Ahuja, G. (2000), Collaboration networks, structural holes and innovation: A longitudinal study, *Administrative Science Quarterly* **45**, 425-455.

Albino, V., Messeni Petruzzelli, A. and D. Rotolo (2010), Measuring Patent Value: An Empirical Analysis of the US Biotech Industry, *Working paper series Polytechnic of Bari*.

Alcácar, J. and M. Gittelman (2006), Patent Citations as a Measure of Knowledge Flows: The Influence of Examiner Citations, *The Review of Economics and Statistics* **88(4)**, 774-779.

Allen, R.C. (1983), Collective invention, *Journal of Economic Behavior & Organization* **4(1)**, 1-24.

Allen, T.J. and S.I. Cohen (1969), Information flow in research and development laboratories, *Administrative Science Quarterly* **14**, 12-19.

Allen, T.J., Hyman, D. and D. Pinckney (1983), Transferring technology to the small manufacturing firm: a study of technology transfer in three countries, *Research Policy* **12**, 199–211.

Almeida, P. (1996), Knowledge sourcing by foreign multinationals: Patent citation analysis in the U.S. semiconductor industry, *Strategic Management Journal* **17**, 155-165.

Almeida, P. and B. Kogut (1999), Localization of Knowledge and the Mobility of Engineers in Regional Networks, *Management Science* **45(7)**, 905-917.

Antonelli, C. (1999), The Evolution of the Industrial Organisation of the Production of Knowledge, *Cambridge Journal of Economics* **23(2)**, 243-60.

Archibugi, D. and J. Michie (1997), Technological globalisation and national systems of innovation: An introduction, in Archibugi, D. and J. Michie (Eds.), *Technology, Globalization and Economic Performance*, Cambridge University Press, Cambridge, 1-23.

Arora, A. and A. Gambardella (1990), Complementarity and External Linkages: The Strategies of the Large Firms in Biotechnology, *The Journal of Industrial Economics* **38(4)**, 361-379.

Arora, A., A. Fosfuri and A. Gambardella (2001), *Markets for Technology: The Economics of Innovation and Corporate Strategy*, Cambridge, MA.

Arora, A., Ceccagnoli, M. and W. M. Cohen (2008), R&D and the patent premium, *International Journal of Industrial Organization* **26(5)**, 1153-1179.

Arrow, K.J. (1962a), The Economic Consequences of Learning by Doing, *Review of Economic Studies* **XXIX (3)**, 155-173.

Arrow, K.J. (1962b), Economic Welfare and the Allocation of Resources for Invention, in: Nelson, R. R. (ed.) *The Rate and Direction of Inventive Activity: Economic and Social Factors*, Princeton, NJ, 609-625.

Arrow, K.J. (1969), Classificatory Notes on the Production and Transmission of Technological Knowledge, *American Economic Review* **59(2)**, 29-35.

Arvanitis, S., N. Sydow and M. Woerter (2008), Do specific forms of university-industry knowledge transfer have different impacts on the performance of private enterprises? An empirical analysis based on Swiss data, *The Journal of Technology Transfer* **33**, 504–533.

Aschhoff, B. and T. Schmidt (2008), Empirical evidence on the success of R&D co-operation – happy together?, *Review of Industrial Organization* **33**, 41–62

Athey, S. and S. Stern (1998), An Empirical Framework for Testing Theories About Complementarity in Organizational Design, *NBER Working Paper* **6600**, Boston.

Audretsch, D. (1995), Innovation and Industry Evolution, MIT Press, Cambridge, MA.

Audretsch, D. and P. Stephan (1996), Company-Scientist Locational Links: The Case of Biotechnology, *American Economic Review* **86(3)**, 641-652.

Balconi, M. (2002), Tacitness, codification of technological knowledge, and the organisation of industry, *Research Policy* **31**, 357-379.

Barney, J.B. (1991), Firm Resources and Sustained Competitive Advantage, *Journal of Management* **17**, 99-120.

Baum, J.A.C, Calabrese, T. and B.S. Silverman (2000), Don't go it alone: alliance network composition and startups' performance in Canadian biotechnology, *Strategic Management Journal* **21(3)**, 267-294.

Baum, J.A.C., Calabrese, T. and B.S. Silverman (2000), Canadian Biotechnology Start-Ups, 1991–1997: Role of Incumbents' Patents and Strategic Alliances in Controlling Competition, *Social Science Research* **29(4)**, 503-534.

Beaver, D. (2001), Reflections on Scientific Collaboration (and its Study): Past, Present and Future, *Scientometrics* **52**, 365-377.

Becker, W. and J. Dietz (2004), R&D cooperation and innovation activities of firms – evidence for the German manufacturing industry, *Research Policy* **33(2)**, 209-223.

Bekhradnia, B. and T. Sastry (2005), *Migration of Academic Staff to and from the UK*, Higher Education Policy Institute (HEPI), London.

Belderbos, R., M. Carree and B. Lokshin (2004), Cooperative R&D and Firm Performance, *Research Policy* **33**, 1477-1492.

Belkhodja, O., and R. Landry (2007), The Triple-Helix Collaboration: Why Do Researchers Collaborate with Industry and the Government? What are the Factors that Influence the Perceived Barriers? *Scientometrics* **70(2)**, 301-332.

Belsley, D.A., E. Kuh and R.E. Welsh (1980), *Regression Diagnostics: Identifying Influential Data and Sources of Collinearity*, New York.

Bertrand, M. and S. Mullainathan (2001), Do People Mean What They Say? Implications for Subjective Survey Data, *American Economic Review* **91(2)**, 67-72.

Blundell, R., Costas Dias, M. Meghir, C. and J. Van Reenen (2004), Evaluating the Employment Impact of a Mandatory Job Search Program, *Journal of the European Economic Association* **2**, 569-606.

Boardman, P.C. (2009) Government Centrality to University-Industry Interactions: University Research Centers and the Industry Involvement of Academic Researchers, *Research Policy* **38**, 1505-1516.

Borgatti, S.P., Mehra, A., Brass, D.J. and G. Labianca (2009), Network analysis in the social sciences, *Science* **323**, 892-895.

Bönte, W. and M. Keilbach (2005), Concubinage or marriage? informal and formal cooperation for innovation, *International Journal of Industrial Organization* **23**, 279-302.

Bozeman, B. (2000), Technology Transfer and Public Policy: A Review of Research and Theory, *Research Policy* **29**, 627-655.

Bozeman, B. and E. Corley (2004), Scientists' Collaboration Strategies: Implications for Scientific and Technical Human Capital, *Research Policy* **33**, 599-616.

Bozeman, B., Dietz, J. and M. Gaughan (2001), Scientific and Technical Human Capital: An Alternative Model for Research Evaluation, *International Journal of Technology Management* **22**, 636-655.

Brennenraedts, R., Bekkers, R. and B. Verspagen, B. (2006), The Different Channels of University-Industry Knowledge Transfer: Empirical Evidence from Biomedical Engineering. *ECISWorking Paper* **2006–04**.

Breschi, S. and F. Lissoni (2001), Knowledge Spillovers and Local Innovation Systems: A Critical Survey, *Industrial and Corporate Change* **10(4)**, 975-1005.

Broström, A. (2010), Firms' Rationales for Interaction with Research Universities and the Principles for Public Co-Funding, *Journal of Technology Transfer*, forthcoming.

Brown, J.S. and P. Duguid (2001), Knowledge and organization: A social-practice perspective, *Organization Science* **12**, 198-213.

Burt, R.L. (1992), *Structural Holes*, Cambridge, MA: Harvard University Press.

Busom, I. (2000), An empirical evaluation of the effects of R&D subsidies, *Economics of Innovation and New Technology* **9(2)**, 111-148.

Caballero, R. J. and A.B. Jaffe (1993), How high are the giants' shoulders: an empirical assessment of knowledge spillovers and creative destruction in a model of economic growth, *NBER Working Papers* **4370**, National Bureau of Economic Research.

Cantner, U. and A. Meder (2008), Innovators and the Diversity of Innovation Systems, *Jena Economic research papers* **2008(043).**

Carlsson, B. (Ed.) (1995), *Technological systems and economic performance: The case of factory Automation*, Kluwer Academic Publishers, Dordrecht.

Carlsson, B. (2006), Internationalization of innovation systems: A survey of the literature, *Research Policy* **35(1)**, 56-67.

Carlsson, B. and S. Jacobsson (1997), In search of a useful technology policy - general lessons and key issues for policy makers, in Carlsson, B. (Ed.), *Technological Systems and Industrial Dynamics*, Kluwer Academic Publishers, Boston.

Carlsson, B., Jacobsson, S., Holmen, M. and A. Rickne (2002), Innovation systems: analytical and methodological issues, *Research Policy* **31(2)**, 233–245.

Carlsson, B. and R. Stankiewicz (1995), On the nature, function and composition of technological systems, in Carlsson, B. (Ed.), *Technological Systems and Economic Performance: The Case of Factory Automation*, Kluwer Academic Publishers, Boston.

Casey, T., S. Mahroum, K. Ducatel and R. Barré (2001), *The Mobility of Academic Researchers: Academic Careers and Recruitment in ICT and Biotechnology*, European Commission: Joint Research Centre (DG JRC), EUR 19905EN.

Cassiman, B. and R. Veugelers (2002), R&D Cooperation and Spillovers: Some Empirical Evidence from Belgium, *The American Economic Review* **92(4)**, 1169-1184.

Cassiman, B. and R. Veugelers (2006), In Search of Complementarity in the Innovation Strategy: Internal R&D and External Knowledge Acquisition, *Management Science* **52(1)**, 68-82.

Cassiman, B., Veugelers, R. and P. Zuniga (2008), In search of performance effects of (in)direct industry science links, *Industrial and Corporate Change* **17(4)**, 611-646.

Cervantes, M. and D. Guellec (2002), *The Brain Drain: Old Myths, New Realities*, OECD observer, Paris.

Chesbrough, H. (2003), *Open innovation: The new imperative of creating and profiting from innovation*, Harvard Business School Press, Boston.

Chesbrough, H., Vanhaverbeke, W. and J. West (2006), *Open Innovation: Researching a New Paradigm*, Oxford University Press, London.

Cohen, W. and D. Levinthal (1990), Absorptive capacity: a new perspective on learning and innovation, *Administrative Science Quarterly* **35**, 128-152.

Cohen, W., Nelson, R. and J. Walsh (2000), Protecting Their Intellectual Assets: Appropriability Conditions and Why U.S. Manufacturing Firms Patent (or Not), *NBER Working Paper* **7552**, National Bureau of Economic Research.

Cohen, W., Nelson, R. and J. Walsh (2002), Links and Impacts: The Influence of Public Research on Industrial R&D, *Management Science* **48(1)**, 1-23.

COM (2005*), A Mobility Strategy for the European Research Area; Researchers in the ERA: One Profession, Multiple Careers*, Commission of the European Communities staff working document: Implementation Report 2004, SEC(2005) 474.

COM (2006), *Mobility of Researchers between University and Industry*, Report of an Expert Group, EUR 22573, Brussels.

Cooke, P. (2002), Regional innovation systems: general findings and some new evidence from biotechnology Clusters, *Journal of Technology Transfer* **27**, 133–145.

Cooke, P., Uranga, M. and G. Etxebarria (1997), Regional innovation systems: Institutional and organisational dimensions, *Research Policy* **26(4-5)**, 475-491.

Coleman, J.S. (1988), Social capital in the creation of human capital, *American Journal of Sociology* **94**, 95-120.

Cowan, R. And D. Foray (1997), The economics of codification and the diffusion of knowledge, *Industrial Corporate Change* **6**, 595-622.

Cox, D. and A. Verbeek (2008), *Evidence on the Main Fators Inhibiting Mobility and Career Development of Researchers*, Report for the European Commission, Brussels.

Crespi, G.A., A. Geuna and B. Verspagen (2006), University IPRs and Knowledge Transfer. Is the IPR Ownership Model More Efficient?, *SEWPS (SPRU Electronic Working Paper Series)* **No. 154**, Brighton.

Criscuolo, P. and B. Verspagen (2008), Does it matter where patent citations come from? Inventor vs. examiner citations in European patents, *Research Policy* **37(10)**, 1892-1908.

Cummings, J.L. and B.-S. Teng (2003), Transferring R&D Knowledge: The Key Factors Affecting Knowledge Transfer Success, *Journal of Engineering and Technology Management* **20**, 39-68.

Czarnitzki, D., Ebersberger, B. and A. Fier (2007), The Relationship between R&D Collaboration, Subsidies and R&D performance: Empirical Evidence from Finland and Germany, *Journal of Applied Econometrics* **22(7)**, 1347-1366.

Czarnitzki, D., Glänzel, W. and K. Hussinger (2007), Patent and Publication Activities of German Professors: An Empirical Assessment of Their Co-Activity, *Research Evaluation* **16(4)**, 311-319.

Czarnitzki, D., Glänzel, W. and K. Hussinger (2009), Heterogeneity of Patenting Activity and its Implications for Scientific Research, *Research Policy* **38**, 26-34.

Czarnitzki, D., Hanel, P. and J.M. Rosa (2011), Evaluating the impact of R&D tax credits on innovation: A microeconometric study on Canadian firms, *Research Policy* **40(2)**, 217-229.

Czarnitzki, D., K. Hussinger and C. Schneider (2008), Commercializing Academic Research: The Quality of Faculty Patenting, *ZEW Discussion Paper* **08-069**, Mannheim.

Dasgupta, P. and P. David (1994), Towards a New Economics of Science, *Research Policy* **3**, 487-521.

David, P.A. (1994), Reputation and agency in the historical emergence of the institutions of open science, *CEPR* **261**, Stanford University.

David, P.A. and D. Foray (2002), An introduction to the economy of the knowledge society, *International Social Science Journal* **54(171)**, 9-23.

De Grip, A., Fourage, D. and J. Saubermann (2010), What Affects International Migration of European Science and Engineering Graduates? *Economics of Innovation and New Technology* **19(5)**, 407-421.

Defazio, D., Lockett, A. and M. Wright (2009), Funding Incentives, Collaborative Dynamics and Scientific Productivity: Evidence from the EU Framework Program, *Research Policy* **38**, 293-305.

Dogson, M., Gann, D. and A. Salter (2006), The role of technology in the shift towards open innovation: The case of Procter & Gamble, *R&D Management* **36(3)**, 333-346.

Dosi G. (1982), Technological paradigms and technological trajectories: A suggested interpretation of the determinants and directions of technical change, *Research Policy* **11(3)**, 147-162.

Dosi G., Llerena P. and M. Sylos Labini (2006), The relationships between science, technologies and their industrial exploitation: An illustration through the myths and realities of the so-called ‘European Paradox’, *Research Policy* **35(10)**, 1450-1464.

Doz, Y., Gary, H. and C.K. Prahalad (1989), Collaborate with your competitors - And win, *Harvard Business Review* **67(1)**, 133-39.

Edler, J. (2003), The Management of Knowledge in German Industry, in: Foray, D. and F. Gould (eds.), *Knowledge Management Practices in the Private Sector: An International Survey*, Ottawa/Paris, 89-118.

Edler, J. (Ed.) (2007), *Internationalisierung der Deutschen Forschungs- und Wissenschaftslandschaft* (Internationalisation of German Research and Science), Karlsruhe.

Edquist, C. (Ed.) (1997), *Systems of Innovation*, Frances Pinter, London.

Edquist, C. (2005), Systems of innovation: perspectives and challenges, in: Fagerberg, J., Mowery, D.C. and R.R. Nelson (Eds.), *The Oxford Handbook of Innovation*, Oxford University Press, New York, 181-208.

Etzkowitz, H. (2003), Research Groups as 'Quasi-Firms': The Invention of the Entrepreneurial University, *Research Policy* **32**, 109-121.

Etzkowitz, H. and L. Leydesdorff (Eds.) (1997), *Universities in the Global Knowledge Economy: A triple helix of university-industry-government relations*, Cassell, London.

European Communities (2007), The Seventh Framework Programme (FP7), EU publication office, Brussels.

European Commission (2011), Innovation Union Competitiveness report 2011, EU publication office, Brussels.

Fagerberg, J. (2005), Innovation. A Guide to the Literature. In: Fagerberg, J., Mowery, D.C., Nelson, R.R. (Eds.) The Oxford Handbook of Innovation. Oxford University Press, New York, 1-26.

Feldman, M.P., Feller, I. Bercovitz, J. and R. Burton (2002), Equity and the Technology Transfer Strategies of American Research Universities, *Management Science* **48**, 105-121.

Feller, I. (1990), Universities as Engines of R&D-Based Economic Growth: They Think they Can, *Research Policy* **19(4)**, 349-355.

Fiani, R. (2003), The Brain Drain: An Unmitigated Blessing, *Centro Studii Luca d'Agliano Development Studies Working Paper* **173**.

Fischer, M., Diez, J. and F. Snickars, (2001), *Metropolitan Innovation Systems; Theory And Evidence From Three Metropolitan Regions In Europe*, Springer, Berlin/Heidelberg.

Fisher, D., Grosjean, J.A. and D. House (1996), Changes in Academy/Industry/State Relations in Canada: The Creation and Development of the Networks of Centres of Excellence, *Research Policy* **39(3)**, 299-325.

Freeman, C. (1991), Networks of innovators: A synthesis of research issues, *Research Policy* **20(5)**, 499-514.

Freeman, L.C. (2004), *The Development of Social Network Analysis*, Empirical Press, Vancouver, BC Canada

Freeman, R. (2010), Globalization of Scientific and Engineering Talent: International Mobility of Students, Workers, and Ideas and the World Economy, *Economics of Innovation and New Technology* **19(5)**, 398-406.

Friedman, J. and J. Silberman (2003), University Technology Transfer: Do Incentives, Management, and Location Matter? *Journal of Technology Transfer* **28**, 17-30.

Fuchs, G. ed. (2003), *Biotechnology in comparative perspective*, Routledge, London.

Gambardella, A. (1995), *Science and Innovation: The US Pharmaceutical Industry during the 1980s*, Cambridge Univ. Press, Cambridge.

Garcia-Muina, F., Pelechano-Barahona, E. and J. Navas-Lopez (2009), Knowledge codification and technological innovation success: empirical evidence from Spanish biotech companies, *Technological Forecasting and Social Change* **76(1)**, 141-153.

Gerybadze, A. and G. Reger (1999), Globalisation of R&D: recent changes in the management of innovation in transnational corporations, *Research Policy* **28**, 251-274.

Gibbons, M., Limoges, C., Nowotny, H., Schwartzman, S., Scott, P. and M. Trow (1994), *The New Production of Knowledge: The Dynamics of Science and Research in Contemporary Societies*, Sage, London.

Gilsing, V., Nooteboom, B., Vanhaverbeke, W., Duysters, G. and A. van den Oord (2008), Network embeddedness and the exploration of novel technologies: Technological distance, betweenness centrality and density, *Research Policy* **37(10)**, 1717-1731.

Gittelman, M. and B. Kogut (2003), Does Good Science Lead to Valuable Knowledge? Biotechnology Firms and the Evolutionary Logic of Citation Patterns, *Management Science* 49(4), 366-382.

Gittelman, M. (2006), National institutions, public–private knowledge flows, and innovation performance: A comparative study of the biotechnology industry in the US and France, *Research Policy* **35(7)**, 1052-1068.

Giuliani, E. (2011), Networks of innovation, in: Cooke, P., Asheim, B., Boschma, R., Martin, R., Schwartz, D. and F. Tödtling (Eds.), *Handbook of Regional Innovation and Growth*, Edward Elgar, Cheltenham.

Gnyawali, D. and R. Madhavan (2001), Cooperative networks and competitive dynamics: a structural embeddedness perspective, *Academy of Management Journal* **26(3)**, 431–445.

Goyal, S. (2007), *Connections: An Introduction to the Economics of Networks*, Princeton University Press, Princeton.

Grant, R. (1996), Toward a knowledge-based theory of the firm, *Strategic Management Journal* **17**, 109-122.

Granovetter, M.S. (1973), The strength of weak ties, *American Journal of Sociology* **78**, 1360-1380.

Granovetter, M. (1985), Economic Action, Social Structure, and Embeddedness, *American Journal of Sociology* **91**, 481-510.

Greene, W.H. (1993), *Econometric Analysis*, New York.

Griliches, Z. (1990), Patent Statistics as Economic Indicators: A Survey, *Journal of Economic Literature* **28(4)**, 1661-1707.

Griliches, Z. and F. Lichtenberg (1984), Interindustry Technology Flows and Productivity Growth: A Re-examination, *The Review of Economics and Statistics* **66(2)**, 324-329.

Grimpe, C. and H. Fier (2010), Informal University Technology Transfer: A Comparison between the United States and Germany, *Journal of Technology Transfer* **35**, 637-650.

Grimpe, C. and K. Hussinger (2008), Formal and Informal Technology Transfer from Academia to Industry: Complementarity Effects and Innovation Performance, *ZEW Discussion Paper* **08-080**, Mannheim.

Grossman, G. and E. Helpman (1991), *Innovation and growth in the global economy*, MIT Press, Cambridge, MA.

Gulati, R. (1998), Alliances and networks, *Strategic Management Journal* **19(5),** 293-317.

Hagedoorn, J. (1995), Strategic technology partnering during the 1980s: trends, networks and corporate patterns in non-core technologies, *Research Policy* **24(2)**, 207-231.

Hagedoorn, J. (2003), Sharing intellectual property rights—an exploratory study of joint patenting amongst companies, *Industrial and Corporate Change* **12(5)**, 1035-1050.

Hagedoorn, J., Link, A. and N. Vonortas (2000), Research partnerships, *Research Policy* **29(2000)**, 567-586.

Hagedoorn, J., van Kranenburg, H. and R.N. Osborn (2003), Joint patenting amongst companies – exploring the effects of inter-firm R&D partnering and experience, *Managerial and Decision Economics* **24(2-3)**, 71-84.

Hall, B., Link, A. and J. Scott (2003), Universities as Research Partners, *Journal of Economic Studies* **85**, 485-491.

Hall, B.H., Jaffe, A.B. and M. Trajtenberg (2001a), The NBER Patent Citation Data File: Lessons, Insights and Methodological Tools, *NBER Working Papers* **8498**, National Bureau of Economic Research.

Hall, B.H., Jaffe, A.B. and M. Trajtenberg, (2001b), *Market Value and Patent Citations: A First Look*, Mimeo, UC Berkeley.

Hansen, M.T. (1999), The search-transfer problem: The role of weak ties in sharing knowledge across organization subunits, *Administrative Science Quarterly* **44(1)**, 82-111.

Harhoff, D., Narin, F., Scherer, F.M. and K. Vopel (1999), Citation frequency and the value of patented inventions. *Review of Economics and Statistics* **81(3)**, 511-515.

Heckman, J.J. (1979), Sample Selection Bias as a Specification Error, *Econometrica* **47(1)**, 153-161.

Heckman, J.J., R.J. Lalonde and J.A. Smith (1999), The Economics and Econometrics of Active Labour Market Programs, in: A. Ashenfelter and D. Card (Eds.), *Handbook of Labour Economics*, Vol. 3, North-Holland: Amsterdam, 1866-2097.

HEFCE (2006), The Higher Education Workforce in England. A Framework for the Future, *Higher Education Funding Council for England Issues Paper* **2006/21**, London.

Heinze, T. and S. Kuhlmann (2008), Across Institutional Boundaries? Research Collaboration in German Public Sector Nanoscience, *Resarch Policy* **37(5)**, 888-899.

Henderson, R., Jaffe, A. and M. Trajtenberg (1998), Universities as a source of commercial technology: a detailed analysis of university patenting, 1965–1988, *Review of Economics and Statistics* **80**, 127–199.

Hicks, D. and F. Narin (2001), Strategic Research Alliances and 360 Degree Bibliometric Indicators, in: *Proceedings from an NSF Workshop on Strategic Research Partnerships, NSF 01-336*, July.

Hu, A.G.Z. and A. B. Jaffe (2003), Patent citations and international knowledge flow: the cases of Korea and Taiwan, *International Journal of Industrial Organization* **21**, 849-880.

Hurlbert, J.S. and A.C. Acock (1990), The Effects of Marital Status on the Form and Composition of Social Networks, *Social Science Quarterly* **71**, 163-74.

Hunter, R. S., A. J. Oswald, and B. G. Charlton (2009), The Elite Brain Drain, *The Economic Journal* **119(538)**, F231-F251.

Imbens, G.W. and J.M. Wooldridge (2009), Recent Developments in the Econometrics of Program Evaluation, *Journal of Economic Literature* **47(1)**, 5-86(82).

Jacobsson, S. (2002), Universities and Industrial Transformation: An Interpretative and Selective Literature Study with Special Emphasis on Sweden, *Science & Public Policy* **29**, 345–365.

Jaffe, A. (1989), The Real Effects of Academic Research, *American Economic Review* **97(5)**, 957-970.

Jaffe, A. B. and M. Trajtenberg (1999), International patent flows: Evidence from patent citations, *Economics of Innovation and New Technology* **8**, 105–136.

Jaffe, A.B. and M. Trajtenberg (1996), Flows of Knowledge from Universities and Federal Labs: Modeling the Flowof Patent Citations Over Time and Across Institutional and Geographic Boundaries, *NBER Working Papers* **5712**, National Bureau of Economic Research.

Jaffe, A.B., Trajtenberg, M. and R. Henderson (1993), Geographic localization of knowledge flows as evidenced by patent citations, *Quarterly Journal of Economics* **108(3)**, 577-98.

Jensen, R.A. and M.C. Thursby (2001), Proofs and Prototypes for Sale: The Licensing of University Inventions, *American Economic Review* **91**, 240-259.

Johnson, B., Lorenz, E. and B. Lundvall (2002), Why all this fuss about codified and tacit knowledge?, *Industrial and Corporate Change* **11**, 245-262.

Kamien, M.I., Muller, E. and I. Zang (1992), Research Joint Ventures and R&D Cartels, *American Economic Review* **82(5)**, 1293-1306.

Katz, J.S. and B.R. Martin (1997), What is Research Collaboration? *Research Policy* **26**, 1-18.

Kaufman, A. and F. Tödtling (2001), Science-industry interaction in the process of innovation: the importance of boundary-crossing between systems, *Research Policy* **30(5)**, 791-804.

Kenney, M. (1986), *Biotechnology: The University-Industrial Complex*, Yale University Press, New Haven, CT.

Khanna, T., Gulati, R. and N. Nohria (1998), The dynamics of learning alliances: competition, cooperation, and relative scope, *Strategic Management Journal* **19(3)**, 193-210.

Khoury, T.A. and E.G. Pleggenkuhle-Miles (2011), Shared inventions and the evolution of capabilities: Examining the biotechnology industry, *Research Policy* **40(7)**, 943-956.

Kilger, C. and K. Bartenbach (2002), New Rules for German Professors, *Science* **298(8)**, 1173-1175.

Kim, C. and J. Song (2007), Creating new technology through alliances: An empirical investigation of joint patents, *Technovation* **27**, 461–470.

Kleinknecht, A. (1989), Firm size and innovation, *Small Business Economics* **1(3)**, 215-222.

Klepper, S. (1996), Entry, Exit, Growth, and Innovation over the Product Life Cycle, *American Economic Review* **86(3)**, 562-583.

Ko, Y. (1992), An economic analysis of biotechnology patent protection, *Yale Law Journal* **102**, 777-804.

Kogut, B. (1988), Joint ventures: Theoretical and empirical perspectives, *Strategic Management Journal* **9(4)**, 319-332.

Kogut, B. and U. Zander (1992), Knowledge of the Firm, Combinative Capabilities, and the Replication of Technology, *Organization Science* **3(3)**, 383-397.

Kortum, S. and J. Lerner (2000), Assessing the Contribution of Venture Capital to Innovation, *The RAND Journal of Economics* **31(4)**, 674-692.

Kreiner, K. and M. Schultz (1993), Informal Collaboration in R & D. The formation of Networks Across Organizations, *Organization Studies* **14**, 189-209,

Lach, S. and M. Schankerman (2004), Royalty Sharing and Technology Licensing in Universities, *Journal of the European Economic Association* **2**, 252-264.

Lechner, M. (1998), *Training the East German labour force: microeconometric evaluations of continuous vocational training after unification*, Physica-Verl.: Heidelberg.

Lechner, M. (2002a), Program Heterogeneity and Propensity Score Matching: An Application to the Evaluation of Active Labor Market Policies, *Review Economics and Statistics* **84(2)**, 205-220.

Lechner, M. (2002b), Some Practical Issues in the Evaluation of Heterogenuous Labour Market Programmes by Matching Methods, *Journal of the Royal Statistical Society (Series A)* **165**, 659-82.

Lee, S. and B. Bozeman (2005), The impact of research collaboration on scientific productivity, *Social Studies of Science* **35**, 673–702.

Leskien, D. (1998), The European Patent Directive on Biotechnology, *Biotechnology and Development Monitor* **36**, 16-19.

Levhari, D. (1966), Extensions of Arrow's "Learning by Doing", *The Review of Economic Studies* 33(2), 117-131.

Liebeskind, J.P (1996), Knowledge, strategy, and the theory of the firm, *Strategic Management Journal* **17** (Winter Special Issue), 93-107.

Link, A.N. and L.L. Bauer (1989), *Cooperative Research in US Manufacturing: Assessing Policy Initiatives and Corporate Strategies*, Lexington Books, Lexington, MA.

Link, A.N. and D.S. Siegel (2005), Generating Science-Based Growth: An Econometric Analysis of the Impact of Organizational Incentives on University–Industry Technology Transfer, *European Journal of Finance* 11, 169-182.

Link, A.N. and D.S. Siegel (2007), *Innovation, Entrepreneurship, and Technological Change*, Oxford: Oxford University Press.

Link, A.N. and J.T. Scott (2005), Universities as Partners in U.S. Research Joint Ventures, *Research Policy* **34**, 385-393.

Link, A.N., Siegel, D.S. and B. Bozeman (2007), An empirical analysis of the propensity of academics to engage in informal university technology transfer, *Industrial Corporate Change* **16(4)**, 641-655.

Lo, S.S. (2010), Scientific linkage of science research and technology development: A case of genetic engineering research, *Scientometrics* **82**, 109-120.

Lundvall, B.A. (1988), Innovation as an interactive process: from user–producer interaction to the national system of innovation, in: Dosi, G., Freeman, C., Nelson, R., Silverberg, G. and L. Soete (Eds.), *Technical Change and Economic Theory*, Pinter Publishers: London, 349–369.

Lundvall, B.-A. (Ed.) (1992)*, National systems of innovation: Towards a theory of innovation and interactive learning*, Pinter, London.

Lundvall, B.A. (Ed.) (2010), *National systems of innovation: Toward a theory of innovation and interactive learning*, Anthem Press: London.

Luoma, T., Paasi, J. and K. Valkokari (2010), Intellectual property in inter-organisational relationships - Findings from an interview study, *International Journal of Innovation Management* **14(3)**, 399-414.

Malerba, F. (2002), Sectoral systems of innovation and production, *Research Policy* **31(2)**, 247-264.

Mansfield, E. (1991), Academic Research and Industrial Innovation, *Research Policy* **20(1)**, 1-12.

Marchese, D. (1999), Joint ownership of intellectual property, *European Intellectual Property Review* **21**, 363-369.

Markman, G.D., Gianiodis, P.T. and P.H. Phan (2008). Full-time faculty or part-time entrepreneurs, *IEEE Transactions on Engineering Management* **55**, 29–36.

Maurseth, P.B. and B. Verspagen (2002), Knowledge Spillovers in Europe: A Patent Citations Analysis, *Scandinavian Journal of Economics* **104(4)**, 531-545.

Mazzoleni, R. and R.R. Nelson (1998), The benefits and costs of strong patent protection: a contribution to the current debate, *Research Policy* **27(3)**, 273-284.

McMillan, G.S., Narin, F. and D.L. Deeds (2000), An analysis of the critical role of public science in innovation: the case of biotechnology, *Research Policy* **29(1)**, 1-8.

Melin, G. (2000), Pragmatism and Self-Organization: Research Collaboration on the Individual Level, *Research Policy* **29**, 31-40.

Merton, R.K. (1973), *The sociology of science: theoretical and empirical investigations*, University of Chicago Press, Chicago.

Meyer-Krahmer, F. and U. Schmoch (1998), Science-Based Technologies: University-Industry Interactions in Four Fields, *Research Policy* **27**, 835-851.

Michel, J. and B. Bettels (2001), Patent citation analysis - A closer look at the basic input data from patent search reports, *Scientometrics* **51(1)**, 185-201.

Minbaeva, D., Pedersen, T., Bjorkman, I., Fey, C. and H. Park (2003), MNC Knowledge Transfer, Subsidiary Absorptive Capacity and Knowledge Transfer*, Journal of International Business Studies* **34 (6)**, 586-599.

Moore G. (1990), Structural determinants of men's and women's personal networks, *American Sociological Review* **55**, 726-35.

Mountford, A. (1997), Can a Brain Drain Be Good for Growth in the Source Economy? *Journal of Development Economics* **53(2)**, 287-303.

Mowery, D.C., Oxley, J.E. and B.S. Silverman (1996), *Strategic alliances and interfirm knowledge transfer*, *Strategic Management Journal* **17**, 77-91.

Munch, A., McPherson, J.M. and L. Smith-Lovin (1997), Gender, children and social contact: the effects of childrearing for men and women, *American Sociological Review* **62**, 509-20.

Murray, F. (2004), The Role of Academic Inventors in Entrepreneurial Firms: Sharing the Laboratory Life, *Research Policy* **33**, 643-659.

Narin, F. Hamilton, K.S. and D. Olivastro (1997), The increasing linkage between U.S. technology and public science, *Research Policy* **26(3)**, 317-330.

Nelson, R.R. (Ed.) (1993), *National Innovation Systems: A Comparative Analysis*, Oxford University Press, New York.

Nelson, R.R. and N. Rosenberg (1993), *Technical innovation and national systems*, in Nelson, R. R. (Ed.), National Innovation Systems: A Comparative Analysis, Oxford University Press, Oxford.

Nelson, R.R. and S.G. Winter (1977), In search of useful theory of innovation, *Research Policy* **6(1)**, 36-76.

Nelson, R.R. and S.G. Winter (1982), *An Evolutionary Theory of Economic Change*, Harvard University Press, Cambridge(MA).

Nguyen, C.H. (2006), Brain Drain or Brain Gain? The Revitalization of a Slow Death, *Essays in Education* **16**.

Nightingale, P. (2003), If Nelson and Winter are only half right about tacit knowledge, which half? A Searlean critique of 'codification', *Industrial and Corporate Change* **12(2)**, 149-183.

Niosi, J. (2000), Science-based industries: a new Schumpeterian taxonomy, *Technology in Society* **22(4)**, 429-444.

Niosi, J. (2003), Alliances are not enough explaining rapid growth in biotechnology firms, *Research Policy* **32(5)**, 737-750.

Nonaka, I. And H. Takeuchi (1995), *The Knowledge Creating Company: How Japanese Companies Create the Dynamics of Innovation*, Oxford University Press, New York.

Nonaka, I., Toyama, R. and N. Konno (2000), SECI, Ba and Leadership: a unified model of dynamic knowledge creation, *Long Range Planning* **33(4)**, 4-34

Nooteboom,B., Gilsing,V., Vanhaverbeke,W. and G. Duysters (2006), *Network embeddedness and the exploration of novel technologies: technological distance, betweenness centrality and density*, Paper presented at the DRUID Summer Conference 2006, CBS: Copenhagen.

OECD (2002), International Mobility of the Highly-Skilled, *Policy Brief*, Paris.

OECD (2006), *OECD Biotechnology Statistics - 2006*, OECD, Paris.

OECD (2007), *The OECD Stan Indicators Database*, Paris.

OECD (2008), *Compendium Of Patent Statistics*, OECD, Paris.

Owen-Smith, J. and W.W. Powell (2001), To Patent or Not: Faculty Decisions and Institutional Success at Technology Transfer, *Journal of Technology Transfer* **26**, 99-114.

Owen-Smith, J. and W.W. Powell (2004), Knowledge Networks as Channels and Conduits: The Effects of Spillovers in the Boston Biotechnology Community, *Organization Science* **15(1)**, 5-21.

Pavitt, K. (1984), Sectoral patterns of technical change: Towards a taxonomy and a theory, *Research Policy* **13(6)**, 343-373.

Perkmann, M. and K. Walsh (2007), University-Industry Relationships and Open Innovation: Towards a Research Agenda, *International Journal of Management Reviews* **9(4)**, 259-280.

Phelps, C.C. (2010), A Longitudinal Study of the Influence of Alliance Network Structure and Composition on Firm Exploratory Innovation, *The Academy of Management Journal* **53(4)**, 890-913.

Phene, A., Fladmoe-Lindquist, K. and L. Marsh (2006), Breakthrough innovations in the U.S. biotechnology industry: The effects of technological space and geographic origin, *Strategic Management Journal* **27**, 369-388.

Pisano, G. (1990), The R&D Boundaries of the Firm: An Empirical Analysis, *Administrative Science Quarterly* **35(1)**, 153–176.

Polanyi, M. (1966), *The Tacit Dimension*, Doubleday, New York.

Ponomariov, B.L. (2008), Effects of University Characteristics on Scientists' Interactions with the Private Sector: An Exploratory Assessment, *Journal of Technology Transfer* **33**, 485-503.

Ponomariov, B.L. and P.C. Boardman (2010), Influencing Scientists' Collaboration and Productivity Patterns through New Institutions: University Research Centers and Scientific and Technical Human Capital, *Research Policy* **39**, 613-624.

Porter, M.E. (2000a), Location, Competition, and Economic Development: Local Clusters in a Global Economy, *Economic Development Quarterly* **14(1)**, 15-31.

Porter, M.E. (2000b), The Economic Performance of Regions, *Regional Studies* **37(6&7)**, 549-578.

Powell, W.W. and S. Grodal (2005), Networks of Innovators, in Fagerberg, J., Mowery, D. and R.R. Nelson (Eds.), *The Oxford Handbook of Innovation*, Oxford University Press, Oxford, 56-85.

Powell, W.W. and J. Owen-Smith (1998), Commercialism in Universities : Life Sciences Research and its Linkage with Industry, *Journal of Policy Analysis and Management* **17(2)**, 253-277.

Powell, W.W., Koput, K.W. and L. Smith-Doerr (1996), Interorganizational collaboration and the locus of innovation: networks of learning in biotechnology, *Administrative Science Quarterly* **41(1)**, 116-145.

Powell, W.W., Koput, K.W., Smith-Doerr, L. and J. Owen-Smith (1999), *Network Position and Firm Performance: Organizational Returns to Collaboration*, in: Andrews, S. and D. Knoke (eds), Research in the Sociology of Organizations, JAI Press, Greewnwich, Conn.

Powell, W.W, White D.R., Koput K.W. and J. Owen-Smith (2005), Network dynamics and field evolution: the growth of inter-organizational collaboration in the life sciences, *American Journal of Sociology* **110(4)**, 1132–1205.

Prevezer, M. (2001), Ingredients in the Early Development of the U.S. Biotechnology Industry, *Small Business Economics* **17(1-2)**, 17-29.

Pyka, A. and P. Saviotti (2005), The Evolution of R&D Networking in the Biotech Industries, *International Journal of Entrepreneurship and Innovation Management* **5**, 49-68.

Pyka A., Gilbert N. and P. Ahrweiler (2007), Simulating Knowledge Generation and Distribution Processes in Innovation Collaborations and Networks, *Cybernetics and Systems* **38**, 667-693.

Quintana-Garcia, C. and C.A. Benavides-Velasco (2008), Innovative competence, exploration and exploitation: The influence of technological diversification, *Research Policy* **37(3)**, 492-507.

Reagans, R. and E.W. Zuckerman (2001), Networks, Diversity, and Productivity: The Social Capital of Corporate R&D Teams, *Organization Science* **12**, 502-517.

Regets, M. (2007), Brain Circulation: The Complex National Effects of High-Skilled Migration, Presentation at the OECD Committee for Scientific and Technology Policy (CSTP) and Steering and Funding of Research Institutions (SFRI) Workshop on the International Mobility of Researchers, Paris, March 28, 2007.

Robinson, S., A. Mentrup, F. Barjak and M. Thelwall (2007), Collection and Analysis of Existing Data on Researchers Careers (Rescar) and Implementation of New Data Collection Activities, Final Report. EU Contract No. 150176-2005-Fisc-Be, Brussels.

Romer, P. (1986), Increasing Returns and Economic Growth, *Journal of Political Economy* **94**, 1002–1037.

Romer, P. (1989), *Capital Accumulation in the Theory of Long Run Growth*, in Robert Barro (Ed.), Modern Business Cycle Theory, Harvard University Press, Cambridge, MA.

Romer (1990), Endogenous Technological Change, *Journal of Political Economy* **98(5)**, S71-S102.

Rosenbaum, P.R. and D.B. Rubin (1983), The central role of the propensity score in observational studies for causal effects, *Biometrika* **70**, 41-55.

Rosenberg, N. (1994), *Exploring the Black Box: Technology, Economics and History*, Cambridge University Press, Cambridge.

Rothaermel, F.T. and M. Thursby (2007), The nanotech versus the biotech revolution: Sources of productivity in incumbent firm research, *Research Policy* **36(6)**, 832-849.

Rothaermel, F.T., Agung, S.D. and L. Jiang (2007), University Entrepreneurship: A Taxonomy of the Literature, *Industrial & Corporate Change* **16(4)**, 691-791.

Sahal, D. (1981), Alternative Conceptions of Technology*, Research Policy* **10**, 2-24.

Salavisa, I., Sousa, C. and M. Fontes (2012), Topologies of innovation networks in knowledge-intensive sectors: Sectoral differences in the access to knowledge and complementary assets through formal and informal ties, *Technovation* **32(6)**, 380-399.

Salt, J. (1997), International Movements of the Highly-Skilled, *OECD NEIM Division Occasional Paper* **No. 3**, Paris.

Salter, A. and B. Martin (2001), The Economic Benefits of Publicly Funded Basic Research: A Critical Review, *Research Policy* **30(3)**, 509-532.

Santarelli, E. and A. Sterlacchini (1990). Innovation, Formal vs. Informal R&D, and Firm Size: Some Evidence from Italian Manufacturing, *Small Business Economics* **2**, 223-228.

Santoro, M.D. and A.K. Chakrabarti (2002). Firm Size and Technology Centrality in Industry-University Interactions. *Research Policy* **31**, 1163-1180.

Saxenian, A. (2002) Brain Circulation: How High-Skilled Immigration Makes Everyone Better Off, *Brookings Review* **20(1)**, 28-31.

Schankerman, M. (1998), How Valuable is Patent Protection? Estimates by Technology Field, *The RAND Journal of Economics* **29(1)**, 77-107.

Scherer, F.M. (1982), Inter-Industry Technology Flows and Productivity Growth, *The Review of Economics and Statistics* **64(4)**, 627-634.

Schettino, F. and A. Sterlacchini (2009), Reaping the Benefits of Patenting Activities: Does the Size of Patentees Matter?, *Industry & Innovation* **16(6)**, 613-633.

Schiff, M. (2005), Brain Gain: Claims about its Size and Impact on Welfare and Growth are Greatly Exaggerated, *IZA Discussion Paper* **1599**.

Schmoch, U., G. Licht and M. Reinhard (Eds.) (2000), *Wissens- und Technologietransfer in Deutschland*, Stuttgart.

Schmookler, J. (1966), *Invention and Economic Growth*, Harvard University Press, Cambridge (MA).

Schrader, S. (1991), Informal technology transfer between firms: Cooperation through information trading, *Research Policy* **20(2)**, 153-170.

Shaw, G.K. (1992), Policy Implications of Endogenous Growth Theory, *The Economic Journal* **102(412)**, 611-621.

Siegel, D.S. and P. Phan (2005), *Analyzing the Effectiveness of University Technology Transfer: Implications for Entrepreneurship Education*, in: Liebcap, G. (ed.) Advances in the Study of Entrepreneurship, Innovation, and Economic Growth, Amsterdam, 1-38.

Siegel, D.S., Waldman, D. and A. Link (2003), Assessing the Impact of Organizational Practices on the Relative Productivity of University Technology Transfer Offices: An Exploratory Study, *Research Policy* **32**, 27-48.

Siegel, D.S., Waldman, D.A., Atwater, L.E. and A.N. Link (2004), Toward a Model of the Effective Transfer of Scientific Knowledge from Academicians to Practitioners: Qualitative Evidence from the Commercialization of University Technologies, *Journal of Engineering and Technology Management* **21(1-2)**, 115-142.

Silverman, B.S. and J.A.C. Baum (2002), Alliance-based competitive dynamics in the Canadian biotechnology Industry, *Academy of Management Journal* **45(4)**, 791–806

Song, J., Almeida, P. and G. Wu (2003), Learning-by-Hiring: When Is Mobility More Likely to Facilitate Interfirm Knowledge Transfer? *Management Science* **49(4)**, 351-365.

Stephan, P.E., Gurmu, S., Sumell, A.J. and G. Black (2006), Who’s Patenting in the University?, *Economics of Innovation and New Technology* **16(2)**, 71-99.

Stolpe, M. (2002), Determinants of knowledge diffusion as evidenced in patent data: the case of liquid crystal display technology, *Research Policy* **31(7)**, 1181-1198.

Stuart, T.E. (1998), Network positions and propensities to collaborate: An investigation of strategic alliance formation in a high-technology industry, *Administrative Science Quarterly* **43(3)**, 668-698.

Stuart T.E. (2000), Interorganizational alliances and the performance of firms: a study of growth and innovation rates in a high-technology industry, *Strategic Management Journal* **21(8)**, 791–811.

Swan, G.M.P., Prevezer, M. and D. K. Stout (Eds.) (1998), *The Dynamics of Industrial Clustering*, Oxford University Press, Oxford.

Teece, D.J., Pisano, G. and A. Shuen (1997), Dynamic capabilities and strategic management, *Strategic Management Journal* **18(7)**, 509-533.

Thompson, P. (2006), Patent Citations and the Geography of Knowledge Spillovers: Evidence from Inventor- and Examiner-added Citations, *The Review of Economics and Statistics* **88(2)**, 383-388.

Thompson, P. and M. Fox-Kean (2005), Patent Citations and the Geography of Knowledge Spillovers: A Reassessment, *The American Economic Review* **95(1)**, 450-460.

Thorn, K. and L.B. Holm-Nielsen (2006), International Mobility of Researchers and Scientists: Policy Options for Turning a Drain into a Gain, *UNU World Institute for Development Economics Research (UNU-WIDER) Research paper series* **2006/83**.

Thorsteinsdottir, O. (2000), External Research Collaboration in Two Small Science Systems, *Scientometrics* **49**, 145-160.

Thursby, J. and M. Thursby (2000), Industry perspectives on licensing university technologies: sources and problems, *Journal of the Association of University Technology Managers* **12**, 9-22.

Thursby, J.G. and M.C. Thursby (2002), Who Is Selling the Ivory Tower? Sources of Growth in University Licensing*, Management Science* **48**, 90-104.

Thursby, J.G. and S. Kemp (2002), Growth and Productive Efficiency of University Intellectual Property Licensing, *Research Policy* **31**, 109-124.

Thursby, J.G. and M.C. Thursby (2003), University licensing and the Bayh-Dole Act, Science 301(5636), 1052.

Thursby, J.G., Fuller, A. and M.C. Thursby (2007), US Faculty Patenting: Inside and Outside the University, *Research Policy* **38**, 14-25.

Tödtling, F., Lehner, P. and A. Kaufmann (2009), Do different types of innovation rely on specific kinds of knowledge interactions? *Technovation* **29(1)**, 59-71.

Trajtenberg, M., Henderson, R. and A.B. Jaffe (1992), Ivory tower versus corporate lab: An empirical study of basic research and appropriability, *NBER Research Paper* **4146**, National Bureau of Economic Research.

Tsai, W. (2001), Knowledge transfer in intra-organizational networks: Effects of network position and absorptive capacity on business unit innovation and performance, *Academy of Management Journal* **44**, 996-1004.

Tsai, W. and S. Ghoshal (1998), Social capital and value creation: The role of intrafirm networks, *Academy of Management Journal* **41(4)**, 464-476.

Utterback, J. M. (1994), *Mastering the Dynamics of Innovation*, Harvard Business School Press, Cambridge, MA.

Uzzi, B. (1997), Social structure and competition in interfirm networks: the paradox of embeddedness, *Administrative Science Quarterly* **42**, 35-67.

Van Aken, J.E. and M.P. Weggeman (2000), Managing learning in informal innovation networks: overcoming the Daphne-dilemma, *R&D Management* **30(2)**, 139-150.

Van der Wende, M. (2009), European responses to global competitiveness in higher education, *Center for Studies in Higher Education Research and Occasional Papers Series* **7**.

Van Looy, B., Landoni, P. Callaert, J. van Pottelsberghe, B., Sapsalis, E. and K. Debackere (2011) Entrepreneurial effectiveness of European universities: An empirical assessment of antecedents and trade-offs, Research Policy 40(4), 553-564.

Van Rijnsoever, F.J., Hessels, L.K. and R.L.J. Vandeberg (2008), A Resource-Based View on the Interactions of University Researchers, *Research Policy* **37**, 1255-1266.

Van Zeebroeck, N. and B. van Pottelsberghe (2011), Filing strategies and patent value, *Economics of Innovation and New Technology* **20(6)**, forthcoming.

Van Zeebroeck, N., van Pottelsberghe de la Potterie, B. and W. Han (2006), Issues in measuring the degree of technological specialisation with patent data, *Scientometrics* **66(3)**, 481-492.

Von Hippel, E. (1987), Cooperation between rivals: Informal know-how trading, *Research Policy* **16(6)**, 291-302.

Von Hippel, E. (1994), "Sticky information" and the locus of problem solving: Implications for innovation, *Management Science* **40(4)**, 429-439.

Wernerfelt, B. (1984), A resource-based view of the firm, *Strategic Management Journal* **5**, 171-180.

Willison, D.J. and S.M. MacLeod (2002), Patenting of genetic material: Are the benefits to society being realized?, *Canadian Medical Association Journal* **167(3)**, 259-262.

Winter, S. (1987), Knowledge and competence as strategic assets. In: Teece, D. (Ed.), *The Competitive Challenge — Strategies for Industrial Innovation and Renewall*, Ballinger, Cambridge, 159-183.

Zaheer A. and G.G. Bell (2005), Benefiting from network position: firm capabilities, structural holes and performance, *Strategic Management Journal* **26(9)**, 809-825.

Zucker L.G., Darby, M.R. and J. Armstrong (1994), Intellectual Capital and the Firm: The Technology of Geographically Localized Knowledge, *NBER Research Paper* **4653**, National Bureau of Economic Research.

Zucker, L.G. and M.R. Darby (1996), Star Scientists and Institutional Transformation: Patterns of Invention and Innovation in the Formation of the Biotechnology Industry, *Proceedings of the National Academy of Sciences* **93**, 12709-12716.

Zucker, L.G. and M.R. Darby (1998), Intellectual Human Capital and the Birth of U.S. Biotechnology Enterprises, *American Economic Review* **88(1)**, 290-306.

Zucker, L.G., Darby, M.R. and J.S. Armstrong (2002), Commercializing Knowledge: University Science, Knowledge Capture, and Firm Performance in Biotechnology, *Management Science* **48**, 138-153.

# 11 Appendix

**Table A1: Correlations (Chapter 4)**

| | 1. | 2. | 3. | 4. | 5. | 6. | 7. | 8. | 9. | 10. | 11. |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **1. Gender** | 1.000 | | | | | | | | | | |
| **2. Tenure** | 0.167 | 1.000 | | | | | | | | | |
| **3. Percent time spent on grants-related research** | -0.021 | -0.237 | 1.000 | | | | | | | | |
| **4. Age (in logs)** | 0.121 | 0.479 | -0.171 | 1.000 | | | | | | | |
| **5. Life sciences** | -0.116 | -0.080 | 0.075 | 0.034 | 1.000 | | | | | | |
| **6. Other natural sciences** | 0.106 | 0.009 | -0.027 | -0.022 | -0.424 | 1.000 | | | | | |
| **7. Engineering sciences** | 0.121 | 0.120 | 0.090 | 0.002 | -0.310 | -0.339 | 1.000 | | | | |
| **8. Research group leader** | 0.092 | 0.239 | -0.016 | 0.152 | 0.073 | -0.052 | 0.015 | 1.000 | | | |
| **9. No of publications (in logs)** | 0.131 | 0.039 | 0.020 | 0.057 | 0.238 | 0.175 | -0.245 | 0.294 | 1.000 | | |
| **10. No of patent applications (in logs)** | 0.097 | 0.081 | 0.064 | 0.067 | 0.072 | -0.048 | 0.221 | 0.147 | 0.128 | 1.000 | |
| **11. Size of the peer group at the scientist's institution (in logs)** | 0.121 | -0.034 | 0.120 | -0.091 | 0.074 | 0.089 | 0.047 | 0.030 | 0.078 | 0.155 | 1.000 |
| Variance inflation factor (mean=1.42) | 1.11 | 1.45 | 1.11 | 1.34 | 2.00 | 1.99 | 1.85 | 1.19 | 1.34 | 1.15 | 1.10 |

Sample restricted to scientists with non-missing values for at least one informal technology transfer channel.

**Table A2: Correlations - first stage of the selection model (Chapter 5)**

| | 1. | 2. | 3. | 4. | 5. | 6. | 7. | 8. | 9. | 10. | 11. | 12. | 13. | 14. | 15. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. Availability of funding (d) | 1.00 | | | | | | | | | | | | | | |
| 2. Relative importance of scientists abroad (d) | 0.02 | 1.00 | | | | | | | | | | | | | |
| 3. Career age (years) | 0.03 | -0.14 | 1.00 | | | | | | | | | | | | |
| 4. Gender (d) | -0.04 | 0.02 | -0.22 | 1.00 | | | | | | | | | | | |
| 5. Employed at university (d) | 0.03 | -0.03 | 0.08 | -0.04 | 1.00 | | | | | | | | | | |
| 6. Employed at Fraunhofer institute (d) | 0.01 | -0.10 | -0.03 | -0.09 | -0.17 | 1.00 | | | | | | | | | |
| 7. Employed at Max Planck institute (d) | 0.02 | 0.11 | -0.08 | 0.02 | -0.29 | -0.11 | 1.00 | | | | | | | | |
| 8. Employed at Helmholtz institute (d) | -0.03 | 0.03 | -0.04 | 0.07 | -0.44 | -0.15 | -0.22 | 1.00 | | | | | | | |
| 9. Patent application (d) | -0.01 | -0.12 | 0.16 | -0.12 | -0.07 | 0.21 | -0.10 | 0.02 | 1.00 | | | | | | |
| 10. Number of publications 0-3 (d) | -0.02 | -0.05 | -0.10 | 0.05 | -0.13 | 0.13 | -0.04 | 0.05 | -0.03 | 1.00 | | | | | |
| 11. Number of publications 4-6 (d) | -0.05 | 0.02 | -0.11 | 0.05 | -0.07 | 0.04 | -0.03 | 0.08 | -0.03 | -0.34 | 1.00 | | | | |
| 12. Environmental sciences (d) | 0.03 | -0.07 | 0.03 | 0.03 | -0.06 | -0.08 | -0.10 | -0.01 | -0.13 | -0.01 | 0.05 | 1.00 | | | |

| | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 13. Biology, chemistry, pharmacy (d) | -0.04 | 0.06 | -0.11 | 0.10 | -0.08 | -0.06 | 0.11 | -0.02 | 0.12 | -0.07 | -0.02 | -0.26 | 1.00 | | |
| 14. Engineering sciences (d) | 0.02 | 0.01 | 0.06 | -0.08 | -0.04 | 0.06 | 0.09 | 0.08 | -0.15 | 0.01 | 0.00 | -0.28 | -0.43 | 1.00 | |
| 15. Medicine, psychology (d) | -0.03 | -0.06 | 0.04 | -0.13 | 0.03 | 0.17 | -0.12 | 0.04 | 0.24 | 0.11 | 0.05 | -0.15 | -0.24 | -0.25 | 1.00 |
| Variance inflation factor (VIF) | 1.01 | 1.06 | 1.15 | 1.10 | 1.95 | 1.36 | 1.57 | 1.81 | 1.23 | 1.26 | 1.22 | 1.85 | 2.33 | 2.41 | 1.83 |
| Condition number | 12.56 | | | | | | | | | | | | | | |

**Table A3: Correlations - second stage of the selection model (Chapter 5)**

| | 1. | 2. | 3. | 4. | 5. | 6. | 7. | 8. | 9. | 10. | 11. | 12. | 13. | 14. | 15 | 16. | 17. | 18. | 19. | 20. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. Medium-term stay (d) | 1.00 | | | | | | | | | | | | | | | | | | | |
| 2. Long-term stay (d) | -0.18 | 1.00 | | | | | | | | | | | | | | | | | | |
| 3. Stay of indeterminate length (d) | -0.22 | -0.25 | 1.00 | | | | | | | | | | | | | | | | | |
| 4. International orientation (ratio) | -0.04 | -0.15 | 0.11 | 1.00 | | | | | | | | | | | | | | | | |
| 5. Grant received (d) | 0.05 | 0.00 | -0.16 | 0.09 | 1.00 | | | | | | | | | | | | | | | |
| 6. Host country in Western Europe (d) | 0.07 | -0.02 | -0.03 | 0.08 | -0.02 | 1.00 | | | | | | | | | | | | | | |
| 7. Host country in North America (d) | 0.00 | 0.08 | 0.15 | -0.08 | -0.04 | -0.71 | 1.00 | | | | | | | | | | | | | |
| 8. Career age (years) | 0.08 | -0.13 | -0.46 | -0.30 | 0.02 | -0.04 | -0.14 | 1.00 | | | | | | | | | | | | |
| 9. Gender (d) | -0.06 | 0.02 | 0.15 | 0.09 | -0.12 | 0.03 | 0.04 | -0.25 | 1.00 | | | | | | | | | | | |
| 10. Employed at university (d) | -0.01 | -0.11 | 0.22 | 0.02 | -0.04 | -0.09 | 0.13 | -0.05 | 0.01 | 1.00 | | | | | | | | | | |
| 11. Employed at Fraunhofer institute (d) | -0.01 | -0.08 | -0.08 | 0.06 | 0.01 | 0.06 | -0.05 | 0.05 | -0.04 | -0.11 | 1.00 | | | | | | | | | |
| 12. Employed at Max Planck institute (d) | -0.03 | 0.21 | -0.15 | 0.03 | -0.06 | 0.00 | 0.01 | 0.01 | 0.00 | -0.37 | -0.07 | 1.00 | | | | | | | | |
| 13. Employed at Helmholtz institute (d) | 0.08 | 0.02 | -0.21 | -0.04 | 0.02 | 0.01 | -0.01 | 0.12 | 0.01 | -0.39 | -0.08 | -0.18 | 1.00 | | | | | | | |

| | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 14. Patent application (d) | 0.00 | 0.01 | -0.07 | -0.13 | -0.02 | -0.08 | 0.08 | 0.15 | -0.12 | -0.03 | 0.18 | -0.07 | 0.00 | 1.00 | | | | | | |
| 15. No. of publications 0-3 (d) | -0.06 | 0.04 | 0.10 | -0.02 | 0.00 | 0.07 | 0.00 | -0.16 | 0.13 | -0.07 | 0.03 | -0.02 | 0.00 | -0.03 | 1.00 | | | | | |
| 16. No. of publications 4-6 (d) | 0.02 | -0.04 | 0.06 | 0.02 | 0.04 | -0.02 | 0.02 | -0.08 | 0.05 | -0.03 | 0.03 | -0.06 | 0.09 | -0.02 | -0.24 | 1.00 | | | | |
| 17. Environmental sciences (d) | -0.05 | -0.02 | -0.06 | 0.10 | 0.05 | 0.03 | -0.21 | 0.03 | 0.00 | -0.01 | -0.04 | -0.11 | -0.01 | -0.12 | -0.02 | 0.02 | 1.00 | | | |
| 18. Biology, chemistry, pharmacy (d) | -0.07 | 0.18 | 0.06 | -0.04 | 0.01 | -0.02 | 0.07 | -0.13 | 0.08 | -0.02 | -0.08 | 0.08 | -0.10 | 0.11 | -0.03 | -0.03 | -0.27 | 1.00 | | |
| 19. Engineering sciences (d) | 0.03 | -0.13 | -0.04 | 0.03 | -0.04 | 0.05 | 0.01 | 0.11 | -0.08 | -0.10 | 0.04 | 0.15 | 0.13 | -0.16 | 0.00 | 0.01 | -0.30 | -0.51 | 1.00 | |
| 20. Medicine, psychology (d) | 0.09 | -0.06 | -0.13 | -0.04 | 0.00 | 0.00 | -0.04 | 0.09 | -0.09 | -0.01 | 0.12 | -0.11 | 0.13 | 0.21 | 0.04 | 0.04 | -0.11 | -0.18 | -0.20 | 1.00 |
| Variance inflation factor (VIF) | 1.19 | 1.44 | 1.84 | 1.24 | 1.08 | 2.26 | 2.46 | 1,75 | 1.13 | 1.73 | 1.17 | 1.60 | 1.60 | 1.18 | 1.16 | 1.12 | 2.11 | 2.65 | 2.94 | 1.63 |
| Condition number | 18.73 | | | | | | | | | | | | | | | | | | | |

**Table A4: Percentiles of the citation lag distribution (Chapter 6)**

| Percentiles of the citation lag distribution for the whole sample (15100 observations) | | Percentiles of the citation lag distribution after excluding observations with a citation lag of more than 9 years (13796 observations) | |
|---|---|---|---|
| 1% | 0 | 1% | 0 |
| 5% | 0 | 5% | 0 |
| 10% | 1 | 10% | 1 |
| 25% | 2 | 25% | 2 |
| 50% | 3 | 50% | 3 |
| 75% | 6 | 75% | 5 |
| 90% | 9 | 90% | 7 |
| 95% | 12 | 95% | 8 |
| 99% | 16 | 99% | 9 |

**Table A5: Distribution of the country of residence of the patent assignees incl. control patent pairs (Chapter 6)**

| Country of residence of the applicant of the cited patent | Frequency | Country of residence of the applicant of the citing patent | Frequency |
|---|---|---|---|
| US | 11552 | US | 11268 |
| JP | 5623 | JP | 5724 |
| DE | 3103 | DE | 3376 |
| GB | 1731 | CH | 1256 |
| CH | 1193 | IT | 444 |
| FR | 827 | BE | 418 |
| NL | 793 | DK | 270 |
| DK | 456 | AU | 228 |
| SE | 403 | CA | 190 |
| IT | 338 | AT | 186 |
| BE | 315 | SE | 168 |
| CA | 223 | IL | 156 |
| AU | 191 | FR | 115 |
| AT | 170 | GB | 111 |
| IL | 146 | KR | 108 |
| FI | 120 | FI | 66 |
| AN | 84 | ES | 64 |
| HU | 56 | CU | 42 |
| ES | 53 | AN | 38 |
| NO | 34 | TW | 38 |
| KR | 32 | CN | 24 |
| BB | 20 | HU | 18 |
| IE | 20 | IE | 14 |
| LI | 18 | SG | 14 |
| ZA | 13 | ZA | 12 |
| PA | 12 | NL | 11 |
| BR | 9 | BB | 10 |
| BG | 7 | BM | 8 |
| LU | 7 | LI | 8 |

| | | | |
|---|---|---|---|
| BM | 6 | LU | 8 |
| TW | 5 | PA | 8 |
| CS | 4 | BR | 6 |
| HR | 4 | HR | 6 |
| PL | 4 | IN | 6 |
| DD | 3 | NO | 6 |
| NZ | 3 | NZ | 6 |
| CN | 2 | BG | 4 |
| VG | 2 | CS | 4 |
| BS | 1 | SU | 4 |
| IS | 1 | TC | 4 |
| MY | 1 | UY | 4 |
| PT | 1 | VE | 4 |
| SG | 1 | VG | 4 |
| SI | 1 | GR | 2 |
| SU | 1 | HK | 2 |
| TC | 1 | LT | 2 |
| UY | 1 | SI | 2 |
| YU | 1 | SM | 2 |
| Total | 27592 | Total | 27592 |

**Table A6: Descriptive statistics for the control patent pairs (13796 observations) and the cited and citing patent pairs (13796 observations) (Chapter 6)**

| | Control patent pairs | | | | Observed citing and cited patent pairs | | | |
|---|---|---|---|---|---|---|---|---|
| | Mean | Std. Dev. | Min | Max | Mean | Std. Dev. | Min | Max |
| *INDSCI* | 0 | 0 | 0 | 0 | 0,107 | 0,309 | 0 | 1 |
| *INDIND* | 0 | 0 | 0 | 0 | 0,909 | 0,288 | 0 | 1 |
| *COMMON_CITED* | 0,018 | 0,135 | 0 | 1 | 0,010 | 0,099 | 0 | 1 |
| *TECHCL* | 0,251 | 0,434 | 0 | 1 | 0,575 | 0,494 | 0 | 1 |
| *INTGINI* | 0,132 | 0,245 | 0 | 2,443 | 0,110 | 0,225 | 0 | 1,644 |
| *CULCL* | 0,228 | 0,420 | 0 | 1 | 0,343 | 0,475 | 0 | 1 |
| *ECVALUE* | 2,981 | 2,061 | 1 | 12 | 4,682 | 6,121 | 1 | 64 |
| *NOPATS_CITED* | 57,566 | 92,432 | 1 | 622 | 80,299 | 107,311 | 1 | 615 |
| *NOPATS_CITING* | 59,678 | 89,859 | 2 | 582 | 59,678 | 89,859 | 2 | 582 |
| *YEAR_DIFF* | 3,368 | 2,302 | 0 | 9 | 3,368 | 2,302 | 0 | 9 |
| *DE_CITED* | 0,124 | 0,329 | 0 | 1 | 0,101 | 0,302 | 0 | 1 |
| *US_CITED* | 0,409 | 0,492 | 0 | 1 | 0,428 | 0,495 | 0 | 1 |
| *JP_CITED* | 0,189 | 0,392 | 0 | 1 | 0,219 | 0,413 | 0 | 1 |
| *CH_CITED* | 0,032 | 0,176 | 0 | 1 | 0,055 | 0,227 | 0 | 1 |
| *FR_CITED* | 0,034 | 0,181 | 0 | 1 | 0,026 | 0,159 | 0 | 1 |
| *GB_CITED* | 0,067 | 0,250 | 0 | 1 | 0,058 | 0,234 | 0 | 1 |
| *NL_CITED* | 0,022 | 0,145 | 0 | 1 | 0,036 | 0,186 | 0 | 1 |
| *DE_CITING* | 0,122 | 0,328 | 0 | 1 | 0,122 | 0,328 | 0 | 1 |
| *US_CITING* | 0,408 | 0,492 | 0 | 1 | 0,408 | 0,492 | 0 | 1 |
| *JP_CITING* | 0,207 | 0,405 | 0 | 1 | 0,207 | 0,405 | 0 | 1 |
| *CH_CITING* | 0,046 | 0,208 | 0 | 1 | 0,046 | 0,208 | 0 | 1 |
| *FR_CITING* | 0,042 | 0,200 | 0 | 1 | 0,042 | 0,200 | 0 | 1 |
| *GB_CITING* | 0,040 | 0,197 | 0 | 1 | 0,040 | 0,197 | 0 | 1 |
| *NL_CITING* | 0,040 | 0,196 | 0 | 1 | 0,040 | 0,196 | 0 | 1 |

## Table A7: Correlations (Chapter 6)

| | *TECHCL* | *INTGINI* | *CULCL* | *ECVALUE* | *ECVALUESQ* | *NOPATS_CITED* | *NOPATS_CITING* | *COMMON_CITED* | *YEAR_DIFF* | *YEAR_DIFFSQ* | *DE_CITED* | *US_CITED* | *JP_CITED* | *CH_CITED* | *FR_CITED* | *GB_CITED* | *NL_CITED* | *DE_CITING* | *US_CITING* | *JP_CITING* | *CH_CITING* | *FR_CITING* | *GB_CITING* | *NL_CITING* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *TECHCL* | 1 | | | | | | | | | | | | | | | | | | | | | | | |
| *INTGINI* | -0,130 | 1 | | | | | | | | | | | | | | | | | | | | | | |
| *CULCL* | 0,046 | 0,001 | 1 | | | | | | | | | | | | | | | | | | | | | |
| *ECVALUE* | 0,116 | 0,281 | 0,052 | 1 | | | | | | | | | | | | | | | | | | | | |
| *ECVALUESQ* | 0,071 | 0,146 | 0,052 | 0,838 | 1 | | | | | | | | | | | | | | | | | | | |
| *NOPATS_CITED* | 0,037 | -0,036 | 0,038 | 0,072 | 0,052 | 1 | | | | | | | | | | | | | | | | | | |
| *NOPATS_CITING* | 0,019 | -0,041 | 0,003 | 0,025 | 0,068 | 0,070 | 1 | | | | | | | | | | | | | | | | | |
| *COMMON_CITED* | -0,024 | -0,015 | -0,007 | -0,020 | -0,011 | -0,041 | -0,007 | 1 | | | | | | | | | | | | | | | | |
| *YEAR_DIFF* | -0,040 | -0,018 | -0,039 | -0,052 | -0,054 | -0,016 | 0,072 | -0,015 | 1 | | | | | | | | | | | | | | | |
| *YEAR_DIFFSQ* | -0,035 | -0,020 | -0,032 | -0,048 | -0,041 | -0,013 | 0,070 | -0,015 | 0,955 | 1 | | | | | | | | | | | | | | |
| *DE_CITED* | -0,033 | -0,006 | -0,091 | -0,064 | -0,039 | 0,205 | 0,012 | 0,042 | 0,036 | 0,034 | 1 | | | | | | | | | | | | | |
| *US_CITED* | 0,060 | 0,022 | 0,310 | 0,110 | 0,080 | 0,073 | 0,012 | -0,019 | -0,026 | -0,023 | -0,302 | 1 | | | | | | | | | | | | |
| *JP_CITED* | -0,047 | -0,037 | 0,019 | -0,070 | -0,045 | -0,083 | 0,002 | -0,014 | -0,006 | -0,010 | -0,180 | -0,429 | 1 | | | | | | | | | | | |
| *CH_CITED* | 0,024 | -0,004 | -0,106 | 0,087 | 0,048 | 0,133 | 0,002 | -0,017 | -0,001 | 0,001 | -0,076 | -0,180 | -0,108 | 1 | | | | | | | | | | |
| *FR_CITED* | -0,008 | -0,004 | -0,072 | -0,044 | -0,021 | -0,101 | -0,007 | 0,044 | 0,011 | 0,010 | -0,063 | -0,149 | -0,089 | -0,037 | 1 | | | | | | | | | |
| *GB_CITED* | -0,005 | -0,001 | -0,132 | -0,017 | -0,021 | -0,093 | -0,005 | -0,020 | -0,009 | -0,010 | -0,092 | -0,220 | -0,131 | -0,055 | -0,046 | 1 | | | | | | | | |
| *NL_CITED* | 0,011 | -0,006 | -0,070 | -0,026 | -0,018 | -0,047 | -0,025 | -0,010 | 0,011 | 0,009 | -0,061 | -0,146 | -0,087 | -0,037 | -0,030 | -0,045 | 1 | | | | | | | |
| *DE_CITING* | 0,018 | -0,018 | -0,106 | -0,031 | -0,022 | 0,035 | 0,282 | -0,006 | 0,044 | 0,035 | 0,053 | -0,025 | -0,004 | -0,005 | -0,001 | -0,005 | -0,008 | 1 | | | | | | |
| *US_CITING* | 0,001 | 0,035 | 0,324 | 0,065 | 0,045 | -0,004 | -0,010 | 0,007 | -0,060 | -0,051 | -0,018 | 0,074 | -0,060 | 0,007 | -0,026 | 0,009 | -0,017 | -0,310 | 1 | | | | | |
| *JP_CITING* | -0,034 | -0,044 | 0,014 | -0,046 | -0,028 | -0,004 | -0,113 | -0,009 | 0,040 | 0,043 | -0,004 | -0,053 | 0,119 | -0,023 | -0,004 | -0,016 | -0,022 | -0,191 | -0,425 | 1 | | | | |
| *CH_CITING* | -0,003 | 0,002 | -0,110 | 0,007 | -0,005 | 0,002 | 0,200 | 0,005 | -0,015 | -0,011 | -0,007 | -0,005 | -0,010 | 0,016 | 0,009 | -0,005 | 0,011 | -0,082 | -0,181 | -0,112 | 1 | | | |
| *FR_CITING* | 0,023 | 0,001 | -0,098 | 0,002 | -0,005 | -0,001 | -0,085 | 0,003 | 0,022 | 0,012 | 0,000 | -0,002 | -0,017 | -0,001 | 0,053 | -0,007 | 0,014 | -0,078 | -0,173 | -0,107 | -0,046 | 1 | | |
| *GB_CITING* | 0,010 | 0,025 | -0,090 | 0,033 | 0,029 | -0,004 | -0,070 | 0,004 | -0,037 | -0,031 | -0,010 | 0,016 | -0,017 | -0,001 | -0,007 | 0,021 | -0,001 | -0,076 | -0,170 | -0,105 | -0,045 | -0,043 | 1 | |
| *NL_CITING* | 0,000 | -0,001 | -0,096 | -0,015 | -0,012 | -0,018 | -0,024 | 0,002 | -0,003 | -0,007 | -0,003 | -0,019 | -0,022 | 0,010 | 0,004 | 0,011 | 0,055 | -0,076 | -0,169 | -0,104 | -0,045 | -0,043 | -0,042 | 1 |

**Table A8: T-Tests and test of proportions of dependent variables (Chapter 6)**

| Variable | Difference between INDIND and INDSCI | |
|---|---|---|
| *TECHCL*[b] | 0.092 | *** |
| *CULCL*[b] | 0.042 | *** |
| *INTGINI*[a] | -0.026 | *** |
| *COMMON_CITED*[b] | -0.019 | *** |
| *ECVALUE*[a] | 0.133 | |
| *ECVALUESQ*[a] | 31.135 | |
| *NOPATS_CITED*[a] | -5.377 | * |
| *NOPATS_CITING*[a] | 44.281 | *** |
| *YEAR_DIFF*[a] | 0.053 | |
| *YEAR_DIFFSQ*[a] | 0.473 | |
| *DE_CITED*[b] | 0.013 | |
| *US_CITED*[b] | -0.021 | |
| *JP_CITED*[b] | 0.032 | *** |
| *CH_CITED*[b] | -0.023 | *** |
| *FR_CITED*[b] | 0.001 | |
| *GB_CITED*[b] | 0.005 | |
| *NL_CITED*[b] | -0.001 | |
| *DE_CITING*[b] | 0.023 | * |
| *US_CITING*[b] | -0.101 | *** |
| *JP_CITING*[b] | 0.107 | *** |
| *CH_CITING*[b] | 0.040 | *** |
| *FR_CITING*[b] | -0.045 | *** |
| *GB_CITING*[b] | 0.011 | ** |
| *NL_CITING*[b] | 0.002 | |

[a] t-test on the means, [b] test of proportions

**Table A 9: Estimation results for selecting cited patents from 1978-2002 (10% percentile of citation lag distribution) (Chapter 6)**

| | Industry to science (INDSCI) | | | Industry to industry (INDIND) | | |
|---|---|---|---|---|---|---|
| | Coef. | Std.Err. | | Coef. | Std.Err. | |
| *TECHCL* | -0,157 | 0,041 | *** | 0,551 | 0,034 | *** |
| *INTGINI* | 0,059 | 0,077 | | -0,522 | 0,059 | *** |
| *CULCL* | -0,074 | 0,048 | | 0,309 | 0,040 | *** |
| *ECVALUE* | 0,021 | 0,010 | ** | 0,031 | 0,009 | *** |
| *ECVALUESQ* | 0,000 | 0,000 | ** | 0,000 | 0,000 | |
| *NOPATS_CITED* | 0,000 | 0,000 | | 0,001 | 0,000 | *** |
| *NOPATS_CITING* | -0,006 | 0,000 | *** | 0,002 | 0,000 | *** |
| *COMMON_CITED* | 0,722 | 0,123 | *** | -0,573 | 0,105 | *** |
| *YEAR_DIFF* | 0,010 | 0,029 | | 0,007 | 0,023 | |
| *YEAR_DIFFSQ* | -0,002 | 0,003 | | 0,003 | 0,003 | |
| *DE_CITED* | -0,066 | 0,094 | | -0,174 | 0,076 | ** |
| *US_CITED* | 0,112 | 0,081 | | -0,230 | 0,066 | *** |
| *JP_CITED* | -0,011 | 0,078 | | -0,091 | 0,064 | |
| *CH_CITED* | 0,378 | 0,118 | *** | -0,266 | 0,094 | *** |
| *FR_CITED* | -0,192 | 0,128 | | 0,066 | 0,105 | |
| *GB_CITED* | -0,121 | 0,110 | | 0,091 | 0,093 | |
| *NL_CITED* | 0,088 | 0,118 | | 0,005 | 0,099 | |
| *DE_CITING* | 0,155 | 0,083 | * | 0,184 | 0,071 | ** |
| *US_CITING* | 0,179 | 0,064 | *** | -0,115 | 0,056 | ** |
| *JP_CITING* | -0,265 | 0,075 | *** | 0,267 | 0,062 | *** |
| *CH_CITING* | -0,467 | 0,124 | *** | 0,286 | 0,083 | *** |
| *FR_CITING* | 0,317 | 0,108 | *** | -0,035 | 0,101 | |
| *GB_CITING* | -0,198 | 0,106 | * | 0,201 | 0,083 | ** |
| *NL_CITING* | 0,136 | 0,118 | | -0,021 | 0,104 | |
| *CONS* | -0,894 | 0,256 | *** | 0,914 | 0,256 | *** |
| *ATRHO* | -1,268 | 0,036 | *** | | | |
| *RHO* | -0,853 | 0,010 | | | | |

*Wald test of rho=0: chi2(1) = 1245,78 Prob > chi2 = 0,000*

*27574 observations*

**Table A10: Estimation results for selecting cited patents from 1978-1996 (90% percentile of citation lag distribution) (Chapter 6)**

| | Industry to science (INDSCI) | | | Industry to industry (INDIND) | | |
|---|---|---|---|---|---|---|
| | Coef. | Std.Err. | | Coef. | Std.Err. | |
| *TECHCL* | -0,134 | 0,044 | *** | 0,564 | 0,036 | *** |
| *INTGINI* | 0,056 | 0,086 | | -0,537 | 0,061 | *** |
| *CULCL* | -0,079 | 0,053 | | 0,325 | 0,042 | *** |
| *ECVALUE* | -0,004 | 0,014 | | 0,029 | 0,010 | ** |
| *ECVALUESQ* | 0,001 | 0,000 | * | 0,000 | 0,000 | |
| *NOPATS_CITED* | 0,000 | 0,000 | | 0,001 | 0,000 | *** |
| *NOPATS_CITING* | -0,006 | 0,001 | *** | 0,002 | 0,000 | *** |
| *COMMON_CITED* | 0,580 | 0,139 | *** | -0,483 | 0,111 | *** |
| *YEAR_DIFF* | -0,003 | 0,031 | | 0,016 | 0,025 | |
| *YEAR_DIFFSQ* | -0,001 | 0,004 | | 0,002 | 0,003 | |
| *DE_CITED* | -0,072 | 0,100 | | -0,188 | 0,080 | ** |
| *US_CITED* | 0,127 | 0,087 | | -0,240 | 0,069 | *** |
| *JP_CITED* | -0,036 | 0,083 | | -0,106 | 0,067 | |
| *CH_CITED* | 0,390 | 0,121 | *** | -0,278 | 0,096 | *** |
| *FR_CITED* | -0,226 | 0,140 | | 0,059 | 0,111 | |
| *GB_CITED* | -0,087 | 0,116 | | 0,072 | 0,097 | |
| *NL_CITED* | 0,143 | 0,125 | | 0,007 | 0,104 | |
| *DE_CITING* | 0,170 | 0,088 | * | 0,189 | 0,075 | ** |
| *US_CITING* | 0,204 | 0,068 | *** | -0,118 | 0,058 | ** |
| *JP_CITING* | -0,283 | 0,082 | *** | 0,276 | 0,065 | *** |
| *CH_CITING* | -0,473 | 0,135 | *** | 0,284 | 0,087 | *** |
| *FR_CITING* | 0,314 | 0,113 | ** | -0,019 | 0,105 | |
| *GB_CITING* | -0,197 | 0,112 | * | 0,208 | 0,087 | ** |
| *NL_CITING* | 0,146 | 0,125 | | -0,021 | 0,108 | |
| *CONS* | -1,083 | 0,159 | *** | 0,610 | 0,139 | *** |
| *ATRHO* | -1,209 | 0,037 | *** | | | |
| *RHO* | -0,836 | 0,011 | | | | |

*Wald test of rho=0: chi2(1) =1079,71 Prob > chi2 = 0,000*

*25580 observations*

**Table A11: Full matching results (Chapter 7)**

| Variable | | Mean | | P-value of two sided t-test on mean equality |
|---|---|---|---|---|
| | | joint patent applicaton | patent with single ownership | |
| PROPENSITY SCORE | Unmatched | 0,069 | 0,037 | 0,000 |
| | Matched | 0,069 | 0,067 | 0,283 |
| PRIOR | Unmatched | 0,661 | 0,362 | 0,000 |
| | Matched | 0,661 | 0,644 | 0,346 |
| LNMEANANZPAT | Unmatched | 3,613 | 2,974 | 0,000 |
| | Matched | 3,613 | 3,538 | 0,243 |
| NONPATCIT | Unmatched | 2,187 | 1,870 | 0,001 |
| | Matched | 2,187 | 2,014 | 0,259 |
| US | Unmatched | 0,429 | 0,559 | 0,000 |
| | Matched | 0,429 | 0,435 | 0,734 |
| JP | Unmatched | 0,227 | 0,172 | 0,000 |
| | Matched | 0,227 | 0,223 | 0,823 |
| GB | Unmatched | 0,195 | 0,079 | 0,000 |
| | Matched | 0,195 | 0,194 | 0,925 |
| FR | Unmatched | 0,028 | 0,045 | 0,002 |
| | Matched | 0,028 | 0,027 | 0,909 |
| DE | Unmatched | 0,121 | 0,145 | 0,013 |
| | Matched | 0,121 | 0,121 | 0,954 |
| IPC1 | Unmatched | 0,090 | 0,090 | 0,988 |
| | Matched | 0,090 | 0,088 | 0,895 |
| IPC2 | Unmatched | 0,013 | 0,011 | 0,366 |
| | Matched | 0,013 | 0,013 | 1,000 |
| IPC3 | Unmatched | 0,770 | 0,771 | 0,894 |
| | Matched | 0,770 | 0,771 | 0,929 |
| IPC4 | Unmatched | 0,004 | 0,001 | 0,000 |
| | Matched | 0,004 | 0,004 | 1,000 |

| | | | | |
|---|---|---|---|---|
| IPC7 | Unmatched | 0,123 | 0,127 | 0,599 |
| | Matched | 0,123 | 0,123 | 1,000 |
| Year1984 | Unmatched | 0,013 | 0,019 | 0,112 |
| | Matched | 0,013 | 0,013 | 1,000 |
| Year1985 | Unmatched | 0,018 | 0,022 | 0,356 |
| | Matched | 0,018 | 0,018 | 1,000 |
| Year1986 | Unmatched | 0,016 | 0,024 | 0,044 |
| | Matched | 0,016 | 0,016 | 1,000 |
| Year1987 | Unmatched | 0,018 | 0,028 | 0,024 |
| | Matched | 0,018 | 0,018 | 1,000 |
| Year1988 | Unmatched | 0,028 | 0,032 | 0,370 |
| | Matched | 0,028 | 0,028 | 1,000 |
| Year1989 | Unmatched | 0,028 | 0,035 | 0,142 |
| | Matched | 0,028 | 0,028 | 1,000 |
| Year1990 | Unmatched | 0,025 | 0,039 | 0,009 |
| | Matched | 0,025 | 0,025 | 1,000 |
| Year1991 | Unmatched | 0,034 | 0,038 | 0,437 |
| | Matched | 0,034 | 0,034 | 1,000 |
| Year1992 | Unmatched | 0,020 | 0,039 | 0,000 |
| | Matched | 0,020 | 0,020 | 1,000 |
| Year1993 | Unmatched | 0,028 | 0,035 | 0,174 |
| | Matched | 0,028 | 0,028 | 1,000 |
| Year1994 | Unmatched | 0,034 | 0,039 | 0,286 |
| | Matched | 0,034 | 0,034 | 1,000 |
| Year1995 | Unmatched | 0,035 | 0,043 | 0,136 |
| | Matched | 0,035 | 0,035 | 1,000 |
| Year1996 | Unmatched | 0,041 | 0,048 | 0,214 |
| | Matched | 0,041 | 0,040 | 0,924 |
| Year1997 | Unmatched | 0,086 | 0,055 | 0,000 |
| | Matched | 0,086 | 0,086 | 1,000 |

| | | | | |
|---|---|---|---|---|
| Year1998 | Unmatched | 0,118 | 0,069 | 0,000 |
| | Matched | 0,118 | 0,119 | 0,954 |
| Year1999 | Unmatched | 0,063 | 0,082 | 0,012 |
| | Matched | 0,063 | 0,064 | 0,939 |
| Year2000 | Unmatched | 0,083 | 0,089 | 0,501 |
| | Matched | 0,083 | 0,083 | 1,000 |
| Year2001 | Unmatched | 0,114 | 0,095 | 0,021 |
| | Matched | 0,114 | 0,114 | 1,000 |
| Year2002 | Unmatched | 0,116 | 0,089 | 0,001 |
| | Matched | 0,116 | 0,116 | 1,000 |
| Year2003 | Unmatched | 0,082 | 0,080 | 0,831 |
| | Matched | 0,082 | 0,081 | 0,946 |
| CITATIONS | Unmatched | 0,380 | 0,384 | 0,910 |
| | Matched | 0,380 | 0,292 | 0,021 |

# 12 Affidavit in German/Eidesstattliche Erklärung

Ich erkläre hiermit an Eides statt, dass ich die vorliegende Dissertation selbständig angefertigt, nur die angegebenen Quellen und Hilfsmittel benutzt und inhaltlich oder wörtlich übernommene Stellen als solche gekennzeichnet habe.

Ich habe noch keinen weiteren Promotionsversuch unternommen.

Heide Fier

Boston, den 11.09.2012 Heide Gesa Fier