Open Intellectual Property Strategies for Emerging Technologies

An Exploratory, Mixed-Method Investigation of Patent Pledges

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Declaration

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Abstract

Title: Open Intellectual Property Strategies for Emerging Technologies - An Exploratory, Mixed-Method Investigation of Patent Pledges.

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Patent owners increasingly employ strategies called *patent pledges*. This strategy involves the owner offering a broad availability of their active patents for free or at a reasonable fee. Patent pledges span across multiple industries from automotive over information and communication technology to biotechnology. This research investigates patent pledges through an exploratory stance and by utilising a mixed-methods approach.

The existing literature is inconsistent and lacks academic rigour. Most patent pledge studies are conceptual and lack the sufficient evidence to offer authoritative results. The first problem is although there exist several preliminary definitions of patent pledges, none are sufficiently derived from empirical data. A second problem is that that existing literature is inconclusive on the reasons why patent owners employ patent pledges. Previous scholars have predominantly relied on findings from studies of other sharing mechanisms, as well as the broad literature on open innovation and patent law. A third point is that research on the effect of patent pledges on technology diffusion remains unclear, because existing studies have utilised research methods with significant limitations and deliver contradictory results.

This research addressed each problem in three distinct studies. Study 1 focused on the definition and taxonomy of patent pledges and derived its results from 60 patent pledge statements of patent owners. This secondary data was analysed by an abductive approach through multiple coding cycles. The result was a three-dimensional taxonomy of patent pledges. The patent pledge taxonomy was then extended to a patent licensing taxonomy which compromised every common type of patent licensing approach. Study 2 explored the motivation behind patent pledges and utilised case study research with two data sets: primary data from 22 semi-structured interviews and secondary data from 50 patent pledge statements. The study was able to access renowned experts directly involved in designing and executing

patent pledges. Experts included presidents of patent departments from global firms and a former president of a national patent office. Study 3 developed an abstract agent-based model to examine the effects of patent pledges on technology diffusion. The simulation model enabled the investigation of inter-firm technology diffusion of two competing technologies, where only one was subject to a patent pledge. Two cases were considered: in case I both technologies were similar, but in case II the pledged technology was inferior.

Study 1 revealed that

- eight patent pledge types exist;
- the most frequent patent pledge type is subject to certain conditions but can be accessed by the unrestricted public free of charge and that
- the majority of patent pledges occur in the are of information and communication technologies.

Study 2 revealed that

- thirteen patent pledge motives in three categories exist;
- the main goal of patent pledges is to drive technology diffusion and that
- most other motives for patent pledges also relate to the goal of fostering technology diffusion.

Study 3 revealed that

- the relationship between the strength of patent pledges and their effect on technology adoption rates is not linear;
- patent pledges can lead to a market share 'win' of an inferior technology that competes with a superior alternative and that
- the time period in which the adopter category '*Early Majority*' adopts is, in most cases, the crucial phase that determines the success of patent pledges.

The three studies provide a substantial intervention in several ways. The empirical development of a patent pledge definition and two taxonomies facilitate the distinction to other licensing approaches and set a common ground for future research. The taxonomies constitute managerial tools that can be used to visualise patent licensing landscapes for specific units of interest. Insights about motives enable a better understanding of patent pledges and help practitioners as well as policymakers making informed decisions. Finally, the investigation of patent pledge effects on technology diffusion adds to the diffusion literature and supports

(i) firms that need to evaluate whether or not to conduct a patent pledge; (ii) firms that need to react to patent pledges of competitors; and (iii) firms that face the decision whether to adopt a pledged technology.

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Nomenclature

Acronyms / Abbreviations

ABM	*Agent-Based Model*
APPE	*Absolute Patent Pledge Effect*
FRAND	*Fair, Reasonable, And Non-Discriminatory*
ICT	*Information and Communication Technology*
IP	*Intellectual Property*
IPRs	*Intellectual Property Rights*
LOT	*License On Transfer*
NPE	*Non-Practicing Entity*
PPI	*Patent Pledge Introduction*
PR	*Public Relations*
R&D	*Research And Development*
RPPE	*Relative Patent Pledge Effect*
RQ	*Research Question*
SME	*Small And Medium-Sized Enterprises*
SPE	*Standard-Essential Patent*

TAM	*Technology Acceptance Model*
TASC	*Technology Adoption In Supply Chains*
TPB	*Theory Of Planned Behaviour*
WIPO	*World Intellectual Property Organisation*
WoM	*Word Of Mouth*
WTP	*Willingness To Pay*

Chapter 1

Introduction

1.1 Research context

The current intellectual property (IP) system is in a state of transition. IP generally refers to intangible assets created by the human mind (Bogers et al., 2012). With its statutory origins dating back to medieval times, intellectual property rights (IPRs), the legal instruments that protect IP, today pose a complex construct (Bogers et al., 2012). Amidst headlines about so-called *patent wars*, firms apply strategies that allow the broad utilisation of active patents, called *patent pledges* (Shaver, 2012). A prominent example is Tesla Motors, for instance. The firm allows the free use of its active patents in the realm of electric vehicles, a strategy that attracted global interest (Musk, 2014; Rimmer, 2018). Albeit less well-known, similar pledges were carried out by firms such as Google, Microsoft, and Toyota, to name just a few. Patent pledges also play a role in the current response to the Covid-19 coronavirus pandemic, as firms publicly commit to make their patents freely available to address this public health emergency (Contreras et al., 2020). This section first describes common obstacles of modern IPRs and then elaborates upon the rise of novel IP models, specifically patent pledges. The last two paragraphs summarise the research questions and methods, as well as the main contributions of this research.

Modern IPRs, first and foremost patents, are subject to ongoing criticism. Studies argued that the traditional IP system is not appropriate for today's inventions (Pollock, 2018). An aggregated view on the subject shows an impenetrable amount of often overlapping IPRs that prevent follow-up inventions. Already 20 years ago, Heller and Eisenberg (1998) noted the problem of the '*anticommons*' which arises when multiple IPRs from different IP-owners are required to produce or perform an invention (see also Contreras (2018a)). This can pose a barrier to innovation-processes and the subsequent development of new technologies. Even patent owners themselves, after having secured patent rights through an often protracted process, face challenges in profiting from their efforts. The stance of Chesbrough was forthright when he said that '*most patents are worth very little*' (Chesbrough, 2003, p. 40). The oftentimes limited return from patents stays in contrast to the high costs of application, examination and maintenance, particularly when approaching several countries (Cohen et al., 2000). Patents are furthermore not self-enforcing, but misappropriation must be identified and managed by the patent owners themselves (Teece, 2018). Another point is that most patents are not exploited. Alexy et al. (2009) stated that Procter & Gamble as well as Siemens only used 10% of their active patents (see also West and Gallagher (2006)). The mentioned points are only some of the obstacles the current system is facing. The conclusion of many studies is that patents in reality do not work like in theory (Al-Aali and Teece, 2013; Chander and Sunder, 2004; Lemley, 2002; Levin et al., 1987; Teece, 1986).

The strongest evidence that supports the assumption that the current IP system is in a state of transition comes from innovative IP models that emerge in a variety of industries. Scholars noted that when there is no improvement from the governmental side, firms come up with creative solutions themselves (Merges, 2004; Rimmer, 2014). One famous example for an emerging IP model are so-called *patent pools*. While patent pools are not new, the fact that '*individual patents have grown much smaller in relation to product value*' implies that patent pools became more important recently (Hovenkamp and Hovenkamp, 2017, p. 359). Another emerging IP model, which benefits from current flaws in the IP system, is pursued by non-practicing entities (NPEs) , often referred to as *patent trolls* (see for instance Greenbaum (2017)). This research, however, is concerned with a less understood emerging model: So-called *patent pledges*.

In recent years, an increasing number of patent owners made their active patents available, either for free or for a reasonable fee. These patent owners retain the rights on their patents and continue to pay maintenance fees, but they allow a large group of people or the general public to utilise them. Examples include the pledges of Tesla, Ford, and Toyota in the automotive sector and the pledges of Google, Microsoft, and the OpenPOWER foundation by IBM in the area of information and communication technology (ICT) . Tesla, for instance, '*pledges that it will not initiate a lawsuit against any party for infringing a Tesla Patent through activity relating to electric vehicles or related equipment for so long as such party is acting in good faith*' (Tesla, 2014, n.p.). The firm provided some details about the conditions that must be met to '*act in good faith*', one of which being that no patent assertion against Tesla must be conducted. Similarly, Google '*promises to each person or entity that develops,* *distributes or uses Free or Open Source Software (a "Pledge Recipient") that Google will not bring a lawsuit or other legal proceeding against a Pledge Recipient for patent infringement under any Pledged Patents based on the Pledge Recipient's (i) development, manufacture, use, sale, offer for sale, lease, license, exportation, importation or distribution of any Free or Open Source Software...*' (Google, 2020, n.p.). This pledge by Google is very broad in the sense that it addresses every person or entity that uses free or open-source software. In contrast to Tesla's patent pledge, which automatically concerns all of its current and future patents in the area of electric vehicles, Google does not automatically pledge all of its patents. Rather, the firm updates a list of pledged patents on its website. This is only one of several distinctions between patent pledges and might be one reason why many different patent pledge definitions exist, as will be shown in Study 1 of this research. Patent pledges pose a challenge for practitioners and scholars alike, because they contradict the exclusionary function of patents and challenge existing theories. The theory of the interplay between the *revenue effect* and the *profit dissipation effect* described by Arora and Fosfuri (2003), for instance, cannot adequately explain why firms would out-license their IP without demanding any monetary compensation. In short, Arora and Fosfuri argued that firms considering licensing need to balance the additional revenues from licenses against the lower price-cost margin and reduced market share that increased competition involves (see also Fosfuri (2006)). It is not surprising that firms react hesitant and almost pejorative when confronted with patent pledges, particularly in industries with costly research and development (R&D) . One of the interview participants of Study 2 in this research said that his firm did not use any of Tesla's pledged patents because the firm did not know if this was a genuine offer. The firm remained uncertain about the exact conditions, despite their publication on Tesla's website.

This research explores the phenomenon of patent pledges by conducting three distinct studies: Study 1 utilises 60 publicly available patent pledges like the one from Tesla and Google described above to abductively derive a patent pledge definition and two taxonomies, the patent pledge and the patent licensing taxonomy. The taxonomies describe eight patent pledge types and 18 general patent licensing approaches. Study 2 analyses 22 semi-structured interviews with IP experts and 50 patent pledge statements to derive motives for patent pledges. The results from Study 2 show that most motives relate to the effort of driving technology diffusion for the pledged technology, which is why Study 3 focuses on the effects of patent pledges on technology diffusion. Specifically, an abstract agent-based model (ABM) that simulates firms' technology adoption decision processes in different scenarios with two competing technologies, only one of which is subject to a patent pledge, is developed. The simulated patent pledge varies in strength and is introduced at different points in time following the adopter categories of Rogers (1962). This simulation setting allows for the calculation of patent pledge effects and the derivation of practical recommendations.

The studies contribute to knowledge in several areas and address academics as well as practitioners: the patent pledge definition and the two taxonomies from Study 1 allow for the distinction of patent pledges from other patent licensing approaches and lay the groundwork for future research in this area. The patent licensing taxonomy can serve as a practical management tool that facilitates the creation of patent licensing landscapes in specific areas. The motives revealed in Study 2 alleviate uncertainties about these strategies and help practitioners as well as policymakers to make informed decisions. The measured effects of patent pledges on technology diffusion in different scenarios add to the vast technology diffusion literature and support (i) firms deciding whether or not to conduct a patent pledge to drive technology diffusion; (ii) firms that are confronted with patent pledges of competitors; and (iii) firms that face the decision whether to adopt a pledged technology.

Disclaimer

The focus of this research lies on patent pledges and while it is conceivable that its results can be conveyed to other IPRs, this verification does not fall within the scope of this research. Since different IPRs protect different innovative matters, it is conceivable that their 'openness' follows different motivations and has different effects. The results of this research focus on patents and are not necessarily valid for other IPRs.

1.2 Research questions

Patent pledges are a phenomenon that raises many questions. The fact that little is known about these strategies labels this research as *exploratory* (Blaikie and Priest, 2019). This makes it necessary to first gain a thorough understanding about the characteristics of patent pledges and potentially different types. All further investigations are not comparable until a comprehensive definition is given, because each study might have a different understanding of the subject. The importance of such questions, specifically '*What*'-questions, was also emphasised by Blaikie and Priest (2019). The literature review, specifically chapter 2.1, shows that many notions about patent pledges exist and that scholars deviate from each other, particularly regarding the requirement of monetary compensation. To address this inconsistency in the literature and to concur with the guidelines of exploratory research, the first research question (RQ) is:

1. **What is the definition of patent pledges and what different types exist?**

RQ1 enables a better understanding of patent pledges and their delimitation to other patent licensing approaches. It then becomes feasible to look at the reasons for patent owners to conduct them. The investigation of these reasons is only useful as long as the subject matter is clearly defined, which again highlights the importance of RQ1. Chapter 2.2 shows that many studies suggested motives for patent pledges, but they were mostly conceptual and relied on sharing mechanisms other than patent pledges. While Contreras et al. (2019) provided useful insights into the motives to join a specific patent pledge, it is desirable to complement their study with new empirical evidence. Blaikie and Priest (2019) stated that '*Why*'-questions are most suitable to gain an understanding of such kinds of inquiries. The second research question is therefore:

2. **Why do patent owners pledge their patents?**

The results of the second research question show that the main motive for patent owners to pledge their patents is to drive technology diffusion. The logical next step is then to investigate whether patent pledges indeed have a measurable effect on technology diffusion rates. Some studies attempted to investigate this question, but chapter 2.3 shows that they either used research methods with major limitations or they investigated phenomena other than patent pledges. This inquiry is further broken down into two sub-research-questions. The measurement of this effect, or change, asks for '*How*'-questions (Blaikie and Priest, 2019):

3. How do patent pledges affect the diffusion and adoption of technologies?

3.a How do different patent pledge types affect technology diffusion?

3.b How does the timing of patent pledges affect technology diffusion?

It is important to provide some clarification about what is meant by technology diffusion and adoption in the context of this research. There is no general definition for the term *technology*, but it is often referred to as technical knowledge or know-how (Bogers et al., 2012). This research follows the description of Arora et al. (2001, p. 422-423), who summarised technology as *'an imprecise term for useful knowledge rooted in engineering and scientific disciplines, which usually also draws from practical experience from production'*. Similar inconsistencies are also true for the term *innovation*, whose definition depends on the paradigms of the respective discipline (Baregheh et al., 2009). Both terms, *technology* and *innovation*, serve as synonyms in this research, which is often the case in diffusion research (see for instance Hall (2005) and Meyer (2004)). Diffusion is defined as '*as the cumulative or aggregate result of a series of individual calculations that weigh the incremental benefits of adopting a new technology against the costs of change. (...) The resulting diffusion rate is then determined by summing over these individual decisions*' (Hall and Khan, 2003, p. 1). *Adopters* are the smallest unit of analysis and can be individuals or organisations, for instance (Meyer, 2004).

The three sequential research questions follow a standardised and common approach in social research by asking *What-*, *Why-*, and *How-questions* (Blaikie and Priest, 2019). They are treated as separate Studies 1-3 in this research, albeit they frequently refer to each other. For instance, the concept of competing technologies is only briefly introduced in Study 2, because a more comprehensive description is given in Study 3.

1.3 Thesis structure

This research is structured as follows: a narrative literature review follows the introduction and is divided by the three research questions. The literature review provides an overview of existing theories in the respective field. Subsequently, the research approach, including the philosophical stance, the logic of inquiry, and the specific research methodologies, are described. Then, the three research questions, which build upon each other, are addressed in consecutive chapters. The final chapter summarises the main findings, elaborates on theoretical and practical contributions, points towards future research directions, and lays out the limitations of this research. The thesis ends with a brief conclusion, followed by the references and the appendices.

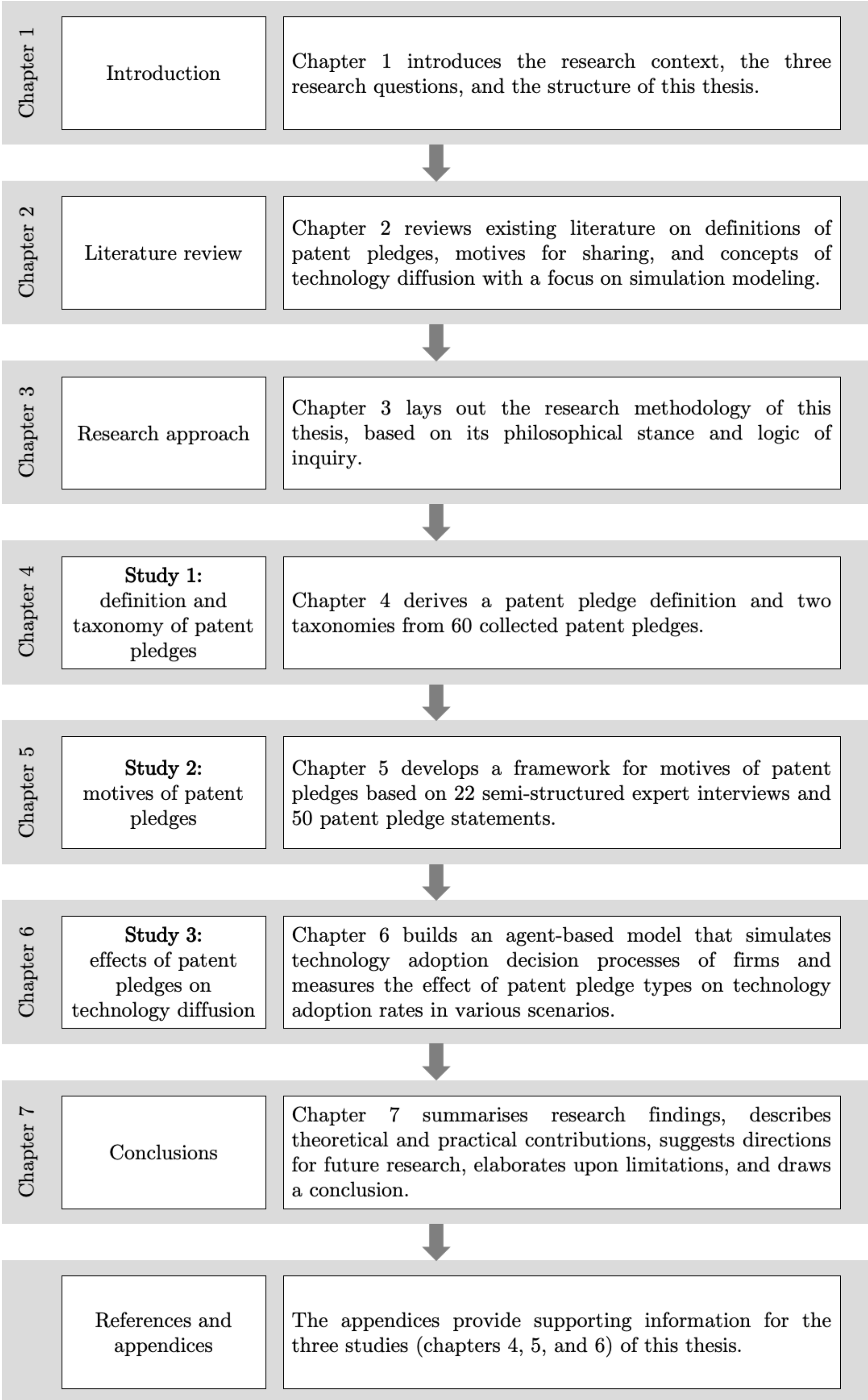


Fig. 1.1 Thesis structure.

Chapter 2

Literature review

This chapter provides a narrative literature review around the topic of patent pledges, separated by and focused on the three research questions. A narrative literature review is suggested to link together studies of different topics and to display their interconnectedness (Baumeister and Leary, 1997). This appears to be the correct choice for this research, because studies from various literature streams including IP strategies, IP licensing, open innovation, technology management, IP law, strategic management and innovation management were researched. As a result of this large number of related topics, a full review cannot be given. Search keywords included patent pledge, open IP, open patent, released patent, royalty-free license, non-assertion, open-source innovation, patent pool, technology diffusion, diffusion simulation, agent-based model, and technology adoption. Studies that relate to the topic of patent pledges are briefly summarised and put in context to each other. Some of the selected studies are particularly relevant and are therefore discussed in greater detail. This review attempts to link together different studies and to evaluate them according to their specific content. The studies are not listed one by one, but follow the argumentation of the review. Therefore, the narrative literature review is complemented with elements of an argumentative strategy (Rowe, 2014).

2.1 Definition and taxonomies of patent pledges

The term patent pledge is used in an inconsistent manner and is often confused with other concepts. In most cases, however, patent pledges involve the simplified access to specific patents. This can range from the promise of a fixed licensing fee, over the prospect for fair, reasonable and non-discriminatory terms (FRAND-terms) to the unconditional and free 'release' of patents.

Openness of IPRs, specifically patents, has experienced greater public interest at the latest since the vast concepts of open innovation and open business models led by Henry Chesbrough. *Openness* is defined as '*...the easing of restrictions on the use, development, and commercialisation of a technology. (...) Closed technologies are wholly owned, proprietary, vertically integrated, and controlled by a single party*' (Boudreau, 2010, p. 1851). Predecessors of patent pledges existed at least since the 1940s (Asay, 2016; Barnett, 2011; Contreras, 2018b), but the study in academic literature began mainly in 2012 (Contreras, 2018b). The increased academic interest partly arose from specific IP disputes, such as the dispute between Microsoft and Google in 2013 (Contreras, 2018b). The following sections summarise existing definitions and taxonomies of patent pledges. The definitions are distinguished between those that do not include monetary compensation to access the respective patents and those that do. These two '*camps*' of definitions pose a problem to the investigation of patent pledges, because they have a different understanding of the subject.

2.1.1 Definitions excluding monetary compensation

Some scholars took the view that only patents that are free, i.e. that can be accessed without any monetary compensation, constitute patent pledges. Ziegler et al. (2014), for instance, understood *patent release approaches*, or *Open IP*, as the donation of or the free access to patents and see them as a result of the increasing appearance of open innovation. They argued that '*...in contrast to classic licensing and cross-licensing agreements, there is no contractual definition of compensation from the receiving end to the original patent holder. Instead, the benefits for the original patent holder are either obtained indirectly through tax benefits in the case of donation, or they are highly uncertain, difficult to quantify, or based on a long-term perspective*' (Ziegler et al., 2014, p. 19). The definition of Ziegler et al. is an exception in the sense that they included patent donations and the resulting tax benefits in their study. It is not entirely clear how the authors arrived at their definition, however. An empirical derivation of the definition is missing. Another critique is that the distinction to other models, particularly patent pools, remains vague.[1] Sundaresan et al. (2017) defined *patent non-assertion* similar to Ziegler et al. (2014). They called it '*...any strategy that allows external inventors and firms the use of technology developed by the focal firm without any financial or cross-licensing*

[1] Shapiro defined patent pools as '*an entire group of patents [which] is licensed in a package, either by one of the patent holders or by a new entity established for this purpose, usually to anyone willing to pay the associated royalties*' (Shapiro, 2000, p. 127). Contreras et al. (2020) pointed out that in contrast to patent pledges, other legal arrangements such as patent pools face more administrative and legal hurdles.

obligation' (Sundaresan et al., 2017, n.p.). An important aspect of their definition is that third parties do not have any financial or cross-licensing obligations to access the patents, which is why Sundaresan et al. labeled it a '*patent non-assertion strategy*'. This condition involves, according to the authors, the patent owner's commitment not to assert her rights against third parties. This concept of non-assertion mirrors related models that do not necessarily involve patents. Raasch et al. (2009), for instance, emphasised the similarity of patent pledges to open-source software and introduced the concept to fields outside of software development. In this context, and by retaining the wording from open-source software, they defined *open-Source Innovation* as '*free revealing of information on a new design with the intention of collaborative development of a single design or a limited number of related designs for market or non-market exploitation*' (Raasch et al., 2009, p. 2). The authors' definition goes beyond patents and comprises all forms of information. This is also the case in the definition provided by Alexy et al. (2013), because the authors referred to '*selective revealing as the voluntary, purposeful, and irrevocable disclosure of specifically selected resources, usually knowledge based, which the firm could have otherwise kept proprietary, so that they become available to a large share or even all of the general public, including competitors*' (Alexy et al., 2013, p. 272). Schultz and Urban (2012), Asay (2016), and Contreras et al. (2019) provided similar definitions but particularly emphasised the legal aspect of patent pledges by focusing on their limited enforcement. Schultz and Urban (2012, p. 30) understood patent pledges as '*promises by patent holders not to enforce their patents under certain conditions*'. As shown in chapter 4, they rightfully included conditions as an important aspect of patent pledges in their definition. Similarly, Asay (2016, p. 261) called patent pledges '*a phenomenon where parties voluntarily commit to limit enforcement of their patent rights*'. Contreras et al. (2019, p. 1) argued that '*...under a pledge model, patent assets are retained by their owners, who continue to incur maintenance and other fees, but the offensive use of such patents is significantly curtailed*' and thereby highlighted the fact that patent pledges usually concern active patents. This, again, is shown to be an important part of the patent pledge definition of Study 1. The following section provides some wider definitions, because they explicitly included monetary compensation in their understanding of patent pledges.

2.1.2 Definitions including monetary compensation

In contrast to the aforementioned definitions of patent pledges, some studies specifically included patents that can be accessed in return for some monetary compensation in their definition. Chander and Sunder (2004, p. 1338) described patent pledges as '*[r]esources for which legal rights to access and use for free (or for nominal sums) are held broadly*' and thereby included the possibility to pay for the access. Contreras (2015, p. 787) followed up on this thought and summarised patent pledges as various promises made by patent owners: '*[t]hese pledges encompass a wide range of technologies and firms: from promises by multinational corporations like IBM and Google not to assert patents against open-source software users; to commitments by developers of industry standards to grant licenses on terms that are fair, reasonable, and non-discriminatory (FRAND)...*'. In a later publication, Contreras argued that '*[p]ledge commitments fall into three general categories: (1) the primary commitment to license patents, either on royalty-free or FRAND terms, or not to assert patents at all...*' Contreras (2017a, p. 12-13). In a similar manner, Valz (2017, p. 37-38) explained: '*[w]hat these pledges have in common is the offering by a patent holder to provide rights under its patents relating to commercially important technology used by a broad array of market participants. Some unilateral pledges offer fair, reasonable and non-discriminatory (FRAND) (i.e., monetary) terms for licensing pledged patents. (...) Others - particularly those involving open source software (OSS) – offer rights under pledged patents for free*'. By including monetary compensation in the definition, patent pledges more clearly resemble a type of licensing approach. As Bogers et al. (2012, p. 57) explained, a license is '*a permission granted by the owner of an IPR (the licensor) to another legal entity (the licensee) to use underlying IP in a particular way and under certain restrictive conditions*'.[2] Table 2.1 summarises exemplary definitions for patent pledges.

[2] Valz (2017) argued that unilateral patent pledges do not constitute licenses. This research focuses on patent pledges from a managerial perspective and leaves the legal distinction to licenses aside. To keep a consistent terminology and to concur with the wording of different patent pledge types described in Study 1, patent pledges are in parts referred to as 'licenses'.

Table 2.1 Exemplary patent pledge definitions.

Definitions	
including monetary compensation	**excluding monetary compensation**
'Resources for which legal rights to access and use for free (or for nominal sums) are held broadly.' (Chander and Sunder, 2004, p. 1338)	*'OSI [Open Source Innovation] is characterised by free revealing of information on a new design with the intention of collaborative development of a single design or a limited number of related designs for market or non-market exploitation.'* [Raasch et al., 2009, p. 2]
'These pledges encompass a wide range of technologies and firms: from promises by multinational corporations like IBM and Google not to assert patents against open-source software users; to commitments by developers of industry standards to grant licenses on terms that are fair, reasonable, and non-discriminatory (FRAND)…' (Contreras, 2015, p. 787)	*'Patent release or give away for free means that in contrast to classic licensing and cross-licensing agreements, there is no contractual definition of compensation from the receiving end to the original patent holder.'* [Ziegler et al., 2014, p. 19]
'Pledge commitments fall into three general categories: (1) the primary commitment to license patents, either on royalty-free or FRAND terms, or not to assert patents at all...' (Contreras, 2017a, p. 12-13)	*'Patent pledges are promises by patent holders not to enforce their patents under certain conditions.'* (Schultz and Urban, 2012, p. 30)
'What these pledges have in common is the offering by a patent holder to provide rights under its patents relating to commercially important technology used by a broad array of market participants. Some unilateral pledges offer fair, reasonable and non-discriminatory (FRAND) (i.e., monetary) terms for licensing pledged patents. (...) Others - particularly those involving open source software (OSS) – offer rights under pledged patents for free.' (Valz, 2017, p. 37-38)	*'…selective revealing as the voluntary, purposeful, and irrevocable disclosure of specifically selected resources, usually knowledge based, which the firm could have otherwise kept proprietary, so that they become available to a large share or even all of the general public, including competitors.'* (Alexy et al., 2013, p. 272)
	'Parties are increasingly engaging in "patent pledging," a phenomenon where parties voluntarily commit to limit enforcement of their patent rights.' (Asay, 2016, p. 261)
	'An open IP strategy is any strategy that allows external inventors and firms the use of technology developed by the focal firm without any financial or cross-licensing obligation.' (Sundaresan et al., 2017, no page number given)

2.1.3 Patent pledge taxonomies

The different definitions for patent pledges described in the previous sections, particularly the dissent regarding the monetary compensation, suggest that the acknowledged concept of patent pledges is diverse and that different types might exist. It therefore seems obvious to examine different types of patent pledges. Particularly Contreras (2017a) and Ziegler et al. (2014) approached this topic.

Contreras (2017a) distinguished between three different commitments of patent pledges and provided the predecessor of a patent pledge taxonomy.[3] The author based his results on his collection of empirical data (Contreras, 2019), which also constitute an important data set for both Study 1 and Study 2. Contreras (2017a) argued that *pledge commitments* fall into three categories: *primary access commitments*, *secondary access commitments*, and *non-royalty commitments*. *Primary access commitments* indicate the general nature of the access to the respective patents. The patent owner can either '*(1) refrain from asserting the patent against a specified class of potential infringers(...), (2) license the patent on FRAND terms, or (3) license the patent on royalty-free terms* (Contreras, 2017a, p. 13). *Secondary access commitments* provide more details about the royalty rates or other monetary compensation, such as a maximum percentage value of the selling price of a product. *Non-royalty commitments*, as the name suggests, describe any non-monetary commitments, such as the promise not to transfer the patents to NPEs (also referred to as '*patent trolls*'). According to McDonough, '*[a] patent troll is a person or entity who acquires ownership of a patent without the intention of actually using it to produce a product. Instead, the patent troll buys the patent and either licenses the technology to a person or entity that will incorporate the patent into a product, or it sues a person believed to already have incorporated the technology in a product without permission*' (McDonough, 2006, p. 189).

Contreras (2017a) mentioned that patent pledges can contain multiple of the described commitments. Taxonomies, in the proper meaning of the word, '*refer to classification systems that categorise phenomena into mutually exclusive and exhaustive sets with a series of discrete decision rules*' (Doty and Glick, 1994, p. 232). The distinction of patent pledge commitments described by Contreras (2017a) is not mutually exclusive and should therefore not be labeled a *Taxonomy* or *Classification Scheme* (Doty and Glick, 1994). It is rather an insightful distinction between the scope of patent pledge commitments. On the other hand, the three different types of commitments described by Contreras can contain mutually exclusive types, for instance patent pledges can either refer to *non-assertion/royalty-free licensing* or to *FRAND licensing* within the *primary access commitments*. Within the *non-royalty commitments*, however, the commitments are non-exclusive. Patent pledgors can commit to more than one of the commitments described within *non-royalty commitments*, for instance, they can promise *non-injuction* and *no non-practicing entity transfer*. It can therefore be argued that Contreras (2017a) provided an insightful precursor of a patent pledge taxonomy.

[3] Contreras (2017a) further distinguished patent pledges in terms of their origin. Specifically, he distinguished between *coordinated* and *unilateral pledges*.

Ziegler et al. (2014) developed a typology of different patent release activities. The dichotomous dimensions in their two-dimensional framework are called *type of patent* (distinguished between core or non-core) and *motive of the firm* (distinguished between financial or non-financial), as shown in table 2.2. The authors thereby directly included the motivation in their taxonomy, which is resumed in chapter 2.2.3. Four types of patent release activities emerge: *cost cutting*, *innovation catalysing*, *technology providing*, and *profit making*. *Cost cutting* refers to the donation of obsolete patents to research institutes and non-profit organisations. This form of patent release activity mainly concerns patent donations, a form of revealing that is seldom referred to as patent pledge elsewhere in the literature. Study 1 of this research does not include patent donations in the definition of patent pledges because the releasing entity is no longer owner of the patents, which is an essential aspect of the paradox behind patent pledges (see chapter 4.3.1). *Innovation catalysing* concerns the revelation of non-core patents to '*trigger innovation activities and open up new fields of business*' (Ziegler et al., 2014, p. 23). *Profit making* refers to the free access to core patents with the intention to benefit from community activities. *Technology providing* also gives away core patents but mainly due to a combination of '*good will, serving society, and accessing third party patents via patent pools*' (Ziegler et al., 2014, p. 23).

Table 2.2 Patent release activities adapted from Ziegler et al. (2014).

		Motive of the firm	
		financial	**non-financial**
Type of Patent	non-core	Cost cutting (e.g. patent donation to research institutions and non-profit organizations)	Innovation catalysing (e.g. patent donation of free-license to research institutions, non- and for-profit organizations)
	core	Profit making (e.g. free-licenses as open source strategy and setting industry standards)	Technology providing (e.g. free-licenses to patent pools, certain geographical regions, and for certain technologies)

The study of Ziegler et al. provided first insights into a taxonomy of patent pledges, but suffers from two major drawbacks: first, they included patent donations in their study and equated them with patent pledges. This inclusion points towards vague data collection processes, which is also strengthened by the fact that Ziegler et al. included patent pools in the patent release type of *technology providing*. Contreras et al. (2020) argued that patent pools, among other legal arrangements, face more administrative and legal hurdles than patent pledges. Patent pools are subject of many articles and there exists a variety of different definitions. Hill (2016) summarised the nature of such pools as an agreement of multiple patent owners to share their patent rights (closed patent pool). In some cases, third parties are allowed to purchase licenses as well (open patent pool). Bogers et al. (2012) more generally defined a patent pool '*as an agreement between two or more parties to cross-license parts of their current or future patent portfolios related to certain technologies to one another (or to third parties)*' (Bogers et al., 2012, p. 45). Prominent non-commercial patent pools, which aimed to serve the society were, according to Ziegler et al., the Golden Rice Project, the Medicines Patent Pool, and the Re:Search Initiative of the World Intellectual Property Organisation (WIPO). It is important to note that these are non-commercial examples and there exists a large number of commercial models. The view of this research is that patent pools inherit essential differences to patent pledges and should not be confused with them, as further described in chapter 4.3.1. Second, from a methodological point of view, it is not clear how Ziegler et al. arrived at their taxonomy. The description of coding processes and category building, for instance, is missing. These two drawbacks, the vague distinction to other sharing mechanisms and the unclear research methods, ask for further investigation of patent pledge taxonomies.

2.1.4 Conclusion

Different definitions of patent pledges exist and their distinction to other patent licensing approaches is often unclear. Some precursors of patent pledge taxonomies are known, but they lack characteristics of classic taxonomies or inherit methodological issues. An empirical definition of patent pledges that is derived through clear research methods and a taxonomy that illustrates different types as well as their boundaries to other patent licensing approaches is still missing. In contrast to the discrepancy for the definition of patent pledges, it is widely acknowledged that these strategies will become more important in the future. Wang et al. (2015), for instance, provided evidence that the openness of IP strategies is a topic of increasing significance in the area of IP management research. This leads to the question why firms pursue such strategies.

2.2 Motives for patent pledges

The previous sections showed that the concept of patent pledges lacks a coherent definition and taxonomy. Many studies touched upon patent pledges and attempted to define them, but few engaged in empirically founded theory building. The same is true for the motives behind these strategies. Motivation generally concerns '*factors or events that energize, channel, and* *sustain human behavior over time*' (Steers and Mowdat, 2004, p. 379). Motivation emerges when '*motives, which represent an underlying need or willingness to act, are stimulated by situational factors or incentives*' (Schweisfurth et al., 2011, p. 102) (see also Nerdinger (1995) and Spieß and von Rosenstiel (2008)). Motives are often differentiated between intrinsic (i.e. taking an action for its own sake) and extrinsic (i.e. taking an action for some reward) motives (Becker, 1976; Frey, 1997). The underlying motives for patent pledges were primarily discussed together with other sharing mechanisms, such as open-source software and collective invention. As noted by Maggiolino and Montagnani (2017), patent pledges emerge within the general trend of open innovation, which led to contorted and blended results. Few attempts were made to provide a comprehensive, broadly applicable taxonomy of motives, and the ones that were made ask for further affirmation. This part of the literature review is divided into three sections that evolve from general to specific models of revealing, all the while focusing on their motives. The first section describes the broad concept of *collective action* and *selective revealing* in general. The second section provides a brief introduction into the vast realm of *open innovation* and focuses on some specific models that inherit similarities to patent pledges. Finally, a review of studies that specifically investigated motives for sharing patents is given.

2.2.1 Information sharing and the collective action model

Almost 40 years ago, Allen (1983) described the phenomenon of *collective invention*, which he observed in the English iron and steel industry of the 19th century. Collective invention relates to the free exchange of information among firms in a specified industry. Allen mentioned improved reputation, difficulties to keep the respective information secret, and increased profits as possible motives behind these strategies (see also Harhoff et al. (2003)). By introducing the concept of collective invention, Allen complemented the three already known 'inventive institutions' (non-profit organisations, firms, and individual inventors) by another one. This early observation of information sharing and collaboration, however, occurred in an industry that, as Allen noted, was characterised by non-appropriability. Hence, the incentive to share information was, due to the lack of patentable inventions, already enhanced. One could therefore argue that the observations in this particular industry apply only to other industries that are similarly characterised by non-patentable inventions. This is not the case, however, as subsequent theories and modern studies showed. Two theories serve as the groundwork for all further understandings regarding motives for sharing information: The *private investment model* on the one hand and the *collective action model* on the other hand. The *private investment model* assumes that private returns can be appropriated from private investments (Demsetz, 1967; von Hippel and von Krogh, 2003). This model lies at the heart of patents and other IPRs, because the exclusionary rights allow inventors to appropriate direct, temporary returns on their inventions. The exclusivity of IPRs often hinders knowledge transfers. Schmidt (2006), for instance, concluded that both, patent and trade secrets, decreased knowledge spillovers, even though patents by law disclose knowledge. He argued that the appropriability effect generally outweighs the disclosure effect of patents, meaning that patent owners primarily aim '*to secure valuable knowledge instead of making it available to others*' (Schmidt, 2006, p. 2).

In contrast to the *private investment model*, the *collective action model* refers to the creation of public goods that are characterised by non-excludability and non-rivalry (Olson, 1971; von Hippel and von Krogh, 2003). Examples for public goods include the provision of public bridges and open-source software (von Hippel and von Krogh, 2003). The central dilemma of public goods is the motivation behind them. Scholars summarised this dilemma when they asked '*[i]f users who do not contribute to a public good—"free riders"—can benefit from that good on equal terms with those who do contribute, how can one motivate users to contribute rather than free ride?*' (von Hippel and von Krogh, 2003, p. 215). von Hippel and von Krogh showed that the suggested reasons to engage in collective action models provided in the literature did not hold true for the application in open-source software. Rather, von Hippel and von Krogh (2003, p. 215) argued that '*private rewards to those who contribute to open-source software collective action projects are considerably stronger than those available to free riders*'. It follows that under certain conditions, free revealing of proprietary innovations can result in a net gain in private profits for its innovators (von Hippel and von Krogh, 2003). Alexy et al. (2013) followed up on this thought and provided a two-dimensional framework that distinguishes between four *selective revealing strategies*: *issue spreading*, *product enhancing*, *agenda shaping*, and *niche creating*. These strategies utilise combinations of *path extension* or *path creation* and *problem revealing* or *solution revealing*, as shown in table 2.3. *Issue spreading* is motivated by the encouragement of others '*to participate in shared problem solving and/or to make complementary investments* (Alexy et al., 2013, p. 283). *Product enhancing* intends to facilitate utilisation of the revealed knowledge to increase the value of complementary assets. *Agenda shaping* refers to the revelation of a problem for which the revealing firm intends to create a future path and hopes to convince others to develop solutions. Finally, *niche creating* is motivated by building '*a critical mass (...) [that supports a] firm's technology trajectory to attain buy-in from crucial actors in [the] ecosystem* (Alexy et al., 2013, p. 283). All four selective revealing strategies proposed by Alexy et al. are motivated through some sort of encouragement of others. These strategies were found to indeed encourage others to engage in some specific practical settings. Henkel (2006), for instance, found evidence that the revealing of source code led to further development by other firms. According to the author, this further development as well as better reputation, are amongst the strongest motives to reveal (Henkel, 2006).

Table 2.3 Selective revealing strategies by Alexy et al. (2013).

		Mode of revealing	
		Problem revealing	Solution revealing
Goal	Path extension	Issue spreading (e.g. broadcast search)	Product enhancing (e.g. open-source software)
	Path creation	Agenda shaping (e.g. open research calls)	Niche creating (e.g. academic publishing)

The collective action model and the private investment model can convey the impression that one can simply choose the most appropriate revealing strategy for any given situation. The concept of open innovation, however, postulates that firms are under pressure to collaborate and that this decision is not as voluntary as it might seem (Chesbrough, 2006a). The following section provides an overview of open innovation models, again with an emphasis on their motives.

2.2.2 Open innovation and open business models

The observation of collective inventions in the English iron and steel industry of the 19th century described by Allen (1983) was, albeit not being the only example, not the norm. Chesbrough (2003) argued that the so-called *closed innovation paradigm* was a major success for the knowledge environment of the 20th century. This was to some extent the result of the large gap between theoretical science and its application in real-world products, which led to the closed accumulation of knowledge within the boundaries of individual firms (Chesbrough, 2003). As times changed, however, several factors led to the erosion of the closed innovation paradigm. Among these factors were the increasing availability and mobility of skilled workers and the increasing capability of external suppliers (Chesbrough, 2003). A new paradigm, the *open innovation paradigm*, emerged. Chesbrough (2003, p. 43) explained: '*Open Innovation means that valuable ideas can come from inside or outside the company and can go to market from inside or outside the company as well. This approach places external ideas and external paths to market on the same level of importance as that reserved* *for internal ideas and paths to market during the Closed Innovation era*'. Chesbrough (2006a) mentioned rising costs of technology development and shorter product life cycles as forces in the 'economics of innovation' that impel firms to open up their innovation processes. He also argued that the widespread diffusion of useful knowledge is a main motive for firms to engage in open innovation activities. The open innovation paradigm, however, is too broad of a concept to allow for the derivation of specific motives. Many forms of open innovation exist and they are often driven by different rationales (Schweisfurth et al., 2011). Spithoven et al. (2013) brought up the important point that open innovation practices differ among large and small firms and that no one-size-fits-all-solution exists. A brief overview of different open innovation models and their motives is given below.

Different models of open innovation are known from the academic literature. The problem is that the '*models are partly overlapping, partly exclusive, and partly encompassing, forming a complex web of interrelationships*' (Schweisfurth et al., 2011, p. 96). The scope of this research does not allow for a thorough description and delimitation of all models. Schweisfurth et al. (2011) provided a review of common open innovation models focused on free revealing and their underlying rationales. The authors specifically addressed *collective invention* (as described in the previous section), *user innovation networks*, *commons-based peer production*, *crowdsourcing*, and *open-source innovation*. *User innovation networks* refer to '*[i]nnovation development, production, distribution and consumption networks that are distributed horizontally across many software users (...) and in many other fields as well*' (von Hippel, 2007, p. 293). They relate to *user innovation communities* and the *community-based model of innovation*, as noted by Schweisfurth et al. (2011). *Commons-based peer production* is '*a socio-economic system of production that is emerging in the digitally networked environment*' and refers to large groups of individuals '*who cooperate effectively to provide information, knowledge or cultural goods without relying on either market pricing or managerial hierarchies to coordinate their common enterprise*' (Benkler and Nissenbaum, 2006, p. 394). Schweisfurth et al. (2011) argued that commons-based peer production focuses on the (often joint) creation of digital content and cultural goods and is related to the concept of *open content* (see also Pfaffenberger (2001)). *Crowdsourcing*, on the other hand, is the concept of outsourcing an assignment to an undefined group of people, often in which only one individual accomplishes the task (Schweisfurth et al., 2011). Finally, *open-source innovation*, which was introduced in chapter 2.1.1, stems from the concept of open-source software, because it extends its characteristics to fields outside of software development (Raasch et al., 2009; Schweisfurth et al., 2011). Schweisfurth et al. investigated the motives for these open innovation models and differentiated between *financial*, *technological*, and *socio-political* motives on the one hand and *organisational* and *individual* motives on the other hand, similar to Feller and Fitzgerald (2002). The authors found that on an organisational level, all described models with the exception of commons-based peer production, which is not considered in organisational settings, exhibit strong financial and technological and only weak socio-political motives. Open-source innovation, which appears to be the most similar model to patent pledges, is often concerned with the technological motives for improvement, standard-setting, and a reduction in time to market (Henkel, 2006; Lakhani and Wolf, 2003; Schweisfurth et al., 2011). Financial motives for open-source innovation include performing contract-manufacturing, selling complementary products, and supplying components, for instance (Henkel, 2006; Raasch et al., 2009; Schweisfurth et al., 2011). Socio-political motives also drive open-source innovation, albeit not as strong as technological and financial motives. Schweisfurth et al. argued that social pressure within communities and expectations to contribute can impel open-source innovation, because otherwise the organisation might induce a negative reputation (see also Bonaccorsi and Rossi (2006)).

This section gave a brief introduction to open innovation and open business models and showed that these models are primarily driven by financial and technological motives and less by socio-political motives. It became clear that no universal motive exists, but that different models can be driven by multiple factors. It seems impossible to derive one specific motive as the main driver for all open business models. The following section therefore takes a more delimited stance by focusing on the motivation behind the revelation of patents only.

2.2.3 Motives focused on patent sharing

Why should firms give away their patents for free? The reason that this appears as a paradox is, according to Chien (2016), because property theory is strongly linked to exclusion. A patent gives its owner '*the right to exclude others from practicing a patented technology or to charge them for the privilege of doing so*' (Contreras et al., 2019, p. 65). Chien pointed out that the overall assumption is that excluding competitors, rather than including them, fosters innovation. Innovation, however, is becoming more collaborative, as Chesbrough (2003) stated (see chapter 2.2.2). This section summarises key motives for patent pledges. Often, previous studies mentioned their motives randomly in the context of other open innovation models. Some studies, however, provided taxonomies or empirically derived motives for patent pledges: Ziegler et al. (2014), Contreras (2017a), and Contreras et al. (2019). These studies are explained in detail while they are being substantiated by other studies. The final paragraph emphasises the specific practical motives for Tesla Motors' patent pledge, arguably the most famous patent pledge to date, to complement the theoretical review.

An increasing number of scholars came up with explanations why firms give away their patents. Teece (2018) and Alexy et al. (2009) took the stance that classical IP licensing has weaknesses and that simply looking at the short-term monetary reward is too myopic. Offering patents on FRAND-terms or even for free might increase adoption rates of a specific technology until it becomes a standard (Chien, 2016; Lampe and Moser, 2010). Alexy et al. (2009) also argued that an open approach to IP increases chances to attract the best possible collaborators. The authors described the deterrence of possible collaborators through too stringent IP strategies as *Medusa-Effect of IP* (Alexy et al., 2009, p. 72). While these authors provide some motives for patent pledges,Ziegler et al. (2014) followed a more comprehensive approach.

Ziegler et al. (2014) proposed four different *patent release activities*, as already discussed in chapter 2.1.3 and shown in table 2.2. They therefore provided a framework that broadly distinguishes between financial and non-financial motives for patent pledges. The authors mentioned further motives, such as benefiting from community activities, triggering innovation activities and opening up new fields, creating good will, serving the society, and gaining access to other patents (Ziegler et al., 2014). These motives seem sound and conclusive and are in line with motives from the open innovation and broader information sharing literature described in the previous sections. The study of Ziegler et al. can be seen as a precursor to a taxonomy for patent pledge motives, because the authors included a dichotomous dimension labeled 'motive of the firm' in their framework. Ziegler et al., however, admitted that their study inherits major limitations. The authors did not gain access to patent managers involved in patent pledges and had to rely on secondary data instead. Furthermore, the delimitation to other patent licensing approaches, as discussed before, is not clear. This poses an obstacle to their proposed motives, because they might apply to licensing approaches other than patent pledges.

Contreras (2017a) provided the most comprehensive taxonomy for patent pledge motives. He distinguished between *inducement*, *collective action*, *voluntary restraint* and *philanthropy* as motives for firms to conduct patent pledges, see fig. 2.1.

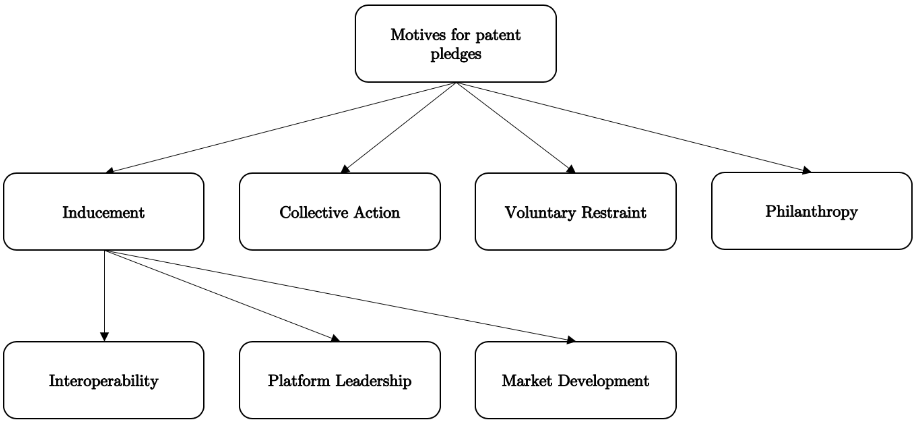


Fig. 2.1 Motives for patent pledges according to Contreras (2017a).

Inducement refers to the goal of engaging other market participants to adopt a certain technology. This is, according to Contreras, the most common motive and is in line with the model described by Alexy et al. (2013) shown in table 2.3. This motive is furthermore the main motive for firms to conduct patent pledges mentioned in the literature, albeit the term 'induce' might not specifically be used (Al-Aali and Teece, 2013; Alexy et al., 2009, 2013; Arora et al., 2001; Barnett, 2011; Contreras et al., 2019; Rimmer, 2014; Simcoe, 2017; Sundaresan et al., 2017; West and Gallagher, 2006). Inducement appears in three different forms: *interoperability*, *platform leadership* and *market development* (Contreras, 2017a). *Interoperability* aims to induce third parties to invest in a particular standard favored by the pledgor with the goal of increasing network effects and, as the name suggests, interoperability (Contreras, 2017a). As early as 1974, Rohlfs (1974) observed that the utility of a communications service increased as more people joined the system. Since then, many influential works on the topic of network effects were published (see for instance Economides and Salop (1992); Katz and Shapiro (1985); Rochet and Tirole (2003); Shapiro and Varian (1999)). *Platform leadership*, in contrast, occurs when patent pledgors exert control over an entire technology platform or '*de facto*' standard. Here, their main goal is to motivate others to '*develop products that operate with or depend on their technology*' (Contreras, 2017a, p. 28). With *market development*, patent pledgors aim to induce the adoption of an emerging or nascent platform technology, often in which they are leaders (Contreras, 2017a). Compared to *interoperability* and *platform leadership*, these patent pledges generally concern broad technology categories rather than single products or standards (Contreras, 2017a).

Collective action refers to activities that are beneficial for all participating parties, but only if enough parties participate (Contreras, 2017a). As a result, firms hesitate to take action, because they are unwilling to invest without knowing if others will do the same. Barnett

(2011) described this phenomenon earlier as the *intertemporal dilemma*. Contreras stated that collective action often occurs in an environmental context and referred to the Eco-Patent Commons as an example. A collective action induced patent pledge might reduce the hesitation of companies to participate (Alexy and Reitzig, 2013; Contreras, 2017a; Wen et al., 2016).

Voluntary restraint relates to a patent owner's commitment not to enforce or exploit specific patents in a predetermined manner (Contreras, 2017a). This aims to appease governmental bodies or courts in a way that is beneficial for the pledgor, for example in a company acquisition approval process. Voluntary restraint is '*often adopted when a fear exists, either across the market or among particular actors, that the patent holder is both able and likely to exert its patents in a manner that is viewed as undesirable.*' (Contreras, 2017a, p. 33).

Finally, Contreras argued that some patent pledges serve the society rather than the patent pledgor herself. Chien (2016) supported this assumption by stating that sharing IPRs can have humanitarian reasons. She pointed out, however, that only few pledges are truly philanthropic and that patent pledgors try to gain benefits through positive public relations (PR) or a stimulated market. This is also supported by other studies (see for instance Alexy et al. (2018); Füller (2010); Lerner and Tirole (2002); Raymond (2001); Schreier et al. (2012)). Contreras et al. (2019), however, found that their interview participants did not perceive PR as a primary motive to join the Eco-Patent Commons. To conclude, Contreras (2017a) provided the most comprehensive taxonomy for patent pledges to date. With his extensive patent pledge collection (see Contreras (2019)), Contreras built his taxonomy on secondary data. As will be further discussed in Study 2, this data set inherits the risk of bias, because the secondary data are predominantly released by the patent pledgors themselves. New forms of empirical evidence, preferably primary data, are desirable. Contreras et al. (2019) followed up on this and collected empirical evidence about the motives to join a specific patent pledge.

The study of Contreras et al. (2019) is one of the most sophisticated studies in the field. This is because the authors gained access to seven interview participants that were involved in the Eco-Patent Commons and were able to collect empirical data about the motives to join the Commons, among other insights. The authors found that the primary motive to join the Eco-Patent Commons was to reach goals related to environmental sustainability. Positive PR played a role, too, but this was, according to the interviewees, not a primary driver. By gaining access to qualified interview participants, Contreras et al. were able to overcome some of the limitations of previous studies, specifically the one of Ziegler et al. (2014). The study of Contreras et al. (2019) is, however, limited in the sense that the findings only apply to the Eco-Patent Commons, because only firms that participated in this specific patent pledge were interviewed. It cannot automatically be inferred that the identified motives hold true for other patent pledges as well. A study that builds upon and extends the findings of Contreras et al. is yet to be carried out.

Other scholars mentioned motives for patent pledges similar to Contreras (2017a), but with a less systematic approach. The majority of studies argued that patent pledges follow economic self-interest. Sundaresan et al. (2017), for instance, stated that the non-assertion of maintained patents lowers barriers to entry a specific technology area and fosters innovation for developers. The authors also named the reduced threat of litigation as an important motive. Valz (2017) argued that for both, patent pledges that include monetary compensation and patent pledges that are available for free, increased adoption of the covered technologies constitutes an important motive. Hall and Helmers (2013) held the view that patents are more likely to be pledged if they are useful for the environment and if licensing of these IPRs is not profitable.[4] The authors did not see patent pledges as an act to generate positive PR and supported this argument with the costly maintenance of released patents for a prolonged time after the pledge. Alexy et al. (2018) mentioned that openness may reduce fixed costs of intangible assets. This point is also taken up by (Sundaresan et al., 2017) when they said that firms save money from costly licensing negotiations and possible litigations through opening up IPRs. Wen et al. (2016) followed up on the same thought, specifically in the context of start-ups. As it stands, many studies suggested that the main motive for reducing restrictions on IPRs is to increase and/or accelerate technology diffusion. West and Gallagher (2006), while investigating open innovation in the context of open-source software, argued that IP might be given away to stimulate demand for related products. Other scholars, too, emphasised that open-source software seldom has altruistic intentions and that the incentive to increase technology diffusion is of major importance (Bonaccorsi and Rossi, 2003). Many authors come to similar conclusions in contexts other than open-source software. Barnett (2011), for instance, described voluntary forfeiture actions and stated that they primarily occur in platform markets that exhibit network effects. The motive for these actions is to induce platform adoption, where the firms' 'generosity' of forfeiting ownership or control rights follows from economic self-interest (Barnett, 2011).

This paragraph briefly summarises motives for Tesla's patent pledge mentioned in the literature. Asay (2016) argued that patent pledges can have a strong signalling character. These signals can, according to the author, attract prospective employees, show the willingness to collaborate with competitors and attract investment (see also Barnett (2011)). In this context, Asay named Tesla Motors' patent pledge from 2014 as an example for a successful signal

[4] The authors also provided a simple decision tree, which suggests to only pledge patents when the respective firm does not intend to use the patents on its own.

to collaborate. Tesla's announcement of the patent pledge caused great media attention and has been subject of many debates since then. Bessen (2014) took the view that this strategy could drive the overall development of the electric vehicle market and that Tesla could benefit from network effects, which links back to the motives mentioned by Contreras (2017a). Bessen compared the Tesla case with US Bessemer steel mills in the past. Competitors in the steel mills business had met regularly and exchanged their knowledge to develop common standards, which, again, leads to the motives of collective invention and open innovation, see chapter 2.2.1 and chapter 2.2.2. As a result of this exchange, production costs for steel decreased by 78 % (Bessen, 2014). Hill (2016) followed up on this idea and presumes that Tesla's ultimate goal is to sell their batteries to competitors which base their electric vehicles at least in part on the automakers design. Hill argued that most rivals would prefer to buy Tesla's battery instead of producing their own. Bessen (2014) reasoned that sharing technology with other electric vehicle manufacturers does not undercut Tesla Motors' profits, because, as Elon Musk himself noted, their true competition comes from firms focused on the production of gasoline cars (Musk, 2014). As long as the gigantic production of gasoline cars continues, Tesla's profits will be determined by the market share of electric vehicles overall rather than by their rivals itself. Regarding the effectiveness of Tesla's efforts to encourage collaboration and to become the standardised battery producer, Hill (2016) stated that simply carrying out a patent pledge is not enough. In his opinion, the promise not to assert patents against third parties as long as they act in '*good faith*' involves too much risk and uncertainty for major companies - an important aspect that is supported through Study 2. While Tesla's patent pledge concerns the manufacturing area, Contreras (2017a) stated that most patent pledges occurred in the area of ICT, as well as in green/clean technology and life sciences. Recent patent pledges of IBM, Microsoft and Red Hat undermine this assumption (Asay, 2016; Contreras, 2018b; Schultz and Urban, 2012; Wen et al., 2016). Wen et al. (2016) justified this with the predominant presence of patent thickets in these industries.

2.2.4 Conclusion

This section gave an overview of motives for engaging in practices that range from general knowledge sharing over open innovation practices to patent pledges. It was shown that no universal motive for all these concepts exists. For patent pledges specifically, however, many studies suggested that the inducement of others to take specific actions, positive PR, and also philanthropy are common motives. While most studies concurred with each other, only few of them provided specific empirical evidence for the motives. Contreras (2017a) built his taxonomy on empirical data, but these data inherit some risk of bias. The study of Ziegler et al. (2014) lacks academic rigour in the sense that the authors did not gain access to patent managers that were directly involved in patent pledges and thus had to rely on secondary data. Furthermore, it remains unclear how Ziegler et al. arrived at their framework. Contreras et al. (2019) provided sophisticated insights into the motives for one specific patent pledge, because the authors were able to collect primary data. A study that builds upon and extends the insights of Contreras et al. (2019) is yet to be carried out.

2.3 Technology diffusion

Technology and innovation diffusion is a vast research area that is of interest to scholars from many fields. As mentioned in chapter 1.2, technology diffusion is defined '*as the cumulative or aggregate result of a series of individual calculations that weigh the incremental benefits of adopting a new technology against the costs of change. (...) The resulting diffusion rate is then determined by summing over these individual decisions*' (Hall and Khan, 2003, p. 1). *Adopters* are the smallest unit of analysis and can be individuals or organisations, for instance (Meyer, 2004). The last 50 years have seen a large increase in the development of models that aim to explain or predict diffusion patterns within and across industries. The field's complexity grows also by another factor: modern processing power enables new ways to investigate diffusion and to overcome limitations of traditional models. Fig. 2.2 provides a general overview of different ways to study a system such as technology diffusion. What is meant by the term *system* depends on the particular study, but it is generally acknowledged that a system consists of a collection of entities that interact with each other (Law, 2015). The notion to investigate a system either analytically or through simulation is used throughout this research, and the literature about technology diffusion is distinguished between these two approaches. Analytical solutions refer to the classic mathematical approach of using differential equations, for instance, to predict diffusion rates. Simulation, on the other hand, makes use of some sort of computer software and overcomes many of the shortcomings of analytical solutions. Limitations of analytical solutions and advantages of simulations are separately discussed in chapter 3.3.3.

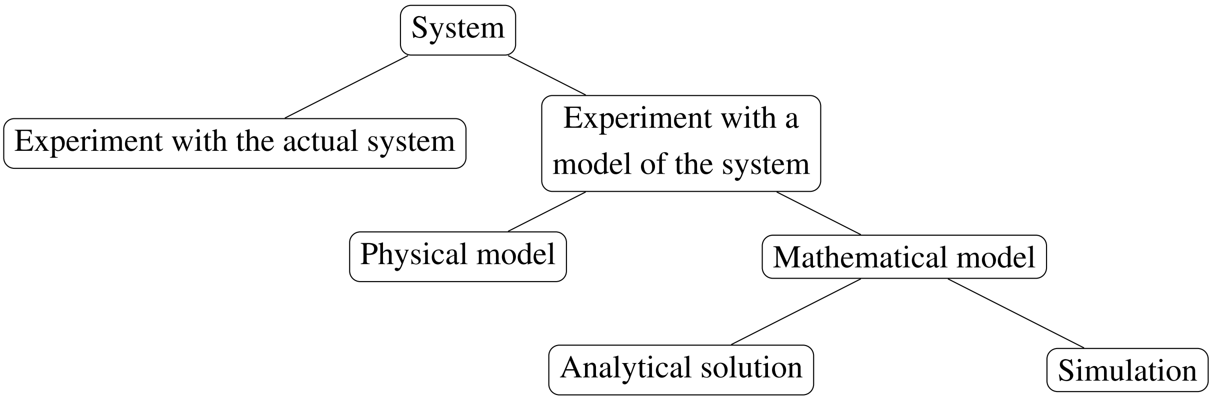


Fig. 2.2 Different ways to study a system according to Law (2015).

2.3.1 Analytical approaches to technology diffusion

Mathematical theories about technology and innovation diffusion date back to the 1960s. Prior to that, Ryan and Gross (1943) established the empirical base for the diffusion paradigm (Kiesling et al., 2012). Fourt and Woodlock (1960) published their penetration-model to predict the diffusion of new grocery products - an early attempt to calculate diffusion rates. Following this mathematical method, Mansfield (1961) provided a stochastic model in which the probability that a firm adopts an innovation increases with the number of firms that have already adopted this innovation. One year later, the first edition of Everett M. Rogers' *Diffusion of Innovations* was published (Rogers, 1962). Today, Rogers' work is often referred to as the groundwork of modern diffusion theory and many scholars built on his assumptions. *Diffusion of Innovations* does not contain mathematical models to calculate diffusion rates, however. Frank M. Bass followed up on this and criticised that Rogers' ideas were largely literary. This led to Bass' groundbreaking publication *A new product growth for model consumer durables* in 1969 in which he described the probability of adoption as a linear function of the number of previous buyers (Bass, 1969). Bass' model is often referred to as the most influential contribution to innovation diffusion theory to date and many diffusion models constitute refinements and extensions of this early model (Kiesling et al., 2012). Bass expressed the probability of innovation adoption as

$$P(t) = p + \frac{q}{m}Y(t) \tag{2.1}$$

where

P = Probability of innovation adoption,
p, q, m = constants,
Y = Number of previous adopters, and
t = time.

Bass published some precursors from 1963 on, but it was the mentioned paper from 1969 that included both, theory as well as empirical data. The constants in equation (2.1) were derived through regression analysis of real world data in specific industries. Importantly, Bass' model consists of two parts. The first part, represented mathematically as the parameter p, refers to what are called innovators. Innovators adopt an innovation without being influenced by other adopters (Bass, 1969). The remainder of the formula is dependent on previous adopters and is summarised as imitators (Bass, 1969). Hall (2005) emphasised that in Bass' diffusion model, mass media plays a vital role in the early stages, while interpersonal communication becomes more important at later stages.[5]

Bass' formula for the probability of adoption can be seen as the groundwork for many subsequent scholars in the field. His early work led to a thorough investigation of parameters for diffusion formulas, because their accuracy ultimately determines the predictive power of the models. Scholars in the field criticised the lack of marketing variables in Bass' model, which led to a variety of extensions of the original model (Radas, 2005). These extensions can be distinguished between diffusion models with constant parameters and diffusion models with parameters that change over time (Radas, 2005). Subsequent, an exemplary, non-exhaustive list of different approaches and extensions to the classic innovation diffusion formula in equation (2.1) is given. For a comprehensive compilation of marketing variables in macro-level diffusion models, see Ruiz-Conde et al. (2006).

2.3.1.1 Diffusion models with constant parameters

In his initial work, Bass assumed that the price for most durable goods declines monotonically over time (Bass, 1980; Jain and Rao, 1990). This assumption constitutes an oversimplification and does not represent pricing strategies such as penetration pricing (see for instance Arthur (1989)). Bass et al. (1994) developed the *Generalised Bass Model* in which they adapted the original equation to include decision variables such as price and advertisement. The

[5] The illustration of the diffusion of a successful innovation with a specific penetration measure, such as the cumulative number of adopters or the produced output generated by the new innovation over time, takes in many cases a S-shaped form and there has been extensive research about why this is the case (Hall, 2005; Stoneman and Ireland, 1983). Geroski provided an overview of different explanations for the S-form, which can be distinguished between epidemic models, probit models, density dependence models (as an interplay between competition and legitimation), and information cascades (see also Cabral (1990)).

Generalised Bass Model adds a multiplicative term containing marketing variables to the original Bass model (Radas, 2005). Importantly, this model constitutes a special case of the original Bass model, not a replacement thereof. A variety of other scholars also provided diffusion models that aimed to remedy some the the shortcomings of the traditional Bass model. Robinson and Lakhani (1975) were one of the first scholars who criticised the short-term thinking of the conventional price theory and suggested aggressive, dynamic pricing models for increased long-term profit (see also Radas (2005)). The authors showed that low initial prices in a dynamic optimum strategy for a hypothetical product result in a long-term profit that is six times higher after six years than it would be at an initially higher price with a conventional marginal pricing strategy. This is to a large extent the result of increased innovation diffusion. Even though the seller makes significant losses in the beginning, the final profit outweighs this investment because of an increased sales volume. The authors included the price as an exponential term to the original Bass expression (Radas, 2005). A similar conclusion was provided by Feichtinger (1982). The author showed that the optimal pricing strategy for a profit-driven firm includes the forgoing of early stage profits in favour of an increased adoption rate. Robinson and Lakhani suggested dynamic pricing models even for organisations that have a temporary monopoly position (e.g. through IPRs such as patents). Similar mathematical models were developed by Dockner and Jørgensen (1988) and Teng and Thompson (1983). Jain and Rao (1990) empirically complemented the pricing factor, which resulted in a more complex analytical solution than Bass' original diffusion model. Kalish (1985) developed an empirically applied diffusion model that also takes the price of a new product into account. Even though this model included advertising as well, Kalish could not empirically test this variable due to a lack of data (Radas, 2005). Kamakura and Balasubramanian (1988) took a different approach. The authors extended Bass' original model by also considering the price index, the population change, and replacement sales in their model. Kamakura and Balasubramanian concluded that the price affects diffusion only for high-priced products. A similar model with constant parameters was introduced by Horsky (1990). To conclude, many scholars extended Bass' original model by additional factors such as specific pricing strategies or a change in population. As Radas (2005) noted, many model parameters were assumed to be constants that do not change over time. More sophisticated models, as described in the following paragraph, put more emphasis on the time-dependence of model parameters to allow for a better prediction of technology diffusion rates.

2.3.1.2 Diffusion models with time-dependent parameters

It is not surprising that diffusion models with parameters that change over time allow for a better match with real data (Easingwood, 1987). In short, time-varying models adapt Bass' original model from 1969 by assuming that outside influences continuously affect either the innovation parameter p or the imitation parameter q in equation (2.1) (Radas, 2005). There exist some variation in how one can determine the rate of change of the parameters, however.

Most scholars depicted this change by using a specific functional form in advance. Such models were often coined flexible diffusion models (Radas, 2005). For instance, Horsky and Simon (1983) specifically focused on the advertising effect on technology diffusion in the case of telephonic banking. The authors concluded that advertising accelerates the diffusion process and suggested advertising heavily in the beginning of the product introduction. The fact that the innovation parameter p in the author's formula is a logarithmic function of advertising efforts at time t classifies this model as a flexible diffusion model (Radas, 2005). Similarly, Easingwood et al. (1983) assumed that the imitation parameter q is a function of penetration (see also Bewley and Fiebig (1988)).

Another way to allow for changing parameters over time is stochastic modelling. Stochastic diffusion models overcome some of the shortcomings of flexible diffusion models, such as the assumption that only one of the parameters, either p or q but not both, change over time (Radas, 2005). For instance, Putsis (1998) introduced a stochastic diffusion model with a variety of time-varying variables such as income and price. Radas (2005) pointed out that the model by Putsis exhibits a better fit to real-world data than most other diffusion models, including the original model from Bass (1969). As a result of the increased number of time-dependent variables compared to flexible diffusion models, stochastic models are more complex and their application is more time-consuming.

So far, a general introduction of analytical models that attempted to calculate technology diffusion rates was given. It was shown that many models built upon the early work of Bass (1969) and introduced novel parameters and dependencies to allow for a better fit with real world data. The following section describes further traditional studies in the area of technology diffusion, this time, however, with a focus on competing technologies.

2.3.1.3 Competing technologies

Rather than contemplating one technology as a natural successor of an older technology, studies in the area of technology diffusion frequently considered the case of two emerging, competing technologies that could to a large extent be a substitute of each other. For instance, the competition between the alternating current and the direct current for electricity distribution is considered a well-known example of competing technologies in which both technologies are still present (David, 1992; Hall, 2005). On the contrary, electricity-powered refrigerators locked the technically superior gas-powered version completely out of the market, due to extensive efforts of General Electric and Westinghouse (Cowan, 1999; Hall, 2005).

Katz and Shapiro (1986) analysed technology adoption of two competing technologies in two consecutive periods and found that a sponsored technology, even if it is inferior to competing technologies, can have a strategic advantage. The authors' analysis is particularly relevant for chapter 6 of this research, given the fact that different scenarios of IP protection are investigated. Katz and Shapiro called a protected technology *sponsored* when its IP owner uses a penetration pricing strategy in the beginning of its market introduction. Penetration pricing in this context refers to an initially low price, even if the supplier makes initial losses (see also Arthur (1989); Hall (2005)). Hall (2005) called this a *subsidised* technology, which links back to the insights about pricing strategies of Robinson and Lakhani (1975) described above. At a later stage, once the respective technology is widely adopted due to its initial low price, the IP owner can demand a higher price while its consumers might be locked-in. Against the background of this research, the strategy of penetration pricing can be compared to patent pledges. The fact that third parties can adopt a technology at a lower price or even for free is comparable to the penetration pricing strategy. Since the patent owner maintains his rights, he could demand a higher price at a later stage. Even if the price will not be raised, Katz and Shapiro indicated that the patent owner gains benefits such as increased adoption rates. The authors arguably laid the groundwork for analysing the diffusion of patent pledges already over 30 years ago, albeit not mentioning the term specifically.

In his widely recognised paper *Competing Technologies, Increasing Returns, and Lock-In by Historical Events*, Arthur (1989) described a mathematical model to investigate the market share of two competing technologies, A and B. Arthur assumed that possible adopters rely on a utility function in the form of the von Neumann-Morgenstern utility theorem. Each adopter, or agent, has a natural preference for one of the technologies ($a_R > b_R$ or $a_S < b_S$) and also considers the number of past adopters ($n_A(t)$/ $n_B(t)$) in his calculation. Through multiplication of the past number of adopters with constants (r/s) and the addition of the natural preference, the utility for each technology is calculated (see table 2.4). The agent then adopts the technology with the highest utility.

Arthur distinguished between three different cases for the constants r and s. If both constants are zero, there exist no increasing returns with greater adoption rate for any one technology

Table 2.4 Utility functions according to Arthur (1989).

	Technology A	Technology B
R-agent	$a_R + rn_A$	$b_R + rn_B$
S-agent	$a_S + sn_A$	$b_s + sn_B$

(constant returns). If both constants take negative values, the improvements or advantages of any one technology become smaller with greater adoption rates (diminishing returns). If both constants take positive values, the technologies show increasing returns. In terms of the market share of competing technologies with constant and diminishing returns, both technologies tend to a 50/50 share. In the case of increasing returns, however, one technology reaches a market share of 100% while the other vanishes completely. Specifically, R-agents with a natural preference for technology A adopt technology B if

$$n_A(n) - n_B(n) < \frac{b_R - a_R}{r} \tag{2.2}$$

Arthur (1989) showed that a superior technology can get locked-out of the market if an inferior technology is initially being adopted more often due to random events. Such events include earlier market entry and political decisions. In sum, Arthur developed a mathematical model for adoption rates of competing technologies and showed that inferior technologies can lock-out superior substitutes. Arthur (1989, p. 116) described that the two technologies compete '*for a market of potential adopters*' and this terminology is used throughout this research, specifically in Study 3. The competition for a market of potential adopters is different from so-called '*patent races*' (see for instance Tirole (1994), De Fraja (1993), and Shaver (2012)). In a patent race, firms compete against each other to be the first to make a patentable discovery (De Fraja, 1993). In simple economic patent race models, '*a firm's probability of making a discovery and obtaining a patent at a point in time depends only on the firm's current R&D expenditure and not on its past R&D experience*' (Tirole, 1994, p. 394). Since patent pledges can only be introduced after the grant of a patent and patent races are concerned with the efforts prior to the grant (or application) of a patent, this research does not focus on patent races. The previously described competition for a market of potential adopters by Arthur (1989), in contrast, is specifically investigated in Study 3. The concept of competing technologies is further discussed in chapter 6.4.1.1.

This section gave a brief introduction into analytical diffusion models and their applications in scenarios with competing technologies. It was shown that many different models exist and that they often built upon the early diffusion model of Bass (1969). The following section describes studies that utilised another 'tool' to model technology diffusion: computer simulation.

2.3.2 Simulation approaches to technology diffusion

Computational solutions to answer questions about technology diffusion were increasingly adopted over the last years. Even more, computer simulation has evolved to a research methodology itself (Silverman, 2018). It must be noted that there exist different methods within simulation approaches, such as ABMs, system dynamics, and discrete event simulation. This overview focuses on ABMs only, due to their prevalence in technology diffusion studies. ABMs inherit essential differences to analytical solutions, such as their ability to model social interactions and decision-making processes (Kiesling et al., 2012). A summary of the advantages of simulation models over aggregate models is given in chapter 3.3.3 when justifying the use of ABMs for Study 3.

Generally, a simulation model can be described as a representation of the assembly and behaviour of some system of interest (Maria, 1997). What is meant by the term *system* depends on the particular study, but it is generally acknowledged that a system consists of a collection of entities that interact with each other (Law, 2015). Fig. 2.2 provided an overview of the classification of different ways to study systems, whereas analytical solutions include aggregate diffusion models. One way to classify simulation models is by focusing on their parameters and time-consideration. When the input and output variables are probabilistic values rather than fixed values, the model is labeled *stochastic*, not *deterministic*. Analogously, when time-varying interactions between variables are included, the model is labeled *dynamic*, not *static* (Law, 2015; Maria, 1997). The collection of variables required to describe the system at a specific time is called its *state* (Law, 2015). Depending on the rate of change for its states, systems can be distinguished between *discrete* (the state variables change instantaneously) or *continuous* (the state variables change continuously) with respect to time (Law, 2015).

Social sciences research has seen a large increase in the use of ABMs since the 1990s (Bruch and Atwell, 2015; Squazzoni, 2010). Many application areas, specifically questions about organisations, markets, and diffusion, are increasingly simulated using ABMs (Bonabeau, 2002). Reasons for this increase lie in the fact that ABMs enable the simulation of heterogeneity of individuals and, as a result, complex emerging phenomena (Kiesling et al., 2012). The main characteristic of these models is the programming of individual decision rules rather than behaviours on an aggregate level (Law, 2015; Sun et al., 2016). Since in all existing ABMs state changes occur at a countable number of points in time, they can be seen as a variation of discrete event simulation (Law, 2015). While there exists no globally accepted definition of an agent, it is commonly seen as decision-making entity that acts autonomous, interdependent, and adaptive, following simple rules (Kiesling et al., 2012; Law, 2015; Macy and Willer, 2002). Already simple models with few underlying rules on an individual level can lead to surprising results on the macro-level. For instance, in his paper *Models of Segregation*, Schelling (1969) simulated two groups of neighbours with relatively high tolerance towards each other. He found that even if the individuals are tolerant, the result on the macro-level is a clearly separated neighbourhood. Another example is the simulation of the formation of a flock of birds. Almost perfectly shaped, the birds do not follow a system-wide program, which makes it very difficult to simulate with an aggregate model (Macy and Willer, 2002). Instead, Reynolds (1987) used three simple rules on the individual bird-level to successfully simulate the flock patterns (Law, 2015).

ABMs generally use two broad categories of inputs, initial conditions and parameters. **Initial conditions** specify the agents' state variables at time zero of the simulation, i.e. at its very beginning. One can differentiate between a homogeneity situation, in which the initial conditions of all agents are equal, and a more heterogeneous situation, in which the agents' initial conditions follow a specific (often empirical) distribution (Fagiolo et al., 2017). **Parameters** can either determine some macro conditions, specify the impact of agent's reactions, or define distributions for agents stochastic decisions (Fagiolo et al., 2017). For the latter, one can use common probability density functions, such as a Weibull density function, or, in cases where a theoretical function does not adequately describe observed data, empirical distributions (Law, 2015).

The number of studies using ABMs to simulate technology diffusion is large. Rather than describing prior work in a specific order, the following paragraphs differentiate between two common aspects most simulation diffusion models implement: the **consumer adoption behaviour** and the **social influence** (Kiesling et al., 2012). Different approaches to simulate these two aspects are summarised and exemplary studies are cited. For a comprehensive description, see Kiesling et al. (2012) and Zhang and Vorobeychik (2019).

2.3.2.1 Approaches to model consumer adoption behaviour

Generally, six broad approaches of consumer adoption behaviour were described in the literature (Kiesling et al., 2012). (1) *Simple decision rules and threshold models* allow an agent to adopt a technology according to a predetermined threshold. For instance, an agent adopts a new product as soon as a specified number of agents in his network have adopted. This decision can be made on a deterministic or probabilistic basis, the latter arguably being the better approach for most models due to the inclusion of uncertainty in predicting consumer behaviour. Valente and Davis (1999), for instance, developed a simulation model in which they assumed that an agent adopts an innovation when the number of connected agents that have already adopted the innovation exceeds the threshold of 15%. Bohlmann et al. (2010) also used a given threshold, but added that after the threshold is reached, the agent adopts only with a given probability. Furthermore, agent heterogeneity can be achieved through a varied threshold-value that follows an empirically derived population distribution. (2) *Utilitarian approaches* describe the adoption behaviour by calculating utilities for different options such as the option between two competing technologies. These utilities can be calculated through multiple product attributes and the weight an agent allocates to these attributes.[6] Generally, an agent adopts the technology with the highest perceived utility. Choi et al. (2010), for instance, included what they called an idiosyncratic reservation utility in their computational model, among a product's stand-alone benefit and network effects. There is a fine line between utilitarian approaches and the previously described decision rules, leading to confusion regarding the terminology in the literature (Kiesling et al., 2012). (3) *State transition technology diffusion approaches* classify agents according to different states they are in at a given time, e.g. being in the 'adopter' or 'non-adopter' state. For instance, Goldenberg and Efroni (2001) modeled a cellular automata in which agents can either be in a state of non-awareness or awareness of a specified trend. Agents can become aware of the trend through neighbouring agents or spontaneously, i.e. independent from adjacent neighbours. Both transformations happen on a probabilistic basis. (4) *Opinion dynamics approaches for technology diffusion* apply insights from the literature stream about general opinion dynamics (Kiesling et al., 2012). Here, agents observe, weigh, and base their adoption decision on the behaviour of their neighbours, which inherits some similarities to threshold models (Hegselmann and Krause, 2002). In their opinion dynamics model, Martins et al. (2009) assigned a subjective probabilistic opinion to each innovation choice that is regularly updated. (5) *Econometric estimation approaches* use statistical methods to initialise choice probabilities and parameters, and could therefore also be used as input for other approaches. This approach is particularly suited for practical applications and policy analyses (Kiesling et al., 2012). Dugundji and Gulyás (2008), for instance, investigated the adoption of various transportation mode alternatives and used pseudo-panel micro-data to feed in their model. The most sophisticated approaches to model consumer adoption behaviour, however, are (6) *social psychology approaches* (Kiesling et al., 2012). These approaches use theories from social psychology to model an agent's adoption behaviour. A widely used approach in this context is the theory of planned behaviour (TPB) (Ajzen, 1991). In brief, the

[6] See (Keeney and Raiffa, 1993) for approaches to calculate utility.

TPB assumes three conceptually independent determinants of intention, namely the *attitude towards the behaviour*, the *subjective norm*, and the *perceived behavioural control* (Ajzen, 1991). While attitude towards the behaviour refers to the degree to which an individual has an appraisal for the behaviour in question, subjective norm relates to the social pressure to perform or not to perform the behaviour (Ajzen, 1991). The latter is especially important in the context of technology diffusion because diffusion studies must take into account the social structures of potential adopters (Katz, 1961; Kiesling et al., 2012). Perceived behavioural control relates to the perceived ease or difficulty of performing the behaviour (Ajzen, 1991). As Ajzen pointed out, the stronger the intention to engage in a behaviour, the more likely is its performance. The relative importance of the three determinants, however, varies across behaviours and situations (Ajzen, 1991). Many studies used this theory to model agent's behaviours in ABMs (Kaufmann et al., 2009; Mashhadi and Behdad, 2018; Muelder and Filatova, 2018; Nguyen et al., 2018; Nnaji et al., 2019; Pouladi et al., 2019; Scalco et al., 2018; Schwarz and Ernst, 2009; Tong et al., 2018; Zhang and Nuttall, 2012), and its validity was supported by several studies from multiple fields (Ajzen, 2011; Armitage and Conner, 1999a,b; Hagger et al., 2002; Rai et al., 2002). The TPB is illustrated in fig. 2.3. The dashed line from perceived behavioural control to the actual behaviour emphasises the dependence of the behaviour on both, the intention as well as the ability to perform a behaviour (Ajzen, 1991).

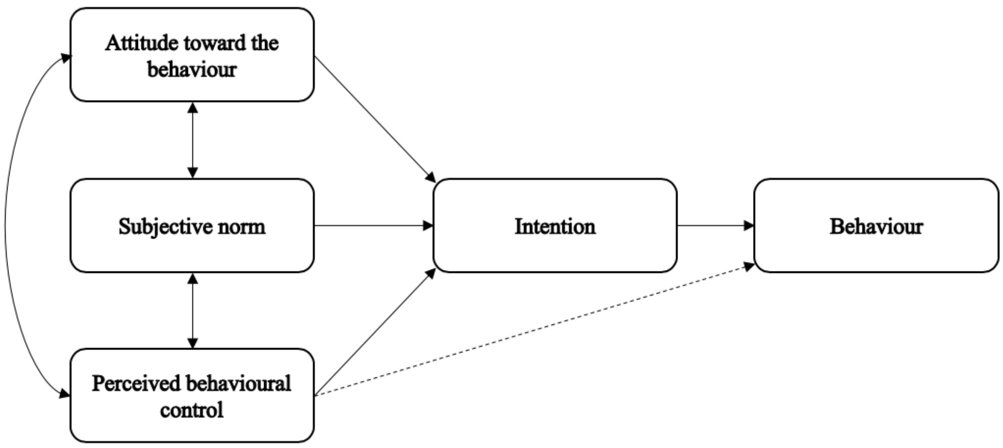


Fig. 2.3 The theory of planned behaviour according to Ajzen (1991) (Ajzen, 1991).

To conclude, six approaches to model consumer adoption behaviour in ABMs were described in the literature. The lines between them, however, are often vague and ABMs can use parts from multiple approaches. It appears that no universal solution exists. Rather, each ABM needs to decide what approach or what combination of approaches could answer a given question. Apart from the adoption behaviour of agents, ABMs also enable the simulation of social influence and interactions between agents. The following section gives an introduction to common approaches in this context.

2.3.2.2 Approaches to model social influence

ABMs constitute a tool to model social interaction in technology diffusion processes, because they allow for the simulation of various '*interaction topologies*'. Kiesling et al. (2012) distinguished between *micro-*, *meso-*, and *macro-levels* of social influence in ABMs. Kiesling et al. also noted that most ABMs in the area of technology diffusion incorporated only one of these levels. *Micro-level* social influence refers to the local transmission through pairwise communication links (Kiesling et al., 2012). *Word of mouth (WoM)* is, according to the authors, the prevalent form of social influence on the micro-level. WoM describes the process by which consumers of a given product tell other people about their experience with that product, all the while influencing, in a positive or negative way, the brand perceptions with whom they communicate (de Matos and Rossi, 2008; Richins, 1983). This influence on the brand perception might lead to a higher (when positive) or lower (when negative) probability to adopt. In the innovation diffusion model of Deffuant et al. (2005), for instance, individuals send messages containing their opinion and further information to other agents. This event, in turn, is triggered by the media and occurs in randomly selected agents. Empirical evidence suggested that negative WoM has a stronger influence than positive WoM (Kiesling et al., 2012; Richins, 1983). *Meso-level* social influence goes beyond one-to-one communication and originates collectively from an agent's immediate social environment (Kiesling et al., 2012). Examples include herding behaviour and local network externalities. In many studies, the term *social influence* refers to the meso-level social influence (Kiesling et al., 2012). *Macro-level* social influence concerns global interactions of the agent population, such as macroeconomic feedback and learning effects (Kiesling et al., 2012). An example for macro-level social influence is the global activity of the network or the aggregate opinion in the model of Deroiain (2002).

The described levels of social influence are only general descriptions and there is much leeway in designing specific networks. An important aspect of simulating technology diffusion is the specific design of nodes/agents and the amount of links between them. This, in turn, influences the WoM, for instance. Bass (1969) assumed a fully connected social network in his original diffusion model, i.e. there exist direct links between all pairs of nodes/agents.

This assumption is a result of the limitations of analytical solutions as further described in chapter 3.3.3 (see also Kiesling et al. (2012)). Modern ABMs, on the other hand, enable the simulation of more realistic networks, particularly for the micro- and meso-level of social influence (Kiesling et al., 2012). Subsequent, an overview of different network types and their resemblance to real-life scenarios is given.

For more than 40 years, the **(a) random graph** proposed by Erdős and Rényi (1960) dominated graph theories (see also Barabási and Bonabeau (2003); Dorogovtsev and Mendes (2003)). Erdős and Rényi suggested to model networks in communication and life sciences by connecting nodes with randomly placed links (Barabási and Bonabeau, 2003). It appears that most nodes in random graphs have approximately the same number of links (Barabási and Bonabeau, 2003). Furthermore, the path length, or diameter, of random graphs, which is defined as the shortest distance between the two most distant nodes, tends to be small (Kiesling et al., 2012). This small diameter is a common characteristic of real-life social networks (Kiesling et al., 2012). Opposed to random graphs are **(b) regular graphs** (also referred to as cellular automata), in which each node has the exact same number of links (Watts and Strogatz, 1998). For many years, real-life networks were assumed to be either completely regular or completely random (Watts and Strogatz, 1998). However, as Watts and Strogatz (1998) showed, many biological, technological, and social networks appeared to lie in between these two extremes. The authors called such networks **(c) small-world networks**. Small-world networks exhibit properties of both, random as well as regular graphs: like regular graphs, they can be highly clustered; like random graphs, they have a small diameter. Watts and Strogatz showed that a power grid and the collaboration network of film actors, for instance, exhibited small-world properties. Small-world networks are the most commonly used network topologies to model technology diffusion in ABMs, due to their similarities with real-life social networks (Kiesling et al., 2012). After studying page links of the world wide web, Barabási and Bonabeau (2003) found that this specific network showed one further property. Most websites had only some connections to others, whereas some websites had a tremendous amount of connections and served as so-called '*hubs*'. The authors found this characteristic in a variety of real-life networks, including molecules in a cellular metabolism, internet router, and sexual relationships, and called them **(d) scale-free networks** (or power-law networks) (Barabási and Bonabeau, 2003). According to Barabási and Bonabeau, two mechanisms explain this property: growth and preferential attachment. '*As new nodes appear, they tend to connect to the more connected sites, and these popular locations thus acquire more links over time than their less connected neighbors*' (Barabási and Bonabeau, 2003, p. 65). The distribution of nodes in scale-free networks follows a power law (Barabási and Bonabeau, 2003). Interestingly, the characteristic of preferential attachment tends to be linear, meaning that '*a new node is twice as likely to link to an existing node that has twice as many connections as its neighbor*' (Barabási and Bonabeau, 2003, p. 65). In short, the probability that a node in scale-free networks establishes a new link increases with the number of links it already has. Scale-free networks are also used in a number of ABMs simulating technology diffusion (Kiesling et al., 2012). An illustration of the described network topologies is given in fig. 2.4.

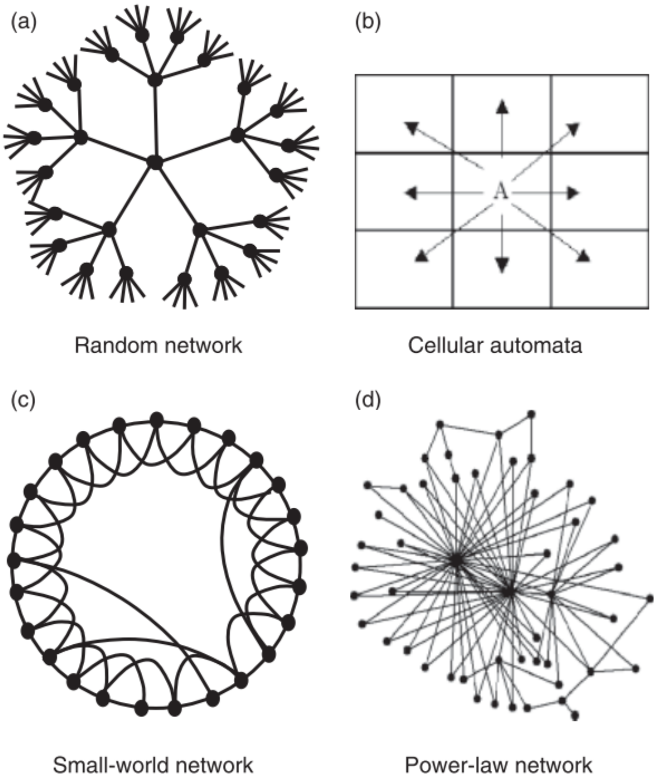


Fig. 2.4 Network structure topologies, adopted from (Bohlmann et al., 2010).

Unsurprisingly, firms exhibit network properties, too. Their connections are not limited to other firms within the same sector, but can reach to regional industries or public agencies, for instance (Polenske, 2004). While it is unlikely that a universal network topology for firms exist, many studies showed, that the automotive-, life sciences- and ICT-industry exhibit properties of a scale-free network (Dömötörfi et al., 2016; Ozman, 2009; Parhi, 2008; Riccaboni and Pammolli, 2002).

2.3.2.3 Validation of agent-based models

This section gives a brief overview of validation approaches of empirically grounded ABMs. Empirically grounded ABMs need to show that they accurately represent or predict the simulated system (Zhang and Vorobeychik, 2019). ABMs that fulfill this requirement are called *reliable* (Zhang and Vorobeychik, 2019). The testing for reliability is accomplished through *model validation*, whereas validation differs between simulation models and even between ABMs (Zhang and Vorobeychik, 2019). Carley (1996) suggested four levels of validation for general computational models: grounding, calibrating, verification, and harmonisation. '*Grounding establishes reasonableness of a computational model, including face validity, parameter validity, and process validity; calibration establishes model's feasibility by tuning a model to fit empirical data; verification demonstrates how well a model's predictions match data; and harmonisation examines the theoretical adequacy of a verified computational model*' (Zhang and Vorobeychik, 2019, p. 733). Windrum et al. (2007) distinguished between the indirect calibration approach, the Werker-Brenner approach, and the history friendly approach for empirical validation of ABMs. The indirect calibration approach combines empirical data and stylised facts to develop a model in which the micro-level description is sufficiently realistic. Stylised facts are '*observations [that are] generally understood to be empirical truths to which theories must fit*' (Garcia et al., 2007, p. 850). The Werker-Brenner approach adds one further step to the indirect calibration approach. Specifically, Bayesian inference procedures are used to compare the model output with real-world data. The history-friendly approach uses one specific case study within an industry to estimate parameters and agent properties (Fagiolo et al., 2006; Garcia et al., 2007; Windrum et al., 2007). '*History-friendly models aim to capture, in stylized form, qualitative and 'appreciative' theories about the mechanisms and factors affecting industry evolution, technological advance and institutional change put forth by empirical scholars of industrial economics, technological change, business organization and strategy, and other social scientists*' (Malerba et al., 1999, p. 3f.). It is not the goal of history-friendly approaches to closely match historical episodes, however. Rather, they aim to match qualitative features of the specific industry (Garcia et al., 2007). This approach is suggested for the simulation of episodic events such as innovation diffusion (Garcia et al., 2007). It is important to note that the evaluation of ABMs, particularly in sociological research, does not aim to replicate real-world scenarios (Bruch and Atwell, 2015). '*Rather, the goal is to explore the systems implications of behavioral mechanisms and the robustness of those mechanisms to changes in the key parameters*' (Bruch and Atwell, 2015, p. 207). It is therefore not desirable to compare the output to empirical patterns (Bruch and Atwell, 2015). A more suitable approach is to determine whether the mechanisms and the architecture of the ABM resemble real-world phenomena (Bruch and Atwell, 2015).

Not all simulation studies are built on empirical data. Abstract ABMs pose a contrast to empirical ABMs and are not validated with the previously described approaches. They rather investigate hypothetical scenarios with specific assumptions. Study 3 of this research develops an abstract ABM where some preliminary empirical data that serve as guidelines to estimate parameter values were collected. A more detailed description of abstract ABMs and a justification for their fit to investigate effects of patent pledges on technology diffusion is given in chapter 3.3.3. The following section introduces attributes that generally influence adoption decision and does not strictly distinguish between aggregate models and computer simulation.

2.3.3 Attributes that influence adoption decisions

Important aspects of technology diffusion processes, equally whether they are calculated with aggregate models or simulated with ABMs, are the perceived attributes that influence the decision to adopt. Many attributes were proposed in the literature, while most included or built upon the five innovation attributes described by Rogers (1962): relative advantage, compatibility, complexity, trialability, and observability. Moore and Benbasat (1996), for instance, compiled a list of eight perceived innovation attributes from previous research (see also Agarwal and Prasad (1997); Karahanna et al. (1999); Venkatesh et al. (2003)). These attributes are relative advantage, image, compatibility, ease of use (also referred to as Complexity), trialability, visibility, result demonstrability, and computer avoidance (IT specific only) and constitute an adaptation of the original attributes of Rogers. Through a meta-analysis of 75 innovation studies, Tornatzky and Klein (1982) found that out of 10 attributes, compatibility, relative advantage, and complexity were most important in adoption decisions. Hall (2005) highlighted the fact that apart from economic factors also non-economic determinants such as cultural attitudes can play a major role in the adoption decision.

One important characteristic of patent pledges is their reasonable or free monetary compensation (see table 2.1), which is why it is worthwhile to provide an overview of the monetary price as a decision attribute in technology adoption processes. Already Mansfield (1961) found that the imitation rate of an innovation tends to be faster when the required investment is relatively small. The original diffusion model developed by Bass (1969) did not consider the price of technologies, which the author himself criticised in a later publication (Bass, 1980).[7] Tornatzky and Klein (1982) found that 10 out of 15 studies that investigated the influence of initial costs of an innovation on its adoption rates reported statistical findings about their correlation. The authors stated that, other attributes being equal, a cheaper innovation is more likely to be adopted. In terms of implementation, however, the costlier the

[7] For early studies that specifically considered the price as an influence factor of innovation diffusion see for instance David and Olsen (1992); Metcalfe (1981); Stoneman and Ireland (1983).

innovation is, the more likely it is to be fully implemented (Tornatzky and Klein, 1982). This is because the adopter is more motivated to use the innovation since she has already invested a large number of resources. Hall (2005) argued that the costs for adopting technologies are not only comprised by the monetary price of the acquisition. She stated that complementary investments as well as learning processes should also be considered as costs in the wider sense. Geroski (2000) summarised different costs that influence an individual's decision in the adoption process. Specifically, Geroski mentioned learning and search costs, switching costs, and opportunity costs as monetary factors that affect the willingness to adopt. Additionally, the author highlighted the importance of technology suppliers and argued that their pricing strategy has a direct influence on the acquisition of the respective technology.

Geroski (2000) furthermore pointed out that suppliers sell technologies to two kinds of buyers: to direct consumers and/or to downstream firms. This is a fact that was often overlooked in empirical diffusion studies, even though Stoneman and Ireland (1983) emphasised the importance of the supply side in technology diffusion studies decades ago. The focus of this research lies on diffusion on an organisational level rather than an individual level. Patent pledges primarily address firms, not individuals, because patents constitute no final products for end-consumers to buy. Rather, they disclose knowledge that can be incorporated into a firm's own products or services. As mentioned earlier, the literature on technology diffusion is vast. Most studies, however, investigated adoption decisions by individuals, which were usually end-consumers. Surprisingly few scholars attempted to explain the adoption behaviour of organisations (commonly referred to as *inter-firm technology adoption*), and the ones that did frequently relied on mechanisms used in adoption theories for individuals (Asare et al., 2016). The term *inter-firm technology diffusion* relates to the adoption of a technology across firms, whereas *intra-firm diffusion* puts the focus on the diffusion within one specific organisation (Schuster and Rueck, 2017). Common theories such as the Technology Acceptance Model (TAM) and the attributes of innovation framework should consider more factors for the adoption process because decision-making in an organisational context is more complex (Asare et al., 2016; Damanpour, 1991). While there exist influential studies that investigated this issue (for instance Grover (1993); Hart and Saunders (2016); O'Callaghan et al. (1992); Premkumar and Ramamurthy (1995); Russell and Hoag (2004)), their results are inconsistent in the sense that they do not comprehensively address the matter on three identified levels: technological, organisational, and inter-organisational (Asare et al., 2016; Chwelos et al., 2001). Asare et al. (2016) resolved this issue by proposing a comprehensive *Technology Adoption in Supply Chains (TASC)* model. Their model includes the widely used technical characteristics of Rogers (1962), but also considers organisation-specific elements, environmental factors, and relationships between firms (see fig. 2.5). The simulation model of Study 3 is built upon the TASC model, which is why a description of each attribute is given in table 6.1 in chapter 6. The TASC model adds costs as an important characteristic of technologies. They can be further broken down into *direct* and *indirect* costs: direct costs relate to the acquisition of the technology, while indirect costs refer to the usage, implementation, and maintenance of the technology (Asare et al., 2016).

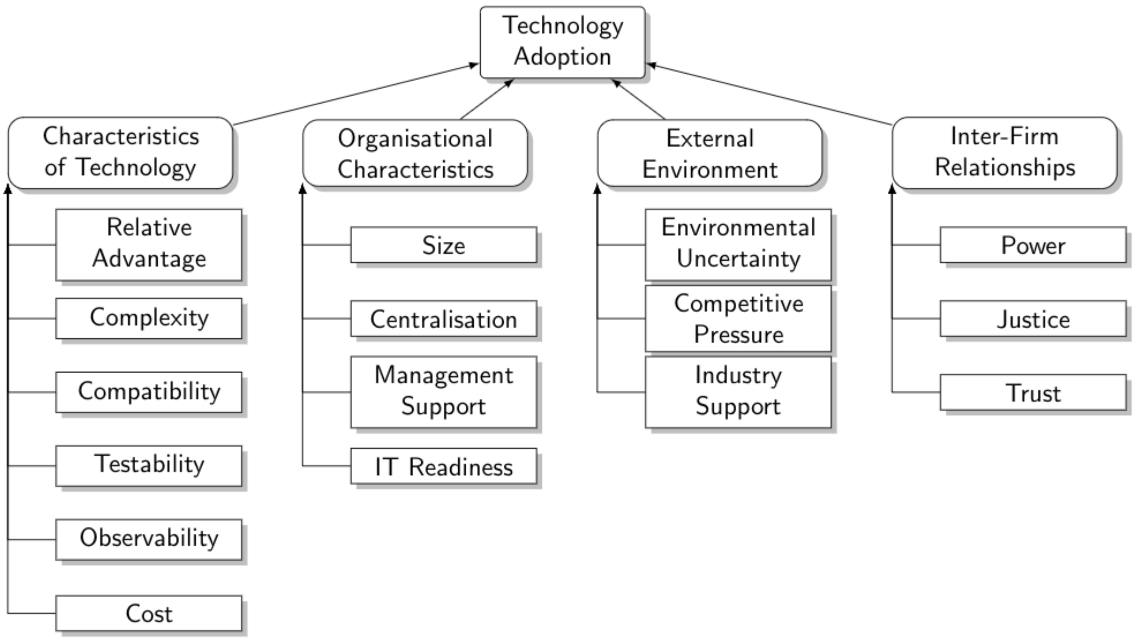


Fig. 2.5 The TASC model proposed by Asare et al. (2016).

This section gave an overview of attributes that influence the decision to adopt technologies. It can be concluded that recent studies complemented early works by additional influence factors, specifically when considering technology adoption in an organisational context. The focus of inter-firm diffusion appears the most suitable for this research because patent pledges primarily address other firms that can incorporate the pledged patents in their products. The following section summarises existing research that attempted to measure the effect of patent pledges on technology diffusion.

2.3.4 Effects of patent pledges on technology diffusion

Chapter 2.2 showed that increased or accelerated technology diffusion is thought of as a primary motive for patent pledges. Whether such strategies really have a significant effect on the diffusion rate of a technology is part of an academic debate. Chien (2016) pointed out that this is difficult to measure. She stated that '*even in cases where a company adopts a* *patented technology and can prove that the patentee's promise not to sue factored into the decision, showing that the company otherwise would not have adopted the technology can be difficult*' (Chien, 2016, p. 844). However, a number of scholars found a positive correlation between patent pledges and technology diffusion (Al-Aali and Teece, 2013; Bessen, 2014; Grewal, 2017; Merges, 2004; Spithoven et al., 2013; Wen et al., 2016; West and Gallagher, 2006). Wen et al. (2016), for instance, provided evidence that a patent pledge of IBM caused an increase in start-ups in the area related to the pledged patents. In contrast, by examining patent citation rates, Sundaresan et al. (2017) and Contreras et al. (2019) found no or even negative correlations between patent pledges and technology diffusion. It is important to note, however, that both studies relied on patent citation data. To prove technology diffusion through patent citation data, improvements of a first patent must be filed as a patent and must also cite the first patent. The studies of Wen et al. (2016), Sundaresan et al. (2017), and Contreras et al. (2019) serve as pioneering investigations of how patent pledges might influence technology diffusion rates. The way how they measured these effects, however, remain questionable and are criticised by an interviewee in Study 2 (see chapter 5.5.3). Before the aforementioned studies were carried out, Chander and Sunder (2004) provided a general explanation about the non-existing or negative correlation between openness and decreased adoption. He called it the 'romance of the commons': '*the belief that because a resource is open to all by force of law, it will indeed be equally exploited by all. But, in practice, differing circumstances - including knowledge, wealth, power, and ability – render some better able than others to exploit a commons*' (Chander and Sunder, 2004, p. 1332). Furthermore, there remain some legal questions regarding patent pledges, which might hinder third parties to adopt (Chien, 2016; Schultz and Urban, 2012; Sundaresan et al., 2017): the absence of a legal contract (Contreras, 2018b), the lack of a guarantee that the IPRs will remain open in the future (Chien, 2016), and the fact that no patent pledge has been tested in court yet (Schultz and Urban, 2012) are all factors that contribute to this obstacle. Also, studies noted that some firms perceive released patents as not valuable (Contreras et al., 2019; Sundaresan et al., 2017).

There were related attempts to measure diffusion effects through analytical approaches as described in chapter 2.3.1, albeit they did not address patent pledges specifically. An analytical approach that describes an innovators incentive to reveal information was described by Harhoff et al. (2003). The authors provided a mathematical model in which the complex business environment is narrowed down into four fundamental variables. Specifically, an innovator generates profit by revealing his innovation if

$$\gamma < \frac{\mu - \frac{c}{\delta}}{\alpha(\mu + 1)} \tag{2.3}$$

where

$\gamma =$ Generality as a measure for how effectively the innovation can be employed by competitors,
$\mu =$ Extent by which an independent manufacturer can improve the innovation,
$c =$ Adoption costs,
$\delta =$ Increment in present discounted profits, and
$\alpha =$ Intensity of competition.

Following this model, the authors concluded that a user adopts the innovation if

$$\gamma\mu > \frac{c}{\delta} \tag{2.4}$$

While Harhoff et al. (2003) provided a simple mathematical model to explain the motive to reveal an innovation on the one hand and the incentive to adopt this innovation on the other hand, the authors' approach lacks an explanation concerning the expression of the parameters in specific, real world cases. Furthermore, Harhoff et al. did not consider consumer heterogeneity - a common limitation of aggregate diffusion models (see chapter 3.3.3). Their model provided valuable insights into decision processes by pointing out important influence factors, however. Niculescu et al. (2018) also used an analytical, game-theoretic model to investigate the interplay of IP-sharing for proprietary technology platforms with network externalities and the absorptive capacity of an entrant. Rather than measuring diffusion and adoption rates in one specific scenario, the authors provided suggestions under which absorptive capacity and network effect intensity values the sharing of IP (further distinguished between basic and extensive sharing) makes economic sense. While Niculescu et al. described a detailed investigation of IP-sharing on technology diffusion, the model inherited the usual limitations of aggregate diffusion models. It assumed, for instance, that the population is homogeneous and that all parties know all model parameters and decision variables. The mathematical model of Parker and Alstyne (2018) inherited similar limitations. The authors investigated optimal degrees of openness and duration of IP in digital platform ecosystems, while also including recursive production formulas. Parker and Alstyne suggested that optimal openness of digital platforms is proportional to developer elasticity. Breaking this concept further down, Boudreau (2010) distinguished between two general approaches of openness in software platforms from the perspective of the platform owner: Granting access to a platform (through released IPRs, for instance) on the one hand and giving up control over the platform itself on the other hand. The author found that technology development of the first approach, compared to the second approach, is accelerated and therefore preferable. However, the arguments and econometric analysis of Boudreau relied on hand-collected data of product releases and were past-oriented. Furthermore, the author did not include individual decision-making into his analysis.

One attempt was made to study technology diffusion under similar concepts to patent pledges through computer simulation. Bonaccorsi and Rossi (2003) developed an abstract ABM with the focus on open-source software instead of patent pledges. In their model, proprietary software had initially a prevalence of 100% and 1000 agents needed to decide whether to adopt open-source software or to continue using the proprietary software (Bonaccorsi and Rossi, 2003). Bonaccorsi and Rossi simulated different scenarios by varying model parameters. For instance, they changed the agents' attitude towards open-source software by varying the distribution of an underlying variable called *intrinsic value*. Their ABM further simulated investments in proprietary software as reactions of incumbents whenever the diffusion of open-source software increased by 1%. A revision of the technology choice after the adoption process was not implemented. The authors found that the diffusion of open-source software depends on the initial belief distribution of the adopters and on the activation of network externalities (Bonaccorsi and Rossi, 2003). Another finding was that in many scenarios, open-source software and commercial software are likely to coexist. Some of the simulation aspects remain unclear, however, such as the specific network topology between agents. Furthermore, the adoption function formula of the individual agents did not comprise different technology attributes such as the ones described in the TASC model (see fig. 2.5). The ABM proposed by Bonaccorsi and Rossi delivered first insights into how one might attempt to investigate technology diffusion under patent pledges through computer simulation.

2.3.5 Conclusion

Existing studies that investigated the effects of patent pledges on technology diffusion were limited and delivered contradictory results. They utilised patent citation data as a measure for diffusion rates and analytical approaches that inherit major limitations (see chapter 3.3.3). The number of analytical solutions in the more general context of free revealing exceeds the number of comparable simulation studies, despite their disadvantages. Abstract simulation studies that address open-source software are known, but it is unclear to what extent their findings can be conveyed to patent pledges. A simulation study that specifically addresses technology diffusion under patent pledges is yet to be carried out.

Chapter 3

Research approach

3.1 Philosophical stance

Research philosophy is generally concerned with the nature of knowledge and its development (Saunders et al., 2009). The choice of the research philosophy determines the research strategy and its subsequent research methods (Saunders et al., 2009). Saunders et al. pointed out that no universal research philosophy exists, but that the different philosophies are better at doing different things. *Ontology* and *epistemology* are two main approaches of thinking about research philosophy (Saunders et al., 2009).[1] As they both influence the way the researcher thinks about the research process, it is important to define and describe them in more detail (Saunders et al., 2009).

3.1.1 Assumptions about the ontological nature

Ontology is concerned with the nature of reality and the basic assumptions about it (Easterby-Smith et al., 2015; Saunders et al., 2009). Social scientists need to take a stance on whether the reality to be investigated is external to the individual or the product of individual consciousness (Burrell and Morgan, 1979). The former stance is referred to as *realism*, while the latter is called *nominalism*. Realists believe that the social world exists independently from the individual and is not created by the individual. Nominalists, on the other hand, see the external world as mere concepts built by the individuals themselves (Burrell and Morgan, 1979). Realism and nominalism are also referred to as *objectivism* and *subjectivism* (Saunders et al., 2009). Saunders et al. used the example of management practices to illustrate

[1] Saunders et al. (2009) further included *axiology* as a way to think about research philosophy. Axiology concerns judgements about the values of the researcher.

this difference. Researchers akin to the realist's view would argue that managers have job descriptions and operating procedures they need to adhere to. Therefore, management is structured and similar across all organisations. Researchers taking the stance of a nominalist, on the other hand, would put more emphasis on the idea that each manager has its own way to think about his job and the way he performs it (Saunders et al., 2009). In between these two extremes lies a third approach called *relativism*, which assumes that multiple truths exist and facts depend on the viewpoint of the observer (Easterby-Smith et al., 2015). Easterby-Smith et al. provided another distinction of ontological assumptions using the concept of profit. Realists would believe that there is one single number that describes profit and that this number is an accurate representation of the difference between income and expenditure. Relativists would take the stance that besides the common figure of profit, other indicators are equally important to determine the financial health of a firm. Finally, nominalists would question how profit is calculated in each company, and how this number might have been manipulated (Easterby-Smith et al., 2015).

3.1.2 Assumptions about the epistemological nature

Research philosophy is also concerned with the epistemological nature and its assumptions. Epistemological assumptions focus on how the researcher might begin to understand the world and what constitutes acceptable knowledge (Burrell and Morgan, 1979; Saunders et al., 2009). Similar to ontological assumptions, epistemology culminates in two contrasting views of social scientists: *positivism* and *anti-positivsm* (also called interpretivism or social constructionism) (Burrell and Morgan, 1979; Easterby-Smith et al., 2015; Saunders et al., 2009). Positivists take the stance that properties of an external world can be objectively measured and therefore act as natural scientists (Easterby-Smith et al., 2015; Saunders et al., 2009). They develop and test hypothesis based on existing theories (Saunders et al., 2009). Social constructionists, in contrast, believe that the observer is part of what is being observed and that research progress is induced by ideas stemming from rich data rather than through hypothesis testing (Easterby-Smith et al., 2015). Easterby-Smith et al. illustrated this difference by using the example of a study about managerial stress. Positivists would implement ways to measure stress in a large number of employees with standardised verbal reports or based on physiological factors. Social constructionists, on the other hand, would talk to a small number of managers and ask them about incidents that they consider as stressful (Easterby-Smith et al., 2015).

3.1.3 Philosophical stance of this research

The two branches of research philosophy described above are not independent from each other. Rather, positivism fits with ontologies of a realist and constructionism with ontologies of a nominalist (Easterby-Smith et al., 2015). The connection between ontology and epistemology is often visualised by a tree trunk, in which ontology represents the heartwood and epistemology the following ring. Research methodology as well as research methods and techniques pose two subsequent layers and complete the metaphorical trunk (Easterby-Smith et al., 2015).

The nature of this research with its three diverse research objectives complicates the choice of ontology and epistemology (see chapter 1.2). This is partly true because of its phenomenon-driven and exploratory approach (Blaikie and Priest, 2019; Saunders et al., 2009; Schwarz and Stensaker, 2014). Schwarz and Stensaker (2014) criticised the restrictions that a theory-driven focus puts on organisational research and promoted phenomenon-driven research as a way to '*take off the theoretical straightjacket*' (Schwarz and Stensaker, 2014, p. 478). Rather than being theory-driven, this research aims to contribute to a frame of knowledge instead of one single theory. It seeks new insights and assesses the phenomenon from a new perspective (Robson, 2002; Saunders et al., 2009). A comparison between theory-driven and phenomenon-driven research is given in table 3.1.

Table 3.1 Comparison between theory-driven and phenomenon-driven research adopted from Schwarz and Stensaker (2014).

	Theory-driven research	**Phenomenon-driven research**
Aim of research	Contribute to a specific (and often pre-existing) theory	Contribute to a body of knowledge; facilitating conventional understanding
Motivation for research	Fill a theoretical gap or make a theoretical contribution; theory as knowledge	Understand a managerial or organizational phenomenon; capturing and extending knowledge
How the contribution is made	By creating or developing construct-to-construct linkages	By mapping (new) constructs on to a phenomenon
The role of theory	Using existing theory to build new theory or enhance current theories	Using empirical data to position or build theory. Eclectically drawing on and integrating multiple theories to describe and explain phenomenon
Primary target audience	Academics	Academics and practitioners
Research output	Incremental advancements to existing theory	Radical advancement of current knowledge through development of new theories or ideas. Also allows for extension and new combinations of existing theories

As a result of the phenomenon-driven, exploratory approach of this research, the philosophical stance of a **pragmatist** is adopted. In this stance, the research objectives are the most important determinants for the researcher, whereas the choice between the ontology and the epistemology are of secondary importance. The pragmatist believes that it is feasible, even preferable, to work with a variety of stances to answer different research questions (Easterby-Smith et al., 2015; Saunders et al., 2009). The three research objectives of this research support the choice of pragmatism as philosophical stance: RQ1 and RQ2 aim to investigate the types and motives for patent pledges and examine rather small sample sizes with rich data. As for the motives, chapter 3.3 justifies that qualitative interviews are a suitable research method to answer RQ2. In such interviews, feelings of the interviewer and the interviewee alike inevitably influence the outcomes. From a positivists point of view, it would be extremely difficult to accurately measure these feelings across the sample (Saunders et al., 2009). RQ3, on the other hand, concerns the impact of patent pledges on technology diffusion and asks for a positivists approach to quantifiable observations and analysis of diffusion rates (Saunders et al., 2009). As a result, this research applies a mixed method research design that includes both, qualitative and quantitative techniques - an important characteristic of the pragmatist, see table 3.2. The choice of specific research methods is described in more detail in chapter 3.3. While realism can also utilise a mixed-method approach to answer the research questions, the stance of this research is that the ontology is not entirely objective, but that subjective meanings (i.e. meanings from interviewees) can provide acceptable knowledge (Saunders et al., 2009).

Table 3.2 Comparison between research philosophies in management research, adapted from Saunders et al. (2009).

	Positivism	Realism	Interpretivism	Pragmatism
Ontology: the researcher's view of the nature of reality or being	External, objective and independent of social actors	Is objective. Exists independently of human thoughts and beliefs or knowledge of their existence (realist), but is interpreted through social conditioning (critical realist)	Socially constructed, subjective, may change, multiple	External, multiple, view chosen to best enable answering of research question
Epistemology: the researcher's view regarding what constitutes acceptable knowledge	Only observable phenomena can provide credible data, facts. Focus on causality and law like generalisations, reducing phenomena to simplest elements	Observable phenomena provide credible data. Insufficient data means inaccuracies in sensations (direct realism). Alternatively, phenomena create sensations which are open to misinterpretation (critical realism). Focus on explaining within a context or contexts	Subjective meanings and social phenomena. Focus upon the details of situation, a reality behind these details, subjective meanings motivating actions	Either or both observable phenomena and subjective meanings can provide acceptable knowledge dependent upon the research question. Focus on practical applied research, integrating different perspectives to help interpret the data
Data collection techniques most often used	Highly structured, large samples, measurement, quantitative, but can use qualitative	Methods chosen must fit the subject matter, quantitative or qualitative	Small samples, in-depth investigations, qualitative	Mixed or multiple method designs, quantitative and qualitative

To conclude, the philosophical stance of a pragmatist appears to provide the most suitable perspective to concur with the phenomenon-driven, exploratory approach and the mixed-method design of this research (see table 3.2).

3.2 Logic of inquiry

After establishing the philosophical stance of a pragmatist, it is important to choose the appropriate logic(s) of inquiry, i.e. how to best answer the research questions. Blaikie and Priest (2019) distinguished between four logics of inquiry for social sciences: inductive, deductive, retroductive, and abductive. While research questions can generally be answered by using more than one logic of inquiry, the produced results might be different (Blaikie and Priest, 2019). Table 3.3 contrasts the four logics of inquiry in social research.

Table 3.3 Four logics of inquiry, adapted from Blaikie and Priest (2019).

	Inductive	**Deductive**	**Retroductive**	**Abductive**
Purpose	To establish *descriptions* of characteristics and regularities	To test *explanations*, to eliminate false ones and corroborate the survivor	To discover underlying mechanisms to *explain* observed regularity	To *understand* social life in terms of social actor's meanings and motives
Start:	Collect data on characteristics and/or regularities Produce descriptions	Identify a regularity that needs to be explained Construct a theory and deduce hypothesis	Identify, document and model a regularity Describe the context and possible mechanisms	Discover everyday lay concepts, meanings and motives Produce a technical account from lay accounts
Finish:	Relate these to a 'what' research question	Test hypothesis by matching them with data	Establish which mechanism(s) provide(s) the best explanation in context	Develop a theory and elaborate it iteratively

The suitability of different logics of inquiry depends on the type of the research question as well as on its purpose. Inductive logic, for instance, is not well suited to answer '*Why*'-questions because '*its use of well-confirmed generalizations to do this has severe limitations*' (Blaikie and Priest, 2019, p. 112). A summary of the suitability of logics of inquiry for different research purposes and questions is provided in table 3.4.

Table 3.4 Logics of inquiry, research purposes and research questions, adapted from Blaikie and Priest (2019).

Purpose	Inductive	Deductive	Retroductive	Abductive	Question type
Exploration	***			***	What
Description	***			***	What
Explanation	*	***	***		Why
Prediction	**	***			What
Understanding				***	Why
Change		*	**	**	How
Evaluation	**	**	**	**	What & Why
Assess impacts	**	**	**	**	What & Why

Key: *** = major activity; ** = moderate activity; * = minor activity

Based on the three research questions described earlier, an *abductive* logic of inquiry is chosen. The justification for this choice is as follows: deductive and retroductive logics are not suggested, because this research is exploratory and lacks the regularities needed for these two logical inquiries. An inductive logic seems to constitute a suitable logic to answer the '*What*'-question of this research. The exploratory nature, the limited amount of units of analysis for RQ1, and the consideration of existing literature to arrive at the sample as described in chapter 4.1, however, are all factors that rule out a purely inductive approach (Blaikie and Priest, 2019; Danermark et al., 2002; Glaser and Strauss, 1967). Since an already existing preconception about patent pledges for the data collection in Study 1 is used, the logic cannot be entirely inductive. Rather, findings from Study 1 constitute a '*move from a conception about something, to a different, possibly more developed or deeper conception of it*' (Danermark et al., 2002, p. 91). Furthermore, inductive as well as deductive logics ignore motives that direct people in their behaviour, which are the essence of RQ2 (Blaikie and Priest, 2019). Abductive logic is furthermore the only approach to investigate '*Why*'-questions with the purpose of understanding, which is the goal of Study 2. Lastly, according to table 3.4, the abductive approach allows for the inquiry of Study 3, a '*How*'-question with the purpose of investigating change. An abductive logic of inquiry therefore appears to be the preferred logic for this research.

3.3 Research methodology

As mentioned earlier, this research utilises a mixed-method research approach. Mixed-method research uses both qualitative and quantitative data collection and analysis techniques, but does not combine them (Saunders et al., 2009). As discussed in chapter 3.1.3, the pragmatist uses the most suitable methods to answer the research questions. A separate description of the justification of the used methods for each research question is given in the following sections. Fig. 3.1 gives an overview of the research design. A detailed description of the respective data collection and analysis is given in the corresponding chapters of the Studies 1-3 (chapters 4-6).

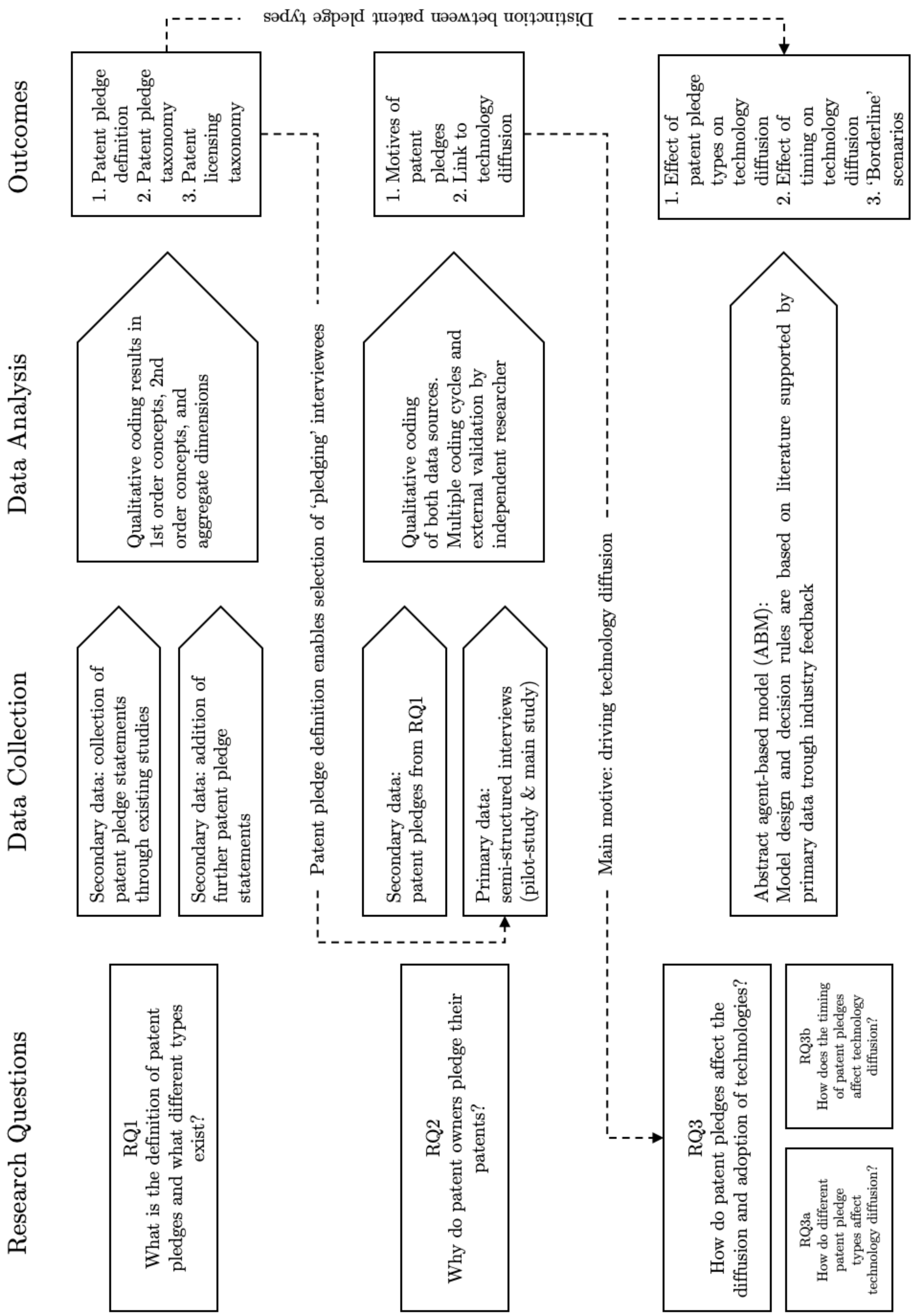


Fig. 3.1 Research design summary.

3.3.1 Study 1: coding secondary data

Study 1 utilises secondary data to answer RQ1. As Contreras (2017a) mentioned, many patent pledges, particularly outside of standard-setting contexts, appear in the form of (online) press releases. This is why it is argued that these press releases constitute useful data for the investigation of a patent pledge definition and different types. The fact that patent pledges are often publicly announced facilitates the process of accessing them (Contreras, 2017a). The collection and analysis of such data is a valid step to investigate RQ1, because public announcements, specifically company reports and media accounts, constitute important sources for secondary data (Contreras, 2017a; Kervin, 1992; Stewart and Kamins, 2012). Generally, secondary data include information that were gathered by persons other than the researcher (Kervin, 1992; Stewart and Kamins, 2012). Most data collected to answer RQ1 were collected by Contreras (2019), whereby the majority of these data constitute online press releases of patent owners. This data collection process is further described in Study 1, see chapter 4.1.

The interpretation of existing reports and documents is a well-established part of exploratory research and therefore fits this phenomenon-driven, exploratory research (Kervin, 1992). Secondary analysis '*overcomes the narrow focus on individuals and their characteristics*' (Hakim, 1982, p. 16). The focus of the researcher lies more closely on the theoretical aims than on the issue of collecting new data (Hakim, 1982; Stewart and Kamins, 2012). Disadvantages may include some form of bias of the collector, as well as the initial collection for other purposes (Stewart and Kamins, 2012). The secondary data analysis process stipulates to (1) formulate the research question, (2) conduct a literature review, (3) establish criteria for inclusion, (4) collect data, (5a) use data collected by others or (5b) use own previously collected data, (6) analyse the data, and (7) report the findings (Brewer, 2012). The process of analysing qualitative data is referred to as *content analysis*, which focuses on '*words, sentences, grammatical structures, tenses, clauses, ratios (of say, nouns to verbs) or even "themes"*' (Prior, 2014, p. 361). Bryman (1989) highlighted the '*quantification of themes*', which leads to the question of how one might arrive at such themes (Bryman, 1989, p. 191). A simple word count, for instance, would fail to capture the content adequately (Prior, 2014). Rather, it is desirable to derive the themes directly from the text data through *qualitative coding*. Saldaña (2009, p. 3) explained: '*[a] code in qualitative inquiry is most often a word or short phrase that symbolically assigns a summative, salient, essence-capturing, and/or evocative attribute for a portion of language-based or visual data*'. This allows for the derivation of themes and is further described in chapter 4.2. The themes, or dimensions, lead to a patent pledge definition and different patent pledge types.

3.3.2 Study 2: case study research consisting of semi-structured interviews and secondary data

The question '*Why do patent owners pledge their patents?*' asks for insights about the thinking process of organisations and individuals. Yin (2009) suggested case study research (i) to approach '*Why*'-questions; (ii) when the researcher has little control over the events; and (iii) when a contemporary real-life phenomenon is of interest. The term *case study* is widely used in the academic literature. According to Simons (2014), a common interpretation of case study research refers '*to research and evaluation using primarily qualitative methods, as well as documentary sources, contemporaneous or historical*' (Simons, 2014, p. 455). '*Ideally, evidence from two or more sources will converge to support the research findings*' (Benbasat et al., 1987, p. 374) (see also Eisenhardt (1989)). The literature thereby suggests to utilise more than one data source in case study research. Yin (2009) argued that particularly '*Why*'-questions require documentary information in addition to qualitative interviews. Units of interest in case studies can be, among others, individual people and institutions (Simons, 2014). Case study research, specifically when utilising qualitative interviews, is commonly used to investigate motives in a managerial context (Bansal and Roth, 2000; Belal and Owen, 2007; West and Gallagher, 2006). West and Gallagher (2006), for instance, combined primary data collected through qualitative interviews and secondary data to understand why firms contribute to open-source software. Therefore, West and Gallagher followed the suggestions by Yin (2009) to use both, qualitative interviews as well as documentary information.[2] Furthermore, Contreras et al. (2019) conducted expert interviews to study motives to join the Eco-Patent Commons. Since case study research was often used to investigate motives in a managerial context (Bansal and Roth, 2000; Belal and Owen, 2007) and was furthermore used in similar studies before (Contreras et al., 2019; West and Gallagher, 2006), qualitative interviews constitute the primary data source for Study 2. Furthermore, to concur with the suggestions above, the secondary data collected for Study 1 act as supporting data to investigate motives for patent pledges. Therefore, Study 2 utilises two sources of data, primary data through qualitative interviews and secondary data, specifically patent pledge statements. These two data sources are then analysed through qualitative coding, similar to the coding process described in the previous section (see chapter 5.3 for a detailed description of the data analysis).

An interview in this context is defined as '*a series of questions posed by an interviewer to obtain response data*' (Kervin, 1992, p. 302). These can be conducted in person or

[2] Eisenhardt (1989) also emphasised the combination of data collection methods, such as interviews and archives, in case study research.

by telephone, whereby telephone interviews are cheaper, have a less pronounced effect of the interviewer on the interviewee, and allow for a considerably wider coverage (Bryman, 1989; Kervin, 1992; Saunders et al., 2009). Bryman (1989) highlighted the fit of telephone interviews to access firms with particular strategies, which arguably is the case for firms that conduct patent pledges. In semi-structured interviews, the list of themes and questions may vary from interview to interview (Saunders et al., 2009). Detailed descriptions about the interview process are given in chapter 5.2.

3.3.3 Study 3: agent-based modeling

The literature on innovation diffusion is vast and studies often used analytical approaches or computer simulation as research methods in the past (see chapter 2.3). Therefore, a decision must be made which of these methods is most suitable to answer RQ3. Chapter 2.3.1 showed that many analytical solutions exist and that they were improved over time to include more adoption decision factors. The consideration of a monetary price as one of the model parameters as described by Bass (1980), for instance, seems like a useful extension to investigate diffusion rates under patent pledges. This is because patent pledges often offer patents free of charge, which can pose a monetary advantage over other competing technologies.

It is important to note, however, that aggregate models inherit some major drawbacks, despite their continuous improvements and addition of influence factors. Kiesling et al. (2012) provided an overview of five general disadvantages of aggregate diffusion models, which are summarised in table 3.5. The authors specifically emphasised the importance of population heterogeneity, which is difficult, if not impossible, to replicate with aggregate models. Homogeneity, according to Bohlmann et al. (2010), implies that all potential adopters in a specific time period have the same probability to adopt, which is unlikely to be the case in real-world scenarios. Heterogeneity results in more irregular diffusion patterns, which leads to significant deviations of the often-described S-curve of diffusion. This deviation, however, often resembles the diffusion of real products more accurately and cannot be reproduced with aggregate models (Kiesling et al., 2012). Furthermore, aggregate diffusion models are not capable to answer '*What-if*'-questions, such as what happens when a patent pledge is introduced at a specific time (Kiesling et al., 2012). Another major drawback of aggregate models is their assumption of a fully connected social network. Many studies provided evidence that in reality, many different network topologies exist. Their nodes (people, firms, etc.) are not fully connected (see chapter 2.3.2.2).

Table 3.5 Limitations of traditional aggregate innovation diffusion models adopted from Kiesling et al. (2012).

Limitation	Explanation
Predictive power	By the time sufficient parameter estimates have been derived from historical events, these estimates might not be applicable anymore.
Explanatory power	Aggregate innovation diffusion models cannot reproduce certain real-world diffusion patterns such as collapses of initially successful diffusion.
Population heterogeneity	Aggregate diffusion models rely on the assumption that the respective population is homogeneous. While there exist attempts to consider heterogeneity of potential adopters, they cannot distinguish between factors such as individual attributes and network effects.
Social processes	Bass-based aggregate diffusion models assume a fully connected social network, in which everyone can potentially influence everyone else. Furthermore, the influence between adopters and non-adopters is assumed to be a linear function during the whole diffusion process.
Prescriptive guidance	Aggregate diffusion models are past-oriented and, despite efforts to include further variables and improve those models, they still are considered to be descriptive rather than normative.

Study 3 utilises ABMs as a research method to investigate the effect of patent pledges on technology diffusion for two main reasons: (i) to overcome the previously described limitations of aggregate diffusion models and (ii) as a result of the increase of ABMs in social sciences (Kiesling et al., 2012). ABMs allow the simulation of population heterogeneity, because each agent can be modeled to inherit individual attributes and preferences. Specifically, real-world populations can be simulated by using empirical distributions for the attributes and preferences of the agents. ABMs also allow the simulation of different network topologies, which means that some agents can be modeled to have only few or none connections to other agents, while some agents can have many. Furthermore, ABMs enable the implementation of sudden events during technology diffusion processes. This is an important consideration for Study 3, because the introduction of patent pledges can be seen as such sudden events.

In a next step, it is important to decide on the goals of the ABM, because these goals determine its required degree of empirical realism (Bruch and Atwell, 2015). While empirically validated simulation models can be used to develop a virtual laboratory of the system of interest, abstract ABMs enable the clarification and development of new theories and are common in sociological research (Bruch and Atwell, 2015). Bruch and Atwell further argued that a classic validation of model outputs against empirical patterns is not useful for abstract ABMs. Rather, '*the model can show what might be expected under a set of empirically plausible assumptions*' (Bruch and Atwell, 2015, p. 207). As Bruch and Atwell put it: '*A model's success is determined not by how realistic it is but by how useful it is for helping understand the problem at hand*' (Bruch and Atwell, 2015, p. 193). Due to the exploratory nature of this research and the frequency of abstract models in sociological research, Study 3 utilises an abstract ABM. Specifically, the ABM is inspired by the model of Bonaccorsi and Rossi (2003). The authors did not collect empirical data, but used reasonable values supported by the literature to compare the effects of different scenarios on technology diffusion. Bonaccorsi and Rossi developed a stochastic ABM that allowed for the exploration of different probability distributions and decision processes. This approach is favourable for this research, because '*...the goal is to explore the systems implications of behavioral mechanisms and the robustness of those mechanisms to changes in the key parameters*' (Bruch and Atwell, 2015, p. 207). In contrast to Bonaccorsi and Rossi (2003), some preliminary industry feedback was collected to simulate a reasonable behaviour of the agents (see chapter 6.1.2.3). The ABM could therefore also be labeled as *low-dimensional* (Bruch and Atwell, 2015). Given its limited sample size, the industry feedback should not be seen as an empirical validation of the ABM. Rather, this preliminary collection of empirical data allowed the simulation of plausible assumptions in abstract or low-dimensional models as described by Bruch and Atwell (2015).

Chapter 4

Study 1: definition and taxonomy of patent pledges

Table 2.1 showed that existing definitions of patent pledges are inconsistent and can be divided into two 'camps': definitions that involve monetary compensation, i.e. the patent pledge users must pay for the utilisation, and definitions that do not involve monetary compensation, i.e. the patent pledge users can use the pledged patent(s) for free. It is important to note, however, that this categorisation only considers the monetary price. Other conditions might still apply (Ehrnsperger and Tietze, 2019; Valz, 2017). This chapter attempts to answer RQ1 of this research and aims to lay the groundwork for later inquiries.[1] The chapter is structured as follows: first, the data collection process and the sources for the secondary data are described. Second, the data analysis, which is based on suggestions from the literature and aligned with the abductive logic of this research, is explained. Third, two taxonomies, namely the patent pledge taxonomy and the patent licensing taxonomy, are developed. Finally, a link to licensing behaviours of firms described in the literature and an example of how the patent licensing taxonomy might be used as a strategic tool concludes the chapter.

4.1 Data collection

Collecting data for theory building is a difficult undertaking. Eisenhardt (1989) stressed that the researcher must be as close to the ideal of not building upon existing theories as possible, but admitted that this is impossible to achieve in practice. To collect patent

[1] Parts of this chapter are based on a peer-reviewed journal article, published by the PhD candidate and his supervisor: *Ehrnsperger, Jonas Fabian, and Frank Tietze. 2019. "Patent Pledges, Open IP or Patent Pools? Developing Taxonomies in the Thicket of Terminologies." PLoS ONE 14 (8): 1–18.*

pledges, an existing notion of these initiatives is inevitable. Lerner et al. (2007), for instance, defined patent pools as their unit of interest before collecting data and therefore had a clear understanding of what they collect.

The view of this research is as follows: patent pledgors offer patents for free or on reasonable terms, address a large number of people, and publicly announce the pledge. This follows up on the ideas of '*primary access commitments*' and '*secondary royalty commitments*' described by Contreras (2017a) and is in line with patent pledge notions from other studies (e.g. Schultz and Urban (2012); Sundaresan et al. (2017); Valz (2017); Ziegler et al. (2014). This existing notion of patent pledges facilitates the data collection process, because the necessity to approach patent owners and ask for confidential information ceases. As noted by Contreras (2017a) and Shanahan (2017), patent pledgors often publish patent pledges as written statements on their websites or through press releases, subsequently also referred to as '*patent pledge statements*'. Such statements constitute a valid ground for further enquiry. Lerner et al. (2007), for instance, collected and analysed agreements and documentation to investigate licensing rules in patent pools. Since the abductive approach of this research allows for the existing notion of patent pledges (see chapter 3.2), it is feasible to utilise secondary data that fall within this notion. Contreras (2019) maintained a collection of '*statements and commitments made with respect to patents and patent licensing outside of formal standards-development organizations*', which linked to 178 documents in which patent owners pledged the compliance to specified practices (Contreras, 2019, n.p.). The number 178 stems from the organisation-specific focus of the data set, i.e. every patent owner that took part in an initiative was counted as one entry. As a result, organisations taking part in the same initiative were counted separately (Ehrnsperger and Tietze, 2019). Furthermore, not all entries relate to the existing notion of patent pledges of this research. These two reasons led to an adapted data set that is used in this research. Specifically, organisations that took part in the same initiative are compiled, which results in the count of patent pledges rather than individual organisations. Thirteen entries that did not adhere to the notion of patent pledges of this research or that included vague information were removed: '*(1) the facilitation for prior-art searches ('The Clearing House', Microsoft, Yahoo, SAS), (2) the promise to enable/improve the community review of IPRs (IBM), (3) entries with vague formulations (Novell's patent policy from 2014, Allergan's social contract with patients), (4) the promise not to sell IPRs to NPEs (Verizon, Cisco Systems), (5) entries with a lack of information (John Gilmore, 'Patent Licensing Principles' by Conversant), (6) an entry with the strict restriction to qualified customers (Microsoft's Azure IP Advantage programme), (7) the mere statement of availability of licenses without the specification of standardised or reasonable terms (Microsoft)*' (Ehrnsperger and Tietze, 2019, p. 4). Similarly, some patent pledges that were found through internet-searches and that fit the patent pledge notion were added: the GreenXchange initiative, the OpenPOWER foundation, and IP practices around the QR-Code (Ehrnsperger and Tietze, 2019). The resulting data set comprises 60 patent pledges made by 80 organisations.[2] The collected patent pledges and information about their technological area, their number of patents, and their corresponding patent pledge type are shown in table A.1 through table A.3 in the appendix. In the cases of the GreenXchange initiative and the Eco-Patent Commons, the information were obtained through the literature, specifically through the studies of Contreras et al. (2019) and Awad (2015). Importantly, some patent pledge statements included more than one patent pledge, which resulted in a higher count of patent pledges than statements (60 patent pledges compared to 50 patent pledge statements). The patent pledge statement 'Microsoft (03.12.2003)', for instance, comprised three different patent pledges (Ehrnsperger and Tietze, 2019). The complete data set used in Study 1 is available to download at Ehrnsperger (2019). It comprises 48 instead of 50 documents because the descriptions for the GreenXchange initiative and the Eco-Patent Commons were obtained through the literature, as described above.

4.2 Data analysis and taxonomy development

The secondary data were analysed using two cycles of qualitative coding with NVivo™ (version 12) software. This software was also used for the data analysis in Study 2 and facilitates the process of organising and structuring codes (Saunders et al., 2009).

Conventional content analysis was applied in a first coding cycle, because the goal was to investigate a phenomenon with limited theoretical evidence (Hsieh and Shannon, 2005; Kondracki et al., 2002). As Saldaña (2009) explained: '*...coding is a cyclical act. Rarely is the first cycle of coding data perfectly attempted. The second cycle (and possibly the third and fourth, and so on) of recoding further manages, filters, highlights, and focuses the salient features of the qualitative data record for generating categories, themes, and concepts, grasping meaning, and/or building theory*' (Saldaña, 2009, p. 8). Content analysis avoids preconceived categories and allows themes to emerge directly from the raw data (Ehrnsperger and Tietze, 2019; Hsieh and Shannon, 2005; Kondracki et al., 2002). This initial coding cycle limited subjective judgement and ensured the adherence to the abductive logic of inquiry of this research, see chapter 3.2 (Charmaz, 2006; Ehrnsperger and Tietze, 2019; Saldaña, 2009).

[2] The Eco-Patent Commons, the GreenXchange initiative, the Open Invention Network, and the OpenPOWER foundation were counted as one organisation. Ericsson, Nokia, Nokia Siemens Networks, Siemens, Sony, and Sony Ericsson were counted separately (Ehrnsperger and Tietze, 2019).

Saldaña (2009) suggested to code quickly and spontaneously and to treat all codes from this coding cycle as tentative ideas.

After content analysis in the first coding cycle, the tentative ideas were then revised through a second coding cycle, specifically through pattern coding. Pattern coding identifies major themes from the data and is suggested as second coding cycle after initial coding (Miles and Huberman, 1994; Saldaña, 2009). Miles and Huberman (1994) explained: '*[p]attern codes are explanatory or inferential codes, ones that identify an emergent theme, configuration, or explanation. They pull together a lot of material into more meaningful and parsimonious units of analysis. They are a sort of meta-code*' (Miles and Huberman, 1994, p. 69). Fig. 4.1 shows exemplary codes from the coding cycles in the software NVivo™.

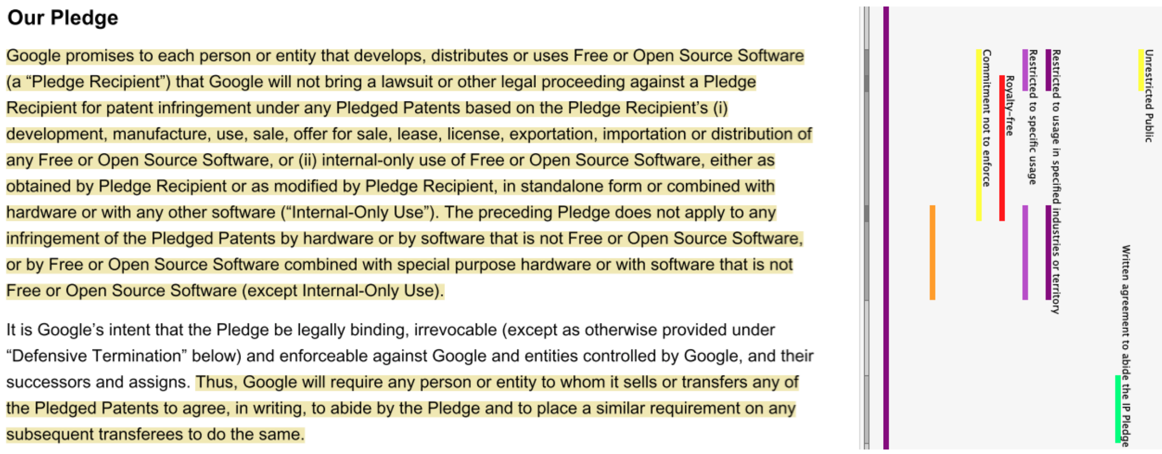


Fig. 4.1 Coding example of Google's 'Open Patent Non-Assertion Pledge'.

After the two coding cycles, major themes were subsumed in categories, which '*explicate ideas, events, or processes*' (Charmaz, 2006, p. 91). As a next step, Gioia et al. (1994) suggested to '*examine the coded data for possible further aggregation into second-order categories and dimensions*' (Gioia et al., 1994, p. 370) (see also Spradley (1980)). The coding process was therefore structured into first order concepts, second order concepts and aggregate dimensions, following Corley and Gioia (2004) and Gioia et al. (1994) (see also Ehrnsperger and Tietze (2019)). Specifically, 12 first order concepts led to six second order concepts, which in turn constituted pairwise values for three final dimensions, as shown in fig. 4.2. The dimensions are described in more detail in chapter 4.3.2.

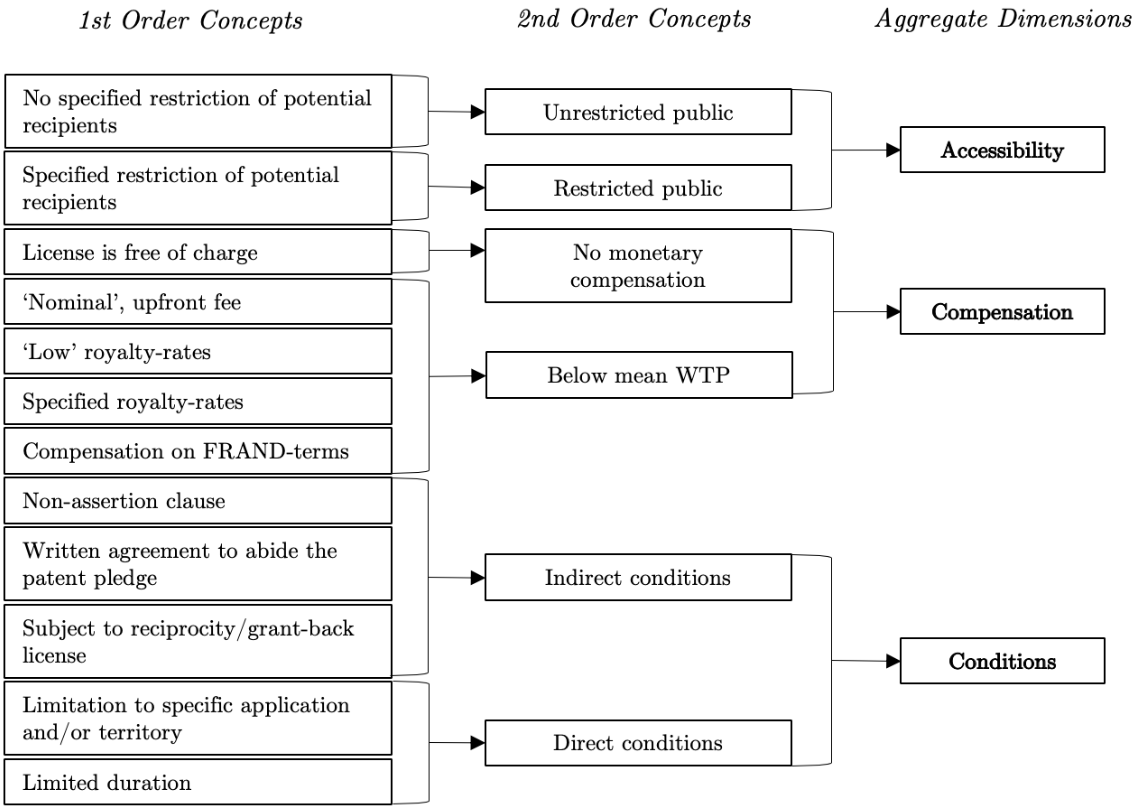


Fig. 4.2 Coding process and aggregate dimensions for RQ1, adapted from Ehrnsperger and Tietze (2019).

The emerging dimensions shown in fig. 4.2 allow for the classification of patent pledges, which is an important characteristic of taxonomies (Doty and Glick, 1994; Ehrnsperger and Tietze, 2019). As opposed to typologies, which relate to a set of ideal types, taxonomies consist of mutually exclusive sets (Doty and Glick, 1994; Ehrnsperger and Tietze, 2019). Doty and Glick (1994) argued that the terms taxonomy and typology are often misunderstood and that many so-called 'typologies' are in fact taxonomies. The second order concepts and aggregate dimensions in fig. 4.2 enable the classification of patent pledges, but do not identify ideal types (Doty and Glick, 1994). Results from this analysis are therefore referred to as 'taxonomies'. Taxonomies that result from this analysis have the advantage that the three aggregate dimensions and the second order concepts are parsimonious, as described by Nickerson et al. (2013). Nickerson et al. explained: '*[a] taxonomy should contain a limited number of dimensions and a limited number of characteristics in each dimension, because an extensive classification scheme with many dimensions and many characteristics may exceed the cognitive load of the researcher and thus be difficult to comprehend and apply*' (Nickerson et al., 2013, p. 341).[3] Furthermore, the resulting taxonomies are comprehensive, because the known objects (patent pledges) can be classified within the domains of the dimension (Ehrnsperger and Tietze, 2019; Nickerson et al., 2013). The taxonomies are also extendible in the sense that additional dimensions or new characteristics within a dimension can be included (Nickerson et al., 2013). This is an important consideration for the development of the second taxonomy, the patent licensing taxonomy, as described further in chapter 4.3.3.

4.3 Results

4.3.1 Definition of patent pledges

The patent pledge definition was partly derived from the coding process and includes the three aggregate dimensions shown in fig. 4.2. In addition to the three dimensions, the definition follows preconceived notions of patent pledges or related concepts. Specifically, it focuses on patent pledges concerning active patents and on announcements that are made public (Alexy et al., 2013; Contreras, 2017a).

> *'A patent pledge is a publicly announced intervention by patent owning entities ('pledgors') to out-license active patents to the restricted or unrestricted public free from or bound to certain conditions for a reasonable or no monetary compensation.'*
> See also Ehrnsperger and Tietze (2019, p. 6).

The definition of patent pledges includes the restriction to active patents only. This clarifies the distinction to patent donations, which concern abandoned patents (Ehrnsperger and Tietze, 2019). The term *reasonable* refers to FRAND-terms and follows the descriptions of Siebrasse and Cotter (2017). One possibility to calculate royalty rates under FRAND-terms is to imagine a hypothetical scenario in which a potential licensee and licensor negotiate the price. Siebrasse and Cotter explained: '*...the most commonly used approach to assessing a reasonable royalty in the FRAND context (...) is to consider what willing parties would have agreed to in a hypothetical negotiation which took place prior to infringement and in which the parties are assumed to know that the patents at issue were valid and infringed*' (Siebrasse and Cotter, 2017, p. 373).[4] In between the licensor's minimum amount he is willing to accept and the licensee's maximum willingness to pay (WTP) lies the reasonable

[3] See also Ehrnsperger and Tietze (2019).
[4] See also Siebrasse and Cotter (2016).

royalty rate (Ehrnsperger and Tietze, 2019; Sidak, 2013).[5] The *mean WTP* is an important element of the developed taxonomies in the following sections and is calculated by averaging the WTP among several parties (Ehrnsperger and Tietze, 2019). It is important to note that the mean WTP is subject to interpretation and varies across industries. While there exist methods to calculate the mean WTP (see for instance Buckland et al. (1999) and Poe et al. (1997)), these values should be treated as estimates in a given industry (Ehrnsperger and Tietze, 2019). This study does not calculate values for the mean WTP. A calculation of the mean WTP would be industry-specific and would contradict the goal of Study 1 to provide general results (Ehrnsperger and Tietze, 2019). The following taxonomies therefore include the value *mean WTP* instead of a specific number.

4.3.2 The patent pledge taxonomy

The development of the patent pledge taxonomy followed a straightforward process, because each aggregate dimension in fig. 4.2 constitutes one dimension. The second order concepts represent values for each dimension. This approach led to a 3-dimensional taxonomy with a dichotomous scale. The following paragraphs describe each dimension in more detail.

The dimension **Accessibility** specifies potential recipients of the pledged patents. The second order concepts show that this dimension can either address the public or a specified restriction thereof. Hence, this dimension can take the values '*Public*' or '*Semi-public*'. Accessibility only refers to recipients that are defined a priori and must not be confused with the dimension *Conditions*. Ehrnsperger and Tietze (2019) provided an example to illustrate this distinction: '*Toyota pledges the availability of specified patents only 'to automakers who will produce and sell fuel cell vehicles, as well as to fuel cell parts suppliers and energy companies'. This patent pledge restricts the number of potential licensees from the outset. On the other hand, IBM's patent pledge from January 2005 does not restrict licensees a priori, but the use of their IPRs is subject to a specified condition: 'IBM hereby commits not to assert any of the 500 U.S. patents listed below, as well as all counterparts of these patents issued in other countries, against the development, use or distribution of Open Source Software*'' (Ehrnsperger and Tietze, 2019, p. 7).[6] Toyota's patent pledge addressed only specific automakers, which translates to the value '*Semi-public*' on the dimension. IBM's patent pledge, in contrast, allowed everyone to make use of the pledge, subject to the stated conditions. Therefore, IBM's patent pledge takes the value '*Public*' (Ehrnsperger and Tietze, 2019).

[5] For a comprehensive definition of the WTP, see for instance Varian (1992), Wang et al. (2007), and Miller et al. (2011).

[6] See 'Toyota 05.01.2015' and 'IBM 11.01.2005' in Ehrnsperger (2019).

The dimension **Compensation** specifies the monetary price that must be paid to make use of the patent pledge. The analysis revealed that pledged patents are available either for free or in return for a reasonable fee. As described above, a reasonable royalty rate lies below the mean WTP. This dimension therefore takes the values '*None*' or '*Below mean WTP*' (Ehrnsperger and Tietze, 2019).

The dimension **Conditions** specifies any restrictions that the a priori defined parties that are allowed to make use of the patent pledge need to honour. Results shows that 42 out of the 60 collected patent pledges were subject to further conditions. These conditions can be further differentiated between direct and indirect conditions. Direct conditions restrict the utilisation of the patent pledge in either space or time, i.e. to a specific area (technological and/or territorial) or for a limited time period. Indirect conditions include the promise not to assert the patent pledgor in return for the utilisation of the patent pledge and 'grant-back licenses', among others (Ehrnsperger and Tietze, 2019). The full list of identified conditions in patent pledges, alongside their frequency and exemplary quotes, is given in table 4.1.

Table 4.1 Conditions in patent pledges, adopted from Ehrnsperger and Tietze (2019).

	Condition	Example
Direct conditions	**Limitation to specific applications and/or territory** (in 25 out of 60 pledges)	'*The policy also broadens Microsoft's commitment to provide the academic community with IP under royalty-free terms for noncommercial use.*' Source: Microsoft pledge, March 2003
	Limited duration (in 3 out of 60 pledges)	'*Patents related to fuel cell vehicles will be available for royalty-free licenses until the end of 2020.*' Source: Toyota pledge, 2015
Indirect conditions	**Non-assertion clause** (in 21 out of 60 pledges)	'*A party is "acting in good faith" for so long as such party and its related or affiliated companies have not: asserted, helped others assert or had a financial stake in any assertion of (i) any patent or other intellectual property right against Tesla or (ii) any patent right against a third party for its use of technologies relating to electric vehicles or related equipment...*' Source: Tesla Motors pledge from 2014, Status: February 2019
	Subject to reciprocity/ grant-back license (in 10 out of 60 pledges)	'*Qualcomm has had a long standing policy of broadly offering to license its standards essential patents for CDMA-based telecommunications standards on terms and conditions that are fair, reasonable, and free from unfair discrimination (FRAND), subject to reciprocity.*' Source: Qualcomm pledge, 2008
	Written agreement to abide the patent pledge (in 1 out of 60 pledges)	'*Thus, Google will require any person or entity to whom it sells or transfers any of the Pledged Patents to agree, in writing, to abide by the Pledge and to place a similar requirement on any subsequent transferees to do the same.*' Source: Google open patent non-assertion pledge. Status: February 2019

Fig. 4.3 shows the 3-dimensional taxonomy from both the front and the rear view. The individual patent pledge types are described below. This description does not include the

dimension *Conditions*, because the conditions from table 4.1 can be equally applied to all types (Ehrnsperger and Tietze, 2019).

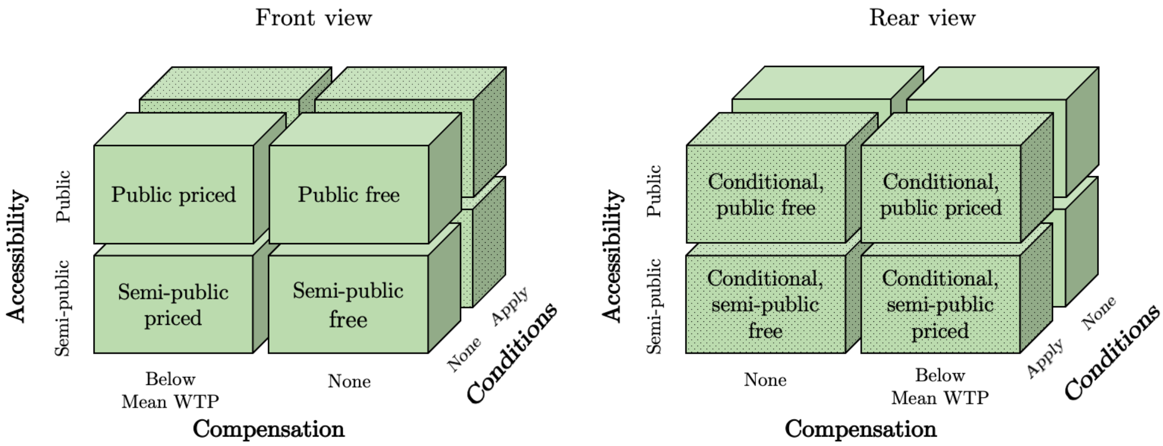


Fig. 4.3 The patent pledge taxonomy adopted from Ehrnsperger and Tietze (2019).

Semi-public priced patent pledges can be utilised by the restricted public in return for a price that is considered below the mean WTP. '*An example for this type is iBiquity's pledge from 2005, in which the organisation commits to license patents on FRAND-terms for 'someone who is skilled in the art to manufacture NRSC-5 compliant transmission devices''* (Ehrnsperger and Tietze, 2019, p. 7).[7]

Priced patent pledges are available to the public in return for a reasonable price. NTTDoCoMo et al., for instance, announced the availability of reasonable licenses concerning the W-CDMA technology in 2002 '*for a cumulative royalty-rate below 5%*' (Ehrnsperger and Tietze, 2019, p. 7).[8]

Semi-public free patent pledges can be utilised for free by the restricted public. The organisation *ThePatentPledge.org* and Toyota both conducted this patent pledge type in the past. The former is a conglomerate of 35 organisations in which they pledged not to assert specific patents against any party that employs less than 25 people. The latter announced the availability of free licenses for certain organisations in the automotive industry (Ehrnsperger and Tietze, 2019).

Public free patent pledges can be utilised for free by the unrestricted public. Tesla's patent pledge from 2014, for instance, falls under this category. The firm allows the free utilisation of its patents for anyone, subject to the condition that the patents are used in the realm of

[7] See 'iBiquity 13.04.2005' in Ehrnsperger (2019).
[8] See 'NTT DoCoMo et al. 06.11.2002' in Ehrnsperger (2019).

electric vehicles (Tesla, 2014). Therefore, Tesla's patent pledge is a *Conditional, public free patent pledge* (Ehrnsperger and Tietze, 2019).

Regarding the distribution of the patent pledges across the patent pledge taxonomy, '*19 pledges (32%) are classified as conditional, public free, 12 as conditional, public priced (20%), 11 as conditional, semi-public free (18%), 9 as public priced (15%), 5 as public free (8%), 3 as semi-public free (5%), and 1 as semi-public priced (2%)*' (Ehrnsperger and Tietze, 2019, p. 8). The sample did not include a *conditional, semi-public priced patent pledge*. Regarding the allocation to distinct industries, 47 patent pledges relate to ICT (78%), six to sustainability (10%), four to biotechnology (7%), and three to automotive (5%) (Ehrnsperger and Tietze, 2019).

4.3.3 The patent licensing taxonomy

One characteristic of robust taxonomies is the possibility to extend its dimensions, as briefly described in chapter 4.2 (Ehrnsperger and Tietze, 2019; Nickerson et al., 2013). The patent pledge taxonomy specifically allows the extension of two of its dimensions: *Compensation* and *Accessibility*. Specifically, it is possible to extend the dimension *Accessibility* so that it ranges from zero parties (i.e. no one is allowed to utilise the patents) to the public. Three additional values are added: '*Selected Clusters*', '*Selected Parties*', and '*None*'. As noted by Ehrnsperger and Tietze (2019), the term 'cluster' is often used to describe the location of organisations. In this context, however, the term addresses a group of entities specified by the patent owner (Ehrnsperger and Tietze, 2019; Martin and Sunley, 2003). The distinction between the values '*Selected Clusters*' and '*Selected Parties*' requires some clarification. The main difference lies in the degree of control the patent owner retains over the number of potential licensees. When the patent owner addresses selected parties, she specifically names them and thereby retains control over the number of potential licensees. In contrast, when she addresses selected clusters, she sacrifices some control by defining an abstract group of potential licensees that can increase without her influence. The number of potential recipients within the value '*Selected Clusters*' in this context is intended to be smaller than the number of the value '*Semi-public*' (Ehrnsperger and Tietze, 2019). For instance, *ThePatentPledge.org* pledged not to assert patents against any party that employs less than 25 people and therefore addresses the restricted public, as described in the previous section. If the organisation would further restrict the potential beneficiaries, for instance by announcing that the licenses are only available to firms with less than 25 people within a specific country, this could be classified as a '*Selected Cluster*'. This would also infer that the announcement of the organisation does not fall under the definition of a patent pledge anymore.

Analogously, the dimension *Compensation* can be extended to include all prices to access patents, not just reasonable prices or no costs at all. To concur with the notation of the patent pledge taxonomy, the values '*Mean WTP*', '*Above Mean WTP*', and '*High-priced*' are added. Ehrnsperger and Tietze (2019) noted that the WTP varies across industries and that the patent licensing taxonomy should be used with regards to specific industries. The simultaneous illustration of several industries with strongly diverging mean WTP values is not suggested.

The extension of the two dimensions *Accessibility* and *Compensation* led to a taxonomy that goes beyond the scope of patent pledges, as defined in chapter 4.3.1. The resulting, new taxonomy is therefore more generally called the *patent licensing taxonomy* and is shown in fig. 4.4. The following paragraphs describe each type of the patent licensing taxonomy in more detail (Ehrnsperger and Tietze, 2019; Eisenhardt, 1989). The colours indicate the general 'openness' of the approaches. Red indicates generally closed approaches, green indicates generally open approaches, and orange indicates hybrid approaches.

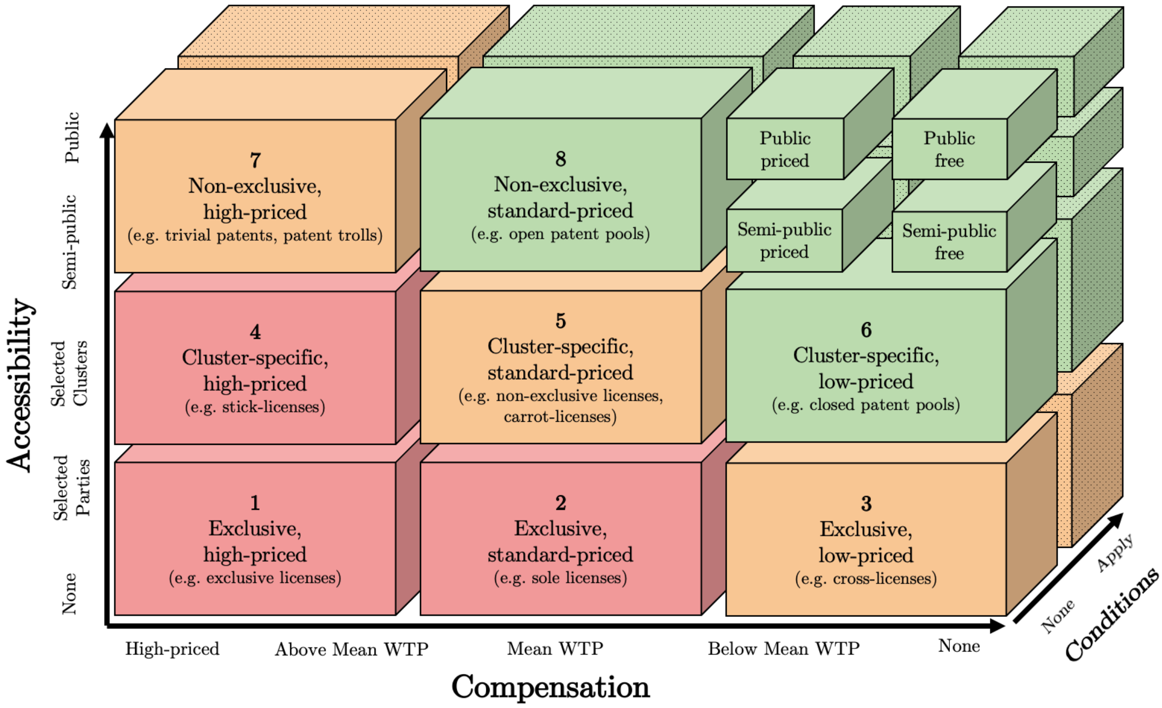


Fig. 4.4 The patent licensing taxonomy adopted from Ehrnsperger and Tietze (2019).

1. Exclusive, high-priced licensing strategies.

This type represents a proprietary approach of patent owners, because they either exclude everyone from using their patents or they allow carefully selected parties to acquire a license at a high price. This can lead to what the academic literature often called a monopoly (Ehrnsperger and Tietze, 2019; Hanel, 2006; Teece, 1986). The pharmaceutical industry is an exemplary industry in which exclusive, high-priced strategies occur. The high R&D costs and long approval processes cause drug developers to often sell their products and technologies exclusively by themselves for as long as the patent protection holds (Al-Aali and Teece, 2013; Ehrnsperger and Tietze, 2019; Resnik, 2004). Other industries, too, provide examples for exclusive, high-priced licensing strategies. For instance, Polaroid aggressively excluded Kodak from the instant camera industry in 1981 and Philips used its patent rights to retain a monopoly over shaving technologies (Bogers et al., 2012; Ehrnsperger and Tietze, 2019; Poltorak and Lerner, 2004). These are extreme examples in which licensing is undermined. Ehrnsperger and Tietze (2019) noted that also exclusive licenses constitute a type of exclusive, high-priced licensing strategies. This is the case when they are offered to one or few selected parties on a relatively high price.

2. Exclusive, standard-priced licensing strategies.
This type of patent licensing strategies differs from type 1 in the sense that the price ranges around the meant WTP. This reduced price is a consequence of exclusive licenses for different territories, for instance. In such a setting, few parties that must adhere to a territorial restrictions hold exclusive licenses. This restriction leads to a reduced price, because the potential profit of the licensees is limited. Du Pont, for instance, held an exclusive license for the initial polyester patent only in the United States, whereas Imperial Chemical Industries held the license for the rest of the world (Ehrnsperger and Tietze, 2019; Rockett, 1990). In general, sole licenses, which grant a license to both the licensor and a licensee, constitute exclusive, standard-priced licensing strategies (Ehrnsperger and Tietze, 2019; Poltorak and Lerner, 2004).

3. Exclusive, low-priced licensing strategies.
Exclusive, low-priced licensing strategies are cheaper than exclusive, standard-priced licensing strategies. Similarly, only carefully selected parties are entitled to a license. This type and its objectives can be illustrated using Hewlett-Packard as an example. The firm offered a wide range of products and inevitably had a large variety of suppliers and competitors. With its licensing activities, Hewlett-Packard aimed to create reliable, long-term partnerships with selected parties rather than to generate additional revenues through royalty rates (Ehrnsperger and Tietze, 2019; Grindley and Teece, 1997). Furthermore, cross-licensing agreements fall under this category, too. Intel and IBM, for instance, licensed a major part of their patents to the other firm for free or under reasonable terms (Ehrnsperger and Tietze, 2019; Shapiro, 2000). In a more general context, IP-transfers as part of open innovation collaborations as described by Chesbrough (2003) could also be classified as exclusive, low-priced licensing strategies (Ehrnsperger and Tietze, 2019).

4. Cluster-specific, high-priced licensing strategies.
Cluster-specific, high-priced licensing strategies represent patent licenses that are available to a selected cluster of potential licensees in return for a price that exceeds the mean WTP. (Ehrnsperger and Tietze, 2019). Hewlett-Packard, again, serves as an example to illustrate this type. In contrast to the firm's strategy described in type 3, some of its patents, which it generated through its vast experience, were of more importance to other firms than to Hewlett-Packard itself. Hence, the firm used these patents to generate additional revenues by offering them at a relatively high price to a cluster of other firms. Hewlett-Packard did not offer the licenses to the unrestricted public to allow licensees to keep a competitive advantage and to keep the price for the licenses high (Ehrnsperger and Tietze, 2019; Grindley and Teece, 1997). Another example for cluster-specific, high-priced licensing strategies comes from the technology market. Qualcomm, for instance, faced high competition for handset devices equipped with the CDMA technology. As a result, the firm changed its strategy from producing these devices itself to out-license the patents for the underlying technology to specific clusters (Arora et al., 2001; Ehrnsperger and Tietze, 2019). Generally, so-called *stick-licenses* that are offered to a cluster of potential licensees are part of this patent licensing type. Stick-licenses occur when firms involuntarily need to license patents they do not own themselves, which often leads to a high price for the license (Ehrnsperger and Tietze, 2019; Poltorak and Lerner, 2004).

5. Cluster-specific, standard-priced licensing strategies.
This type refers to patent licenses that are available to a cluster of potential licensees for a price that ranges around the mean WTP. This type constitutes the center of the patent licensing taxonomy. Cambridge Display Technologies, a spin-off of Cambridge University, provides an example for cluster-specific, standard-priced licensing strategies. The firm initially produced light-emitting plastics itself, but needed to change its business strategy because of imminent insolvency. In an attempt to generate a fast income-stream, the start-up out-licensed its technology to large manufacturers on common royalty rates (Ehrnsperger and Tietze, 2019; Eppinger, 2015). This is different from Hewlett-Packard's strategy described in the previous type because Hewlett-Packard was not equally reliant on the revenues and could therefore demand a higher price. For Cambridge Display Technologies, on the other hand, the additional revenues were essential and the firm needed to incentivise potential licensees to acquire a license through a cheaper price. The licensing strategy of trying to incentivise other parties to buy a license is also known as *carrot-license* (Ehrnsperger and Tietze, 2019; Poltorak and Lerner, 2004).

6. Cluster-specific, low-priced licensing strategies.

Cluster-specific, low-priced licensing strategies are offered at a cheaper price than licenses of type number 5. These strategies differ from patent pledges only in the sense that they are offered to fewer third parties (Ehrnsperger and Tietze, 2019). This is supported by Valz (2017, p. 41) when he said that '*[p]atent pools are, roughly speaking, the community analog of FRAND patent pledges*'. A common example for cluster-specific, low-priced licensing strategies are closed patent pools, which cross-license the patents of its members to each other, either for free or at a reasonable price den Uijl et al. (2013); Ehrnsperger and Tietze (2019); Lerner et al. (2007); Maher (2016). The License on Transfer Network (LOT-Network) , for instance, offered both free and reasonable licenses to its members in case one of its patents is being transferred to a NPE. The membership fee depended on the size of the firm and ranged from zero to 20.000 US-Dollars annually (Ehrnsperger and Tietze, 2019). It is argued that the LOT-Network conducted a cluster-specific, low-priced licensing strategy instead of a patent pledge because only its members can make use of its patents and the membership usually involves a fee. As a further, more general distinction to patent pledges, Contreras et al. (2020) brought up the important point that patent pools often face administrative and legal hurdles. In this context, the LOT-Network as an independent organisation constitutes a sophisticated construct with many administrative obligations. This stays in contrast to the less elaborate patent pledge statements analysed in the previous section.

7. Non-exclusive, high-priced licensing strategies.

Non-exclusive, high-priced licensing strategies occur when licenses for patents are available to the restricted or unrestricted public for a price that lies above the mean WTP. Trivial patents that have not (yet) been declared standard-essential patents are an example for this type. Amazon's 1-click patent from 1999, for instance, forced an entire industry into paying high royalty rates (Bessen and Meurer, 2009; Ehrnsperger and Tietze, 2019; Pohlmann and Opitz, 2013; Shapiro, 2000). Furthermore, NPEs fall under this category. One business-model of NPEs is to buy patents from third parties and then demand licensing fees or compensation from other parties that might infringe these patents (Pohlmann and Opitz, 2013).[9] Even though the success rate of NPEs as plaintiffs in court is low, many firms cannot afford the legal fees to prove that they indeed do not infringe the patents (Allison et al., 2011). As a result, they pay settlement fees to the NPEs. The value of the compensation in non-exclusive, high-priced licensing strategies is thereby also influenced by the threat of a court action (Bessen and Meurer, 2009; Diessel, 2007; Ehrnsperger and Tietze, 2019; Pohlmann and Opitz, 2013).

[9] Chesbrough (2006b) and Greenbaum (2017) stated that NPEs can take many forms and seldom use a consistent business model (see also Ehrnsperger and Tietze (2019)).

8. Non-exclusive, standard-priced licensing strategies.
Non-exclusive, standard-priced licensing strategies differ from patent pledges in the sense that they are more expensive, i.e. the price ranges about the mean WTP. Open patent pools are an example for this type. In contrast to closed patent pools described in type number 6, open patent pools address the unrestricted public. The price for the license can be higher, however (den Uijl et al., 2013; Ehrnsperger and Tietze, 2019; Eppinger, 2015; Lerner et al., 2007). Patents relating to the 3G mobile communication standard, the DVD technology, and the MPEG2 technology were part of an open patent pool, for instance (den Uijl et al., 2013; Ehrnsperger and Tietze, 2019; Eppinger, 2015; Franzinger, 2003). Furthermore, SEPs are another example for non-exclusive, standard-priced licensing strategies, because they are made available to the unrestricted public (Ehrnsperger and Tietze, 2019).

4.4 Study 1 discussion

The results from the previous section add to the academic literature in multiple ways. The empirically derived patent pledge taxonomy complements existing classifications in this field, specifically the ones proposed by Contreras (2017a) and Ziegler et al. (2014). The taxonomy also supplements characteristics of patent pledges that were previously mentioned. The dimension *Conditions*, for instance, supports the description of Valz (2017, p. 38) who said that '*...free pledges typically come with conditions or some other form of quid pro quo*'. Similarly, the patent pledge definition extends table 2.1 by an empirically derived alternative.

The link of the patent licensing taxonomy to existing studies is diverse. This section shows how it can be used to illustrate patent licensing transitions and how practitioners can use the patent licensing taxonomy to make informed decisions about the acquisition of patent licenses. Specifically, chapter 4.4.1 describes how transitions of patent licensing practices reported in the academic literature relate to the patent licensing taxonomy and how these practices can be visualised. This facilitates the interpretation and comparison of patent licensing approaches described in previous and prospective studies. Chapter 4.4.2 provides an exemplary visualisation that shows how firms can use the patent licensing taxonomy to draw a patent licensing landscape for technologies of interest. This landscape can support firms when they face the decision to acquire patent licenses from multiple patent owners, particularly when they need to choose between two competing technologies. The patent licensing taxonomy therefore adds to the literature about technology management tools described by Phaal et al. (2006) and Kerr et al. (2013), for instance.

4.4.1 Paths through the patent licensing taxonomy

The previous section described each type of the patent licensing taxonomy and illustrated them using various examples. It is obvious that patent owners thereby apply different strategies for different technologies. BP Chemicals, for instance, used to license its patents regarding acetic acid only selectively, whereas the firm licensed its rights for polyethylene extensively (Arora et al., 2001; Ehrnsperger and Tietze, 2019). This section shows that patent owners not only utilise different strategies for different technologies, but that they also change their strategies for the same technology over time. This causes them to transition to different areas in the patent licensing taxonomy. Licensing examples described in the literature are used to illustrate these transitions in the following paragraphs.

Transitions towards openness.
One common change in patent licensing strategies is the shift from exclusive to more open approaches. Du Pont, for instance, was in the position to create a quasi-monopoly for its moisture-proof cellophane in the 1930s (Rockett, 1990). The firm only licensed the technology to one other firm at high costs, which constitutes an *exclusive, high-priced licensing strategy* in the lower left corner of the patent licensing taxonomy. As soon as its competitor Dow Chemicals produced a new packaging material (among other reasons) Du Pont changed its strategy and licensed its patents on reasonable terms to firms that had previously, without success, asked for a license. This was an attempt to deter Dow Chemicals' entry into this distinct market (Ehrnsperger and Tietze, 2019; Rockett, 1990). Du Pont therefore transitioned to *cluster-specific, low-priced licensing strategies*. In a similar manner, Union Carbide kept its production process for glycol secret, but later out-licensed this process selectively due to increased competition (Ehrnsperger and Tietze, 2019; Fosfuri, 2006). An example for a firm that involuntarily transitioned to a more open approach is AT&T. For the first 30 years after its foundation in 1885, the firm followed a very closed licensing approach. An antitrust consent decree in 1956, however, forced AT&T to out-license its patents on reasonable terms below market value. As soon as the consent decree ended, the firm transitioned back to a more closed approach, although not as exclusive as to its beginnings (Ehrnsperger and Tietze, 2019; Grindley and Teece, 1997).

Transitions towards exclusiveness.
It is also possible that patent owners initially adopt an open licensing approach and transition to a more exclusive approach over time. Study 3 shows that the attempt to increase technology diffusion rates in the early phases of technology adoption cycles constitutes an important rationale for this. Toyota's patent pledge from 2015, for instance, was initially only valid until

2020.[10] There is no information about what happens after this deadline and it is possible that Toyota switches to a more closed approach to regain competitive advantages (Ehrnsperger and Tietze, 2019). Nippon Shokubai and its process for producing acrylic acid in the 1970s serves as another example in this context. The firm changed its business model from initially supplying licenses for the process to producing acrylic acid itself. After this change, Nippon Shokubai only licensed the technology to markets it could not supply itself (Ehrnsperger and Tietze, 2019; Fosfuri, 2006). Transitions towards exclusiveness illustrate an essential distinction between patent pledges and patent donations, in which all rights are abandoned: with patent donations, patent owners could not demand higher royalty rates at a later stage or impose additional conditions.[11]

Transitions along single dimensions.

It is furthermore possible that patent owners adapt royalty rates for licenses to align with changing market conditions. Alliacanse, for instance, which was sometimes referred to as a NPE, offered early licensee's reduced royalty rates to encourage fast agreements (Pohlmann and Opitz, 2013). If an influential organisation adhered to such an early agreement, other firms were forced to follow, often in return for a higher price (Ehrnsperger and Tietze, 2019; Pohlmann and Opitz, 2013). Such transitions are also related to an economical concept called *penetration pricing*. Penetration pricing strategies describe initially low prices for products or services to incentivise purchases (Katz and Shapiro, 1986). Once enough people rely on these products and services, their price can be gradually increased (Ehrnsperger and Tietze, 2019; Katz and Shapiro, 1986).

Fig. 4.5 illustrates the exemplary transitions described in this section in the patent licensing taxonomy.

[10] This deadline was extended to 2030 in 2019.

[11] See Grzegorczyk (2020) and Ziegler et al. (2014) for examples of patent donations.

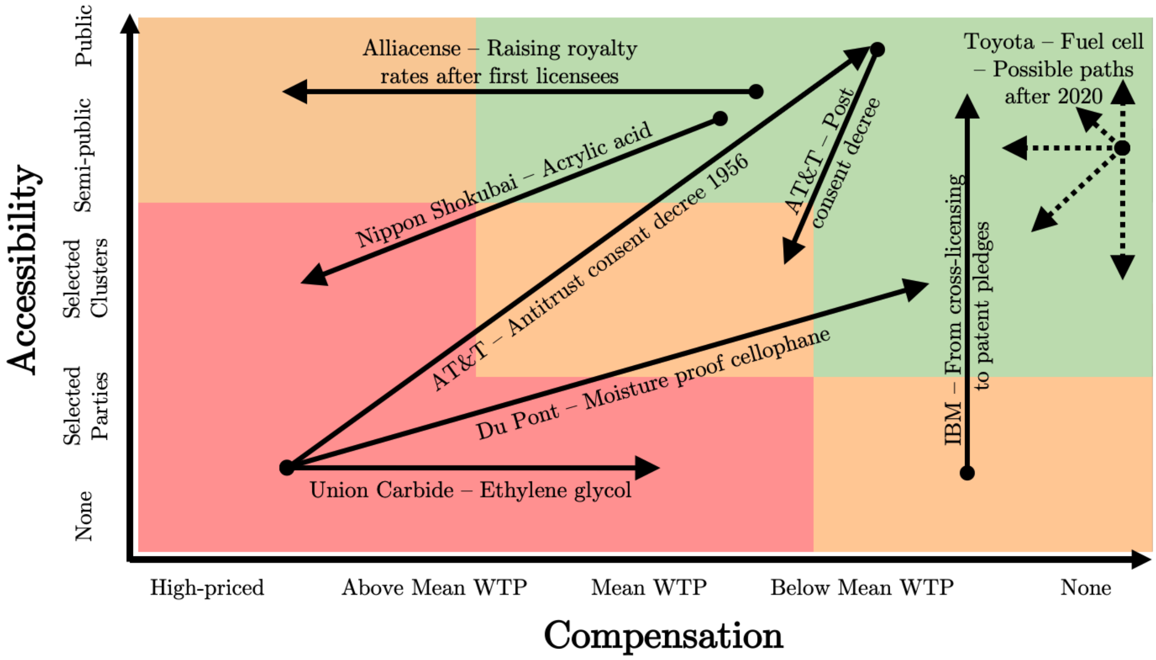


Fig. 4.5 Changes in patent licensing strategies adopted from Ehrnsperger and Tietze (2019).[12]

4.4.2 The patent licensing taxonomy as a strategic instrument

The patent licensing taxonomy can be used as a strategic instrument to support practitioners in their decision processes. It specifically resembles a matrix or grid management tool as discussed by Phaal et al. (2006). Such strategic instruments are common technology management tools to help firms cope with emerging technologies or changing market conditions (Kerr et al., 2013; Phaal et al., 2012). The increasing complexity of patent landscapes makes it difficult for firms to keep an overview of licenses in a specific technological area. Patents relating to a particular technology are often held by multiple parties, which is one of the reason why patent pools are important (Lerner et al., 2007). In such a setting, firms face the problem that they may need to acquire licenses from several parties to utilise the technology. They need to keep an overview of the patent owners and their licensing terms, particularly when they can choose between two competing technologies. Consider the hypothetical scenario where a firm intends to develop a product that inherits one out of two competing technologies, technology A or technology B, that are patented by other firms. In this scenario, the firm needs to decide which of the competing technologies it chooses to incorporate into the product. Many factors influence this decision, patent licenses and their conditions being

[12] Start- and endpoints of the arrows are estimated based on descriptions in the literature.

one of them. The firm can use the patent licensing taxonomy as a strategic instrument to visualise the licensing landscape for technology A and technology B.

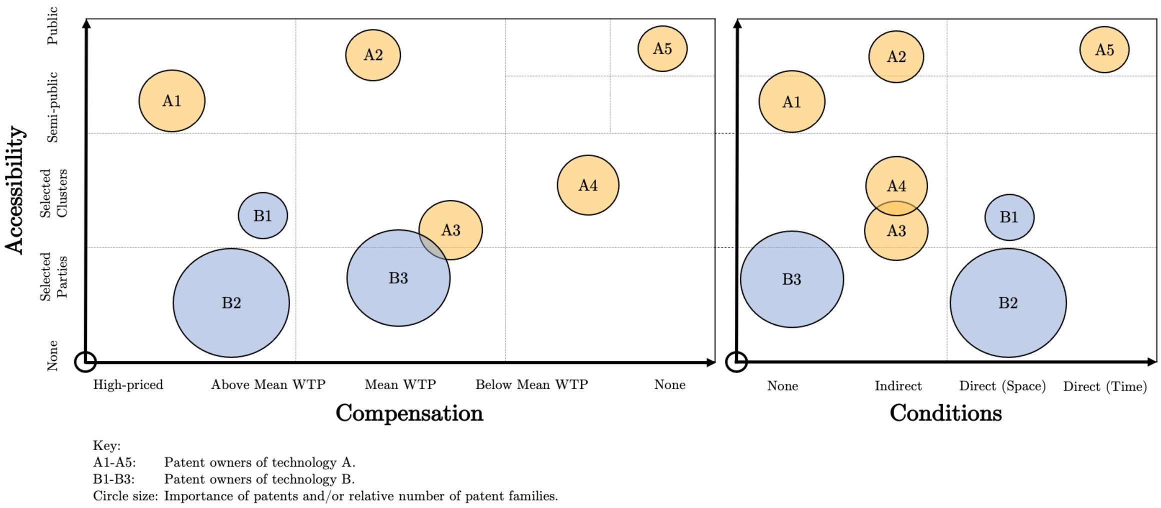


Fig. 4.6 Example of the patent licensing taxonomy as a strategic instrument in a hypothetical scenario.

Fig. 4.6 illustrates different patent owners of technology A and B using the patent licensing taxonomy. The position of the circles depends on the respective licensing terms, whereas the size of the circle indicates the importance of the patents and/or the number of patent families that are required to utilise the technology. In this example, patents for technology A are held by five parties and exhibit similar importance across the owners (similar circle size). Patents for technology B are held by three parties of which two own many and/or important patents. Patent licenses for technology B are often more expensive and restricted, because the blue circles are positioned left of the circles A3-A5 on the compensation axis and B2 and B3 lie below all yellow circles on the accessibility axis. One patent owner for technology A (A5) conducted a conditional, public free patent pledge with limited duration. Some licenses for technology B are only available for specific territories or applications (B1 and B2). The dimension *Conditions*, which specifies any restrictions on the use of the patent licenses, can be adjusted to fit the interests of the firm. In fig. 4.6, for instance, the dimension distinguishes between four values: '*none*', '*indirect*', '*direct (space)*', and '*direct (time)*'. This distinction follows table 4.1 and allows for the visualisation of restrictions regarding the territory/application or the duration of the licenses. In this scenario, the firm needs to balance the higher price for licenses of technology B against the larger dispersion of licenses for technology A. If patents from all patent owners of technology A are required, the costs to negotiate licenses with all five patent owners might exceed the costs to acquire licenses for technology B. Licenses for technology B, however, are more restricted and the firm needs to verify that it could indeed acquire those licenses.

The optimal licensing-approach depends on the individual firm's circumstances and goals. While it seems unlikely that universal recommendations can be derived, some circumstances qualify specific approaches as more suitable than others. From the perspective of firms that aim to access patents through licensing, patent pledges and other approaches that offer licenses in return for reasonable fees appear optimal when the firms' funds for buying licenses are limited. The relatively easy and affordable access of these licenses, however, infer that competitors, too, could access these patents. It is therefore argued that firms with the goal of offering their products at competitive prices benefit from the more open licensing approaches because the costs to acquire licenses are limited. In contrast, firms that aim to offer premium products with distinct features might benefit from the more closed approaches because competitors are not able to access and/or afford the respective licenses. From the perspective of firms that aim to provide licenses to their patents, more open approaches such as patent pledges are recommended when generating revenues through licensing is not the firms' primary goal. The return from these approaches might arise indirectly through increased adoption rates at later stages (see Study 3). Inversely, firms that focus on generating direct and fast revenues could achieve this through more expensive, selective licensing approaches.

Fig. 4.6 assumes that the licensing terms of a patent owner apply equally to all their patents, because every patent owner is positioned only once in the taxonomy. It is also conceivable that licensing terms of a patent owner differ across patents, which could be illustrated by drawing multiple circles for one patent owner. This could be the case when a patent owner holds a large number of patents for a technology, for instance. In this case, the patent owner might demand a high price for the license of some patents, whereas the price might be lower for other patents.

The patent licensing taxonomy can thus support practitioners to obtain an overview of the price of patent licenses, their availability to other parties, and their conditions. When facing the decision to choose between two competing technologies, the patent licensing taxonomy can facilitate the evaluation of the optimal choice for the firm.

Chapter 5

Study 2: motives for patent pledges

5.1 Introduction

During past decades, various firms engaged in sharing their patent rights for free or at a reasonable fee through patent pledges. Examples include Tesla Motors, Toyota, and Ford, because they announced that their active patents relating to alternative powertrains can be used free of charge (Tesla and Toyota) or for a reasonable fee (Ford), see appendix A and Ehrnsperger (2019). Microsoft, IBM, and Google furthermore applied multiple patent pledges in the area of ICT. Additional patent pledges occurred in recent developments during the Covid-19 pandemic, such as the Open Covid Pledge, the Japanese 'Countermeasure Declaration pledge', and the 'Technology Access Framework' (Contreras et al., 2020). At first sight, patent pledges seem to contradict the main motives to patent, namely the protection from imitation and the defensive blockade of competitors (Blind et al., 2006). The related literature on sharing information and IP includes studies about sharing mechanisms such as collective inventions, open-source software, user-innovation and open innovation in general (see chapter 2.2.2). As described in chapter 2.2.3, only few studies focused on patent rights and provided frameworks that classify motives for patent pledges (see Contreras (2017a); Contreras et al. (2019); Simcoe (2017); Ziegler et al. (2014)). While Contreras et al. (2019) collected empirical evidence about the motives to join the Eco-Patent Commons, their study is focused on this specific patent pledge. A study that builds upon and extends the findings of Contreras et al. (2019) is yet to be carried out. To further deepen the understanding of motives for patent pledges, it is desirable to place them within the context of the classical theory of motivation (Becker, 1976; Frey, 1997). Specifically, it is of interest if patent pledges stem from intrinsic (i.e. taking an action for its own sake) or extrinsic (i.e. taking an action for some reward) motivation (Frey, 1997).

Case study research with two main sources of data, expert interviews (primary data) and patent pledge statements (secondary data), was applied to investigate the motives for patent pledges (Yin, 2009). As described in chapter 3.3, this combination of data sources is a recommended procedure for case study research (Eisenhardt and Graebner, 2007; Yin, 2009). West and Gallagher (2006), for instance, combined both qualitative interviews and documentary information to study motives for engaging in open-source software development activities. Contreras et al. (2019) also used expert interviews to investigate motives to join the Eco-Patent Commons. Fig. 5.1 depicts the research design of Study 2. The specific components of the data collection and the data analysis are described in the following sections.

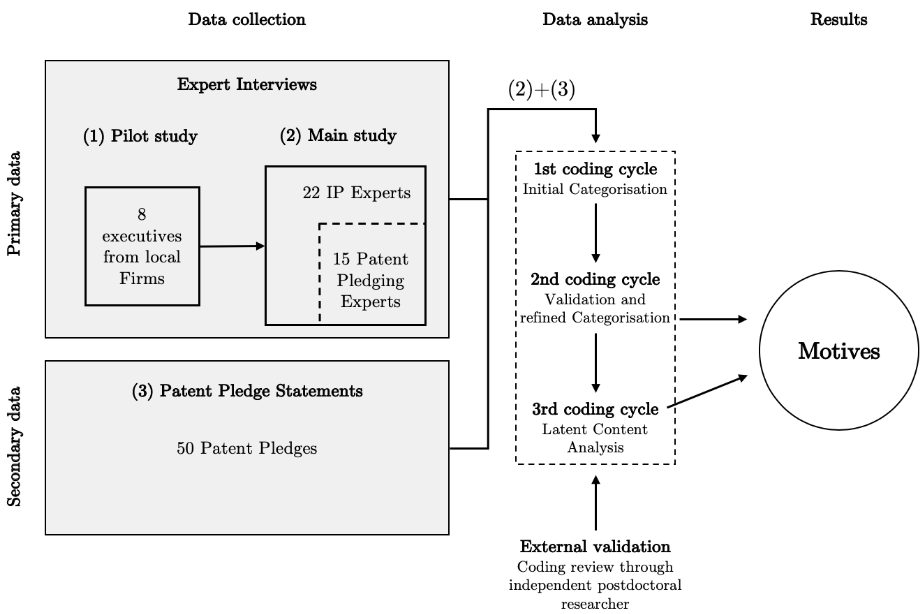


Fig. 5.1 RQ2: Study design.

5.2 Data collection

The data collection process consisted of three steps, with data being collected through interviews during the first and second steps: (i) collecting primary data from participants for a pilot study, (ii) collecting primary data from the main participants, and (iii) collecting secondary data from publicly available patent pledge statements (see West and Gallagher (2006) for a similar approach). Each step is described in more detail below.

5.2.1 Primary data - pilot study

The standard literature for case study research suggests pilot studies in exploratory research (Yin, 2009). Therefore, a pilot study prior to the main study was conducted. Specifically, eight CEO's, founders, and other top-level managers of eight local small and medium-sized enterprises (SMEs) in the biotechnology sector in and around Cambridge, UK were interviewed. Non-IP-executives were targeted for this pilot study, because patent pledge decisions are not only made by IP experts, but also other managers. It was assumed that executives from SMEs need to deal with IP-related issues from time to time. Targeting non-IP-executives allowed to gain an understanding of patent pledge motives from a managerial perspective before interviewing IP experts. This helped to assess if non-IP-experts could deliver useful insights for Study 2. The pilot study followed Yin (2009) by targeting geographically convenient interviewees that are unrelated to the main study. Due to time constraints and the geographical constraints of the pilot study, only firms from the biotechnology industry could be interviewed. The interview guideline for the pilot study is shown in fig. B.2 in appendix B. Due to the non-IP-expertise of the interviewees from the pilot study, a broader, more general scope of questions was chosen (Yin, 2009; Zinatelli et al., 1996).

5.2.2 Primary data - main study

In contrast to the pilot study, only IP experts without any geographical restriction were targeted as participants for the main study. This way, some IP experts that worked for an organisation that has applied at least one patent pledge in the past, or did so at the time of the interview, could be identified. These participants are referred to as '*pledging interviewees*' throughout this research.

Given the limited number of patent pledges, the population of qualified respondents was relatively small and individuals were difficult to track down. The inability to gain access to experts in the field was a major limitation of previous studies (see for instance the study of Ziegler et al. (2014)). A theoretical sampling approach was applied to gain access to the main interview participants and to overcome this difficulty (Eisenhardt, 1989; Glaser and Strauss, 1967; Goffin et al., 2019). Specifically, expert and snowball sampling techniques were applied. Expert sampling as a form of non-probability sampling was conducted because the area of patent pledges required insights from highly specialised individuals with IP expertise (Daniel, 2012). Participants were identified by directly contacting organisations from the data set provided in Ehrnsperger (2019). Individuals were identified through internet searches and informal inquires, similar to the approach of Contreras et al. (2019). Snowball-sampling was then conducted to complement the process of expert sampling, given the particularly limited population of experts with direct experience in patent pledges. Snowball sampling describes the referral of further contacts through a participant (Biernacki and Waldorf, 1981). It became clear that IP experts in the field are highly interconnected with each other, which is why this technique supported the identification and the process of contacting potential interviewees. Non-pledging IP experts, that is IP experts that have not worked in organisations that applied patent pledges in the past, were included because of the risk of biased results. The mere consideration of pledging interviewees inherits the risk that the interviewees speak in an overly optimistic way about the motives for patent pledges, which could lead to distorted results. Non-pledging participants were initially selected through personal contacts, then through snowball sampling as well.

In total, 22 semi-structured interviews with experts from 16 distinct organisations were conducted (see table 5.1). The interviewees had an average cumulative professional IP experience of more than 21 years. Fifteen of these 22 participants were pledging interviewees from 10 distinct pledging organisations. Six out of the 22 IP experts were referred through other participants (snowball sampling), three out of these six were pledging interviewees. Eighteen of the interviewees were identified through internet searches, four through personal contacts. Nine out of the 16 organisations were based in the US, four in Germany, one in Sweden, one in Finland, and one in Japan. Most organisations were large, global firms, because recent studies showed that patent pledges were primarily conducted by major organisations (Ehrnsperger and Tietze, 2019). The sample consisted of renowned IP experts with vast knowledge about the concept of patent pledges. Participants included the former president of a major national patent office, the president of the IP department of a technology firm that is valued at more than 1 trillion US-Dollar (March 2020), and the CEO of a large community that aims to foster patent pledges.

Table 5.1 Interview participants for Study 2.

Participant No.	Job description	Industry No.	Organisation No.	Organisation Type[A]	Professional IP experience in years[C]
1	Patent Counsel*	1	1	Enterprise	38
2	Chief IP Counsel	2	2	Multinational	18
3	Former President of National Patent Office	3	3	Large[B]	35
4	Partner	3	4	Other[B]	39
5	Patent Attorney / VP Patent Department	2	5	Enterprise	N/A
6	Head of IP	4	6	Enterprise	N/A
7	CEO*	1	7	Other	19
8	Head of IP Strategy	4	6	Enterprise	6
9	CEO	5	8	Other	N/A
10	Senior Patent Counsel*	1	9	Enterprise	18
11	Former Patent Strategist*	1	9	Enterprise	17
12	Patent Counsel*	2	10	Enterprise	N/A
13	Patent Attorney*	2	11	Enterprise	N/A
14	Former Head of Patents*	2	12	Multinational	19
15	Former Senior Patent Counsel*	2	12	Multinational	13
16	Senior Patent Counsel*	2	13	Enterprise	24
17	Corporate VP and Chief IP Counsel*	1	14	Enterprise	24
18	IP Counsel*	1	14	Enterprise	16
19	Former IPR Director*	1	15	Enterprise	16
20	Head of IPR Policy*	1	16	Multinational	9
21	Head of National Patent Unit*	1	16	Multinational	21
22	Head of IPR Defensive Strategies*	1	16	Multinational	28

[A] As of December 2018. In cases where a pledging interviewee has switched firms, the type refers to the organisation that has conducted the patent pledge.
[B] Legal firms (the number of attorneys determines the organisation type).
[C] Cumulative professional IP experience excluding doctorates and study programmes. Calculated in whole years until the date of the interview.
* Pledging interviewees.
Industry key:
1=ICT 2=Automotive 3=IP Law Firms 4=Industrial Engineering 5=Nuclear
Organisation type (in numbers of employees):
Other<50 SME<250 Large<1,000 Multinational<100,000 Enterprise>100,001

Fourteen interviews were conducted by phone, five via video conference software, two per written exchange, and one in person and lasted on average for about 30 minutes. The interviews took place between July 2018 and August 2019. Five interviews were held in German, the rest in English. Eleven interviewees allowed to be recorded and these recordings were then transcribed after the interviews. For the remaining 11 cases, rigorous notes were taken. Since the unit of interest is small and responses could be linked to certain organisations or individuals, parts of the quotes are censored and the participants are anonymised. The interview guideline for the main study is shown in fig. B.1 in appendix B.

5.2.3 Secondary data

The collection of publicly available documents for 60 patent pledges used in Study 1 (see table A.1 through table A.3 in appendix A) complemented the interviews. Patent pledge statements often included information about their motivation. Some of the collected pledges were announced together in one statement, however. This posed a problem, because information regarding the motives for individual pledges could not be differentiated without a clear reference. In these cases, multiple patent pledges were treated as one. Specifically, the individual patent pledges of GreenXChange, Microsoft (2003 and 2008), the OpenPower foundation, and iBiquity were treated as one patent pledge statement each (see appendix A). This resulted in the collection of 50 publicly available statements.

The focus of the analysis lies on the interview data from the main study, whereas data from the patent pledge statements are used to corroborate the findings. The collected patent pledges are predominantly public statements that were officially released by the respective organisation, which is why it is assumed that they are valid. They might, however, be not entirely reliable as these patent pledges are PR statements of organisations. They inherit a risk of bias and are therefore only used to complement findings from the main study.

5.3 Data analysis

The data collection processes were followed by an analysis through qualitative coding, similar to the analysis in Study 1. In contrast to deductive categorisation, no a priori categories for the codes were defined. Rather, the research question itself served as a guide to develop categories (Mayring, 2000). The following two sections describe the coding process and measures that were taken to ensure the reliability of the results.

5.3.1 Coding cycles

Qualitative coding was used for both, the transcripts/notes from the interviews and the patent pledge statements. This is an established method for motivational studies in a managerial context. Bansal and Roth (2000), for instance, used qualitative coding for in-depth interviews, participant observation, and archival documents to examine the motives for companies to ‘go green’. Bansal and Roth thereby used data from multiple source to strengthen their inferences. The collected data described in the previous section was coded using NVivo™ 12 software, a commonly used software package for these kind of exercises in innovation research (see for instance Langner and Seidel (2015)). The software facilitated the coding process and allowed for an advanced comparison between codes from different organisations and industries, as well as between primary and secondary data.[1] The literature suggests to conduct multiple coding cycles in qualitative coding (Saldaña, 2009). Saldaña explained that qualitative coding is a progressive refinement of codes and takes a cyclical rather than a linear form. He generally distinguished between *first cycle methods* and *second cycle methods*, but added that

[1] See also chapter 4.2 for the use of the software.

often three or four cycles are applied. While first cycle methods occur during the initial coding of data, second cycle methods concern the refinement, conceptualisation, and classification of the initial codes and ultimately lead to theory building, see also the descriptions in chapter 4.2 (Saldaña, 2009).

Two coding cycles for the patent pledge statements and three for the interviews were applied, following the approach suggested by Saldaña (2009). Initial coding was used for the first coding cycle, because this method is applicable to both data sets and generally all qualitative studies (Saldaña, 2009). Initial coding implies to '*remain open to exploring whatever theoretical possibilities (...) [one] can discern in the data*' (Charmaz, 2006, p. 47). It refers to the examination and comparison of discrete parts of data (Saldaña, 2009; Strauss and Corbin, 1998). The first coding cycle was applied relatively quickly and spontaneously to avoid preconceived categories (Kondracki et al., 2002). After the first coding cycle, it became clear that some of the codes were indistinguishable. '*Driving technology diffusion*' and '*driving ecosystem industry growth*', for instance, were initially two distinct categories resulting from the first coding cycle. Their goal and therefore their motive, however, is to increase the user-base of the respective technology. A second coding cycle, specifically pattern coding, was conducted to develop a smaller and more delimitable list of categories, similar to the process described in chapter 4.2 (Goffin and Koners, 2011; Mayring, 2000; Saldaña, 2009). Again, '*[p]attern codes are explanatory or inferential codes, ones that identify an emergent theme, configuration, or explanation. They pull together a lot of material into more meaningful and parsimonious units of analysis*' (Miles and Huberman, 1994, p. 69). Pattern coding is suggested after initial coding in the first coding cycle and also to develop main themes from the data (Miles and Huberman, 1994; Saldaña, 2009). The second coding cycle enabled the unification of similar codes to categories, for instance the two codes mentioned above were allocated to the category '*Driving technology diffusion and ecosystem and infrastructure growth*'.

The occurrence of codes belonging to individual categories in both data sets was counted. This serves as a supporting measure for the importance of patent pledge motives. There has been much debate and criticism about the use of numbers in qualitative research (see for instance Maxwell (2010)). The frequency of codes should not be used as a conclusive measure of importance. Rather, the values indicate the focus of the interviews and the secondary data. The mere consideration of absolute numbers would be misleading, partly because the interviews varied in lengths. Therefore, a third coding cycle for the interviews was conducted. This third coding cycle allowed the indication of particularly important categories for individual interviewees. This approach is known as latent content analysis, which generally refers to the process of interpreting content (Holsti, 1969; Hsieh and Shannon, 2005). Specifically, the language of the respondents and the researchers subjective judgement was used to determine this importance, which is why this third coding cycle was only applied to the interviews. For instance, if an interviewee responded with '*we did this because...*' or '*It was to enable...*', this was classified as strong evidence. One interviewee, for instance, responded with '*To push a technology or a service is the main motive*'. This stays in contrast to '*this could/might be because...*' in a coded phrase, which was not considered as strong evidence. An example from the interviews is the response '*I guess that (...) tries to provoke an ecosystem*'. The results of this study are mainly based on the content analysis from the third coding cycle. The occurrence of distinct categories, however, supports internal generalisability and diversity and is shown in table B.1 and table B.2 in appendix B (Maxwell, 2010).

5.3.2 Reliability of results

Good qualitative research asks for methods that enhance reliability (Campbell et al., 2013; Fahy, 2001). The problem of discriminant capability due to a lack of exclusiveness among categories, particularly in qualitative coding, constitutes a major obstacle that needs to be addressed by more studies (Fahy, 2001). For this reason, an intermediate step in which an independent, postdoctoral IP researcher confirmed or rejected the coding categories was taken. Specifically, the independent researcher accessed all codes that were allocated to each category, but without the label of the category. She was able to change the allocation of codes between categories and to label each category. This enabled the enhancement of reliability and the minimisation of discriminant capability (Campbell et al., 2013; Fahy, 2001; Goffin et al., 2019). The supervisor of this research, as a final authority, compared both the initial categorisation and the reviewed categorisation and found no significant deviations in neither the concepts nor the terminologies. To clarify this step, an example for the aggregation of codes into a category and its labeling is given: initially, four quotes from the interviews were allocated to one category, which was called '*Improving and fostering technology and innovation*'. These four quotes were: (1) '*It encouraged people to develop (...) that read on the functionality of the patents that (...) pledged*'; (2) '*They really believe that more (...) drives innovation faster than really insular technology*'; (3) '*The idea was that if (...) open-sourced the patent portfolio, this allows other players to engage and push the industry forward*'; (4) '*Different motive: Fostering technology*' (this last quote is a direct translation from German notes). The independent researcher allocated these codes to one category, too, which means she did not add or delete codes to or from this category. She labeled this category '*Fostering innovation and subsequent development*'. As a final authority, the supervisor compared both labels and a decision about the final wording was made.

5.4 Results

In this section, the results of Study 2 are described. They are based on the main study and on the secondary data only. The pilot study revealed that, despite not having been involved directly in any patent pledge, the interviewees were familiar with the general concept. Yet, they were unanimously hesitant and sceptical of these strategies. The pilot study did not deliver conclusive results, because the interviewees' responses were limited and based on guessing, which is why the pilot study is not included in this section. It served, however, as a refinement for the sampling method of the main study. Initially, non-IP-experts were intended to participate in the main study. After the insights of the pilot study, however, specifically the realisation that non-IP-experts could not deliver conclusive answers, only IP-experts were included in the main study. A further pilot study was not feasible because of the limited number of suitable participants for the main study.

Fig. 5.2 shows the 13 motives that resulted from the data analysis. These 13 motives cluster into three categories: (i) *economic motives* (five), (ii) *perceptional motives* (six), and (iii) *technological motives* (two). Ten out of the 13 motives were mentioned in both data sets. The motives '*Encouraging competition*' and '*Fostering integrity*' were not mentioned in the interview data. The motive '*Building reputation and PR*' was not mentioned in the secondary data. For a full comparison between the two data sets, see table B.1 and table B.2 in appendix B.

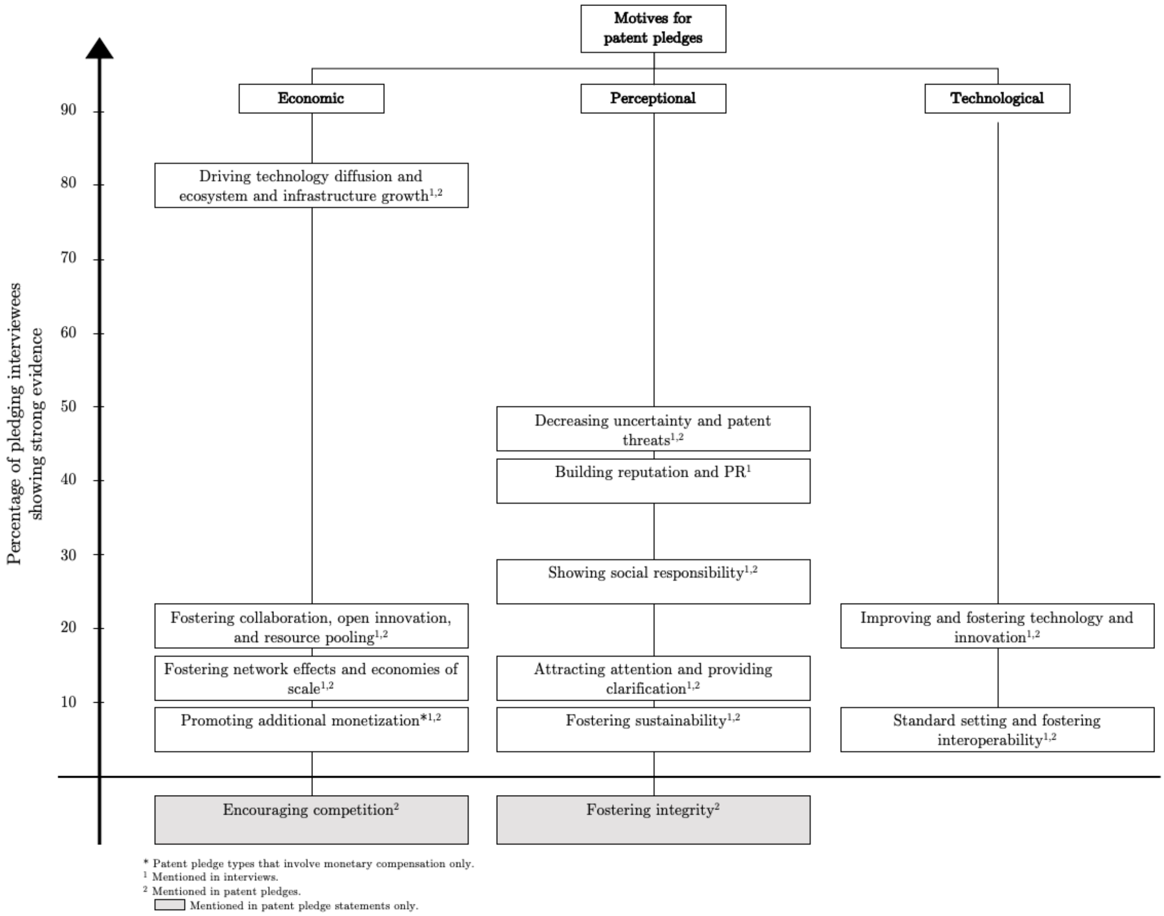


Fig. 5.2 Motives for patent pledges.

The following paragraphs describe the motives with supportive exemplary quotes from the interviews. The three most prominent motives, based on the number of interviewees that show strong evidence, are thereby emphasised. These are *Driving technology diffusion and ecosystem and infrastructure growth*, *Decreasing uncertainty and patent threats*, and *Building reputation and PR*. Percentage values in parentheses represent the share of pledging interviewees showing strong evidence for a particular motive. The data revealed that the most prominent motive is an economic motive, while the other two key motives are of perceptional nature. None of the key motives appears to be primarily technological. Except for the economic motive '*Promoting additional monetisation*', all motives relate to patent pledges that do not involve any direct monetary compensation (Ehrnsperger and Tietze, 2019).

5.4.1 Economic motives

Economic motives relate to the prospect of direct or indirect monetary rewards through the engagement of other firms. The five economic motives found from the data include (i) '*Driving technology diffusion and ecosystem and infrastructure growth*' (80% of pledging interviewees showed strong evidence for this motive); (ii) '*Fostering collaboration, open innovation and resource pooling*' (20%); (iii) '*Fostering network effects and economies of scale*' (13%); (iv) '*Promoting additional monetisation*' (7%), and (v) '*Encouraging competition*' (0%).

Driving technology diffusion and ecosystem and infrastructure growth appears to be the main economic motive. In other words, this motive indicates that patent pledgors intend to increase the adoption rates of technologies. While this motive was mentioned by 80% of pledging interviewees, it also had the highest coding count in both data sets (63 counts in the interview data, 65 counts in the secondary data). Interviewee number 16, a senior patent counsel at a pledging firm with 24 years of professional IP experience, explained: '*[t]he problem with [specific technology] is another good example until you have the infrastructure build up, nobody is gonna make money selling those (...). Because nobody is gonna buy them. When you enforce your patents, what you are gonna do is hurt yourself by eliminating the market penetration for that particular type of product*'.

Firms pledging patents because they want to **foster collaboration, open innovation and resource pooling** aim to strengthen existing or building new forms of collaboration by facilitating access to their patented inventions. Interviewee number 19, a senior expert and former IPR director of a global firm in the ICT industry, called patent pledges in the context of fostering collaboration '*a subtle way to kick start cross licensing*'.

Another economic motive for patent owners to conduct patent pledges is to **foster network effects and economies of scale**. In this context, patent pledgors primarily intend to gain advantages through the utilisation of the pledged patents through others. Interviewee number 3, a former president of a national patent office, said that '*these companies [the patent pledgors] understand the power of network effects*'. While it could be argued that this motive is similar to the motive '*Driving technology diffusion and ecosystem and infrastructure growth*', this motive is more about the learning effects that come through the utilisation of the patents through others. Interviewee number 22, the head of IPR defensive strategies of a global firm with 28 years of IP experience, said that his firm wanted '*companies to learn from each other*' through their patent pledge.

Promoting additional monetisation appears to be another motive for patent owners to conduct patent pledges. This motive, however, only applies to patent pledge types that involve monetary compensation, because the patent pledgors' primary goal is to generate additional revenues through licensing (Ehrnsperger and Tietze, 2019). Interviewee number 22 explained: '*...we also think that companies that are heavily investing in R&D, [Company name] is spending (...) US Dollars on R&D, it is important that the companies that put a lot of resources, a lot of money in R&D, get a reasonable amount back. And this money enables new R&D, which is some kind of a positive wheel*'.

Encouraging competition as a motive for patent pledges was only mentioned in the secondary data and appears to be similar to '*Driving technology diffusion and ecosystem and infrastructure growth*' and '*Fostering network effects and economies of scale*'. This motive is kept separate from them, however, to limit speculation about their similarity. This is because the secondary data did not allow for clarifications of the motives or their wordings. A patent pledge made by Microsoft (July 2006), for instance, intended to '*promote competitive opportunities*' (see 'Microsoft July 2006' in Ehrnsperger (2019)). For reasons of transparency, this motive was treated as a distinct motive. As a result of its appearance in the secondary data only, this motive is also kept separate from the other motives in fig. 5.2.

5.4.2 Perceptional motives

Perceptional motives relate to the potential benefits through the improvement of a patent owner's reputation, as well as through the reduced uncertainty and patent threats of a technology Feller and Fitzgerald (2002); Hars and Ou (2002); Schweisfurth et al. (2011). Six perceptional motives were found: (i) '*Decreasing uncertainty and patent threats*' (47%); (ii) '*Building reputation and PR*' (40%); (iii) '*Showing social responsibility*' (27%); (iv) '*Attracting attention and providing clarification*' (13%); (v) '*Fostering sustainability*' (7%); and (vi) '*Fostering integrity*' (0%).

Firms pledging patents to **decrease uncertainty and patent threats** primarily aim to correct general negative perceptions in an industry and to restore trust. 47% of pledging interviewees provided strong evidence that this is a primary motive to employ patent pledges, which makes it the second most prominent motive overall. This motive was also mentioned in the secondary data by 14 patent pledges. The main goal is to create a more peaceful and transparent IP environment. Interviewee number 16, a senior patent counsel with 24 years of IP experience, said that '... *if you stumble upon one of (...) patents as you are operating, it creates the ability to eliminate the fear of infringement. Because you have that free license*'. For instance, the so-called *patent wars* caused many firms to be extremely cautious and sceptical regarding patent licenses, which ultimately might hinder collaboration. Interviewee number 3, the former president of a national patent office, explained: '*[y]ou are trying to send messages in addition to reconciling actual or perceived issues. You take tension out in places where tension is perceived. Whether you believe there is tension, if others believe there is, you have to deal with that*'.

Building reputation and PR, in contrast to '*Decreasing uncertainty and patent threats*', relates to the potential reputational benefits for the individual patent pledgor. This is the third most prominent motive overall and the second most important perceptional motive. 40% of pledging interviewees showed strong evidence for this (36% when considering all interviewees). This motive was however not mentioned in the secondary data. It comprises all cases in which the patent pledgor explicitly aimed to gain some reputational benefits. Interviewee number 17, the head of patents at a company with a market capitalisation of over 1 trillion US-Dollar at the time of writing, called a specific patent pledge a '*move to position yourself as a white knight and being anti-patent and being free innovation*'.

Showing social responsibility is another perceptional motive for patent pledges. Here, patent owners take a general view by addressing the public and not specific issues in certain industries as in '*Decreasing uncertainty and patent threats*'. Interviewee number 7, the CEO of a large community whose members automatically pledged patents, said that '*it was not really to support any one company or a group of companies, the members did this really for the benefits of the entire community. Not because they wanted to get some benefits uniquely themselves*'.

Attracting attention and providing clarification is a further perceptional motive. Interviewee number 1, a patent counsel at a global firm in the ICT industry with 38 years of IP experience, said that a patent pledge '*turned people's heads around*'. This is not necessarily intended to build positive PR, as would be the case with the motive '*Building reputation and PR*'. Rather, it is to attract attention. Furthermore, a patent pledge can serve as a mechanism to clarify and build upon previous announcements. Interviewee number 21 said: '*in fact, I think [company name] was not always so good at communication with third parties. They would have conversations with people and explain things one-on-one, but in the public forum, they have not always been so good at explaining things. I guess around that period, they thought 'we should get a message out on what our position is a bit more widely'. (...) Otherwise, people can turn around and say 'you license patents, you are some sort of troll or non-practising entity*''.

Fostering sustainability as a motive for patent pledges specifically aims to achieve environmental benefits. This motive falls under perceptional motives because it can be argued that sustainable practices are conducive to the perception of a patent pledgor. Interviewee number 1 used the example of pledged patents for improved recycling processes and argued that they were ‘*maybe not the most valuable patents, but if many people use them, it could make the world better*’.

Fostering integrity as a motive for patent pledges was only mentioned in the secondary data and could be related to ‘*Building reputation and PR*’. IBM’s patent pledge from September 2006, for instance, ’*[was] designed to foster integrity, a healthier environment for innovation, and mutual respect for intellectual property rights*’ (see ’IBM 26.09.2006’ in Ehrnsperger (2019)). It is treated as a separate motive, however, because it is only mentioned in the secondary data and the similarity to the motive *Building reputation and PR* could not be verified through further inquiry (see the motive ’*Encouraging competition*’ for a similar approach).

5.4.3 Technological motives

Technological motives relate to the improvement of a technology and its interoperability with other technologies. Two motives fall into this category : (i) ‘*Improving and fostering technology and innovation*’ (20%); and (ii) ‘*Standard setting and fostering interoperability*’ (7%).

Improving and fostering technology and innovation relates to the advancement of technologies through patent pledges. This motive is different from the economic motive ‘*Driving technology diffusion and ecosystem and infrastructure growth*’ because here the motivation is primarily to improve, not necessarily to diffuse the technology. Interviewee number 11, a former patent strategist at a company that is valued at more than 1 trillion US-Dollar with 17 years of experience, emphasised that a patent pledge ‘*encouraged people to develop open source software that read on the functionality of the patents that [company name] pledged*’.

Through **standard setting and fostering interoperability** patent pledgors intend to either establish an industry standard or to allow for better compatibility with other technologies. Interviewee number 20, the head of IPR policy at a global firm, said that patent pledgors want the pledged technology ‘*to get standardised*’.

Further quotes for all motives from both data sets, the interviews and the secondary data, are provided in table B.3, table B.4, and table B.5 in appendix B.

5.5 Study 2 discussion

In this section, the main results from the analysis are linked to existing theories. It is argued that the majority of the identified motives for patent pledges relate to the overarching goal of fostering technology diffusion, despite their different labels and allocation to the three distinct categories. Building upon a proven framework, the TASC model by Asare et al. (2016), the motives for patent pledges are linked to decision factors of firms when confronted with technology adoption decisions. The discussion also emphasises that the main motive to increase technology diffusion not only applies to unrivaled, but especially to competing technologies. Finally, some further insights from the interviews that are not directly related to the motives for patent pledges are given.

5.5.1 Link of patent pledge motives to technology adoption attributes

The results suggest that the main motive for patent pledges is '*Driving technology diffusion and ecosystem and infrastructure building*'. The interview participants saw patent pledges as a strategy to increase and accelerate technology diffusion. Strong evidence was found that patent pledgors try to reduce the barriers to adopt a specific technology as much as possible, predominantly when they aim to build a wider technology platform. This is in line with the findings of prior studies (Alexy et al., 2013; Barnett, 2011; Chien, 2016; Contreras, 2017a; Contreras et al., 2019; Rimmer, 2018; Valz, 2017; West and Gallagher, 2006; Ziegler et al., 2014). The results support that patent pledges reduce the direct costs of acquiring a new technology (Sundaresan et al., 2017; Wen et al., 2016) and act as industry-wide initiatives that aim to promote the related technology (Asare et al., 2016). The main motive to join the Eco-Patent Commons as described by Contreras et al. (2019), however, is only partially supported by the results of Study 2. Contreras et al. found that improving environmental conditions and sustainability were the main drivers to join the Eco-Patent Commons, whereas the motive '*Fostering sustainability*' was found to be only a minor motive in the previous results (see fig. 5.2).

The main motive for patent pledges links to the literature about technology diffusion, which started with the early work of Rogers (1962). Technology diffusion is the cumulative result of individual adoption decisions, in which individuals weigh the incremental benefits of adopting against the costs of change Hall and Khan (2003). As described in the literature review, the focus of this research lies on diffusion on an organisational level rather than an individual level. Patent pledges primarily address firms, not individuals, because patents constitute no final products for end-consumers to buy. Rather, they disclose knowledge that can be incorporated into a firm's own products or services. When technology diffusion is the sum of individual adoption decisions, it becomes necessary to reflect on how patent pledges might affect attributes that influence these individual adoption decisions. Because of the focus on inter-firm diffusion, the vast literature that deals with influence attributes on adoption decisions is limited (Asare et al., 2016; Robertson and Gatignon, 1986). A comprehensive model that describes 16 attributes that influence the adoption decision is the TASC model by Asare et al. (2016), which was introduced in chapter 2.3.3. The 16 attributes are explained in more detail in Study 3, specifically in table 6.1. The four key-determinants in the TASC model, i.e. categories for influence attributes, are technology characteristics, organisational characteristics, inter-firm relationships, and the external environment. The TASC model builds upon proven studies, e.g. it includes the technology characteristics of Rogers (1962) as an important but not exclusive determinant. As mentioned above, it is argued that most identified motives for patent pledges relate to technology adoption decisions. Fig. 5.3 illustrates this link between the three motive categories and the TASC model proposed by Asare et al. (2016). The following paragraphs describe their interconnectedness in more detail.

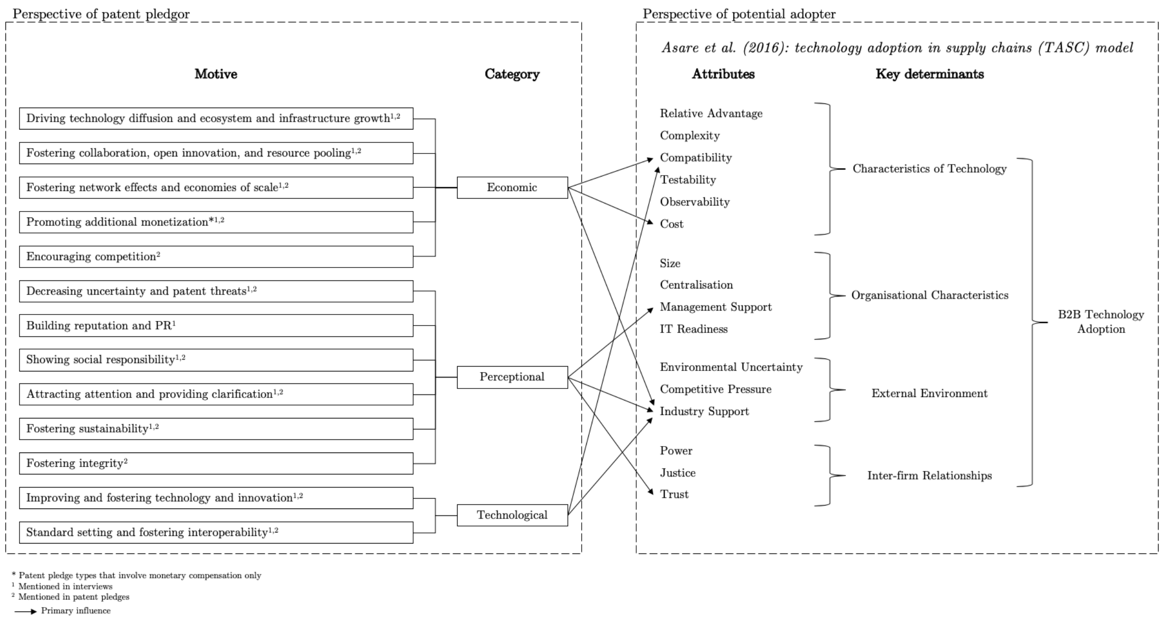


Fig. 5.3 Link between patent pledge motives and the TASC model.

The three remaining economic motives apart from the main motive '*Driving technology diffusion and ecosystem and infrastructure building*' and the motive '*Promoting additional monetisation*', which only applies to patent pledges that require monetary compensation, primarily relate to the '*cost*', '*compatibility*' and the '*industry support*' attributes in the TASC model. Interviewee number 16, a senior patent counsel at a global automotive firm with 24 years of professional IP experience, said that patent pledgors try to achieve economies of scale as a result of increased technology adoption. He explained: '*[t]heir motivation is also self-serving in the fact that as you produce [specific technology], the cost is still pretty expensive. In order to bring that cost down, you need volume. And I think the motivation to provide these licenses is to get people to use these technologies, and hopefully the same suppliers, and by the way of doing that you get economies of scale*'. The incentive to adopt technologies because of their cheaper price due to patent pledges was also described by Sundaresan et al. (2017) and Wen et al. (2016). The motives '*Encouraging competition*' and '*Fostering collaboration, open innovation, and resource pooling*' also relate to the increased utilisation of the pledged technology (Arora et al., 2001). They specifically address the '*compatibility*' and the '*industry support*' attributes in the TASC model, because more collaboration and increased resource sharing allow for compatible technologies and general support from the industry. Interviewee number 5, a senior patent attorney at a German automotive firm, said that his organisation perceived the patent pledge of a competitor as a positive signal to cooperate in this specific technological area. To summarise, most economic motives for patent pledges relate to specific influence attributes that affect technology adoption decisions and can result from increased technology diffusion. Whether the motive is to foster network effects and economies of scale or to foster collaboration, open innovation, and resource pooling, they all result from the increased technology diffusion of the pledged technology.

Not only the economic motives for patent pledges, but also the perceptional motives relate to a patent pledgor's effort to drive technology diffusion. Data from 40% of pledging interviewees showed strong evidence for the motive '*Building reputation and PR*', which indicates that this motive is more important than some prior studies suggested. Contreras et al. (2019), for instance, noted that their interviewees mentioned PR only as a secondary motive to join the Eco-Patent Commons. Furthermore, positive PR was not mentioned as a motive for patent pledges in the secondary data. One needs to keep in mind, however, that publicly released documents constitute official statements by the respective organisations, in which one would not expect them to mention positive PR as a motive. Rather, it can be argued that these statements are already part of building positive reputation. The motive '*Building reputation and PR*', alongside the other perceptional motives, relates to an organisation's effort to increase technology diffusion. Robertson and Gatignon (1986), for instance, argued that suppliers of a new technology can affect the diffusion speed and potential by improving their reputation, especially during early diffusion stages. Grossman (2004) and Asare et al. (2016) emphasised the importance of inter-firm relationships in the adoption process. In fact, all perceptional motives relate to attributes in the adoption decision. They specifically link to the '*trust*', '*management support*', and '*industry support*' attributes of the TASC model (Asare et al., 2016). While positive reputational benefits are hoped for by the patent pledgor, patent pledges can also have negative reputational effects for a pledging firm. Interviewee number 5, the vice president of the global patent department at an automotive firm, said that Tesla Motors' patent pledge from 2014 caused distrust in his firm because the firm remained uncertain if Tesla's offer is genuine. This was despite the publication of the exact conditions on Tesla's website. Jacob (2017) rightfully pointed out that the clarification of terms from the initial patent pledge on Tesla's website constituted a 'best practice' act of the patent pledgor. Nevertheless, the insights from interviewee number 5 show that this clarification was not sufficient to convince his firm from the credibility of the patent pledge. This suggests that further best-practices for patent pledgors as described by Jacob (2017) might be necessary. These insights also add to existing suggestions on how to make patent pledges described by Simcoe (2017). The issues raised by interviewee number 5 constitute an important element for the correct design of patent pledges: when the goal is to incentivise people to adopt, its conditions must be clearly laid out and explained. A mere publication might not be sufficient. Similarly, Contreras et al. (2019) concluded that in the case of the Eco-Patent commons, more outreach activities and technology transfer assistance would have fostered its success. In this context, a patent pledge registry as described by Contreras (2017b) might advance the success of patent pledges. The results further revealed that the decreased risk of patent infringement is another perceptional motive, which also appears to be related to technology diffusion. As mentioned above, it specifically addresses the '*trust*' attribute in the TASC model. Interviewee number 21 explained: '*[I] guess that you know the US patent litigation system. Quite often you end up in (...) a trial by jury (...). And there you have people who don't necessarily understand the patent system so well and would be very influenced by what they see in the media. I guess it is getting the message out to everybody rather than just people who are patent specialists. (..) The optics that it looks good when you say 'You can use our patents for free'. When you end up in patent litigation with them, they can also wave this pledge in front of the jury and say 'But we said they can use our patents for free, and they are being really mean by trying to sue us'. It is about making other people look bad*'. While only the patent pledgor directly benefits from this in the courtroom, it is in the interest of all patent pledge users that they use a technology that does not infringe third parties' patents. It should be noted that the motive '*Decreasing uncertainty and patent threats*' was exclusively mentioned in secondary data concerning the ICT industry. This is also true for some other motives (see table B.2 in appendix B), but this is possibly a result of the prevalence of patent pledges in ICT in general Ehrnsperger and Tietze (2019). An industry comparison would be, due to the small sample size of patent pledges in specific industries (see appendix A), premature and should be subject to future research.

The technological motives also relate to the efforts of driving technology diffusion. They specifically address the '*systems compatibility*' and '*industry support*' attributes of the TASC model (Asare et al., 2016). Already Robertson and Gatignon (1986) argued that standardisation can enhance the speed of technology diffusion. Interviewee number 11, a former patent strategist with 17 years of IP experience, emphasised the importance to foster interoperability with other technologies and, ultimately, to establish a standard. He said that the patent pledge of his company '*encouraged people to develop (...) that read on the functionality of the patents that [patent pledgor] pledged.*'. While technological motives were mentioned less often in the interviews than economic and perceptional motives, these came out clearly from analysing the secondary data (see table B.2).

Reflecting on the findings it can be concluded that the identified motives with one exception (*Promoting additional monetisation*, which only applies to patent pledge types that involve monetary compensation (Ehrnsperger and Tietze, 2019)) relate to a patent pledgor's incentive to drive technology diffusion. Hence, the motives for patent pledges appear to be extrinsic (taking an action for some reward) rather than intrinsic (taking an action for its own sake), which constitutes an important characteristic of economic theory (Becker, 1976; Frey, 1997; Lakhani and Wolf, 2003). While most patent pledges took place in the ICT industry, the findings stay in contrast to motives reported for engaging in open-source software development, which were mentioned occasionally alongside patent pledges in prior literature (Vu, 2015; Wen et al., 2016). Even though some studies proposed a rationale cost-benefit model stemming from extrinsic motivation to explain why individuals contribute to open-source software (e.g. Lerner and Tirole (2002)), Lakhani and Wolf (2003) provided evidence that the motives are rather intrinsic than extrinsic. Chesbrough (2006a) noted that firms generally do not share their rights and resources for intrinsic reasons, but to react to changing economics of innovation such as rising costs and shorter product life cycles. In this context, increased technology diffusion was mentioned by Nuvolari (2004) as a motive for collective invention. In a similar manner, the motives for patent pledges and their overarching goal to foster technology diffusion appear to be of extrinsic nature. The findings from Study 2 therefore support previous studies that found extrinsic motives for engaging in open innovation activities (Chesbrough, 2006a; Lakhani and Wolf, 2003; Nuvolari, 2004).

5.5.2 Patent pledges in the realm of competing technologies

In the last section, it was shown that motives for patent pledges relate to adoption attributes of the TASC model, assuming that adopters can either decide to adopt or not to adopt a technology. Often, potential adopters also face the decision to choose between a number of competing technologies (Arthur, 1989; Katz and Shapiro, 1986; Mamer and McCardle, 1987). As it stands, patent pledges frequently occurred in the realm of emerging technologies that act as substitutes to existing technologies. Examples include the patent pledges of Tesla, Ford, and Toyota, which promote alternatives to conventional powertrains. The pledges of Tesla and Ford thereby concern electric vehicles, whereas Toyota's patent pledge relates to fuel-cell vehicles (see table A.1 and table A.3 in appendix A). Here, two emerging technologies are subject to a patent pledge and compete with one entrenched technology. Similarly, the patent pledge of the OpenPOWER foundation by IBM was established to compete with established microprocessors (see table A.3). This, in combination with the main motive for patent pledges, i.e. to drive technology diffusion, relates to the literature about competing technologies.

Patent owners have an incentive to conduct patent pledges when competing with established technologies. Arthur (1989) showed that an early lead in market share can lead to a '*lock-in*' of a technology, even if this technology is inferior to alternatives (see table 2.4). Lock-in effects were shown to contribute to a large extent to the dominance of technologies such as the dominance of the inefficient QWERTY-keyboard (Arthur, 1989; David, 1985; David and Bunn, 1988). Katz and Shapiro (1986) also found that inferior technologies can be chosen over a superior alternative, particularly when the inferior technology is *sponsored*. Sponsored technologies relate to the concept of patent pledges, which is discussed in more detail in chapter 6.4.1.1. Firms have thus learnt to accelerate diffusion of novel technologies early on. Patent pledges seem to be a strategy they can use to achieve this. Statements made by interviewee number 1, a pledging interviewee with 35 years of experience as senior patent counsel in a global firm, supported this. His firm conducted a patent pledge to incentivise people to use the firm's patents over patents relating to competing technologies. In this context, perceptional motives of patent pledges seem to play an important role to drive technology diffusion. Already Robertson and Gatignon (1986, p. 4) noted that '*particularly when a supplier group is in competition with another supplier group, reputation may be quite important*'. Patent pledges in the realm of competing technologies are further discussed in Study 3, specifically in chapter 6.4.1.1.

5.5.3 Further insights from the interviews

In addition to the motives for patent owners to pledge their patents, the interviews revealed further insights that are described below. While these insights are not directly linked to the motives, they might be of interest to future scholars in the field or to firms that are confronted with patent pledges.

Design of patent pledges
The pledging interviewees provided some insights about how the patent pledges were set up. One interviewee estimated that the establishment of his patent pledge within the firm took no longer than one month. Interviewee number 11 explained that he had to get the 'buy-in' from a variety of other employees before he could start the pledge. The selection process of patents to be pledged involved patent attorneys and technical people alike and was carefully reviewed (quote from interviewee number 11: '*[i]t required buy in from senior executives, other members of the patent and the legal team, the creators of (...) technology and others. I got all of the stakeholders to weigh in and then the initial selection of patents was driven by (...). But over time as we released more patent[s] relating to other technologies, this selection process happened under the consultation of other patent team members. We had criteria for what would make suitable patents under the (...) pledge*'). Contreras et al. (2019) also mentioned that some members of the Eco-Patent Commons used sophisticated approaches to identify patents that could be pledged. The authors, however, also found evidence that in other cases, less formal selection approaches were used. Interestingly, interviewee number 1 mentioned that the physical space (direct quote from interviewee number 1: '*...fellow next door...*') between a licensing professional and an engineer played a vital role in the establishment of a patent pledge. Contreras et al. (2019) noted that the patents that were pledged through the Eco-Patent Commons were not central to the pledgors commercial interest. This is supported by the statement of interviewee number 1, a patent counsel at a global ICT firm with 38 years of professional IP experience: '*maybe not most valuable patents, but if many people use them, it could make the world better*'. Nevertheless, Valz (2017, p. 50) warned that '*[t]he willingness of a pledger to offer rights under pledged patents for free should not be used to undermine the value or potency of such patents*'.

Questionable research methods
Interviewee number 4 took a critical stance regarding specific quantitative studies in this area. The interviewee specifically criticised studies that used patent citation data or start-up foundations as an indicator of the success of patent pledges. In his view, more studies like this one, specifically qualitative studies, should be conducted. He said: '*[a]ll too often researchers do their research in vacuums. They should make more calls like you [the*

researcher] are making rather than just using data. For example, some researchers looked at patent citation data of pledges and also at the increase of startup. These attempts completely failed, because the [...] pledges were exclusively made for PR purposes. Also, such patents were not being asserted in this area. Startups did not worry about other people's patents'.

Reasons to keep patents alive

The concerns of interviewee number 5 towards Tesla's patent pledge described earlier showed that scepticism towards patent pledges remains. Particularly patent pledges that do not involve any monetary compensation encounter distrust. Interviewee number 3, the former president of a national patent office, explained in detail that pledged patents still work as leverage to prevent misconduct from licensees: '*[t]ake Tesla for instance. They do not offer a free lunch, nobody gets a free lunch. What Elon Musk offers is a bilateral cross-license. If you look at the print, what Tesla is saying is if you agree not to come after us with your patents, we will agree not to come after you with our patents. That is an offer for a bilateral cross-license. It is a perfectly reasonable and smart thing to do. But you cannot do that if you give up your patents. You have no leverage, you have nothing to offer anymore. Nobody does that. What they are trying to achieve is creating an ecosystem*'.

Tracking users

Some previous studies showed an interest in the suitability of patent pledges to increase technology diffusion and used different indicators, such as the number of users of the pledged technology, to measure this effect (see for instance Wen et al. (2016)). Several pledging interviewees, however, believed that the attempt of tracking patent pledge users is difficult, which was also found by Contreras et al. (2019). One interviewee described his firm's pledge as a free license offering, and license agreements are confidential in nature. Interviewee number 13 explained: '*... if i am an attorney of the other firm, [I] will never say I am using your patent (...) This is why measuring effects is difficult*'. Interviewee number 14 added: '*[patent pledgor] will never know if someone uses the patents really. No one has ever notified [the patent pledgor] about the usage*'.

Chapter 6

Study 3: effect of patent pledges on technology diffusion

6.1 Simulation design

Chapter 3.3.3 justified the choice of a simulation model, specifically an ABM, to investigate technology diffusion under patent pledges. The literature review in chapter 2.3.4 showed that existing studies in this area inherited major limitations and that they delivered inconclusive results. This section describes the developed simulation model and focuses on: (i) general settings of the model; (ii) the agents' behaviour including their approach to maximise utility, the patent pledge types and their influence on technology attributes, the agents' decision process throughout the simulation, the underlying adopter types, and the agents' social network; (iii) assumptions of this study; and (iv) the experiment framework.

6.1.1 General simulation settings and structure

The ABM was developed using AnyLogic™ (version 8) software. AnyLogic is a widely used multi-method simulation modeling tool, which is primarily used to model ABMs, system dynamics, and discrete-event models (Borshchev, 2014). Dong et al. (2009), for instance, used AnyLogic to simulate software diffusion with a multi-agent model and used AnyLogic's simulation experiment feature to investigate diffusion rates. While there exist open-source software solutions to develop similar simulation models, AnyLogic was chosen because of the large number of parameters that the model required. The combination of its user-friendly interface to handle the large number of parameters and the possibility to include custom code written in the Java programming language enabled an efficient and flexible modeling process. In total, about 100 parameters and variables, as well as numerous other model handles (including events, functions, data sets, histograms, and plots) were created. In some parts of the model, custom Java code was added. This custom code is disclosed throughout this chapter and calculates or runs some specific simulation aspects, such as the share of connected agents in a certain state. The model time used by the simulation engine was set to days. This is an arbitrary choice, however, and could be adjusted to fit different scenarios. To retain generality, the expression *time unit* is used throughout this chapter. All events in the model are instantaneous and inseparable, which means that the model time does not progress during the execution of an event (Borshchev, 2014).

Fig. 6.1 gives an overview of the simulation design. The model simulates the adoption decision of 1000 firms between two competing technologies, technology 1 (T1) and technology 2 (T2).[1] Fig. 6.1 shows a *case*, and two cases are being simulated for this study. Each case consists of four *schemes* and each scheme comprises several *scenarios*. Two cases are considered: in case I, both T1 and T2 are similar; in case II, T2 is inferior.

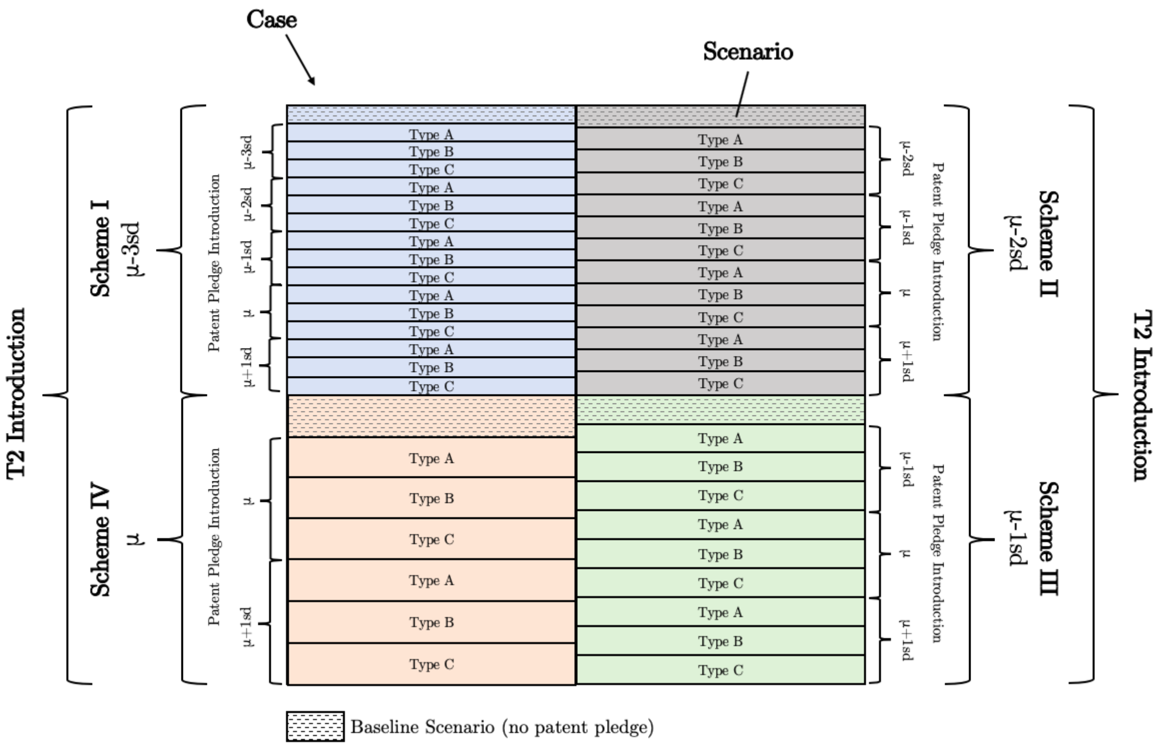


Fig. 6.1 Simulation design.

T1 is always available from the beginning of the simulation, whereas T2 is introduced at different time units (the *schemes* in fig. 6.1) and is also influenced by the introduction of

[1] See Bonaccorsi and Rossi (2003) for a similar approach and the implementation of 1000 agents.

a patent pledge of patents relating to T2. Only T2 is influenced by a patent pledge and this pledge is simulated with different *strengths* (the patent pledge types A, B, and C in fig. 6.1). Both, the general introduction of T2 as well as the occurrence of its patent pledge are designed to happen at the threshold between different adopter types, specifically at the mean value plus/minus some standard deviation ($\mu \pm \sigma$) of the adoption curve (see Rogers (1962)). They therefore occur when the *Innovators* (i.e. simultaneous to the introduction of T1), the *Early Adopters*, the *Early Majority*, the *Late Majority*, and the *Laggards* begin to adopt (see fig. 6.8). Scheme I simulates the introduction of T2 at the beginning of the simulation and at the same time as T1; Scheme II models the introduction of T2 after the *Innovators* have adopted T1; Scheme III introduces T2 after the *Early Adopters* have adopted T1; and Scheme IV simulates the introduction of T2 after the *Early Majority* has adopted T1. There is no scheme for the introduction of T2 after the *Late Majority* has adopted, because there is no following adopter category after which a patent pledge could be introduced. Every scheme includes a *baseline* scenario. These baseline scenarios simulate the adoption decisions without a patent pledge, which is why they serve as a 'benchmark' to measure the patent pledge effects. Generally, the later T2 is introduced, the less possibilities for the announcement of a patent pledge exist. Scheme IV therefore comprises fewer scenarios than Scheme I, for instance. The schemes consist of 16, 13, 10, and seven scenarios respectively, which add up to 46 scenarios for each case, or 92 scenarios for both cases. Each scenario is run 500 times and the results of these runs are statistically analysed to derive patent pledge effects.

6.1.2 Simulation of firms as agents

The simulation of the agent's decision rules is important, because it determines which one of the technologies, T1 or T2, they adopt. Many different approaches to model decision rules for the adoption of technologies exist. Zhang and Vorobeychik (2019) broadly distinguished between mathematical optimisation-based models, economics-based models, cognitive agent models, heuristic models, statistics-based models, and social influence models, whereas they can be further broken down into more detailed approaches. Individual human beings are often modeled using the theory of planned behaviour, which puts much emphasis on opinions, attitudes, and emotions (Zhang and Vorobeychik, 2019). Because this study deals with firms as agents, however, it is assumed that they follow a more rational and calculated decision process than individuals. Even though decision-makers in firms are human beings, it is assumed that they generally behave less spontaneous and more thoughtful. Economics-based models therefore appeared more suitable to replicate firms decision processes. The following section describes how the agents decide between the two competing technologies.

6.1.2.1 Utility maximisation

In economics-based models, agents either behave to minimise cost or to maximise profit or utility (Zhang and Vorobeychik, 2019). Particularly the approach of utility maximisation is a well studied and frequently used concept in technology diffusion ABMs (see for instance Plötz et al. (2014); Schwoon (2006); Sopha et al. (2017)). In this study, the utility of technology k for agent j at time t is given with

$$u_{k,j,t} = \sum_{i=1}^{16} w_i \times att_{k,i,t} \tag{6.1}$$

where

$$\begin{aligned} \text{w} &= \text{weight of the attribute, where } 0 \leq w_i \leq 1 \text{ and } \sum_{i=1}^{16} w_i = 1 \text{ and} \\ \text{att} &= \text{attribute, where } 0 \leq att_i \leq 10. \end{aligned}$$

The 16 attributes from equation (6.1) stem from Asare et al. (2016) and are described in table 6.1. The attribute values lie in the interval between 0 and 10, but not all agents exhibit the same value for an attribute. Both the weights and the attribute values in equation (6.1) for any given agent follow normal probability density functions (apart from two attributes, see the following paragraph). The mean values for the weights are derived from industry feedback, see chapter 6.1.2.3. The mean values for the technology attributes depend on the specific *scenario* and the *case* that is simulated. The concept of bounded rationality stipulates that agents exhibit rational behaviour '*that is compatible with the access to information and the computational capacities that are actually possessed*' instead of a global rationality (Simon, 1955, p. 99). Therefore, agents do not perceive technology attributes exactly the same for different reasons such as strong biases, bad experiences, or wrong information. This is why the attribute parameters are assumed to be dynamic (i.e. agents take on different values) based on a truncated normal distribution between 0 and 10. For instance, a mean value $\mu = 5$ and a standard deviation $\sigma = 2$ for the attributes implies that the majority of agents under this setting take on values that range around 5, but outliers close to 0 or 10 exist. For case I, where both technologies are similar, the attributes for T1 and T2 both have a mean value $\mu = 5$ and standard deviation $\sigma = 2$ (similar technologies). For case II, where T2 is inferior, T2 has a mean value $\mu = 4$ and a standard deviation $\sigma = 2$. Four out of the 16 attributes, however, take equal values across different technologies, i.e. they are technology-independent. These attributes are *size of the firm*, *centralisation*, *IT readiness*, and *environmental uncertainty*. These four attributes follow the truncated normal distribution as described above, but the same mean values apply to both, T1 and T2. For instance, take the scenario that a given firm with a given size can decide between two technologies. In this scenario, the size of the firm is independent of the technology choice and, therefore, the attribute remains the same for T1 and T2. In contrast, the costs of the two technologies, for instance, can vary and therefore take on different attribute values. The ABM consists of many input parameters, which can either be equal for all agents (deterministic parameters) or different according to some probability (stochastic parameters). Each technology, following the TASC model by Asare et al. (2016), inherits 16 attributes and 16 respective weights. Because of the utility function in equation (6.1), larger parameter values lead to a higher utility. Therefore, the better a technology's perceived attribute, the higher its value. While Asare et al. (2016) noted that some of the attributes are negatively associated with a firm's intention to adopt, the model consistently treats higher values as better. For instance, the cost attribute in the TASC model is negatively associated with the intention to adopt, because higher costs usually constitute a barrier to adoption (Asare et al., 2016). In the simulation model, a higher value of the cost attribute represents an increased intention to adopt and, therefore, equals fewer costs. Since the attribute-values range from 0 to 10, a value of 10 means there are no costs associated with the adoption, whereas a value of 0 means that the technology is being perceived as extremely expensive. This approach applies to all attributes that are negatively associated with a firm's intention to adopt a technology according to Asare et al. (2016), namely complexity, cost, and centralisation. It is important to note that the attribute values do not represent the real characteristic of the technology, but only the perceived characteristic of the respective agent. Different agents perceive these characteristics and their importance differently, which is why the values for the attributes and their weights follow normal distributions and are not fixed. As mentioned above, the attribute parameters range from 0 to 10, whereas the weights are normalised and sum up to 1. The attributes and weights are stochastic and vary between firms (attributes and weights) or technologies (attributes only). This means that the perceived importance of a technology attribute to an agent differs from other agents, but is the same for both T1 and T2. For instance, an agent might weigh the costs of both technologies T1 and T2 with a value of 0.4, whereas another agent exhibits a value of 0.2 for the costs of both technologies. The former agent, therefore, rates the cost of a technology higher than the latter agent.

Table 6.1 Technology attributes influencing the technology adoption decisions by Asare et al. (2016).

Key determinants	Attributes	Description
Characteristics of technology	Relative Advantage	The degree to which a technology is perceived as being better than the technology that it replaces.
	Complexity	The degree to which a technology is difficult to implement, use, and understand.
	Compatibility	The compatibility of the technology with the adopter's internal culture, business processes, existing technology, etc.
	Testability	The degree to which a technology can be experienced on a limited basis prior to the adoption.
	Observability	The degree to which the results of the technology can be easily demonstrated or quantified (increased sales, return on investment, ...)
	Costs	Costs associated with acquiring, implementing, using, and maintaining the technology.
External environment	Environmental uncertainty	Uncertain environments make firms feel vulnerable and more willing to adopt a technology.
	Competitive pressure	Firms are under pressure to adopt a technology when their competitors or partners have either already adopted the technology or have the capability and desire to adopt it.
	Industry support and reputation	Support from industry associations, industry-wide standards, and initiatives promoting the technology. This also includes the technology's reputation, such as a positive reputation because of its sustainability.
Organisational characteristics	Size of the organisation	Large organisations usually have more resources that they can use to adopt the technology.
	Centralisation	The extent to which decision-making is limited in a firm. Organisations with decentralized structures are expected to adopt more innovative and cutting-edge technologies.
	Managements support	The extent to which senior executives of an organization support a technology.
	IT readiness	The level of sophistication of IT management. It is assumed that firms with sophisticated IT environments adopt technologies easier than those with less sophisticated ones.
Inter-firm relationships	Power	Power is defined as the ability of a firm to exert influence on another firm. A persuasive approach could be used to convince the adopting firm of the benefits of adopting technology, or a more coercive approach could be used in which threats and punishments instead of inducements are used. See Asare et al. (2016) for more information.
	Justice	The extent that the prospect of justice in an 'unfair' relationship between firms influences the adoption decision. This can be distinguished between distributive, procedural, an interactional. See Asare et al. (2016) for more information.
	Trust	Trust is important in the adoption process, because the use of inter-firm technologies introduces collaborations that entail more sharing and access to confidential information, leading to increased vulnerability and interdependence.

Two attributes are not calculated by drawing a number from a normal probability density function: *competitive pressure* and *size of the firm*. Their values depend on each agent's individual network. The competitive pressure is calculated as the share in percentage of connected agents using T1 or T2, multiplied by 10.[2] The raw Java code without the multiplier of 10 is

```
nconnections = getConnectionsNumber();
nTechnology2Connections = 0;
nTechnology1Connections = 0;
for(Agent a :  getConnections())
if (((Firm)a).inState(UseTechnology2))
nTechnology2Connections++;
else if
(((Firm)a).inState(UseTechnology1))
nTechnology1Connections++;
```

```
shareTechnology2Connections = (nTechnology2Connections/nconnections);
shareTechnology1Connections = (nTechnology1Connections/nconnections);
```

which translates to

$$cp_{j,k} = \frac{ca_{j,k}}{con_j} \times 10 \tag{6.2}$$

where

$cp_{j,k} =$ competitive pressure on agent j to adopt technology k, where $0 \leq cp_{j,k} \leq 10$,
$ca_{j,k} =$ number of connections of the jth agent that have already adopted technology k, and
$con_j =$ total number of connections of the jth agent.

The Java code iterates through all the connections of an agent and counts the ones that use one of the two technologies. It then divides these values by the total number of connections of the agent and multiplies it with 10 (not shown in the raw code). These values change constantly as the simulation proceeds, because connections of an agent might adopt one of the two technologies at any time.

It is assumed that the relative size of an agent depends on its number of connections, whereby larger firms have a larger network. The calculation includes the multiplier of 10 to adhere to the other parameter values, similar to the calculation of the competitive pressure. The

[2] The multiplication by 10 ensures the concurrence with the attributes drawn from the truncated normal distributions.

value for the size of an agent does not change while the simulation is running, because it is assumed that an agent's network does not change over time. Specifically, the size of an agent is calculated as

$$size_j = \frac{con_j}{con_{max}} \times 10 \tag{6.3}$$

where

$size_j$ = the relative size of agent j, where $0 < size_j \leq 10$,
con_j = number of connections of the jth agent, and
con_{max} = number of connections of the agent with most connections.

Five model parameters are static and deterministic, which means they do not change over time and are equal for all agents. These parameters are the *criticalMarketShare* and the *criticalConnectionShare* (see fig. 6.7), the number of agents, the time for the introduction of T2, and the time until T2 is being pledged (if at all). The different scenarios of the model are simulated by altering the mean values of the normal probability density functions, among other parameters such as the introduction or the type of the patent pledge. For instance, if an initial setting assumed an attribute that is drawn from a truncated normal distribution between 0 and 10 with a mean $\mu = 5$ and a standard deviation $\sigma = 2$, then a patent pledge might change this parameter to a truncated normal distribution with $\mu = 6$ and a standard deviation $\sigma = 2$. This results in a higher attribute value for some, but not all agents. The following section describes the patent pledge types that are simulated and how they influence the probability density functions of the technology attributes.

6.1.2.2 Patent pledge types

Patent pledges alter technology attributes of the ABM, whereby the specific type determines the degree of change. Since truncated normal distributions are used for the attributes, one obvious way to alter these distributions while preserving the underlying probability is to shift the mean value of the function, as mentioned previously. When a patent pledge has a positive effect on an attribute, for instance, the mean value of the respective probability density function increases compared to the scenario without a patent pledge. The strength of the patent pledge thereby determines the intensity of this shift.

Three types of patent pledges are considered: type A, B, and C. These types represent three types from the patent pledge taxonomy on page 71, see fig. 6.2 below.

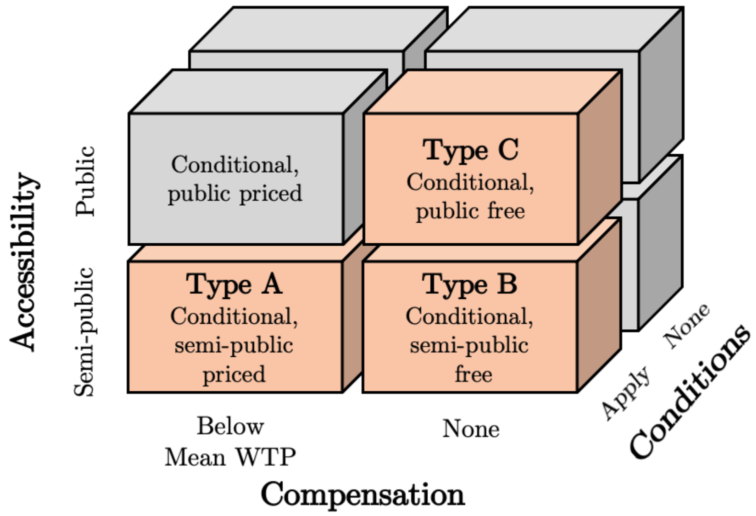


Fig. 6.2 Patent pledge types considered in the simulation (in orange).

It is assumed that a higher accessibility and a lower compensation represent a stronger patent pledge. The strongest patent pledge, therefore, is of the type *conditional, public free*, and the weakest one is of the type *conditional, semi-public priced*. The remaining type lies in between these two. Consider Tesla's patent pledge which was categorised as a conditional, public free patent pledge (type C, see chapter 4.3.2 and appendix A). This patent pledge can be used to access Tesla's patents free of charge as long as the beneficiary does not assert rights against Tesla. This stays in contrast to Toyota's conditional, semi-public free patent pledge (type B), which only addresses other automakers, fuel cell part suppliers, and energy companies in this specific technology realm. While this 'field restriction' does not automatically limit the number of potential adopters, Toyota's patent pledge exhibits some further characteristics that qualify it as 'inferior' to Tesla's pledge. For instance, interested parties need to negotiate individual contracts with Toyota and cannot automatically start using the patents as in Tesla's case. It is therefore assumed that Tesla's patent pledge, due to its ease of access (no negotiations required) and lack of restricted accessibility, is 'stronger' and attracts more adopters. Similarly, Ford's patent pledge from 2015 is assumed to be inferior to Tesla's patent pledge because Ford's patents are only available at a fee. It is assumed that a patent pledge type C exhibits the strongest shift of the mean values of the technology attributes, while gradually lowering the shift for types B and A. A type C patent pledge is referred to as *strong*, a type B patent pledge as *medium*, and a type A patent pledge as *weak* throughout this chapter. The ABM was implemented with a truncated normal probability density function in the interval [0;10] with a mean value $\mu = 5$ and a standard deviation $\sigma = 2$ as standard parameters for the attributes. The three patent pledge types A, B, and C shift the mean values closer to 10. Even mean value increments of 1.5 are assumed, so that the mean value for type A is 6.5, for type B 8.0, and for type C 9.5. This allows the exploration of the remaining parameter space without assuming a shift to the limit of 10. A value of 10 for the cost attribute, for instance, would imply that the technology can be adopted without any costs. A shift to this limit seems unrealistic because it should not be assumed that patent pledges allow the completely free adoption of a technology. Even if a patent pledge does not require any monetary compensation, certain costs for the technology adoption, such as labour and transitioning costs, are likely to occur.

A visual representation of the probability density functions of the three patent pledge types and a comparison to the probability density function without a patent pledge of T2 (baseline scenario) is illustrated in fig. 6.3 (case I in which T1 and T2 are similar) and fig. 6.4 (case II where T2 is inferior). Fig. 6.3 shows that T1 and T2 are perceived as similar, because they follow the same distribution (the grey normal probability density function). While T1 always exhibits this function for all technology attributes apart from the *competitive pressure* and *size of the firm* (see descriptions above), the normal probability density functions for the attributes of T2 shift to the right with varying patent pledge strengths.

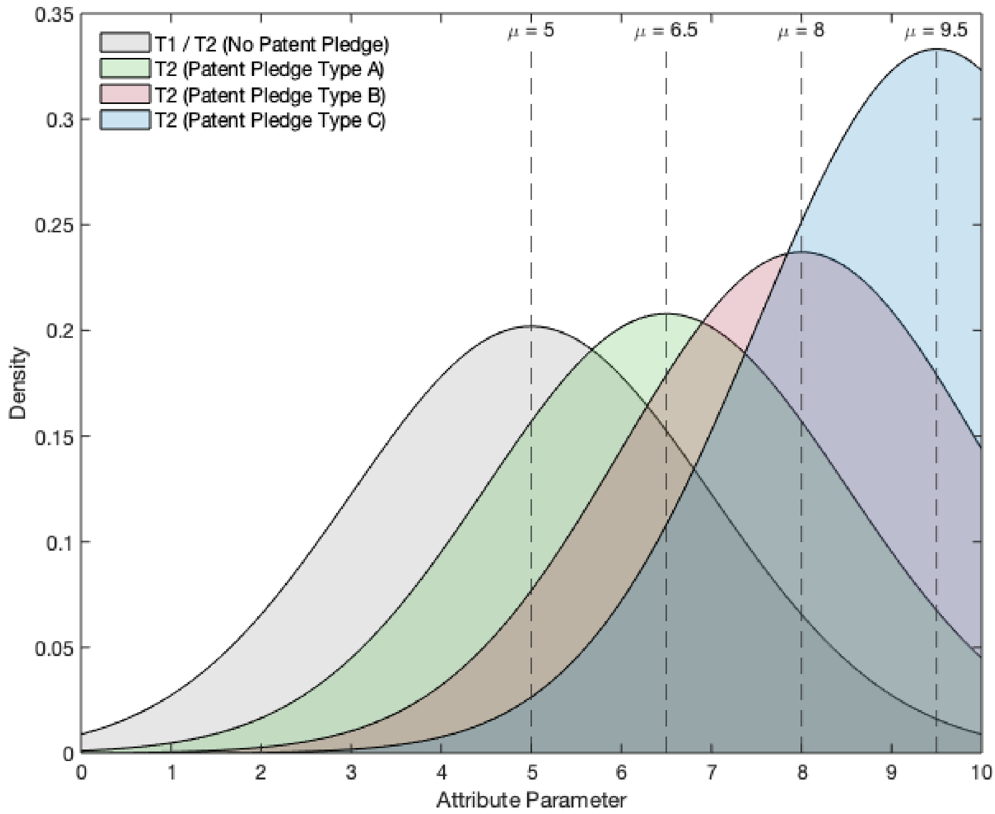


Fig. 6.3 Case I: probability density functions for technology attributes.

This is also true for fig. 6.4, but here T2 exhibits a normal probability density function with a peak that lies left to the peak of T1 when no patent pledge is introduced. This is because in case II, T2 is inferior to T1.

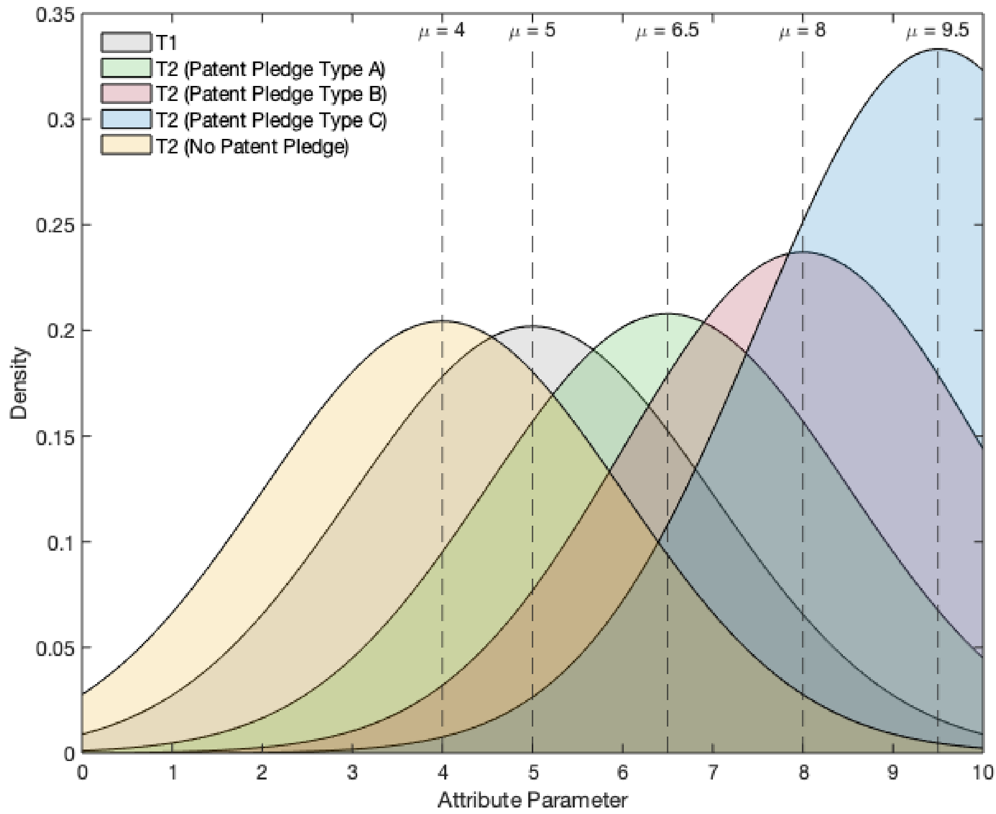


Fig. 6.4 Case II: probability density functions for technology attributes.

So far it was assumed that the three patent pledge types influence all technology-dependent attributes of the technology that is being pledged. Patent pledges, however, might influence only some of the technology attributes, not all of them. The following section therefore investigates which of the attributes are influenced by a patent pledge.

6.1.2.3 Influence of patent pledge types on attributes

It is necessary to decide which attributes are influenced by a patent pledge. Abstract simulation models and analytical solutions usually assume reasonable inputs (see for instance Arthur (1989) and Bonaccorsi and Rossi (2003)). Therefore, no large-scale data collection was conducted. Nevertheless, preliminary discussions with four IP managers and one external IP researcher were held to overcome speculations about which attributes might be influenced by patent pledges (see chapter 3.3.3). This allowed for an estimation of the importance of technology attributes (weights) and their possible suggestibility by patent pledges.

The four IP managers were highly experienced in patent matters and partly in technology acquisition processes, and were sampled through personal contacts. They worked in three automotive firms in Germany, i.e. two of the participants worked in the same firm. One respondent, for instance, was the vice-president of the patent department of a major German automobile manufacturer. The respondents were given a document comprising eight DIN A4 pages, see fig. C.1 through fig. C.8 in appendix C. In part A of the document, the respondents were given a template with the explanation of the technology attributes according to Asare et al. (2016), see fig. C.2 in the appendix for an excerpt. The respondents evaluated the importance of each attribute in technology acquisition processes by labeling it *Not important at all*, *Of little importance*, *Of medium importance*, or *Of high importance*. They also evaluated if each attribute might be influenced by a patent pledge and if yes, to what degree and in what direction (i.e. positive, negative, or both directions are possible). In part B, the respondents were given the agent's decision rules (see fig. 6.7) and general assumptions of the ABM, and were asked to comment on them. In a second feedback round, their answers were individually discussed and confirmed.

The qualitative feedback for the attributes was translated into quantitative data to allow the implementation in the simulation model. The four feedback possibilities mentioned above were assigned numbers from 0 - 3, 0 equaling *Not at all important* and 3 equaling *Of high importance*. These values were divided by the total sum of all translated values, and summed up across attributes, which resulted in normalised weights for the attributes (see fig. 6.5). The sum of all weights therefore equaled 1. *Relative Advantage*, *Costs*, and *Competitive Pressure* were the most important attributes to the respondents. The normalised weights were used as mean values for the truncated normal distribution of weights used in the model.[3] As a result of the implementation of the weights as mean values, not all agents value individual technology attributes similar. This enables the simulation of individual preferences of agents. The weights constitute an estimate for the importance of the technology attributes to the respondents. The small sample size of the respondents did not allow for a thorough statistical analysis.

[3] Similar to the attribute parameters, the weights shown in fig. 6.5 were multiplied by 100 to result in mean values between 0 and 10.

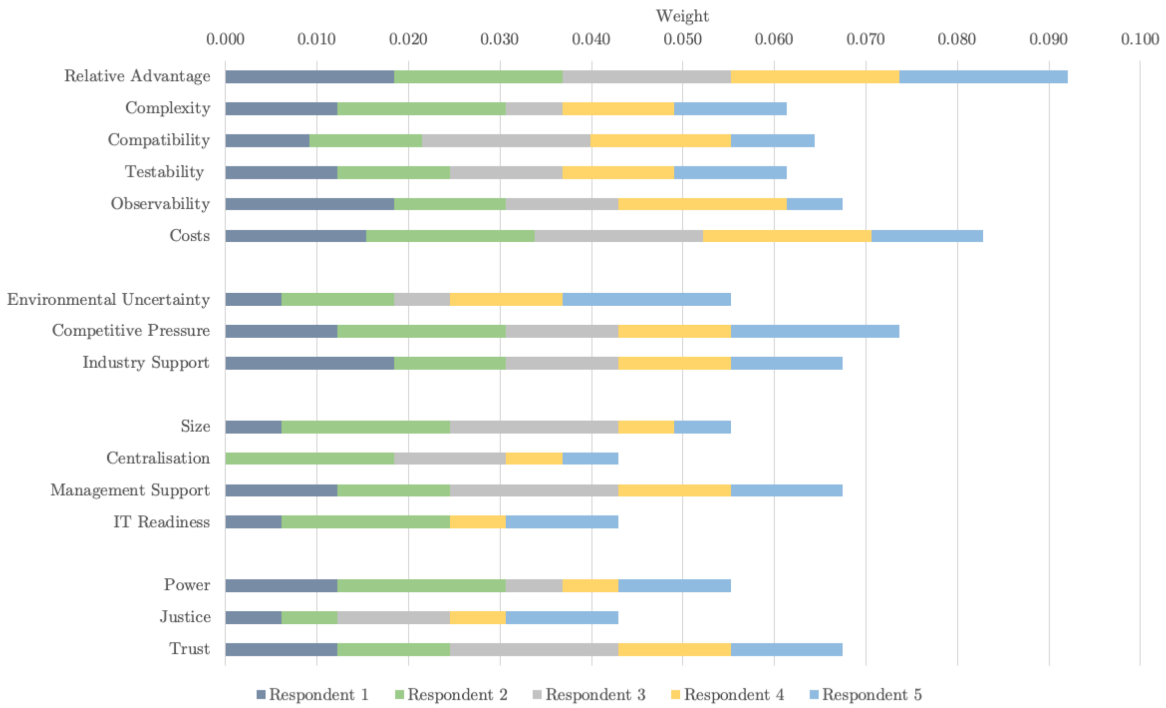


Fig. 6.5 Technology attribute weights derived from industry feedback.

In a similar manner, it was estimated which technology attributes might be influenced by a patent pledge. The respondents' feedback was translated into values between 0 and 3, and all respondents' feedback for each attribute was summed up. These sums indicated how strongly the respondents believed an attribute is being influenced by a patent pledge. For instance, when all respondents answered with 1 (low influence through patent pledges), then the resulting value for this attribute was 5 for all five respondents. The mean value across all technology attributes was $\mu = 5.75$ with a standard deviation of $\sigma = 3.09$. A conservative view was taken and only the attributes that exceeded the threshold $\mu + \sigma$ were considered to be influenced by a patent pledge. This resulted in three attributes being influenced by a pledge: **costs**, **industry support**, and **management support** (see fig. 6.6). These technology attributes are therefore subject to the aforementioned shift of the mean value due to the introduction of the patent pledge types A, B, and C in the simulation model. The respondents also estimated values for the parameters *criticalMarketShare* (70%) and *criticalConnectionShare* (60%) and verified the implemented decision process of the agents, which is further explained in the following section.

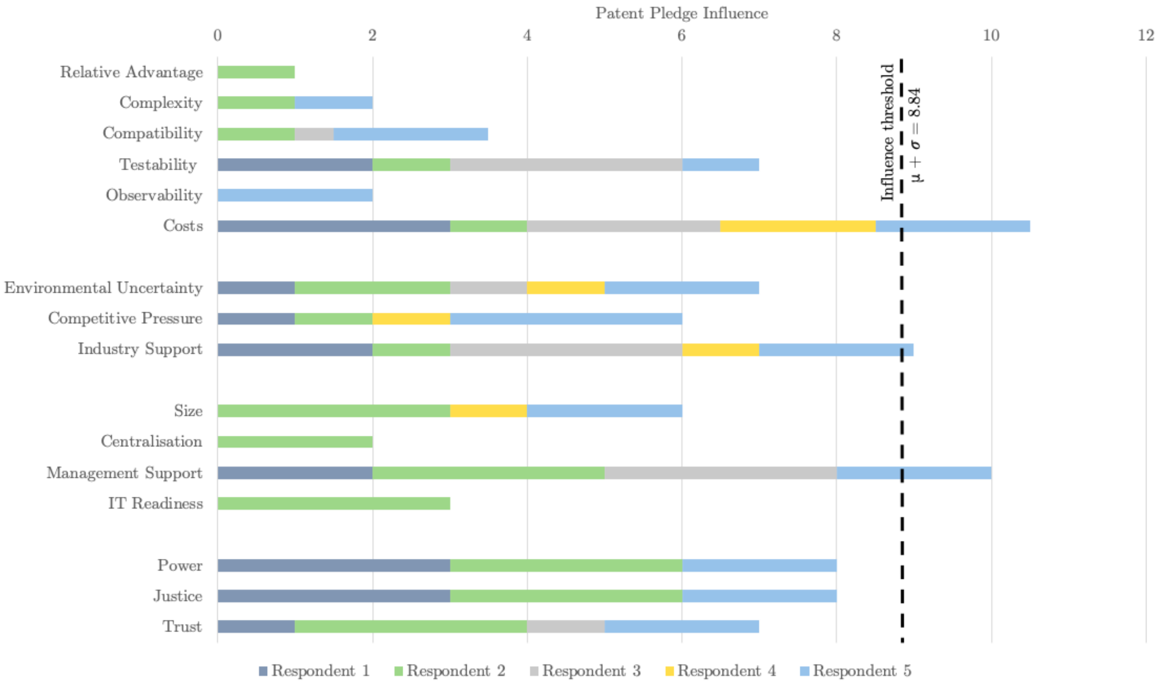
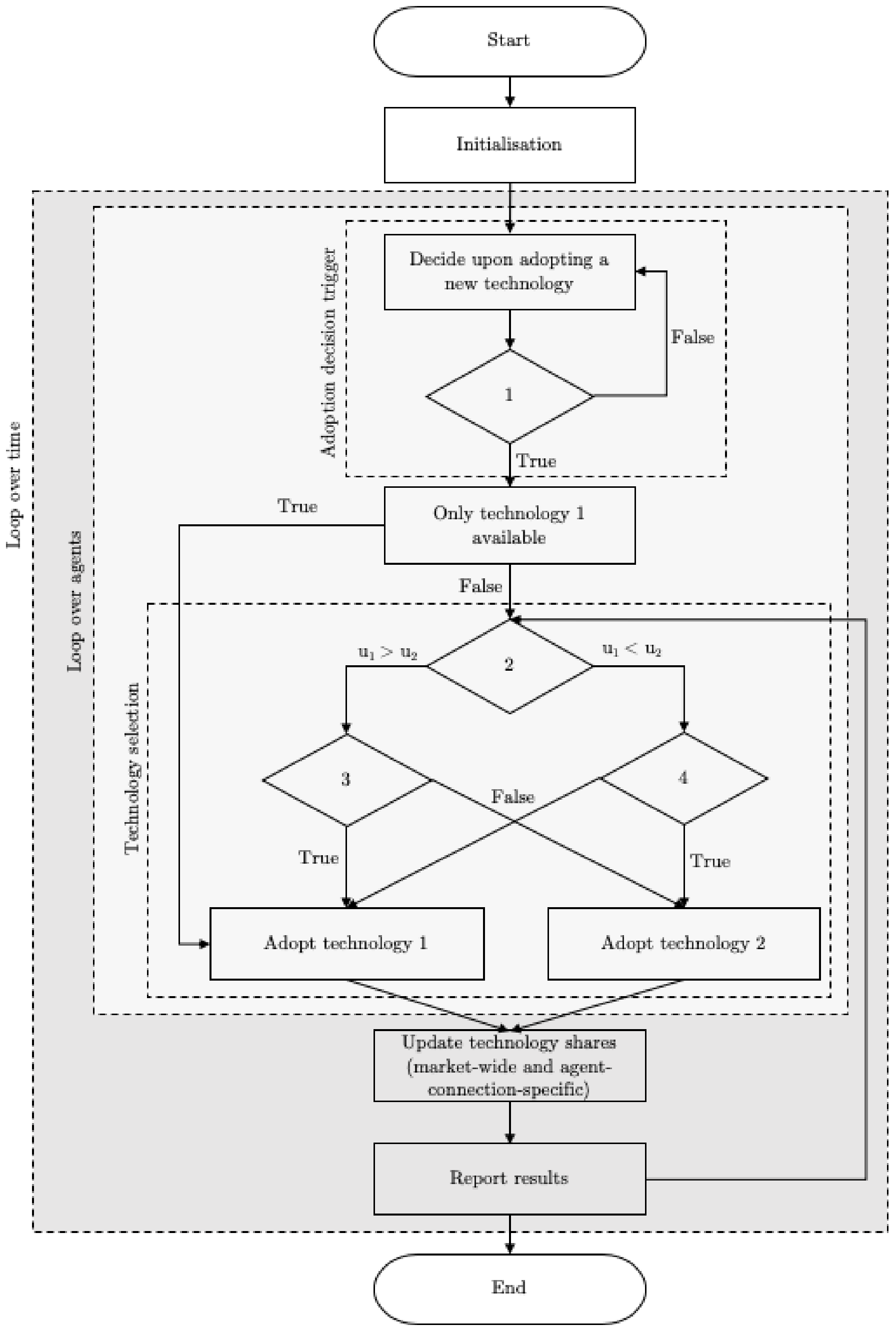


Fig. 6.6 Influence of patent pledges on technology attributes.

6.1.2.4 Decision process

The decision process with four main decision of each agent *j* is shown in fig. 6.7 and was adjusted and verified through the feedback from industry experts described above. The illustration includes excerpts from the added Java code in the software. Decisions 3 and 4 follow suggestions from the literature. Sopha et al. (2017), for instance, described a simulation model of natural gas adoption in which the intention calculation was overwritten when the number of connections of a focal agent using a specific technology exceeded a given threshold. Similarly, the critical market share threshold in the model enabled the implementation of the 'lock-in' effect of a technology (see for instance Arthur (1989)).



Decisions

1	Each agent inherits a constant parameter ('adoptionParameter'), which is drawn from the assumed technology adoption function. Therefore, the conditional transition `adoptionParameter < time()` results in the assumed adoption function.
2	The utility for each technology k at time t is calculated. The agent chooses the path with the higher utility.
3, 4	The agent changes his technology preference after the utility calculation if • a predefined percentage value ('criticalMarketShare') of all agents ('market') has already adopted the other technology or • a predefined percentage value ('criticalConncectionShare') of the agent's network connections has already adopted the other technology. The Java code is as follows: For 3: `(get_Main().shareTechnology2Users <= get_Main().criticalMarketShare) && (shareTechnology2Connections <= get_Main().criticalConnectionShare)` For 4: `(get_Main().shareTechnology1Users <= get_Main().criticalMarketShare) && (shareTechnology1Connections <= get_Main().criticalConnectionShare)`

Syntax key:

Bold	Custom parameters and variables
&&	Logical AND-operator
time()	Returns the current model time in time units
get_Main()	Location of the the subsequent parameter in the main agent

Fig. 6.7 Simulation flowchart oriented on Sopha et al. (2017).

The decision process illustrated in fig. 6.7 was confirmed by the respondents from the previous section. One respondent, a senior IP manager with a doctorate in engineering, said that the decision process is '*valid and highly useful*'. One insight from the respondents was that the parameter *criticalConnectionShare* should be lower than the parameter *criticalMarketShare*, because the connected firms are more important to a focal firm than the general market (see decisions 3/4 in fig. 6.7).

6.1.2.5 Adopter types

Agents not only differ in the way how they perceive the importance and the values of technology attributes, but they also differ in their willingness to adopt. Rogers (1962) differentiated between five adopter types and showed that adopter distributions approach a normal probability density function. He distinguished between *Innovators*, *Early Adopters*, *Early Majority*, *Late Majority*, and *Laggards*. The transition from one type to another, when using a normal distribution, is determined by the distance from the mean-value μ, measured in multiples of the standard deviation σ (see fig. 6.8).

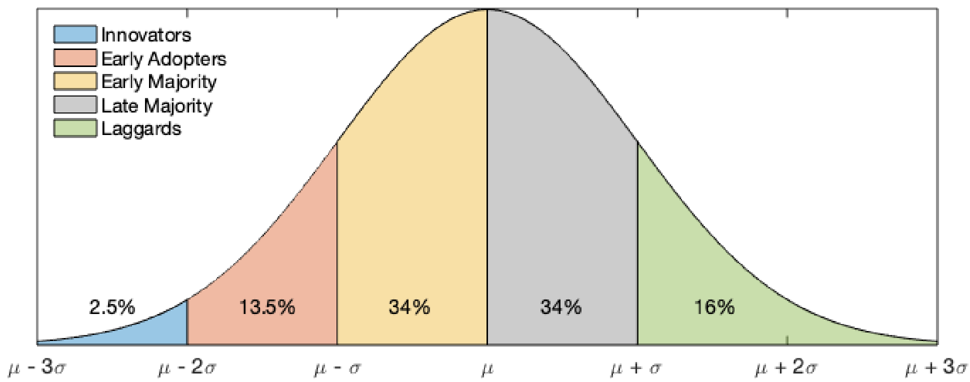


Fig. 6.8 Technology adopter types after Rogers (1962).

The adoption rate therefore follows a bell-shaped function, which, when summed up, results in the classic S-shape (see fig. 6.9). This simulation model implemented a (truncated) normal probability density function to concur with the literature and to simulate the adopter types described by Rogers (see fig. 6.9).[4] When the technology is being released, only few agents, the *Innovators*, are willing to adopt. As the technology adoption progresses, the agents' willingness to adopt follows the described function and reaches its peak at mean time units μ. The limit of 2000 time units in fig. 6.9 is assumed, because the length of technology

[4] The truncation discards every sample outside the interval and repeats the draw until it falls within the interval.

adoption cycles varied to a large extent between technologies (Hall, 2005). Ryan and Gross (1943), for instance, found that it took about 13 years for hybrid corn to fully diffuse among communities and Hall (2005) stated that it took over 40 years for clothes washer to reach three quarters of all considered households. Other inventions, such as the videocassette recorder, completed the classic S-curve in shorter time periods (Hall, 2005). The assumption of 2000 time units (days) was chosen to simulate a reasonably fast diffusion, but other values are possible.[5] The model was implemented so that the choice of the time units is practically irrelevant. This is because the ABM and its decision rules do not use absolute time unit values, but measure time as distance from the mean value in steps of standard deviation, as shown in fig. 6.9. As long as all adopter types, according to Rogers (1962), adopt within the distance of three σ from the mean-value μ and follow a normal distribution, the outcomes should be similar.

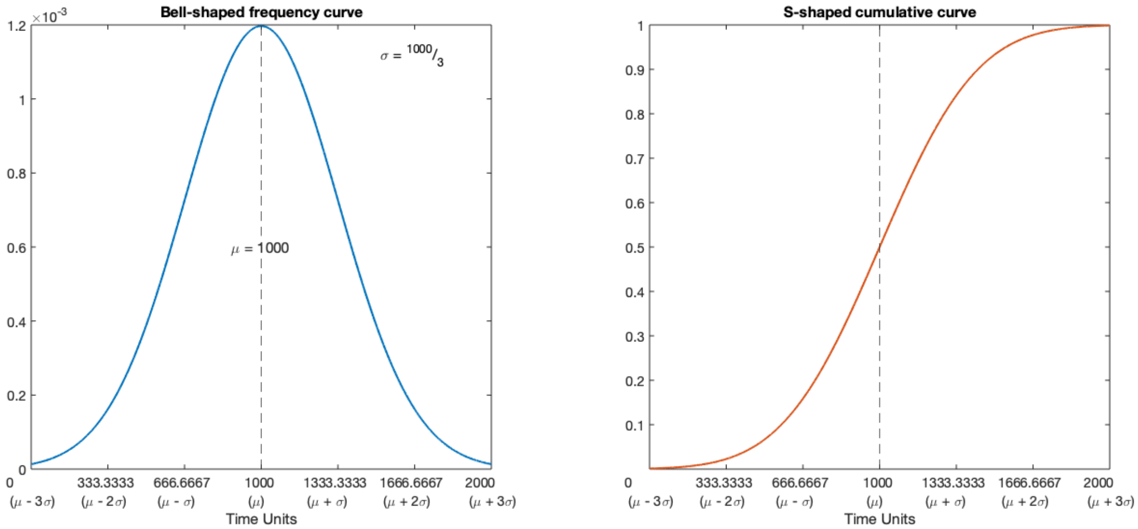


Fig. 6.9 Assumed technology adoption function: Truncated normal probability density function (left) and cumulative curve (right) with $0 \leq x \leq 2000$, $\mu = 1000$, and $\sigma = \frac{1000}{3}$ time units following Rogers (1962).

6.1.2.6 Social network

Regarding the network structure between agents, the choice to apply a scale-free network that followed the power-law was made. Fig. 2.4 in chapter 2.3.2.2 showed that different types of network topologies exist. The literature on network structures between firms is limited, partly because it is unlikely that a 'one-fits-all' solution exists. Riccaboni and Pammolli (2002) showed that firms in life sciences and ICT are connected by scale-free networks, where

[5] The majority of agents will, on average, decide to adopt a new technology at $\mu = 1000$ time units, or 1000 days.

most firms have a limited amount of connections but few firms serve as large 'connection-hubs' (see also Ozman (2009)). This is why this research assumed a scale-free network, too. Scale-free networks, as described by Barabási and Bonabeau (2003) and discussed in chapter 2.3.2.2, are characterised by many nodes with relatively few links, but few nodes with a large number of links. The specific setup for the simulation used is as follows: The mean value was $\mu = 9.95$ connections with a deviation of approximately $\sigma = 10.4$.[6] Every firm in the model had on average about 10 connections, while few large firms had more than 100 connections and served as 'hubs'.

6.1.3 Assumptions

Table 6.2 provides an overview of the simulation assumptions. These assumptions are distinguished between general model assumptions, agent assumptions, and literature assumptions. General model assumptions relate to universal settings of the ABM, whereas agent assumptions concern the agents' individual technology adoption decision processes. The ABM furthermore relies on existing theories, which are summarised under literature assumptions.

[6] Note that these values are stochastic and vary between runs, despite the use of fixed seeds described in chapter 6.1.4. In three random setups, the value for the maximum number of connections was 102, 114, and 139. The minimum value equaled five in all setups, because the scale-free parameter M of the software was set to five. The values of the mean, deviation, and mean confidence varied slightly, too.

Table 6.2 Model assumptions.

Category	No.	Assumption
General model assumptions	1	All agents adopt a technology within 2000 time units.
	2	Only technology T2 is pledged.
	3	Technology T1 is released at the beginning of the simulation.
	4	The technology supplier of technology T1 does not react to the patent pledge of technology T2.
	5	Higher accessibility and a lower compensation represent a stronger patent pledge.
	6	The patent pledge relating to T2 occurs only at the transition between adopter types.
	7	Three patent pledge types are considered.
	8	The agents are connected through a scale-free network.
	9	All patents for each of the technologies T1 and T2 are held by one technology supplier only.
Agent assumptions	10	The perception of technology attributes follows a truncated normal distribution with varying mean values and a fixed standard deviation of σ=2.
	11	The mean values of the attributes influenced by patent pledges are incremented evenly across the three types A, B, and C.
	12	Three technology attributes (Cost, Industry Support, and Management Support) are influenced by a patent pledge.
	13	Patent pledges have a positive effect on the technology attributes.
	14	Agents adopt either technology T1 or technology T2, not both.
	15	Agents do not discard their adopted technology.
	16	Agent's connections do not change over time and are established at the beginning.
	17	Larger firms have more network connections.
	18	The critical market share and the critical connection share override, when reached, any calculated utility of the remaining adopters.
Literature assumptions	19	Agents decide based on utility maximisation as described by Zhang and Vorobeychik (2019).
	20	The technology attributes of Asare et al. (2016) apply.
	21	The adoption curve follows Rogers (1962).
	22	The transition between adopter types follows Rogers (1962).
	23	The concept of bounded rationality of Simon (1955) applies.
	24	The study addresses patent pledges that fall under the 'platform development' type described by Contreras (2017a). Other types, such as 'interoperability', are not considered.

An alternative model might allow agents to re-evaluate their adoption decision and, in some cases, discard their initial choice. Similarly, parameter values could change over time due to external circumstances such as political and environmental events. This would, however, complicate the simulation and ultimately its outcomes. The goal of this research is to provide an exploratory investigation that allows future research to build upon. The simulation model was therefore implemented as general as possible.

6.1.4 Experiment framework

The stochastic parameters in this simulation study entail a degree of uncertainty. Two different experiments with identical settings could lead to different results. It was therefore important to run each experiment with its unique settings multiple times to capture the most probabilistic outcomes. Most scenarios in this study were run 500 times, and all relevant statistical indicators were calculated. Only some settings in which specific data of individual model runs were obtained required single experiment runs. The number of experiment runs for each setting is indicated using the letter N.

While a large number of experiment runs increases the reliability of the outcomes, one can never be certain that these outcomes are not the result of some unlikely but possible draws from the probability density functions. This makes it difficult to measure a patent pledge effect, for instance, because it remains unclear if the outcomes are the result of a patent pledge or of some random parameter combinations. One way to overcome this issue is by configuring the simulation *seeds*. A (random) seed constitutes a vector that initialises a deterministic random bit generator (see Borshchev (2014)). This generator, or algorithm, produces a sequence of pseudo-random numbers which are determined by the seed and which in turn determine the draws from the probability density functions. Random seeds for each simulation scenario therefore lead to different values that are drawn from the normal probability density functions. Hence, if a scenario is run twice for 500 times with random seeds, the outcomes are likely to be different. To overcome this uncertainty, fixed instead of random seeds were implemented (Borshchev, 2014). The simulation was programmed to use 500 fixed seeds for the 500 experiment runs of each scenario, which means that the replication of a scenario without altering the normal probability density functions resulted in almost identical outcomes.[7] This implies that any observed difference for this ABM cannot be a result of other draws from the normal probability density functions. The use of fixed instead of random seeds is a common approach in simulation modeling. Elbert et al. (2017), for instance, used fixed seeds for a random number generator with the software AnyLogic to ensure reproducibility. The respective Java code for the configuration of the fixed seeds is given below.

```
root.getDefaultRandomGenerator().
setSeed(variable[getCurrentIteration()]);
```

[7] The outcomes are not identical because of the changing connections of the firms in each experiment run. The network structure was not determined by the seed. This influenced the model outcomes only marginally, however, because the mean value and the standard deviation of the number of connections remained similar across all experiment runs.

Variable in this code excerpt referred to an array of 501 fixed numbers, which means that for every experiment, the seed was drawn from this array (Borshchev, 2014).[8] This ensured that the measured effects are, with high certainty, the result of patent pledges.

6.2 Simulation results

In this section, the simulation results for both cases are presented. The results for each of the four schemes for case I and II are summarised in a table and a corresponding chart. The scenarios within each scheme are labeled so that they can be uniquely identified in the respective figures. Ten key indicators are used to investigate the scenarios and to compare them with each other. These indicators display settings of the scenarios (e.g. at what time a patent pledge was introduced), measure specific values (e.g. the market share saturation at the time of the patent pledge introduction), or calculate patent pledge effects on technology diffusion, among others. The indicators are described below and follow the order in which they appear in the tables.

Patent pledge introduction (PPI) describes the point in time in which the patent pledge of T2 is introduced. The PPI is measured in standard deviations σ from the mean value μ of the adoption function and occurs at the transition between different adopter types, see fig. 6.8 in chapter 6.1.2.5. T1 is always introduced at the beginning of the simulation (at $\mu - 3\sigma$) and T2 is introduced with respect to the specific scheme (at $\mu - 3\sigma$, $\mu - 2\sigma$, $\mu - 1\sigma$, and μ). The PPI of T2 can only occur at the same time or after the introduction of T2.

Patent pledge type describes the type (or strength) of the patent pledge. Three patent pledge types (A, B, and C) are simulated. The types are implemented by shifting the mean values of the three attributes *Cost*, *Management Support*, and *Industry Support* of T2 according to fig. 6.6, see fig. 6.3 for case I and fig. 6.4 for case II.

Market share saturation at time of patent pledge describes the mean value of the total market share of both T1 and T2 at the time of the patent pledge, i.e. the share of agents that have already adopted any of the two technologies T1 or T2 when the patent pledge is introduced. Since patent pledges in the simulation model are introduced at the transition between adopter types, the values approach the cumulative percentage values of the adopter types after Rogers (1962), as shown in fig. 6.8 (2.5%, 16%, 50%, and 84%). The values serve as a validation for the correct implementation of the adoption function.

[8] The variable consisted of 501 instead of 500 numbers, because the experiment resulted in an error when the limit of the variable is reached while the experiment is still running. Note that the network initialisation for each agent is not determined by the seed, which is why small deviations between runs still occurred.

Intercept of T2 at total market share indicates the final point in which the number of T2 adopters exceeds the number of T1 adopters (if at all), measured in total market share and absolute time units. This indicator is used to compare different scenarios and to gain insights about when T2 '*wins the adoption competition*' as described by Arthur (1989) (see chapter 2.3.1.3. Intercepts can occur multiple times during the simulation runs, especially during the early phases of the adoption curve and when both technologies are similar (case I) and are also introduced at the same time. In these cases where several intercepts occur, only the last intercept where the number of T2 adopters exceeds the number of T1 adopters is considered. Importantly, only the experiment runs in which the number of final adopters of T2 exceeds the number of final adopters of T1 are used to calculate this indicator. This could lead to misinterpretations, however. Consider the case where in scenario A, T2 wins the adoption competition only occasionally but when it does, it wins early. Compared to another scenario B in which T2 always wins the adoption competition but at later stages, the mere consideration of experiment runs in which T2 wins against T1 could be misleading. In these hypothetical scenarios, scenario A would exhibit a sooner intercept than scenario B, even though scenario A only occasionally wins the adoption competition and scenario B always does. This might pose a misleading picture of the adoption rates and could lead to wrong interpretations. To overcome this, the indicator *Intercept Occurrence* is introduced.

Intercept Occurrence is a measure for how often, out of the 500 experiment runs, T2 wins the adoption competition against T1. This indicator serves as additional information for the previously described indicator *Intercept of T2 at total Market Share*.

T2 reaches 50% market share at time indicates the point in time in which the number of T2 adopters reaches 50%, or 500 agents, if at all. It is important to note that this indicator constitutes a mean value that is calculated from all observed values, but data for the standard deviation and the mean confidence interval are given. Furthermore, this indicator can only be calculated in cases where the indicator *Intercept Occurrence* is greater than 0, because only when the number of T2 adopters exceeds the number of T1 adopters can T2 reach a market share of more than 50%.

Gradient difference is an indicator for the fast effect of the patent pledge on the adoption rate of T2, measured in change of slope between two standard deviations. The gradient difference indicates how strongly a patent pledge affects the adoption curve of T2 in the short term. This is also referred to as *fast effect* throughout this study, because it measures the effect after one standard deviation of the patent pledge introduction. The subsequent indicators described below, in contrast, measure the patent pledge effect at the end of the simulation. The calculation of the gradient difference before and after the patent pledge is computed on ten additional experiment runs for each scenario in which a patent pledge is introduced. The gradient difference $\bar{g}$ is calculated as

$$\bar{g} = \frac{\sum_{i=1}^{N} \Delta s_{i,scenario} - \Delta s_{i,baseline}}{N} \tag{6.4}$$

where

$$\begin{aligned} s &= \tfrac{\sum(x-\bar{x})(y-\bar{y})}{\sum(x-\bar{x})^2} \\ \Delta s &= s_{[PPI;PPI+1\sigma]} - s_{[PPI-1\sigma;PPI]} \\ N &= 10 \end{aligned}$$

Ten instead of 500 experiment runs as described in chapter 6.1.4 were used to calculate the gradient difference.[9] This is because the slope calculation required adoption data for any time unit in the interval $PPI \pm \sigma$ of any experiment run. Due to time-constraints of this research, this could not be done for all 500 experiment runs of each scenario.

Final Adopters of T2 describes the share of the 1000 agents that have adopted T2 at the end of the adopter curve at $\mu + 3\sigma$, or 2000 time units. This indicator is used to calculate the two slow patent pledge effects described below. Since the simulation model assumes that all agents ultimately adopt, every agent that has not adopted T2 at the end of the simulation has adopted T1 instead.

Absolute patent pledge effect (APPE) measures the absolute market share gain of T2 as a result of the patent pledge in percentage points. In contrast to the gradient difference, which measures the fast effect of patent pledges after one standard deviation of its introduction, the APPE uses the final number of T2 adopters to calculate the *slow effect*. The mean value of the final number of T2 adopters in the baseline scenario of the respective scheme (see fig. 6.1) is thereby subtracted from the mean value of the final number of T2 adopters of the respective scenario. The baseline scenario introduces T2 at the same time, but T2 is not subject to a patent pledge (see chapter 6.1.1). The only difference between the scenarios is the patent pledge and the slightly varying network structures, which implies that the change in T2 adopters is the result of the pledge. Chapter 6.1.4 described the simulation settings that ensures this causality and the simulation's reproducibility. The APPE is calculated as

$$APPE = \frac{\bar{A}_{T2} - \bar{A}_{T2,Baseline}}{A_{Total}} \times 100 \tag{6.5}$$

where

[9] Random seeds were used for the calculation of the gradient difference.

$\bar{A}_{T2}$ = Final number of T2 adopters in this specific scenario (mean value),
$\bar{A}_{T2,Baseline}$ = Final number of T2 adopters in the baseline scenario (mean value), and
A_{Total} = Total number of final adopters.

The APPE calculates the absolute effect of the patent pledge on the number of final T2 adopters and does not take into account that at the time of the patent pledge, only agents that have not yet adopted a technology can be influenced by the pledge. Therefore, the following indicator 'relativises' the APPE.

Relative patent pledge effect (RPPE) measures the relative market share gain, or *normalised slow effect*, of T2 due to the patent pledge. The RPPE is used to measure the patent pledge effect relative to the remaining market share at the time of the patent pledge and takes into account that only agents that have not adopted a technology at the time of the patent pledge can be influenced by the pledge. This is because this simulation model does not simulate technology discards or multiple adoptions. Whereas the APPE calculates the absolute increase in final adopters as a result of the patent pledge, the RPPE normalises this effect on the remaining adopters. Specifically, the RPPE is calculated as

$$RPPE = \frac{\frac{\bar{A}_{T2}-\bar{A}_{T2,Baseline}}{A_{Total}}}{1-MS_{PPI}} \times 100 = \frac{APPE}{1-MS_{PPI}} \tag{6.6}$$

where

$\bar{A}_{T2}$ = Final number of T2 adopters in this specific scenario (mean value),
$\bar{A}_{T2,Baseline}$ = Final number of T2 adopters in the baseline scenario (mean value),
A_{Total} = Total number of final adopters, and
MS_{PPI} = Total market share at time of patent pledge (PPI), where $0 \leq MS_{PPI} \leq 1$.

The APPE and the RPPE produce the same results only when both T2 and its patent pledge are introduced at the beginning of the simulation together with T1. This is because at that time, none of the agents have adopted a technology yet, i.e. the market share for agents that have not yet adopted either of the technologies is 100%.

The following sections present the simulation results of the two cases. Every scheme is presented separately with one table and one summarising chart. The results include the raw data from the simulation runs. They are included to allow the complete documentation of the experiment but are not essential to follow the discussion. Chapter 6.3 continues with the narrative of the thesis. Note that the charts do not illustrate all experiment runs of each scenario, but only the runs with the most frequent path. This means that even in scenarios where the curve of T2 adopters (blue) lies above the curve of T1 adopters (orange), there might exist some experiment runs in which T1 won the adoption competition. This is, however, shown in the respective tables that contain data for all indicators. The tables should therefore be used for the thorough investigation of the schemes, whereas the charts allow for a gross visual representation of the results.

6.2.1 Case I: results where T1 and T2 are similar

6.2.1.1 Scheme I: introduction of T2 simultaneous with T1

Scheme I of case I simulated the introduction of T2 at the beginning of the simulation simultaneous to T1. Both technologies were perceived as being similar. The scheme consisted of a baseline scenario where the technology relating to T2 was not pledged and 15 scenarios in which it was subject to a patent pledge. As described earlier, three patent pledge types with different strengths (type A being a 'weak', type B being a 'medium', and type C being a 'strong' patent pledge) and varying patent pledge introduction points were simulated. Patent pledges in all schemes occurred at the transition between adopter types according to Rogers (1962), see fig. 6.8.

Table 6.3 and fig. 6.10 summarise scheme I of case I. The baseline scenario without a patent pledge resulted in a market share of 49.9% for T2 adopters, because T1 and T2 were, on average, perceived as being similar. This approximately equal market share split for both technologies validates the ABM because as long as the technology attributes follow the same normal probability density function, no aggregate agent preference should occur. The introduction of patent pledges in the subsequent scenarios led to higher adoption rates of T2, which declined the later the patent pledge was introduced. The maximum patent pledge effect occurred when the strongest patent pledge (type C) was introduced at the same time as T2 (in scenario I M(-3sd_-3sd_C). In this scenario, a APPE/RPPE of 44.7 was reached, meaning that the final number of T2 adopters increased by 44.7 percentage points compared to the baseline scenario without a patent pledge. With the introduction of a weak patent pledge (type A) after the *Late Majority*, in contrast, the APPE reached 2 percentage points. The patent pledge introduction prior to the adopter category *Late Majority* at $\mu + 0\sigma$ led to higher adoption rates of T2 in all 500 experiment runs of every scenario. This is because the intercept occurrence reached 100% for these scenarios. After the late majority, however, T2 won the adoption competition in 67.6% (Type A), 83.2% (Type B), and 91.4% (Type C) of cases. This indicates that a patent pledge does not always lead to a market share win of T2 when the patent pledge is introduced after the adopter category *Late Majority*. A weak patent pledge (type A), for instance, does so in approximately two out of three cases. In scenario I M(-3sd)_-3sd_C, T2 reached 50% market share at 1043.7 time units ($\mu + 0.13\sigma$) compared to 1596.7 time units ($\mu + 1.79\sigma$) in the baseline scenario. Therefore, a strong patent pledge (type C) that is introduced together with T2 can reduce the time to reach 50% market share by approximately 1.65 standard deviations of the adoption curve. The fast effect (gradient difference) of the patent pledge was largest when a strong patent pledge (type C) was introduced at $\mu - 1\sigma$. This stayed in contrast to the previously discussed APPE and RPPE, which measure the slow effect of the patent pledge. For those, the largest effect occurred when the patent pledge was introduced together with T1 at $\mu - 3\sigma$. Generally, in cases where T2 won the competition against T1, it did so at latest after a mean of 1563.4 time units.

Table 6.3 Table Case I, Scheme I: Introduction of T2 at $\mu - 3\sigma$.

Reference	I M(-3sd)_Baseline	I M(-3sd)_-3sd_A	I M(-3sd)_-3sd_B	I M(-3sd)_-3sd_C	I M(-3sd)_-2sd_A	I M(-3sd)_-2sd_B	I M(-3sd)_-2sd_C	I M(-3sd)_-1sd_A	I M(-3sd)_-1sd_B	I M(-3sd)_-1sd_C	I M(-3sd)_0sd_A	I M(-3sd)_0sd_B	I M(-3sd)_0sd_C	I M(-3sd)_+1sd_A	I M(-3sd)_+1sd_B	I M(-3sd)_+1sd_C
Patent Pledge Introduction (PPI)	**Baseline** N/A	**Before Innovators** -3sd			**After Innovators** -2sd			**After Early Adopters** -1sd			**After Early Majority** 0sd			**After Late Majority** +1sd		
Patent Pledge Type	N/A	A	B	C	A	B	C	A	B	C	A	B	C	A	B	C
Market Share Saturation at time of Patent Pledge (mean)	N/A	0	0	0	**0.021** (0.005) [3.991E-4]	**0.021** (0.004) [3.94E-4]	**0.021** (0.005) [3.994E-4]	**0.155** (0.011) [9.366E-4]	**0.155** (0.011) [9.661E-4]	**0.155** (0.012) [0.001]	**0.496** (0.016) [0.001]	**0.497** (0.016) [0.001]	**0.495** (0.015) [0.001]	**0.840** (0.011) [0.001]	**0.841** (0.011) [9.982E-4]	**0.841** (0.012) [0.001]
Intercept of T2 at total Market Share {After Mean Time Units} min	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
mean	**0.364** (0.321) [0.039] {822.906}	**0.007** (0.013) [0.001] {158.14}	**0.002** (0.003) [2.305E-4] {94.212}	**7.4E-4** (0.002) [1.342E-4] {72.84}	**0.027** (0.021) [0.002] {331.1}	**0.020** (0.013) [0.001] {296.408}	**0.019** (0.011) [9.786E-4] {297.496}	**0.134** (0.077) [0.007] {585.092}	**0.130** (0.067) [0.006] {582.332}	**0.122** (0.065) [0.006] {568.688}	**0.402** (0.236) [0.021] {861.812}	**0.382** (0.206) [0.018] {846.724}	**0.367** (0.203) [0.018] {832.24}	**0.479** (0.37) [0.039] {947.107}	**0.568** (0.36) [0.035] {1058.226 }	**0.587** (0.356) [0.033] {1081.897 }
max	0.998	0.112	0.022	0.01	0.116	0.07	0.05	0.356	0.25	0.226	0.908	0.67	0.644	0.998	0.998	0.998
Intercept Occurrence in %	50.8	100	100	100	100	100	100	100	100	100	100	100	100	67.6	83.2	91.4
T2 reaches 50% market share at time	**1596.654** (131.384) [16.158]	**1165.164** (24.262) [2.127]	**1074.892** (16.518) [1.448]	**1043.664** (14.556) [1.276]	**1172.992** (24.619) [2.158]	**1083.24** (16.863) [1.478]	**1052.148** (14.769) [1.295]	**1223.324** (30.547) [2.678]	**1137.052** (19.318) [1.693]	**1107.348** (16.338) [1.432]	**1377.928** (68.522) [6.006]	**1293.188** (33.044) [2.896]	**1266.776** (29.316) [2.57]	**1563.361** (134.49) [14.338]	**1547.611** (118.767) [11.413]	**1539.91** (114.924) [10.537]
Gradient Difference (mean)	N/A	N/A	N/A	N/A	**0.0704**	**0.1252**	**0.1447**	**0.1964**	**0.3270**	**0.3937**	**0.1926**	**0.3153**	**0.3869**	**0.0700**	**0.0773**	**0.1457**
Final Adopters of T2 in % min	39.8	70.3	86.4	92.1	69.0	84.6	90.9	62.5	76.8	83.6	51.3	59.3	62.5	40.8	44.6	44.3
mean	**49.9** (34.052) [2.985]	**77.9** (25.664) [2.25]	**90.2** (13.401) [1.175]	**94.6** (8.897) [0.78]	**77.0** (26.113) [2.289]	**89.2** (14.196) [1.244]	**93.6** (9.49) [0.832]	**71.6** (29.659) [2.600]	**82.7** (18.569) [1.628]	**86.9** (13.766) [1.207]	**60.2** (34.352) [3.011]	**66.7** (27.226) [2.386]	**69.8** (24.333) [2.133]	**52.0** (38.043) [3.335]	**53.5** (34.588) [3.032]	**54.4** (32.525) [2.851]
max	59.1	84.6	94.3	96.8	83.5	93.6	96.0	80.2	87.1	91.4	68.9	73.9	76.5	62.0	64.0	62.6
Absolute Patent Pledge Effect (APPE)	N/A	**27.949**	**40.214**	**44.701**	**27.056**	**39.213**	**43.661**	**21.628**	**32.752**	**36.957**	**10.225**	**16.779**	**19.858**	**2.019**	**3.597**	**4.471**
Relative Patent Pledge Effect (RPPE)	N/A	**27.949**	**40.214**	**44.701**	**27.636**	**40.054**	**44.598**	**25.595**	**38.760**	**43.736**	**20.288**	**33.358**	**39.323**	**12.619**	**22.623**	**28.120**

Note:
- Values in parentheses indicate the standard deviation.
- Values in square brackets indicate the mean confidence interval, assuming that the confidence level equals 95%.
- Standard deviation and mean confidence intervals constitute absolute values with 1000 agents as reference. Adopter values are shown in percentage.
- Values in 'Final Adopters of T2 in %' are rounded to one decimal for illustration purposes. APPE and RPPE are calculated using three decimals.

Fig. 6.10 shows that in all scenarios with a patent pledge T2 won the adoption competition against T1. Importantly, the chart only displays the most frequent corridors of the adoption curves where outliers or extreme scenarios are not shown. For a comprehensive data description, see table 6.3 above. The chart illustrates the market share split in the baseline scenario, because the curve of T2 adopters was covered by the curve of T1 adopters. This overlap of the two curves occurred in all the scenarios of this scheme until the introduction of the patent pledge. This is a result of the fact that both technologies in case I were perceived as being similar. The closest competition between the different technology adopters occurred with the patent pledge type A at the patent pledge introduction of $\mu + 1\sigma$. In table 6.3 it was shown that in some experiment runs, T1 reached more adopters than T2 despite the patent pledge of T2. When a patent pledge was introduced at this late stage in the simulation, stronger patent pledges widened the gap between the technology adoption curves, but only to a small extent (see the last last row in the chart and also table 6.3 above). In contrast, the gap between the curves became larger the earlier the patent pledge was introduced. In the strongest scenario of T2 (a patent pledge type C that was introduced together with T1 and T2 at $\mu - 3\sigma$), the curve of T1 adopters approached a flat line. This indicates that only few adopters chose T1 over T2. Similarly, the adoption curve of T1 adopters (orange) exhibited no growth at the later stages in some scenarios (see for instance I M(-3sd)_-3sd_B).

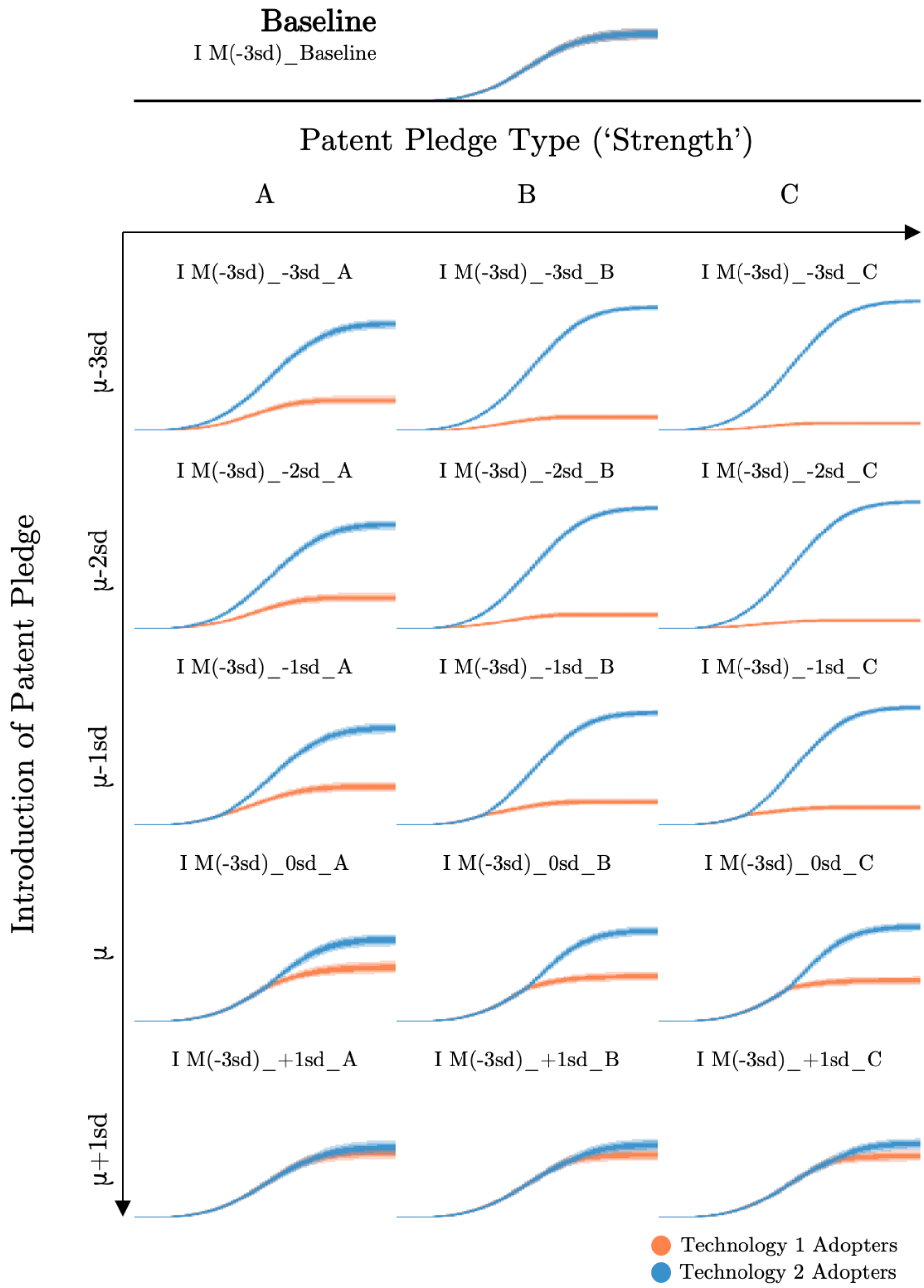


Fig. 6.10 Chart Case I, Scheme I: Introduction of T2 at $\mu - 3\sigma$.

6.2.1.2 Scheme II: introduction of T2 after the Innovators have adopted T1

Scheme II of case I simulated the introduction of T2 after the *Innovators* have adopted T1 (at time $\mu - 2\sigma$). Both technologies were perceived as being similar. The scheme consisted of a baseline scenario where the technology relating to T2 was not pledged and 12 scenarios in which it was subject to a patent pledge. The 12 scenarios differed in the introduction time of the patent pledge and also in its strength (patent pledge types A, B, and C).

Table 6.4 and fig. 6.11 depict scheme II of case I. The baseline scenario resulted in a market share of 46.8% for T2, which was about 3 percentage points less than in scheme I. The later introduction of T2 by one standard deviation compared to scheme I led to the adoption competition win of T2 in only 18% of the experiment runs in the baseline scenario (about 50% in scheme I). This is despite the fact that only about 2.1%, the *Innovators* according to Rogers (1962), of all adopters have already adopted T1 when T2 was introduced. This shows that small differences in availability of the technologies can have large effects on the adoption rates. The largest RPPE of this scheme reached 46.3 percentage points; the largest APPE 45.3 percentage points (both at a patent pledge introduction of $\mu - 2\sigma$ with a strong patent pledge type C). These values were slightly higher than the maximum values for the APPE/RPPE of scheme I (44.7). The introduction of patent pledges in the subsequent scenarios led to higher adoption rates of T2, but declined the later the patent pledge was introduced, similar to scheme I. In contrast to the 100% of scheme I, a weak patent pledge (type A) in the adopter category *After Early Majority* led to the competition win of T2 in 97.4% of the runs. One standard deviation later, this occurred in 38.6% of runs (67.6% in scheme I). This shows that the later introduction of T2 compared to the previously described scheme led to a decline in the number of adoption competition wins for T2 in these scenarios. It also shows that the difference in market share wins between μ and $\mu + 1\sigma$ was large. In scenario I M(-3sd)_-2sd_C, T2 reached 50% market share at 1064.2 time units ($\mu + 0.19\sigma$) compared to 1684.4 time units ($\mu + 2.05\sigma$) in the baseline scenario. T2 reaches 50% market share 74 time units (mean value) faster than in the baseline scenario when a strong patent pledge (type C) is introduced at $\mu + 1\sigma$. One standard deviation earlier, this time could be reduced by about 390 time units (mean value). T2 consistently reached 50% market share later than in scheme I, which is expected when the technology is introduced later on. The largest fast effect (gradient difference) occurred when a strong patent pledge type C was introduced at $\mu - 1\sigma$, similar to scheme I.

Table 6.4 Table Case I, Scheme II: Introduction of T2 at $\mu - 2\sigma$.

Reference	I M(-2sd)_Baseline	I M(-2sd)_-2sd_A	I M(-2sd)_-2sd_B	I M(-2sd)_-2sd_C	I M(-2sd)_-1sd_A	I M(-2sd)_-1sd_B	I M(-2sd)_-1sd_C	I M(-2sd)_0sd_A	I M(-2sd)_0sd_B	I M(-2sd)_0sd_C	I M(-2sd)_+1sd_A	I M(-2sd)_+1sd_B	I M(-2sd)_+1sd_C
Patent Pledge Introduction (PPI)	**Baseline** N/A	**After Innovators** -2sd			**After Early Adopters** -1sd			**After Early Majority** 0sd			**After Late Majority** +1sd		
Patent Pledge Type	N/A	A	B	C	A	B	C	A	B	C	A	B	C
Market Share Saturation at time of Patent Pledge (mean)	N/A	**0.021** (0.005) [3.991E-4]	**0.021** (0.004) [3.94E-4]	**0.021** (0.005) [3.994E-4]	**0.155** (0.011) [9.366E-4]	**0.155** (0.011) [9.661E-4]	**0.155** (0.012) [0.001]	**0.496** (0.016) [0.001]	**0.497** (0.016) [0.001]	**0.495** (0.015) [0.001]	**0.840** (0.011) [0.001]	**0.841** (0.011) [9.982E-4]	**0.841** (0.012) [0.001]
Intercept of T2 at total Market Share {After Mean Time Units} min	0.128	0.032	0.022	0.02	0.056	0.09	0.068	0.068	0.09	0.10	0.068	0.09	0.128
Intercept of T2 at total Market Share {After Mean Time Units} mean	**0.651** (0.254) [0.053] {1189.622}	**0.092** (0.03) [0.003] {558.46}	**0.059** (0.015) [0.001] {458.216}	**0.051** (0.012) [0.001] {463.612}	**0.235** (0.056) [0.005] {760.424}	**0.200** (0.03) [0.003] {723.684}	**0.191** (0.026) [0.002] {712.452}	**0.603** (0.143) [0.013] {1097.645}	**0.546** (0.094) [0.008] {1042.092}	**0.532** (0.08) [0.007] {1031.624}	**0.742** (0.242) [0.034] {1284.42}	**0.806** (0.203) [0.024] {1356.229}	**0.833** (0.181) [0.019] {1388.31}
Intercept of T2 at total Market Share {After Mean Time Units} max	0.992	0.204	0.12	0.106	0.452	0.296	0.264	0.972	0.756	0.716	0.998	0.998	0.996
Intercept Occurrence in %	18	100	100	100	100	100	100	97.4	100	100	38.6	55.0	67.2
T2 reaches 50% market share at time	**1684.444** (132.18) [27.685]	**1195.132** (26.618) [2.333]	**1097.336** (17.871) [1.566]	**1064.200** (15.241) [1.336]	**1250.472** (33.16) [2.907]	**1153.712** (20.045) [1.757]	**1121.86** (16.929) [1.484]	**1435.813** (88.168) [7.831]	**1326.508** (38.087) [3.339]	**1294.4** (32.564) [2.854]	**1619.321** (131.513) [18.554]	**1609.436** (118.524) [14.009]	**1610.935** (115.389) [12.338]
Gradient Difference (mean)	N/A	N/A	N/A	N/A	**0.2265**	**0.3267**	**0.413**	**0.2140**	**0.3595**	**0.4048**	**0.0430**	**0.0956**	**0.0954**
Final Adopters of T2 in % min	35.5	66.0	82.8	88.4	60.1	73.8	80.9	47.4	57.0	58.7	37.5	40.9	41.2
Final Adopters of T2 in % mean	**46.8** (33.882) [2.97]	**74.5** (27.501) [2.411]	**87.4** (15.598) [1.367]	**92.2** (10.89) [0.955]	**69.0** (29.569) [2.592]	**80.8** (19.385) [1.699]	**85.2** (15.155) [1.328]	**57.4** (35.596) [3.12]	**64.2** (27.581) [2.418]	**67.4** (25.222) [2.211]	**49.0** (38.154) [3.344]	**50.6** (34.448) [3.019]	**51.4** (30.044) [2.896]
Final Adopters of T2 in % max	56.9	81.8	92.2	95.4	78.4	85.2	89.9	66.8	71.6	73.8	59.2	59.1	60.7
Absolute Patent Pledge Effect (APPE)	N/A	**27.671**	**40.604**	**45.320**	**22.131**	**33.932**	**38.404**	**10.536**	**17.381**	**20.594**	**2.139**	**3.766**	**4.552**
Relative Patent Pledge Effect (RPPE)	N/A	**28.265**	**41.475**	**46.292**	**26.191**	**40.156**	**45.449**	**20.905**	**34.555**	**40.780**	**13.369**	**23.686**	**28.629**

Note:
- Values in parentheses indicate the standard deviation.
- Values in square brackets indicate the mean confidence interval, assuming that the confidence level equals 95%.
- Standard deviation and mean confidence intervals constitute absolute values with 1000 agents as reference. Adopter values are shown in percentage.
- Values in 'Final Adopters of T2 in %' are rounded to one decimal for illustration purposes. APPE and RPPE are calculated using three decimals.

Fig. 6.11 shows that in the baseline scenario, T1 reached more adopters than T2. All charts except the one with a weak patent pledge (type A) that was introduced at $\mu + 1\sigma$ show that the adoption curve of T2 (blue) overtook the adoption curve of T1 (orange) the sooner the patent pledge was introduced and the stronger the patent pledge was. Early, strong patent pledges led to a thinner adoption curve (blue line) than late and weak patent pledges. This illustrates a smaller standard deviation (see also the standard deviations for the mean value of the final adopters of T2 in table 6.4).

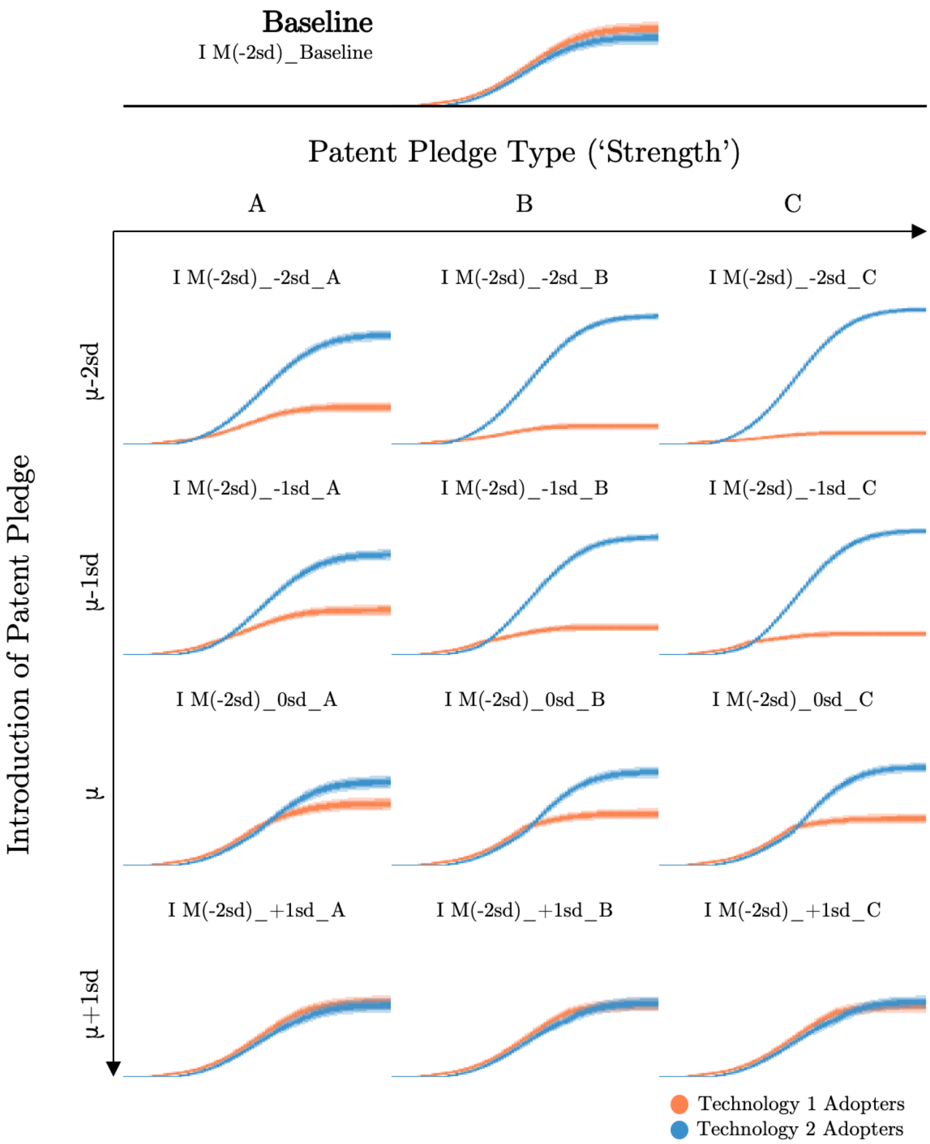


Fig. 6.11 Chart Case I, Scheme II: Introduction of T2 at $\mu - 2\sigma$.

6.2.1.3 Scheme III: introduction of T2 after the Early Adopters have adopted T1

Scheme III of case I simulated the introduction of T2 after the *Innovators* and the *Early Adopters* have already adopted T1 (at time $\mu - 1\sigma$). Both technologies were perceived as being similar. The scheme consisted of a baseline scenario where the technology relating to T2 was not pledged and nine scenarios in which it is subject to a patent pledge. The nine scenarios differed in the introduction time of the patent pledge and also in its strength (patent pledge types A, B, and C).

Table 6.5 and fig. 6.12 depict scheme III of case I. The baseline scenario resulted in a market share of 29.8% for T2, which was about 17 percentage points less than scheme II (the decrease from scheme I to scheme II was about 3 percentage points). The maximum market share of T2 adopters in the baseline scenario was 38.7%, the minimum 19.9%. This indicates that without a patent pledge, T2 reaches approximately between 20 and 40% market share when it is introduced after the *Early Adopters* have already adopted T1. The intercept occurrence in this scheme was different from scheme I and II, because no experiment run led to more than 50% market share of T2 when the patent pledge was introduced after the *Late Majority*. When it was introduced one standard deviation earlier, after the *Early Majority*, the patent pledge strength affected the market share win to a great extent. A weak patent pledge (type A) led to a win in 0.4% of the cases, whereas a strong patent pledge (type C) achieved 83.8%. The maximum patent pledge effects reached 54.3 (RPPE) and 45.8 (APPE) for scenario M(-1sd)_-1sd_C, which was the earliest scenario with the strongest patent pledge in this scheme. This result was in line with results from the previous schemes. In the same scenario, T2 reached 50% market share at 1208.4 time units ($\mu + 0.84\sigma$), which also posed the fastest adoption competition win of the scheme. The patent pledge effects increased compared to the same patent pledge introduction in scheme I and II. This was a result of the lower value of the baseline scenario without a patent pledge, similar to the previous scheme. The strongest fast effect (gradient difference) occurred at $\mu + 0\sigma$, which was one standard deviation later than in scheme I and II. The gradient difference could not be measured when the patent pledge was introduced at the same time as T2, which is why there was no fast effect at $\mu - 1\sigma$. The fast effect after the *Early Majority* was similar to the one in scheme II described above, which indicates that the later introduction of T2 compared to scheme II did only marginally affect the fast effect.

Table 6.5 Table Case I, Scheme III: Introduction of T2 at $\mu - 1\sigma$.

Reference		I M(-1sd)_Baseline	I M(-1sd)_-1sd_A	I M(-1sd)_-1sd_B	I M(-1sd)_-1sd_C	I M(-1sd)_0sd_A	I M(-1sd)_0sd_B	I M(-1sd)_0sd_C	I M(-1sd)_+1sd_A	I M(-1sd)_+1sd_B	I M(-1sd)_+1sd_C
Patent Pledge Introduction (PPI)		**Baseline** N/A	**After Early Adopters** -1sd			**After Early Majority** 0sd			**After Late Majority** +1sd		
Patent Pledge Type		N/A	A	B	C	A	B	C	A	B	C
Market Share Saturation at time of Patent Pledge (mean)		N/A	**0.155** (0.011) [9.45E-4]	**0.156** (0.011) [9.629E-4]	**0.156** (0.012) [0.001]	**0.496** (0.016) [0.001]	**0.497** (0.016) [0.001]	**0.495** (0.015) [0.001]	**0.840** (0.011) [0.001]	**0.841** (0.011) [9.982E-4]	**0.841** (0.012) [0.001]
Intercept of T2 at total Market Share {After Mean Time Units}	min	0	0.448	0.340	0.254	0.93	0.752	0.658	N/A	N/A	N/A
	mean	0	**0.755** (0.116) [0.011] {1262.346}	**0.452** (0.047) [0.004] {963.432}	**0.384** (0.035) [0.003] {906.612}	**0.945** (0.021) [0.042] {1563.000}	**0.909** (0.061) [0.009] {1496.58}	**0.863** (0.072) [0.007] {1396.427}	N/A	N/A	N/A
	max	0	0.998	0.680	0.494	0.96	0.998	0.998	N/A	N/A	N/A
Intercept Occurrence in %		0	87.4	100	100	0.4	36.2	83.8	0	0	0
T2 reaches 50% market share at time		N/A	**1535.737** (121.201) [11.346]	**1267.304** (28.769) [2.522]	**1208.364** (20.96) [1.837]	**1738.000** (77.782) [152.68]	**1659.884** (130.616) [19.029]	**1567.759** (114.547) [10.968]	N/A	N/A	N/A
Gradient Difference (mean)		N/A	N/A	N/A	N/A	**0.2071**	**0.3442**	**0.4047**	**0.0656**	**0.0775**	**0.0794**
Final Adopters of T2 in %	min	19.9	43.4	56.6	69.6	29.0	40.3	42.5	20.3	21.3	21.8
	mean	**29.8** (33.781) [2.961]	**53.8** (32.547) [2.853]	**68.9** (24.957) [2.188]	**75.6** (20.682) [1.813]	**40.4** (36.479) [3.197]	**48.8** (34.103) [2.989]	**53.4** (34.317) [3.008]	**31.4** (36.514) [3.201]	**32.9** (37.425) [3.28]	**33.7** (39.918) [3.499]
	max	38.7	64.0	76.4	82.3	51.8	56.9	62.4	40.8	41.9	44.8
Absolute Patent Pledge Effect (APPE)		N/A	**24.01**	**39.139**	**45.802**	**10.616**	**19.075**	**23.585**	**1.611**	**3.098**	**3.930**
Relative Patent Pledge Effect (RPPE)		N/A	**28.414**	**46.373**	**54.268**	**21.064**	**37.923**	**46.703**	**10.069**	**19.484**	**24.717**

Note:
- Values in parentheses indicate the standard deviation.
- Values in square brackets indicate the mean confidence interval, assuming that the confidence level equals 95%.
- Standard deviation and mean confidence intervals constitute absolute values with 1000 agents as reference. Adopter values are shown in percentage.
- Values in 'Final Adopters of T2 in %' are rounded to one decimal for illustration purposes. APPE and RPPE are calculated using three decimals.

Data displayed in fig. 6.12 show a more inconsistent behaviour of the adoption curves compared to scheme I and II. In some scenarios, T2 clearly won the adoption competition (see I M(-1sd)_-1sd_B and I M(-1sd)_-1sd_C), whereas in others it did not (I M(-1sd)_+1sd_A, I M(-1sd)_+1sd_B, and I M(-1sd)_+1sd_C). This indicates that the adoption curve was highly dependent on the time when the patent pledge was introduced. In the baseline scenario, the adoption curve of T2 (blue) laid more clearly below the adoption curve of T1 (orange), compared to the baseline scenario of scheme II. This is an expected result when T2 is introduced later on, because more adopters have already adopted T1. This is particularly relevant because this simulation study did not allow for technology discards once an agent has adopted a technology (see table 6.2). An early patent pledge introduction for T2 led to a visible 'crease' of the T1 adoption curve when the patent pledge was introduced, i.e. the orange adoption curve exhibited a smaller growth rate from that time on. This 'crease' was most clearly visible in the scenarios with a patent pledge introduction at $\mu - 1\sigma$. When the patent pledge was introduced later on, the 'crease' was less distinct and barely visible, which indicates a weaker effect on the adoption curve of T1.

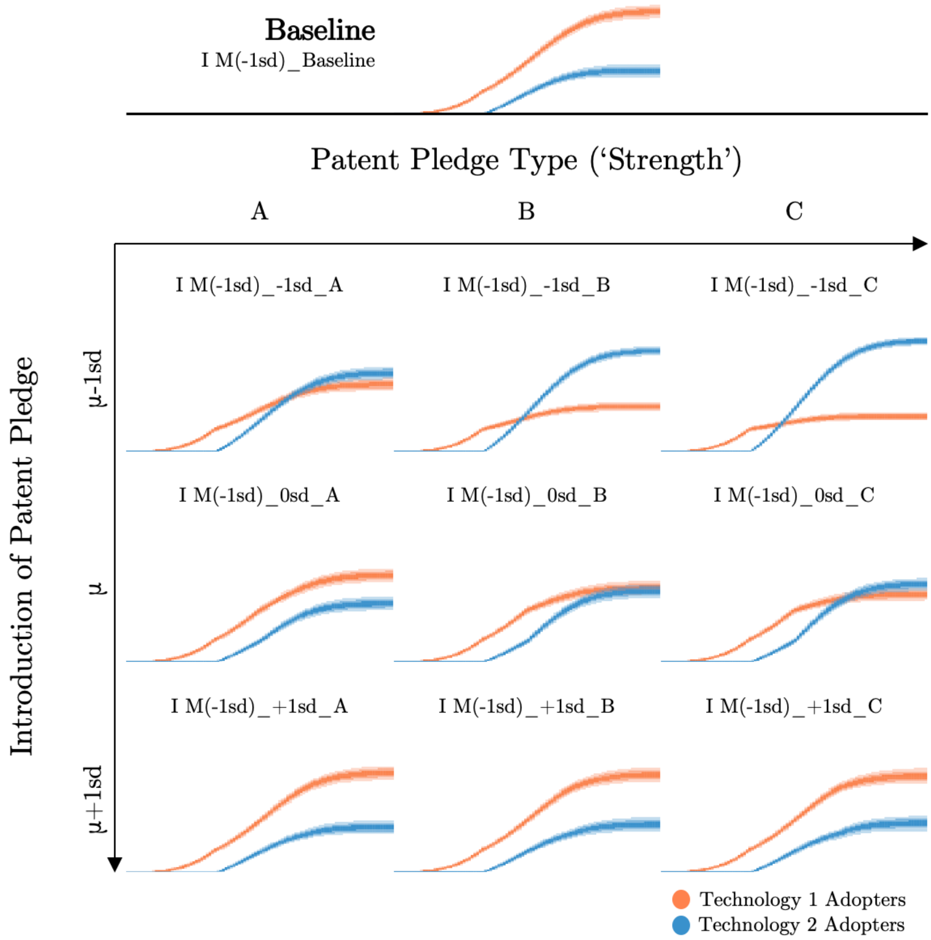


Fig. 6.12 Chart Case I, Scheme III: Introduction of T2 at $\mu - 1\sigma$.

6.2.1.4 Scheme IV: introduction of T2 after the Early Majority has adopted T1

Scheme IV of case I simulated the introduction of T2 after the *Innovators*, the *Early Adopters*, and the *Early Majority* have already adopted T1 (at time $\mu - 0\sigma$). The introduction of T2 therefore occurred approximately in the middle of the adoption period. Both technologies were perceived as being similar. The scheme consisted of a baseline scenario where the technology relating to T2 was not pledged and six scenarios in which it was subject to a patent pledge. The six scenarios differed in the introduction time of the patent pledge and also in its strength (patent pledge types A, B, and C).

Table 6.6 and fig. 6.13 depict scheme IV of case I. The baseline scenario resulted in a market share of 4.5% for T2, which was about 25.3 percentage points less than scheme III (the decrease from scheme II to scheme III was about 17 percentage points). Therefore, T2 adopters reached between 2.0 and 8.5% of the market share without a patent pledge. T2 furthermore did not reach 50% market share in any of the scenarios of scheme IV, which was different to the previous schemes. The intercept occurrence was therefore zero for all scenarios of scheme IV. The maximum patent pledge effects reached 27.9 (RPPE) and 14.1 (APPE) in scenario I M(0sd)_0sd_C. This indicates that in the best scenario with a strong patent pledge (type C) and a patent pledge introduction together with T2, a mean value of 18.6% market share can be reached. In the best case of this scenario, T2 reached a maximum of 31.5% market share. This shows that the introduction of T2 after the *Early Majority* (at $\mu - 0\sigma$) was too late for a patent pledge to win the adoption competition against T1. Furthermore, the introduction of a patent pledge after the *Late Majority* did not exhibit any effects on the adoption rate of T2. While the slow effects at this late patent pledge introduction point were relatively small in the schemes I-III, they were nonexistent in scheme IV. This indicates that the later introduction of T2 compared to the previous schemes hindered patent pledge effects. The fast effect (gradient difference) at this last patent pledge introduction point, too, approached zero and therefore further decreased compared to the fast effects in the previous schemes.

Table 6.6 Table Case I, Scheme IV: Introduction of T2 at $\mu - 0\sigma$.

Reference		I M(0sd)_Baseline	I M(0sd)_0sd_A	I M(0sd)_0sd_B	I M(0sd)_0sd_C	I M(0sd)_+1sd_A	I M(0sd)_+1sd_B	I M(0sd)_+1sd_C
Patent Pledge Introduction (PPI)		**Baseline** N/A	**After Early Majority** 0sd			**After Late Majority** +1sd		
Patent Pledge Type		N/A	A	B	C	A	B	C
Market Share Saturation at time of Patent Pledge (mean)		N/A	**0.496** (0.016) [0.001]	**0.497** (0.016) [0.001]	**0.495** (0.015) [0.001]	**0.840** (0.011) [0.001]	**0.841** (0.011) [9.982E-4]	**0.841** (0.012) [0.001]
Intercept of T2 at total Market Share {After Mean Time Units}	min	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	mean	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	max	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Intercept Occurrence in %		0	0	0	0	0	0	0
T2 reaches 50% market share at time		N/A	N/A	N/A	N/A	N/A	N/A	N/A
Gradient Difference (mean)		N/A	N/A	N/A	N/A	**-0.0185**	**0.0046**	**-0.0085**
Final Adopters of T2 in %	min	2.0	3.9	6.4	7.8	1.7	1.9	2.0
	mean	**4.5** (11.01) [0.965]	**8.4** (19.226) [1.685]	**13.6** (31.912) [2.797]	**18.6** (45.306) [3.971]	**4.4** (10.572) [0.927]	**4.4** (10.987) [0.963]	**4.5** (11.01) [0.965]
	max	8.5	17.4	26.3	31.5	9.1	7.9	8.5
Absolute Patent Pledge Effect (APPE)		N/A	**3.920**	**9.062**	**14.091**	**-0.067**	**-0.082**	**0**
Relative Patent Pledge Effect (RPPE)		N/A	**7.778**	**18.016**	**27.903**	**-0.419**	**-0.516**	**0**

Note:
- Values in parentheses indicate the standard deviation.
- Values in square brackets indicate the mean confidence interval, assuming that the confidence level equals 95%.
- Standard deviation and mean confidence intervals constitute absolute values with 1000 agents as reference. Adopter values are shown in percentage.
- Values in 'Final Adopters of T2 in %' are rounded to one decimal for illustration purposes. APPE and RPPE are calculated using three decimals.

Fig. 6.13 shows that in the baseline scenario, the adoption curve of T2 exhibited a marginal growth after its introduction and then transitioned to a flat line. This indicates that the number of T2 adopters increased slightly with the introduction of T2, but showed no further increase after that. The adoption curve of T1, in contrast, displayed a distinct S-curve. The curve of T1 (orange) was affected the most when the patent pledge as well as T2 were introduced after the *Early Majority* (at $\mu + 0\sigma$). This effect on the adoption curve of T1, however, did not result in an adoption competition win of T2. Nevertheless, a 'crease' in the adoption curve of T1, similar to the 'crease' in previous schemes, could be observed when the patent pledge was introduced after the *Early Majority*. This shows that a patent pledge in this scheme exhibited an effect on the adoption curve of T2, but not to the extent that T2 wins the adoption competition. In scenario I M(0sd)_0sd_C, both adoption curves displayed the largest standard deviation and the adoption curve of T2 reached its maximum of this scheme. The standard deviation was indicated through the width of the adoption curves in this scenario and is in line with the data from table 6.6. At a later patent pledge introduction point (at $\mu + 1\sigma$), the adoption curve of T2 was barely visible and was not affected by the patent pledge strength (all strengths depicted the same outcome). This indicates that it was too late for patent pledges to affect the adoption rate of T2.

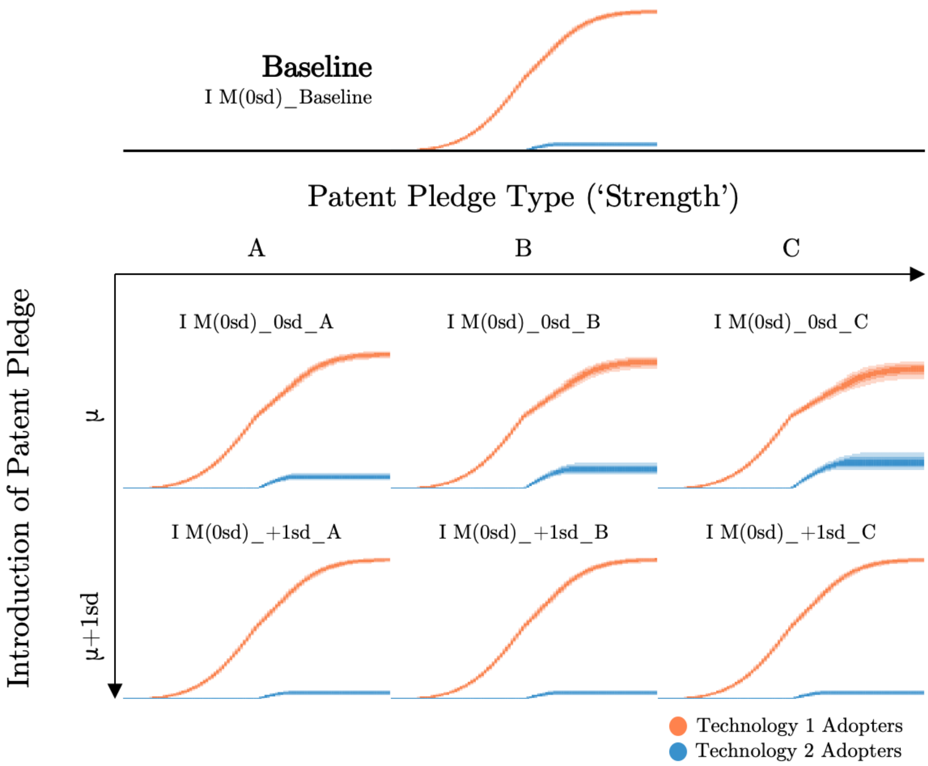


Fig. 6.13 Chart Case I, Scheme IV: Introduction of T2 at $\mu - 0\sigma$.

6.2.2 Case II: results where T2 is inferior to T1

6.2.2.1 Scheme I: introduction of T2 simultaneous with T1

Scheme I of case II simulated the introduction of T2 at the beginning of the simulation simultaneous to T1. T2 was, on average, perceived as being inferior to T1 in all technology attributes (see fig. 6.4). The scheme consisted of a baseline scenario where the technology relating to T2 was not pledged and 15 scenarios in which it was subject to a patent pledge. As described before, three types of patent pledges with different strengths and varying patent pledge introduction points were simulated. Patent pledges in all schemes occurred at the transition between adopter types according to Rogers (1962), see fig. 6.8.

Table 6.7 and fig. 6.14 summarise scheme I of case II. The baseline scenario without a patent pledge resulted in a market share of 6.3% for T2 adopters. This was, in contrast to the baseline scenario of scheme I in case I with 49.9% market share, significantly lower. It therefore appears that the inferiority of T2 led to a large decrease in final adopters. T1 always won the adoption competition when T2 was not subject to a patent pledge. This changed, however, when a patent pledge of T2 was introduced early on. A strong patent pledge (type C) that was introduced before the *Innovators*, after the *Innovators*, and after the *Early Adopters*) still led to a mean market share of 74.4%, 71.6%, and 54.9% for T2 respectively. This shows that a strong patent pledge, on average, led to the adoption competition win of T2 as long as it was introduced before the *Early Majority*. After that, the effects of a strong patent pledge (type C) exhibited a large decline (37.0 percentage points change in APPE and 34.6 points change in RPPE for the patent pledge types C). This decrease was larger than the one between the same adopter categories of scheme I in case I, where both technologies were introduced at the same time but T2 was similar to T1. In scenario II M(-3sd)_-3sd_C, T2 reached 50% market share at 1192.5 time units ($\mu + 0.58\sigma$) compared to 1043.7 time units ($\mu + 0.13\sigma$) of the same scenario in scheme I of case I. This indicates that with an early, strong patent pledge, 50% market share could be reached about 0.45 standard deviations later when the pledged technology is inferior than when it is similar to its substitute. While the intercept occurrence of T2 in scheme I of case I was 100% until the patent pledge introduction after the *Late Majority*, it reached either very high values or zero in this scheme. For instance, when a patent pledge was introduced after the *Early Adopters*, a strong patent pledge (type C) led to the competition win of T2 in 93% of experiment runs, whereas a medium patent pledge (type B) resulted in a loss against T1 in any of the runs. This indicates a strong dependence of the adoption competition win of T2 on the patent pledge strength. Scenario II M(-3sd)_-3sd_C exhibited the largest patent pledge effect of approximately 68.1 of both APPE and RPPE across all scenarios in Study 3. This shows that an early, strong patent pledge for an inferior technology under these settings can result in a gain of 68 percentage points in final adopters for T2. The fast effect (gradient difference), too, exhibited its largest value across all scenarios in this scheme, specifically in scenario II M(-3sd)_-1sd_C. It was 36.86% larger than the same fast effect in scheme I of case I. This indicates that the fast effect increased when T2 was inferior, compared to when T2 was similar to T1.

Table 6.7 Table Case II, Scheme I: Introduction of T2 at $\mu - 3\sigma$.

Reference	II M(-3sd)_Baseline	II M(-3sd)_-3sd_A	II M(-3sd)_-3sd_B	II M(-3sd)_-3sd_C	II M(-3sd)_-2sd_A	II M(-3sd)_-2sd_B	II M(-3sd)_-2sd_C	II M(-3sd)_-1sd_A	II M(-3sd)_-1sd_B	II M(-3sd)_−1sd_C	II M(-3sd)_0sd_A	II M(-3sd)_0sd_B	II M(-3sd)_0sd_C	II M(-3sd)_+1sd_A	II M(-3sd)_+1sd_B	II M(-3sd)_+1sd_C
Patent Pledge Introduction (PPI)	**Baseline** N/A	**Before Innovators** -3sd			**After Innovators** -2sd			**After Early Adopters** -1sd			**After Early Majority** 0sd			**After Late Majority** +1sd		
Patent Pledge Type	N/A	A	B	C	A	B	C	A	B	C	A	B	C	A	B	C
Market Share Saturation at time of Patent Pledge (mean)	N/A	0	0	0	**0.021** (0.004) [3.933E-4)]	**0.021** (0.004) [3.891E-4]	**0.021** (0.005) [4.106E-4]	**0.154** (0.012) [0.001]	**0.155** (0.011) [9.877E-4]	**0.155** (0.012) [0.001]	**0.495** (0.016) [0.001]	**0.497** (0.016) [0.001]	**0.496** (0.016) [0.001]	**0.840** (0.012) [0.001]	**0.841** (0.012) [0.001]	**0.840** (0.012) [0.001]
Intercept of T2 at total Market Share {After Mean Time Units} – min	N/A	N/A	0	0	N/A	0.032	0.026	N/A	N/A	0.398	N/A	N/A	N/A	N/A	N/A	N/A
Intercept of T2 at total Market Share {After Mean Time Units} – mean	N/A	N/A	**0.136** (0.184) [0.016] {510.663}	**0.01** (0.014) [0.001] {191.48}	N/A	**0.352** (0.239) [0.022] {864.105}	**0.083** (0.031) [0.003] {535.688}	N/A	N/A	**0.677** (0.129) [0.012] {1173.847}	N/A	N/A	N/A	N/A	N/A	N/A
Intercept of T2 at total Market Share {After Mean Time Units} – max	N/A	N/A	0.976	0.11	N/A	0.998	0.214	N/A	N/A	0.998	N/A	N/A	N/A	N/A	N/A	N/A
Intercept Occurrence in %	0	0	97.4	100	0	89.4	100	0	0	93.0	0	0	0	0	0	0
T2 reaches 50% market share at time	N/A	N/A	**1427.696** (100.177) [8.897]	**1192.524** (28.174) [2.47]	N/A	**1497.421** (129.699) [12.024]	**1218.436** (30.605) [2.683]	N/A	N/A	**1496.011** (107.695) [9.789]	N/A	N/A	N/A	N/A	N/A	N/A
Gradient Difference (mean)	N/A	N/A	N/A	N/A	**0.0982**	**0.1565**	**0.2101**	**0.2386**	**0.3886**	**0.5388**	**0.0952**	**0.2111**	**0.3321**	**-0.0066**	**-0.0091**	**-0.0012**
Final Adopters of T2 in % – min	4.1	22.8	45.5	65.3	21.6	43.4	63.0	15.5	28.6	42.2	6.4	8.0	10.8	4.2	4.2	4.1
Final Adopters of T2 in % – mean	**6.3** (9.37) [0.821]	**31.0** (31.282) [2.742]	**56.7** (35.988) [3.154]	**74.4** (28.094) [2.463]	**29.7** (31.113) [2.727]	**54.3** (36.404) [3.191]	**71.6** (29.614) [2.596]	**21.9** (26.235) [2.300]	**40.2** (36.846) [3.23]	**54.9** (34.833) [3.053]	**10.1** (14.894) [1.306]	**13.8** (21.218) [1.86]	**17.9** (30.673) [2.689]	**6.5** (9.46) [0.829]	**6.4** (9.102) [0.798]	**6.4** (9.363) [0.821]
Final Adopters of T2 in % – max	9.4	40.4	68.2	82.2	39.7	66.5	79.4	30.3	49.5	65.3	15.1	22.7	29.4	9.9	10.7	9.4
Absolute Patent Pledge Effect (APPE)	N/A	**24.621**	**50.361**	**68.058**	**23.304**	**47.928**	**65.267**	**15.492**	**33.850**	**48.533**	**3.708**	**7.455**	**11.522**	**0.101**	**0.05**	**-0.001**
Relative Patent Pledge Effect (RPPE)	N/A	**24.621**	**50.361**	**68.058**	**23.804**	**48.956**	**66.667**	**18.312**	**40.059**	**57.436**	**7.343**	**14.821**	**22.861**	**0.631**	**0.315**	**-0.006**

Note:
- Values in parentheses indicate the standard deviation.
- Values in square brackets indicate the mean confidence interval, assuming that the confidence level equals 95%.
- Standard deviation and mean confidence intervals constitute absolute values with 1000 agents as reference. Adopter values are shown in percentage.
- Values in 'Final Adopters of T2 in %' are rounded to one decimal for illustration purposes. APPE and RPPE are calculated using three decimals.

The baseline scenario without a patent pledge of T2 exhibited a distinct S-curve for the adoption of T1 and an almost flat curve for T2 adopters in fig. 6.14. As shown in table 6.7 above, T1 clearly attracted more adopters than T2. The adoption curves in the chart posed a strong contrast to the baseline scenario of scheme I in case I, where they overlapped. Nevertheless, the adoption curve of T2 reached above the one of T1 in five out of 15 simulated patent pledge scenarios of this scheme. This was particularly the case when a strong patent pledge was introduced early on. In contrast, the adoption curve of T2 in scheme

I of case I always laid above the adoption curve of T1. This shows that the inferiority of T2 led to lower adoption rates of T2, particularly when the patent pledge was weak and was introduced late. Scenario II M(-3sd)_-1sd_C, in which a strong patent pledge (type C) was introduced after the *Early Adopters*, showed that the adoption curves of both technologies were close together, but T2 usually had more adopters. Here, the number of T2 adopters exceeded the number of T1 adopters shortly after the middle of the adoption period (at μ time units). In contrast, when a patent pledge was introduced after the *Late Majority* (at $\mu + 1\sigma$), the patent pledge showed no effect on the adoption curve of T2, despite varying strengths.

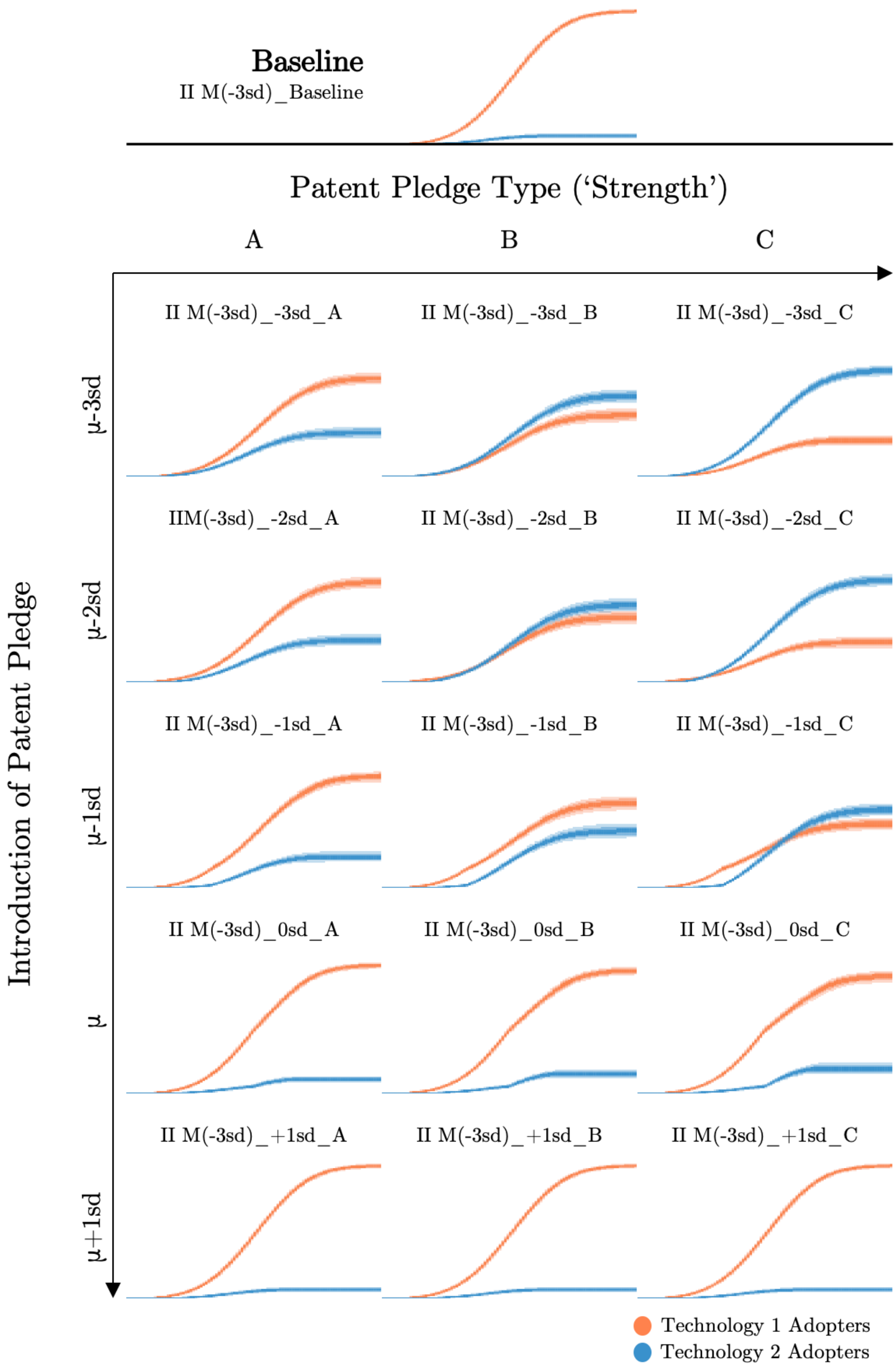


Fig. 6.14 Chart Case II, Scheme I: Introduction of T2 at $\mu - 3\sigma$.

6.2.2.2 Scheme II: introduction of T2 after the Innovators have adopted T1

Scheme II of case II simulated the introduction of T2 after the *Innovators* have adopted T1 (at time $\mu - 2\sigma$). T2 was, on average, perceived as being inferior to T1 (see fig. 6.4). The scheme consisted of a baseline scenario where the technology relating to T2 was not pledged and 12 scenarios in which it was subject to a patent pledge. The 12 scenarios differed in the introduction time of the patent pledge and also in its strength (patent pledge types A, B, and C).

Table 6.8 and fig. 6.15 below summarise scheme II of case II. The baseline scenario without a patent pledge resulted in a market share of 6.0% for T2 adopters, which was comparable to the baseline scenario of the previous scheme. Specifically, the introduction of T2 after the *Innovators* have adopted led to a decrease of about 0.3 percentage points, compared to the scenario where it was introduced together with T1. An early introduction of a strong patent pledge (type C) together with T2 still led to a mean market share of 70.9% for T2. The patent pledge effects reached 66.3 percentage points (RPPE) and 64.9 percentage points (APPE), similar to scheme I. Compared to scheme II of case I, this was an increase of about 20 percentage points, which indicates that the patent pledge effects were larger when the pledged technology was inferior. The previously discussed large decrease in patent pledge effects between *After Early Adopters* and *After Early Majority* was present in this scheme, too. While a strong patent pledge (type C) that was introduced after the *Early Adopters* led to a mean market share of 54.1% for T2, the same patent pledge resulted in a mean market share of 17.1% for T2 when it was introduced after the *Early Majority*. In the 'strongest' scenario of this scheme, scenario II M(-2sd)_-2sd_C, T2 reached 50% market share at 1226.4 time units ($\mu + 0.68\sigma$), compared to 1192.5 time units ($\mu + 0.58\sigma$) of the strongest scenario in scheme I of case II. The scenarios in which an intercept occurred, that is where the final number of T2 adopters exceeded the one of T1 adopters, further decreased compared to scheme I of case II, as would be expected. In cases where T2 did exhibit higher adoption rates, these rates were relatively high. For instance, when a patent pledge was introduced after the *Early Adopters*, a medium patent pledge (type B) did not lead to a adoption competition win of T2 in any of the experiment runs, whereas a strong patent pledge (type C) did so in 88.2% of runs. The strongest fast effect (gradient difference) was similar to the one of the previous scheme and could be observed in scenario II M(-2sd)_-1sd_C. In general, a strong, early patent pledge can lead to almost 70% market share (almost 80% as maximum value) of T2, even though the technology is inferior to T1.

Table 6.8 Table Case II, Scheme II: Introduction of T2 at $\mu - 2\sigma$.

Reference	II M(-2sd)_Baseline	II M(-2sd)_-2sd_A	II M(-2sd)_-2sd_B	II M(-2sd)_-2sd_C	II M(-2sd)_-1sd_A	II M(-2sd)_-1sd_B	II M(-2sd)_-1sd_C	II M(-2sd)_0sd_A	II M(-2sd)_0sd_B	II M(-2sd)_0sd_C	II M(-2sd)_+1sd_A	II M(-2sd)_+1sd_B	II M(-2sd)_+1sd_C
Patent Pledge Introduction (PPI)	**Baseline** N/A	**After Innovators** -2sd			**After Early Adopters** -1sd			**After Early Majority** 0sd			**After Late Majority** +1sd		
Patent Pledge Type	N/A	A	B	C	A	B	C	A	B	C	A	B	C
Market Share Saturation at time of Patent Pledge (mean)	N/A	**0.021** (0.004) [3.933E-4]	**0.021** (0.004) [3.891E-4]	**0.021** (0.005) [4.106E-4]	**0.154** (0.012) [0.001]	**0.155** (0.011) [9.877E-4]	**0.155** (0.011) [0.001]	**0.495** (0.016) [0.001]	**0.497** (0.016) [0.001]	**0.496** (0.016) [0.001]	**0.840** (0.012) [0.001]	**0.841** (0.012) [0.001]	**0.840** (0.012) [0.001]
Intercept of T2 at total Market Share {After Mean Time Units} min	N/A	N/A	0.070	0.026	N/A	N/A	0.426	N/A	N/A	N/A	N/A	N/A	N/A
mean	N/A	N/A	**0.419** (0.247) [0.024] {942.894}	**0.105** (0.038) [0.003] {580.66}	N/A	N/A	**0.707** (0.129) [0.012] {1207.023}	N/A	N/A	N/A	N/A	N/A	N/A
max	N/A	N/A	0.998	0.266	N/A	N/A	0.998	N/A	N/A	N/A	N/A	N/A	N/A
Intercept Occurrence in %	0	0	82.8	100	0	0	88.2	0	0	0	0	0	0
T2 reaches 50% market share at time	N/A	N/A	**1518.377** (134.872) [12.992]	**1226.42** (31.87) [2.794]	N/A	N/A	**1517.308** (116.234) [10.849]	N/A	N/A	N/A	N/A	N/A	N/A
Gradient Difference (mean)	N/A	N/A	N/A	N/A	**0.253**	**0.3829**	**0.5334**	**0.1006**	**0.2143**	**0.3005**	**-0.0005**	**0.0004**	**0.0067**
Final Adopters of T2 in % min	3.5	19.2	43.1	61.3	14.0	28.3	41.0	5.6	7.2	10.1	3.7	3.7	3.5
mean	**6.0** (9.044) [0.793]	**28.9** (31.306) [2.744]	**53.4** (36.234) [3.176]	**70.9** (29.977) [2.628]	**21.1** (25.727) [2.255]	**39.4** (36.166) [3.17]	**54.1** (35.1) [3.077]	**9.5** (14.339) [1.257]	**13.2** (20.522) [1.799]	**17.1** (29.491) [2.585]	**6.1** (9.118) [0.799]	**6.0** (8.787) [0.770]	**6.0** (9.041) [0.792]
max	8.8	38.5	65.5	79.3	29.0	49.2	64.2	13.9	21.7	29.2	9.3	9.7	8.8
Absolute Patent Pledge Effect (APPE)	N/A	**22.898**	**47.478**	**64.896**	**15.164**	**33.398**	**48.100**	**3.569**	**7.205**	**11.102**	**0.096**	**0.046**	**-0.001**
Relative Patent Pledge Effect (RPPE)	N/A	**23.389**	**48.496**	**66.288**	**17.924**	**39.524**	**56.923**	**7.067**	**14.324**	**22.028**	**0.6**	**0.289**	**-0.006**

Note:
- Values in parentheses indicate the standard deviation.
- Values in square brackets indicate the mean confidence interval, assuming that the confidence level equals 95%.
- Standard deviation and mean confidence intervals constitute absolute values with 1000 agents as reference. Adopter values are shown in percentage.
- Values in 'Final Adopters of T2 in %' are rounded to one decimal for illustration purposes. APPE and RPPE are calculated using three decimals.

The baseline scenario of scheme II of case II in fig. 6.15 was similar to the one of scheme I in the same case, because the adoption curve of T2 approached a flat line. The final number of T2 adopters thereby exhibited minor growth after the patent pledge introduction and no growth shortly thereafter. A late patent pledge introduction at $\mu + 1\sigma$ did not visibly affect this flat line, similar to the previous scheme. This stays in contrast to scheme II of case I, where the latest patent pledge type C resulted in a close market share lead (mean values) of T2. The inferiority of T2 therefore influenced the adoption rate of T2 in this late stage to a large extent. The clearest intercept was visible in scenario II M(-2sd)_-1sd_C, similar to the previous scheme. In this scenario, T2 won the adoption competition in most cases, specifically in 88.2% according to table 6.8). The aforementioned decrease in patent pledge effects between *After Early Adopters* ($\mu - 1\sigma$) and *After Early Majority* ($\mu + 0\sigma$) is clearly visible in fig. 6.15. Whereas a strong patent pledge (type C) led to a higher adoption rate of T2 compared to T1 at $\mu - 1\sigma$, one standard deviation later (at μ) the curve of T2 laid clearly below the one of T1.

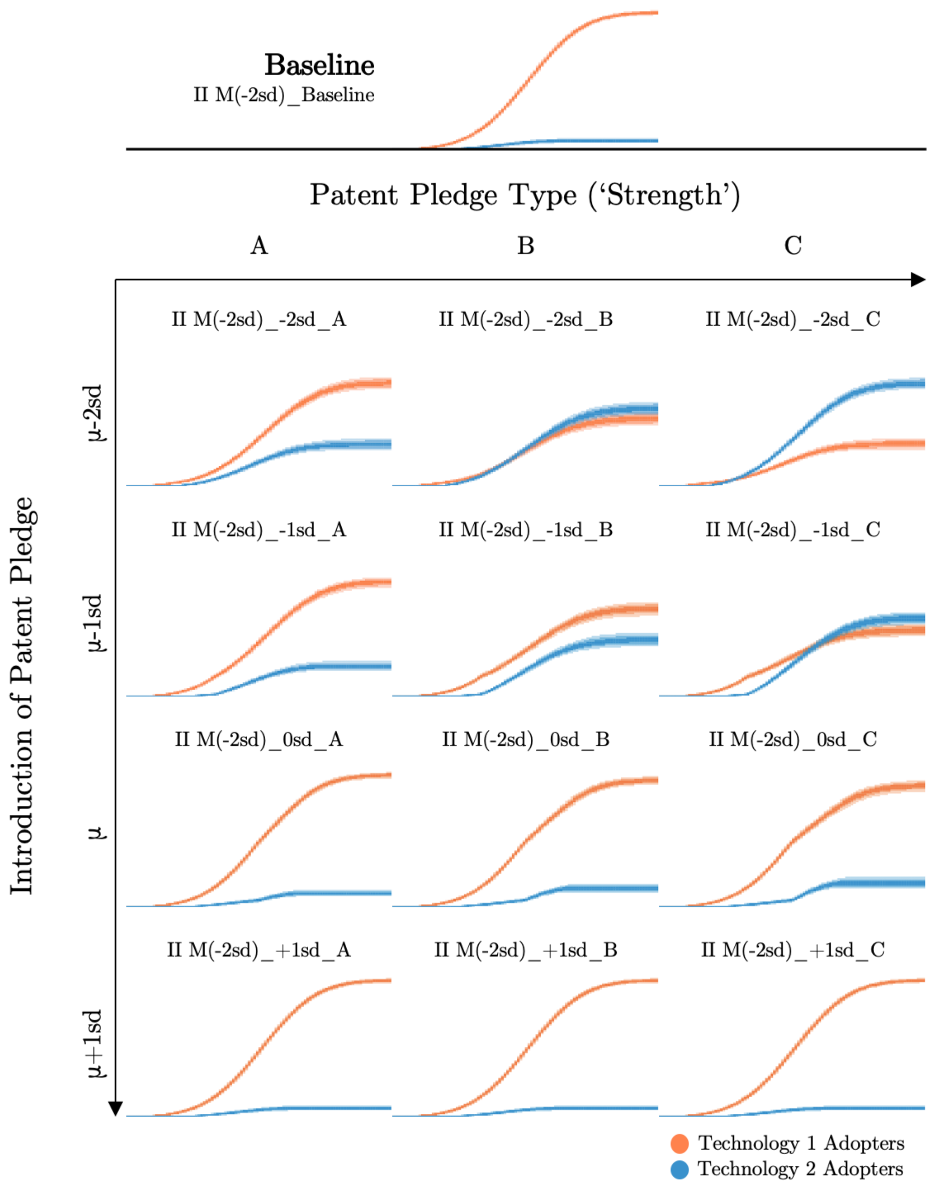


Fig. 6.15 Chart Case II, Scheme II: Introduction of T2 at $\mu - 2\sigma$.

6.2.2.3 Scheme III: introduction of T2 after the Early Adopters have adopted T1

Scheme III of case II simulated the introduction of T2 after the *Innovators* and the *Early Adopters* have adopted T1 (at time $\mu - 1\sigma$). T2 was, on average, perceived as being inferior to T1 (see fig. 6.4). The scheme consisted of a baseline scenario where the technology relating to T2 was not pledged and nine scenarios in which it was subject to a patent pledge. The nine scenarios differed in the introduction time of the patent pledge and also in its strength (patent pledge types A, B, and C).

Table 6.9 and fig. 6.16 below summarise scheme III of case II. The baseline scenario without a patent pledge resulted in a market share of 3.8% for T2 adopters, which was a decrease of 2.2 percentage points from to the baseline scenario of the previous scheme. In scenario II M(-1sd)_-1sd_C, T2 reached 50% market share at 1616.7 time units ($\mu + 1.85\sigma$). This was, however, only true in the 46.4% of experiment runs in which T2 won the adoption competition. In the previous scheme, where T2 was introduced one standard deviation earlier, this was true in 100% of the runs. The patent pledge effects still reached relatively high values with a RPPE of 54.3 and an APPE of 45.9 in scenario II M(-1sd)_-1sd_C. This indicates that a strong patent pledge (type C) that was introduced together with T2 after the *Early Adopters* led to an increase of 45.9 percentage points in market share of T2 compared to the baseline scenario without a patent pledge. The decrease in patent pledge effects between $\mu - 1\sigma$ and μ, as described in the previous schemes, could be observed in this scheme, too. While a strong patent pledge (type C) that was introduced after the *Early Adopters* resulted in a market share of almost 50% for T2, the same patent pledge led to 12.9% market share when introduced one standard deviation later, after the *Early Majority*. In general, when a strong patent pledge (type C) was introduced together with T2, the market share reached a mean value of 49.6% and a maximum value of 60%. This indicates that in some experiment runs, T2 won the adoption competition even though it was inferior to T1 and was introduced after the *Innovators* and the *Early Adopters* have already adopted T1. The fast effect (gradient difference) at $\mu + 0\sigma$ was lower than the one in the same scheme of case I, which indicates that the inferiority of T2 led to a decrease in the fast effect.

Table 6.9 Table Case II, Scheme III: Introduction of T2 at $\mu - 1\sigma$.

Reference		II M(-1sd)_Baseline	II M(-1sd)_-1sd_A	II M(-1sd)_-1sd_B	II M(-1sd)_−1sd_C	II M(-1sd)_0sd_A	II M(-1sd)_0sd_B	II M(-1sd)_0sd_C	II M(-1sd)_+1sd_A	II M(-1sd)_+1sd_B	II M(-1sd)_+1sd_C
Patent Pledge Introduction (PPI)		**Baseline** N/A	**After Early Adopters** -1sd			**After Early Majority** 0sd			**After Late Majority** +1sd		
Patent Pledge Type		N/A	A	B	C	A	B	C	A	B	C
Market Share Saturation at time of Patent Pledge (mean)		N/A	**0.155** (0.012) [0.001]	**0.156** (0.011) [9.817E-4]	**0.156** (0.012) [0.001]	**0.495** (0.016) [0.001]	**0.497** (0.016) [0.001]	**0.496** (0.016) [0.001]	**0.840** (0.012) [0.001]	**0.841** (0.012) [0.001]	**0.840** (0.012) [0.001]
Intercept of T2 at total Market Share {After Mean Time Units}	min	N/A	N/A	N/A	0.546	N/A	N/A	N/A	N/A	N/A	N/A
	mean	N/A	N/A	N/A	**0.829** (0.102) [0.013] {1359.414}	N/A	N/A	N/A	N/A	N/A	N/A
	max	N/A	N/A	N/A	0.998	N/A	N/A	N/A	N/A	N/A	N/A
Intercept Occurrence in %		0	0	0	46.4	0	0	0	0	0	0
T2 reaches 50% market share at time		N/A	N/A	N/A	**1616.716** (125.594) [16.162]	N/A	N/A	N/A	N/A	N/A	N/A
Gradient Difference (mean)		N/A	N/A	N/A	N/A	**0.0990**	**0.2106**	**0.2804**	**0.0476**	**0.0394**	**0.0423**
Final Adopters of T2 in %	min	2.0	11.1	22.8	37.6	3.5	5.3	7.3	1.9	1.8	2.0
	mean	**3.8** (7.071) [0.62]	**17.3** (23.306) [2.043]	**34.7** (36.167) [3.17]	**49.6** (36.58) [3.206]	**6.8** (12.615) [1.106]	**9.8** (17.376) [1.523]	**12.9** (24.289) [2.129]	**3.9** (7.608) [0.667]	**3.8** (6.836) [0.599]	**3.8** (7.071) [0.62]
	max	5.9	24.0	46.4	60.0	11.0	17.4	20.3	6.6	5.9	5.9
Absolute Patent Pledge Effect (APPE)		N/A	**13.559**	**30.957**	**45.850**	**2.984**	**5.984**	**9.139**	**0.082**	**0.048**	**0**
Relative Patent Pledge Effect (RPPE)		N/A	**16.046**	**36.679**	**54.325**	**5.909**	**11.897**	**18.133**	**0.513**	**0.302**	**0**

Note:
- Values in parentheses indicate the standard deviation.
- Values in square brackets indicate the mean confidence interval, assuming that the confidence level equals 95%.
- Standard deviation and mean confidence intervals constitute absolute values with 1000 agents as reference. Adopter values are shown in percentage.
- Values in 'Final Adopters of T2 in %' are rounded to one decimal for illustration purposes. APPE and RPPE are calculated using three decimals.

The baseline scenario in fig. 6.16 posed a similar picture to the baseline scenarios of the previous schemes, where the adoption curve of T2 approached a flat line. The curve of T2 (blue) grew marginally after the introduction of the technology, but stagnated for the most part. The decrease in patent pledge effects was visible between the patent pledge introduction points $\mu - 1\sigma$ and $\mu + 0\sigma$. While a strong patent pledge (type C) that was introduced at the earliest introduction point resulted in an overlap of the adoption curves, the same patent pledge led to a lower and stagnating adoption curve of T2 when it was introduced later. Almost 50% market share of T2 could be reached in the strongest scenario of this scheme (scenario II M(-1sd)_-1sd_C). The adoption curves of T2 in all other scenarios laid clearly below the ones of T1, which indicates that T2 lost the adoption competition against T1 in most scenarios. This is a distinct difference to scheme III in case I, where the adoption curve of T2 laid above the one of T1 in four out of the nine scenarios with a patent pledge. Late patent pledge introduction points (at $\mu + 1\sigma$) did not result in any visible effect of patent pledges on the adoption curve of T2, similar to the previous schemes.

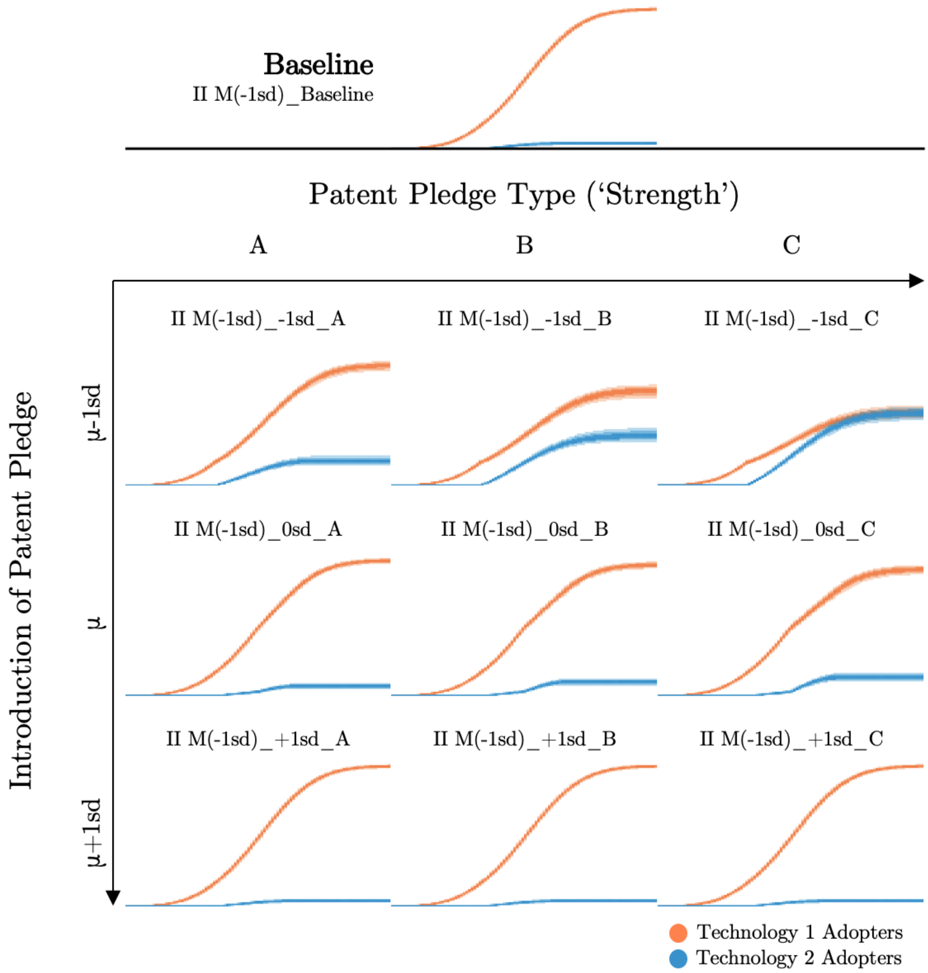


Fig. 6.16 Chart Case II, Scheme III: Introduction of T2 at $\mu - 1\sigma$.

6.2.2.4 Scheme IV: introduction of T2 after the Early Majority has adopted T1

Scheme IV of case II simulated the introduction of T2 after the *Innovators*, the *Early Adopters*, and the *Early Majority* have already adopted T1 (at time μ). The introduction of T2 therefore occurred approximately in the middle of the adoption period. T2 was, on average, perceived as being inferior to T1 (see fig. 6.4). The scheme consisted of a baseline scenario where the technology relating to T2 was not pledged and six scenarios in which it was subject to a patent pledge.

Table 6.10 and fig. 6.17 depict scheme IV of case II. The baseline scenario resulted in a market share of 0.7% for T2, which indicates that without a patent pledge, only few firms adopted T2. A patent pledge did not lead to comparable effects observed in scheme I and scheme II. In the best case, in scenario II M(0sd)_0sd_C, T2 adopters reached a mean market share of 7.4% and a maximum market share of 12.4%. This posed a large decrease compared to the previous scheme, where T2 adopters reached a maximum market share of 60%. T2 did not reach 50% market share in any of the experiment runs, which means that T2 did not win the adoption competition when it was introduced after the *Early Majority*, despite the introduction of a patent pledge. When a patent pledge was introduced one standard deviation later than T2, after the *Late Majority* has already adopted T1, no patent pledge effects were observed. The fast effect (gradient difference) diminished with late patent pledge introduction points, similar to scheme IV of case I.

Table 6.10 Table Case II, Scheme IV: Introduction of T2 at $\mu - 0\sigma$.

Reference		II M(0sd)_Baseline	II M(0sd)_0sd_A	II M(0sd)_0sd_B	II M(0sd)_0sd_C	II M(0sd)_+1sd_A	II M(0sd)_+1sd_B	II M(0sd)_+1sd_C
Patent Pledge Introduction (PPI)		**Baseline** N/A	**After Early Majority** 0sd			**After Late Majority** +1sd		
Patent Pledge Type		N/A	A	B	C	A	B	C
Market Share Saturation at time of Patent Pledge (mean)		N/A	**0.495** (0.016) [0.001]	**0.497** (0.016) [0.001]	**0.496** (0.016) [0.001]	**0.840** (0.012) [0.001]	**0.841** (0.011) [0.001]	**0.840** (0.012) [0.001]
Intercept of T2 at total Market Share {After Mean Time Units}	min	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	mean	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	max	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Intercept Occurrence in %		0	0	0	0	0	0	0
T2 reaches 50% market share at time		N/A	N/A	N/A	N/A	N/A	N/A	N/A
Gradient Difference (mean)		N/A	N/A	N/A	N/A	**-0.0038**	**-0.0031**	**-0.0069**
Final Adopters of T2 in %	min	0.1	1.2	2.3	3.4	0.1	0.1	0.1
	mean	**0.7** (2.919) [0.256]	**2.9** (7.433) [0.652]	**5.1** (11.502) [1.008]	**7.4** (17.102) [1.499]	**0.7** (2.776) [0.243]	**0.7** (2.811) [0.246]	**0.7** (2.919) [0.256]
	max	1.5	5.0	9.7	12.4	1.7	1.6	1.5
Absolute Patent Pledge Effect (APPE)		N/A	**2.214**	**4.424**	**6.734**	**0.028**	**-0.008**	**0**
Relative Patent Pledge Effect (RPPE)		N/A	**4.384**	**8.795**	**13.361**	**0.175**	**-0.050**	**0**

Note:
- Values in parentheses indicate the standard deviation.
- Values in square brackets indicate the mean confidence interval, assuming that the confidence level equals 95%.
- Standard deviation and mean confidence intervals constitute absolute values with 1000 agents as reference. Adopter values are shown in percentage.
- Values in 'Final Adopters of T2 in %' are rounded to one decimal for illustration purposes. APPE and RPPE are calculated using three decimals.

The baseline scenario of fig. 6.17 exhibited a further decrease of T2 adopters compared to the previous scheme. The adoption curve of T2 was barely visible and was lower than the one in scheme IV of case I. The deviation of the curves for the patent pledge introduction point at μ further decreased compared to the same scheme in case I, see also the standard deviations of the final T2 adopters in table 6.10 and table 6.6. The patent pledge types did not show any visible effect on the adoption curve of T2 when the patent pledge was introduced at $\mu + 1\sigma$, similar to the schemes before.

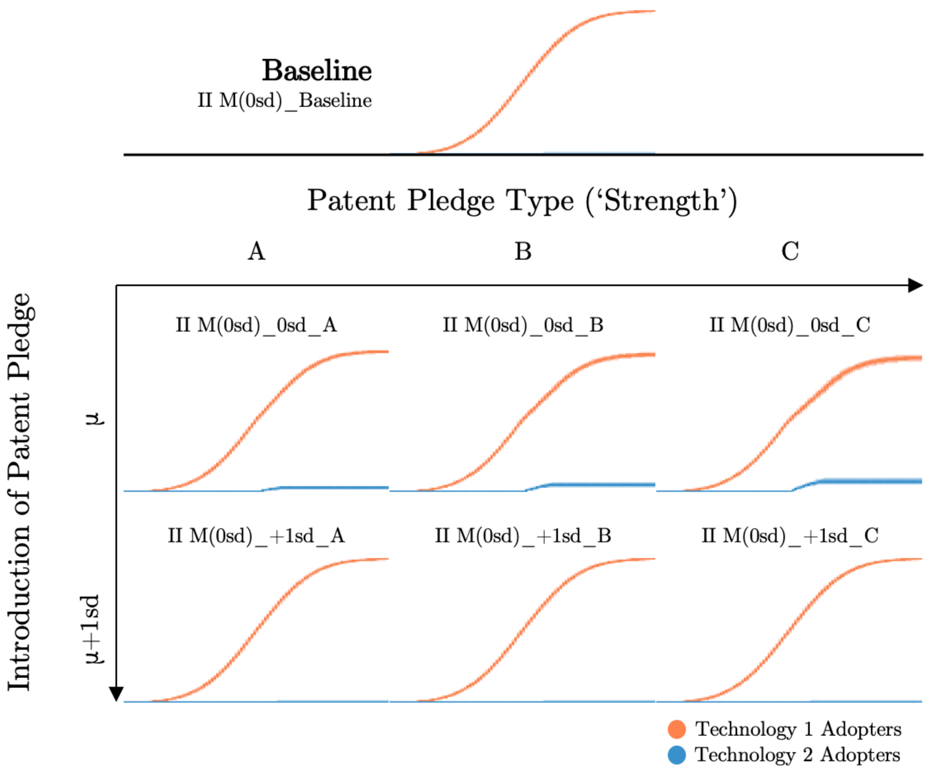


Fig. 6.17 Chart Case II, Scheme IV: Introduction of T2 at $\mu - 0\sigma$.

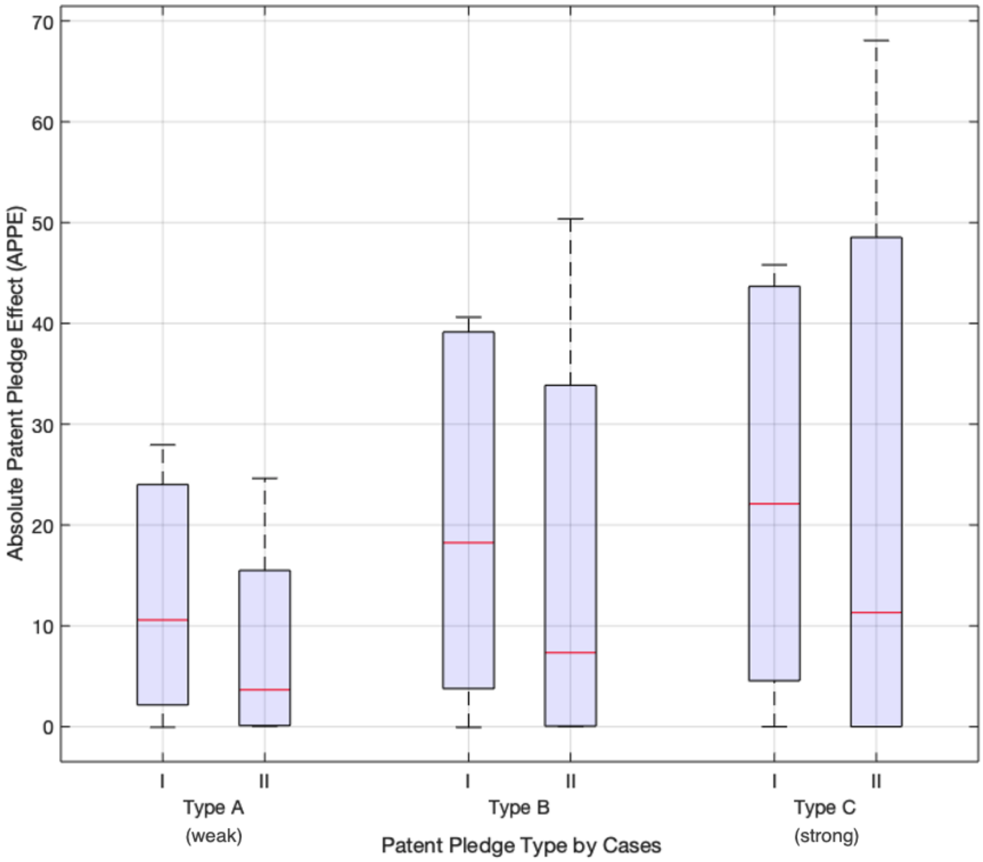
6.3 Aggregate findings

This section provides compounded illustrations and interpretations of the results from the previous section. First, sub-study 3.1 is addressed by aggregating the absolute and the relative patent pledge effects (APPEs and RPPEs) of different patent pledge types (strengths). Second, the effect of the patent pledge timing as subject of sub-study 3.2 is investigated. Third, specific scenarios in which a patent pledge of T2 results in a market share of approximately 50% are elaborated. These scenarios, so-called *borderline-scenarios*, indicate the latest possible time to pledge in order to win the competition for potential adopters described by Arthur (1989). These three topics are chosen for further investigation because they allow for the derivation of specific practical implications. Other results, such as the intercept values and their standard deviations, are not discussed on an aggregate level.

6.3.1 Study 3.1: effect of patent pledge types on technology diffusion

Study 3 simulated three types of patent pledges, type A, B, and C, that are in line with the findings about patent pledge types from Study 1. These types were implemented by shifting the mean values of the normal probability density functions of the technology attributes that were found to be influenced by a patent pledge by +1.5, +3.0, and +4.5 to the right (see chapter 6.1.2.2). These even increments might suggest a linear relationship between patent pledge types and final adopters, i.e. a linear increase of the next stronger patent pledge type. The results, however, showed that this relationship is not linear, but that the difference of final adopters between type A and type B was, in some cases, more than twice as large as the difference between type B and type C. This section first discusses the results by comparing the APPEs and RPPEs for the different patent pledge types and then summarises their main insights.

Fig. 6.18 and fig. 6.19 show whisker-plots for the APPE and RPPE respectively, with table 6.11 and table 6.12 providing the statistical data. Each bar (in blue/green, including the attached dashed lines) in the whisker-plots represents the distribution of the effects of one patent pledge type for one case. This means that for both cases, all measured patent pledge effects from every introduction point of T2 (scheme) are included in the whisker-plots. High effects were achieved through an early, strong patent pledge; low effects through a weak, late patent pledge. The whisker-plots give an indication about the dispersion of patent pledge effects.



Key:
I: Case I where T1 and T2 are similar.
II: Case II where T2 is inferior to T1.

Explanation of whisker-plots:
The red line indicates the median value.
The box (blue) indicates the range between the 25th and the 75th quartile.
The dashed lines ('whiskers') indicate the range from the lower/upper extreme to the lower/upper quartile.

Fig. 6.18 Absolute Patent Pledge Effect (APPE) distribution by patent pledge types and cases.

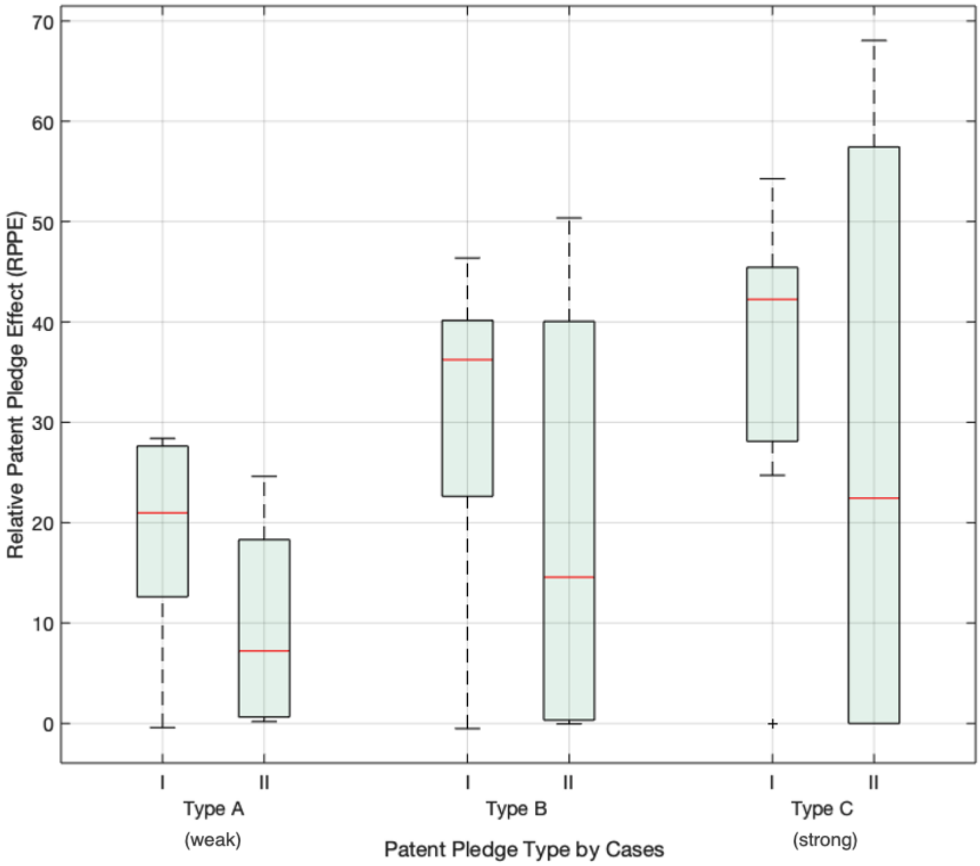
Table 6.11 Statistical indicators of the APPE across patent pledge types and cases.

	Type A		Type B		Type C	
	Case I	Case II	Case I	Case II	Case I	Case II
Median	10.576	3.639	18.228	7.330	22.090	11.312
Q1*	2.584	0.629	5.090	1.144	6.937	1.684
Q3**	23.540	15.410	37.837	33.737	42.347	48.425
Max.	27.949	24.621	40.604	50.361	45.802	68.058
Min.	-0.067	0.028	-0.082	-0.008	0	-0.001
Standard deviation	10.919	9.611	15.836	20.181	17.495	27.719
Mean	13.675	9.130	21.324	19.227	24.709	27.086

Key:
* 25^{th} percentile.
** 75^{th} percentile.

Fig. 6.18 and table 6.11 show that the median for the APPE of case II (where T2 was inferior to T1) was less than the median for case I (T1 and T2 are similar) in all three patent pledge types. The increase of the median from type A to type B was 72.35% for case I (101.43% for case II) compared to an increase of 21.19% (54.32% for case II) from type B to type C. The increase of the mean from type A to type B was 55.34% for case I (110.50% for case II) compared to an increase of 15.87% (40.87% for case II) from type B to type C. This smaller growth rate from type B to type C can also be inferred from the interquartile range (the blue boxes) of the whisker-plots in fig. 6.18. Particularly in case I, the whisker-plots of type B and type C show that type C reached maximum values of only about six percentage points above the ones of type B. In contrast, the difference between the maximum values of type A and type B was about 13 percentage points. Generally, the stronger the patent pledge was, the more dispersed its APPE and the larger its standard deviation. By only considering the median values, it could be inferred that the APPE is generally larger when the technologies are being perceived as similar (case I) than in cases where the pledged technology is inferior (case II). This is, however, not always the case. The patent pledge types B and C in case II exhibited larger maximum values compared to case I. This infers that in case II, higher APPEs could be achieved than in case I, but only for the patent pledge types B and C. This indicates that a weak patent pledge (type A) could not offset the inferiority of the technology, in contrast to a medium one (type B) and a strong one (type C). Another observation is that for patent pledge types B and C, the APPE was generally more dispersed when the pledged technology was inferior than when it was similar to T1 (this can be observed through the size of the whisker-plots in case II in fig. 6.18). Interestingly, all whisker-plots of the APPE in case II barely exhibit the lower whisker (the lower dashed line out of the blue body) and their median values are closer to the bottom of the body than in case I. This indicates a right-skewed data set in which, when plotted, most data points lie to the right of the peak. This is a result of the small APPEs when patent pledges are introduced at later stages, particularly after the *Early Majority* (at μ time units) and after the *Late Majority* (at $\mu + 1\sigma$ time units) have already adopted. In the best case of the simulation, a strong patent pledge (type C) resulted in an APPE of approximately 68.1 percentage points when the pledged technology was inferior. This maximum value could only be achieved when both T2 and the patent pledge were introduced early and when the pledge strongly affected the respective technology attributes.

Fig. 6.19 and table 6.12 show that the median for the RPPE of case II was less than the median for case I in all three patent pledge types, similar to the APPE described above. The increase of the median from type A to type B was 72.69% for case I (102.22% for case II) compared to an increase of 16.61% (54.05% for case II) from type B to type C. The increase of the mean from type A to type B was 61.70% for case I (108.86% for case II) compared to an increase of 18.13% (41.71% for case II) from type B to type C. These numbers were similar compared to the ones of the APPE. The standard deviations of the RPPE, too, were similar to the standard deviations of the APPE, particularly in case II. Interestingly, the RPPE in case I was less dispersed than the APPE, especially within the 25th and 75th percentile. The median of patent pledge type A in case I was the only one in all APPEs and RPPEs that laid outside the box of its counterpart in case II, which generally indicates the most uniform difference between the two cases. While the RPPEs in types B and C exposed larger differences than in case I, they were also more dispersed. In general, the stronger the patent pledge, the more dispersed was the RPPE and the larger was its standard deviation, similar to the APPE. One obvious difference between the APPE and the RPPE was that in case I, the RPPE's interquartile range was less dispersed (the green boxes are smaller). Specifically in type C of case I, the RPPEs were closer together, even though outliers around zero existed (indicated by a small cross at 0 RPPE for type C in case I in fig. 6.19). These outliers were a result of the late patent pledge introduction points, as described for the APPE above.



Key:
I: Case I where T1 and T2 are similar.
II: Case II where T2 is inferior to T1.

Explanation of whisker-plots:
The red line indicates the median value.
The box (green) indicates the range between the 25^{th} and the 75^{th} quartile.
The dashed lines ('whiskers') indicate the range from the lower/upper extreme to the lower/upper quartile.
Crosses outside of the body and the dashed lines indicate outliers.

Fig. 6.19 Relative Patent Pledge Effect (RPPE) distribution by patent pledge types and cases.

Table 6.12 Statistical indicators of the RPPE across patent pledge types and cases.

	Type A		Type B		Type C	
	Case I	Case II	Case I	Case II	Case I	Case II
Median	20.985	7.205	36.240	14.570	42.260	22.445
Q1*	12.808	1.568	22.8875	2.440	28.248	3.340
Q3**	27.278	18.213	40.133	39.925	45.263	57.310
Max.	28.410	24.620	46.370	50.360	54.270	68.060
Min.	-0.420	0.180	-0.520	-0.050	0	-0.010
Standard deviation	9.149	9.488	12.834	20.313	13.821	28.010
Mean	19.267	10.765	31.154	22.484	36.801	31.862

Key:
* 25th percentile.
** 75th percentile.

This paragraph briefly summarises the key insights from the descriptions above. Practical implications from these insights are given in chapter 6.4.2.1. It was shown that the relationship between patent pledge types and the final number of adopters is not linear, albeit the shifts of the mean values of the patent pledge types were even. The results suggest that a patent pledge type B generally leads to higher patent pledge effects than type A. A type C patent pledge further increases these effects, but not to the same extent as from type A to type B. A further insight is that the stronger the patent pledge, the more dispersed its effect. This is a result of the late introduction of patent pledges in some scenarios, because even though some patent pledges influence specific technology attributes to a large extent, the technology-choice at late adoption stages is primarily driven by the behaviour of neighbours and the general direction of the market (Arthur (1989, p. 116) argued that the adoption lead '*may eventually 'corner the market'*'). These strong patent pledges, however, can result in large patent pledge effects when introduced at the right time. The effect of patent pledges is therefore dependent on their introduction points. This leads to the question about the timing of patent pledges and at what time their introduction results in large effects on the technology adoption.

6.3.2 Study 3.2: effect of patent pledge timing on technology diffusion

In the previous section, it was shown that the relationship between patent pledge types and the number of final adopters is not linear. This section further supports this and shows that the same is true for the timing of patent pledges. While the difference in APPE/RPPE was relatively small for the first two phases of the adoption curve, an introduction before or after the *Early Majority* was critical for the effect of patent pledges, especially when the pledged technology was inferior. Fig. 6.20 and fig. 6.21 below show the APPEs and the RPPEs for all schemes of both cases. Every chart numbered (1)-(8) illustrates the patent pledge effects for one scheme (for different introduction points of T2) and for all three patent pledge types (strengths). The charts are placed in two columns to allow for the comparison of case I (where T1 and T2 were similar) and case II (where T2 was inferior). The results described earlier showed that the patent pledge effects decreased with later introduction points of the patent pledge, which is why the effects in the figures generally decline from left to right (from the earliest introduction of the patent pledge at $\mu - 3\sigma$ to the latest introduction at $\mu + 1\sigma$). Since a patent pledge could only be introduced at the same time or after the introduction of T2, the effect could only be measured from that time on. This is why there are less effects to illustrate the later T2 is introduced.

The data displayed in both fig. 6.20 and fig. 6.21 further illustrate the non-linearity of the patent pledge effects described in the previous section because the distance between type B and type C (the orange and blue curves) is generally smaller than the distance between type A and type B (the grey and orange curves). The effects for type B and type C were larger in case II in the first two schemes (charts (1)-(4)) of both figures, as was also shown in the whisker-plots in fig. 6.18 and fig. 6.19. An exception were the effects of type A because they were less in case II. This highlights the larger dispersion of patent pledge effects in case II when the pledged technology was inferior, as described in the previous section.

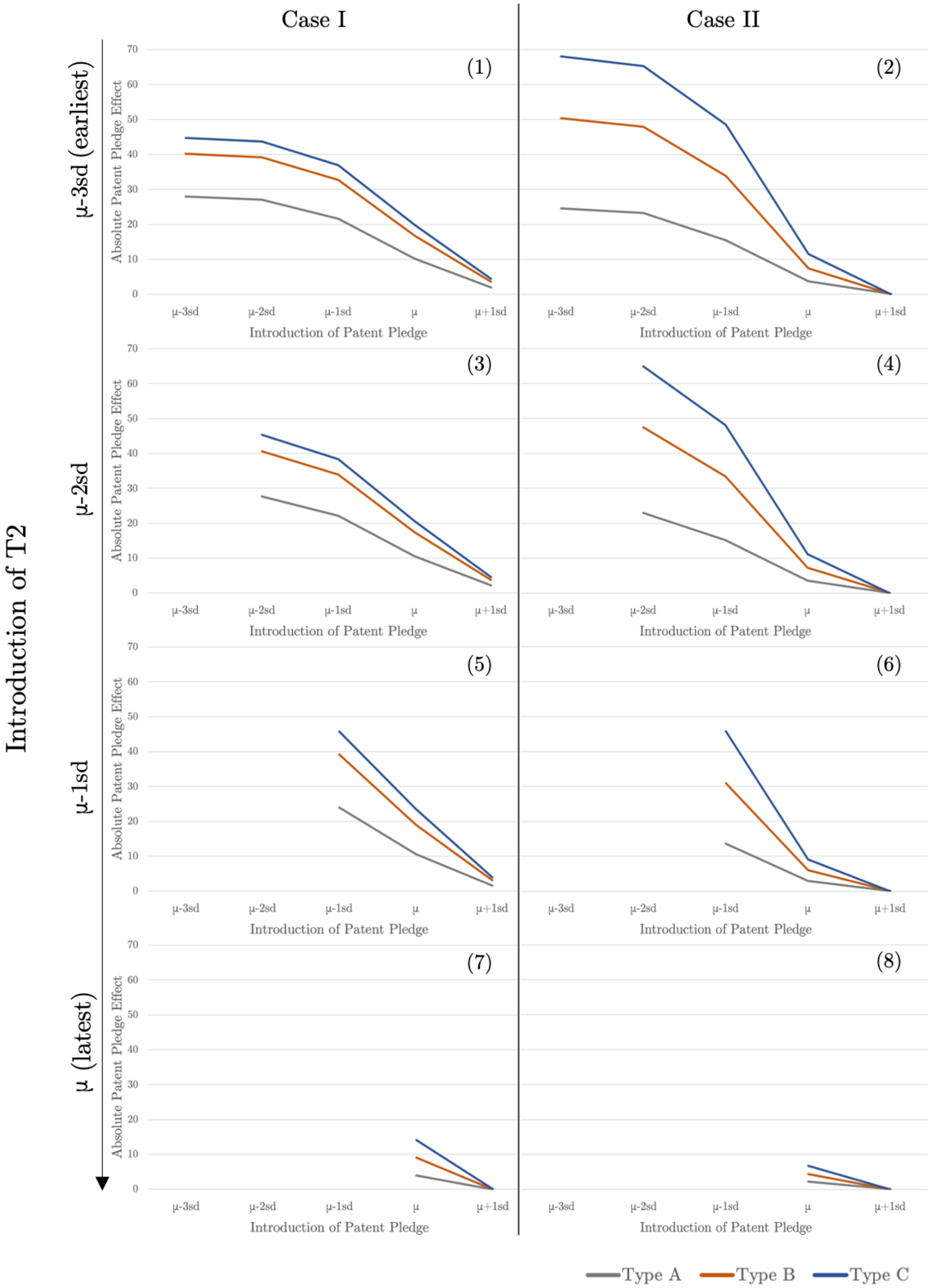


Fig. 6.20 Absolute Patent Pledge Effect (APPE) among cases and scenarios.

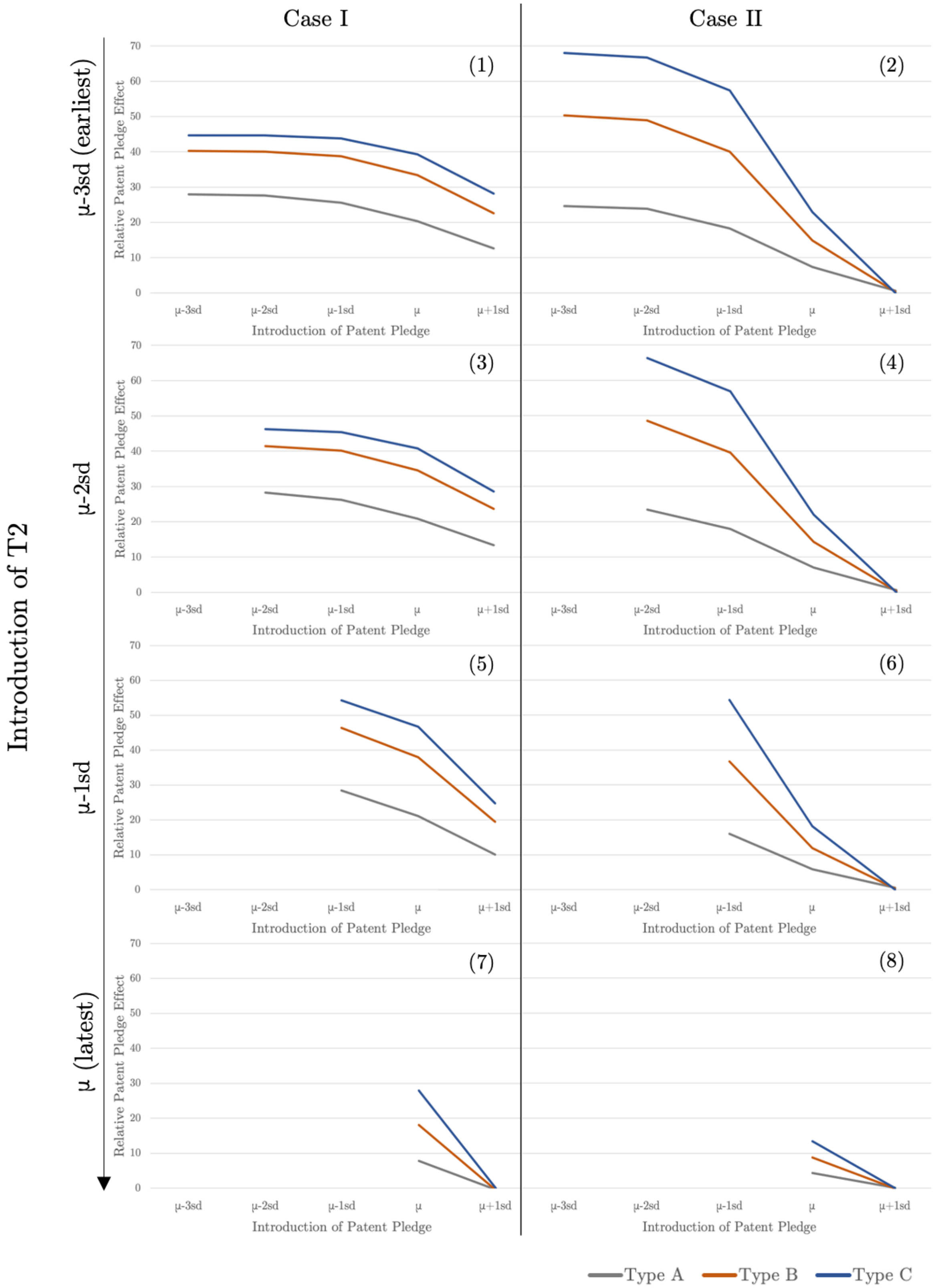


Fig. 6.21 Relative Patent Pledge Effect (RPPE) among cases and scenarios.

An interesting observation from fig. 6.21 is that the patent pledge effects in case II showed their largest decrease between the patent pledge introduction points $\mu - 1\sigma$ and μ. This is illustrated in the charts (2), (4), and (6) of the figure. This is further shown in table 6.13 and table 6.14. These 'heatmaps' illustrate the change in patent pledge effects relative to the patent pledge introduction point one standard deviation earlier (i.e. one adopter category earlier). Take the value of -1.04 in the first row of case I in table 6.13, for instance. The value appears in the column $\mu - 2\sigma$, which means that one standard deviation earlier (at $\mu - 3\sigma$) the patent pledge effect was 1.04 percentage points larger. The next value to the right, -6.704, indicates that when the patent pledge was introduced one standard deviation later (at $\mu - 1\sigma$), the patent pledge effect decreased by 6.704 percentage points. The values are colour-coded to allow for a better visualisation of the patent pledge effect changes. Green indicate low, yellow medium, and red large changes in patent pledge effects. In case II, both the APPE and the RPPE exhibited the largest change between the introduction points at $\mu - 1\sigma$ and μ, which constitutes the *Early Majority* adopter category according to Rogers (1962). In case I this was also true for the APPE, while for the RPPE the largest change occurred in the phase *Late Majority* (between μ and $\mu + 1\sigma$). The difference in patent pledge effects after the first adopter category *Innovators* (at $\mu - 2\sigma$), in contrast, was marginal in all scenarios. The critical phase for patent pledges to unfold their effects therefore appears to occur when the *Early Majority* starts to adopt (at $\mu - 1\sigma$). Implications from these observations are given in chapter 6.4.2.1.

Table 6.13 APPE-change to previous period over adopter categories, schemes, and cases.

		Patent Pledge Introduction (PPI)									
		Case I					Case II				
Introduction of T2		μ-3sd	μ-2sd	μ-1sd	μ	μ+1sd	μ-3sd	μ-2sd	μ-1sd	μ	μ+1sd
μ-3sd	Type C	-	-1.04	-6.704	-17.099	-15.387	-	-2.791	-16.734	-37.011	-11.523
	Type B	-	-1.001	-6.461	-15.973	-13.182	-	-2.433	-14.078	-26.395	-7.405
	Type A	-	-0.893	-5.428	-11.403	-8.206	-	-1.317	-7.812	-11.784	-3.607
μ-2sd	Type C	-	-	-6.916	-17.81	-16.042	-	-	-16.796	-36.998	-11.103
	Type B	-	-	-6.672	-16.551	-13.615	-	-	-14.08	-26.193	-7.159
	Type A	-	-	-5.54	-11.595	-8.397	-	-	-7.734	-11.595	-3.473
μ-1sd	Type C	-	-	-	-22.217	-19.655	-	-	-	-36.711	-9.139
	Type B	-	-	-	-20.064	-15.977	-	-	-	-24.973	-5.936
	Type A	-	-	-	-13.394	-9.005	-	-	-	-10.575	-2.902
μ	Type C	-	-	-	-	-14.091	-	-	-	-	-6.734
	Type B	-	-	-	-	-9.144	-	-	-	-	-4.432
	Type A	-	-	-	-	-3.987	-	-	-	-	-2.186

Key:

Decrease in patent pledge effects (values in red indicate the largest decrease).

Table 6.14 RPPE-change to previous period over adopter categories, schemes, and cases.

Introduction of T2		Case I: μ-3sd	Case I: μ-2sd	Case I: μ-1sd	Case I: μ	Case I: μ+1sd	Case II: μ-3sd	Case II: μ-2sd	Case II: μ-1sd	Case II: μ	Case II: μ+1sd
μ-3sd	Type C	-	-0.103	-0.862	-4.413	-11.203	-	-1.391	-9.231	-34.575	-22.867
	Type B	-	-0.16	-1.294	-5.402	-10.735	-	-1.405	-8.897	-25.238	-14.506
	Type A	-	-0.313	-2.041	-5.307	-7.669	-	-0.817	-5.492	-10.969	-6.712
μ-2sd	Type C	-	-	-0.843	-4.669	-12.151	-	-	-9.365	-34.90	-22.034
	Type B	-	-	-1.319	-5.601	-10.869	-	-	-8.972	-25.2	-14.035
	Type A	-	-	-2.074	-5.286	-7.536	-	-	-5.465	-10.857	-6.467
μ-1sd	Type C	-	-	-	-7.565	-21.986	-	-	-	-36.19	-18.133
	Type B	-	-	-	-8.45	-18.439	-	-	-	-24.782	-11.595
	Type A	-	-	-	-7.35	-10.995	-	-	-	-10.137	-5.396
μ	Type C	-	-	-	-	-27.903	-	-	-	-	-13.361
	Type B	-	-	-	-	-18.532	-	-	-	-	-8.845
	Type A	-	-	-	-	-8.197	-	-	-	-	-4.209

Patent Pledge Introduction (PPI)

Key:

Decrease in patent pledge effects (values in red indicate the largest decrease).

Fig. 6.22 summarises the gradient difference of the patent pledge types relative to the adoption curve without a patent pledge (baseline scenario). The gradient difference measures the fast effect of the patent pledge and is given in change of slope of the adoption curve. A value of 0.1, for instance, indicates an increase of 0.1 in the slope of the adoption curve as a result of the patent pledge relative to the same scenario without a patent pledge (see chapter 6.2 for the specific calculation). This indicates the fast effect of patent pledges, because it is only measured in the interval of one standard deviation before and after the patent pledge introduction. In contrast, the absolute and relative patent pledge effects (APPE and RPPE) refer to the final number of adopters and indicate slow effects that are measured at the end of the simulation. Similar to these slow effects, the gradient difference was larger when T2 was inferior (case II). A strong patent pledge that was introduced after the *Early Adopters* (at $\mu - 1\sigma$) led to a maximum fast effect of more than 0.5 (see the peak of the blue line (type C) in (2) in fig. 6.22). An interesting observation is that when the technologies were similar (case I), the gradient difference was relatively stable between $\mu - 1\sigma$ and μ (see (1) and (3) in fig. 6.22). When T2 was inferior (in case II), however, the gradient difference was larger at $\mu - 1\sigma$ (see (2) and (4) in fig. 6.22). This indicates that when the technology was inferior, a patent pledge had a larger fast effect when it was introduced right before the *Early Majority* (at $\mu - 1\sigma$) than when it was introduced after this adopter category (at μ). This is in line with the slow effects (APPEs and RPPEs) described above. When the technologies were similar (case I), no such difference was observed. In case where T2 was introduced after the *Early Majority* has adopted (at μ), only marginal fast effects were measured. To conclude, the fast effect was largest at the beginning of the adopter category *Early Majority*, similar to the slow effects described previously. The fast effect was usually larger when T2 was inferior and subject to a strong patent pledge within the first two adopter categories. This supports the observations from the slow effects described above, specifically that the critical timing for patent pledges appears to be when the *Early Majority* begins to adopt (at $\mu - 1\sigma$).

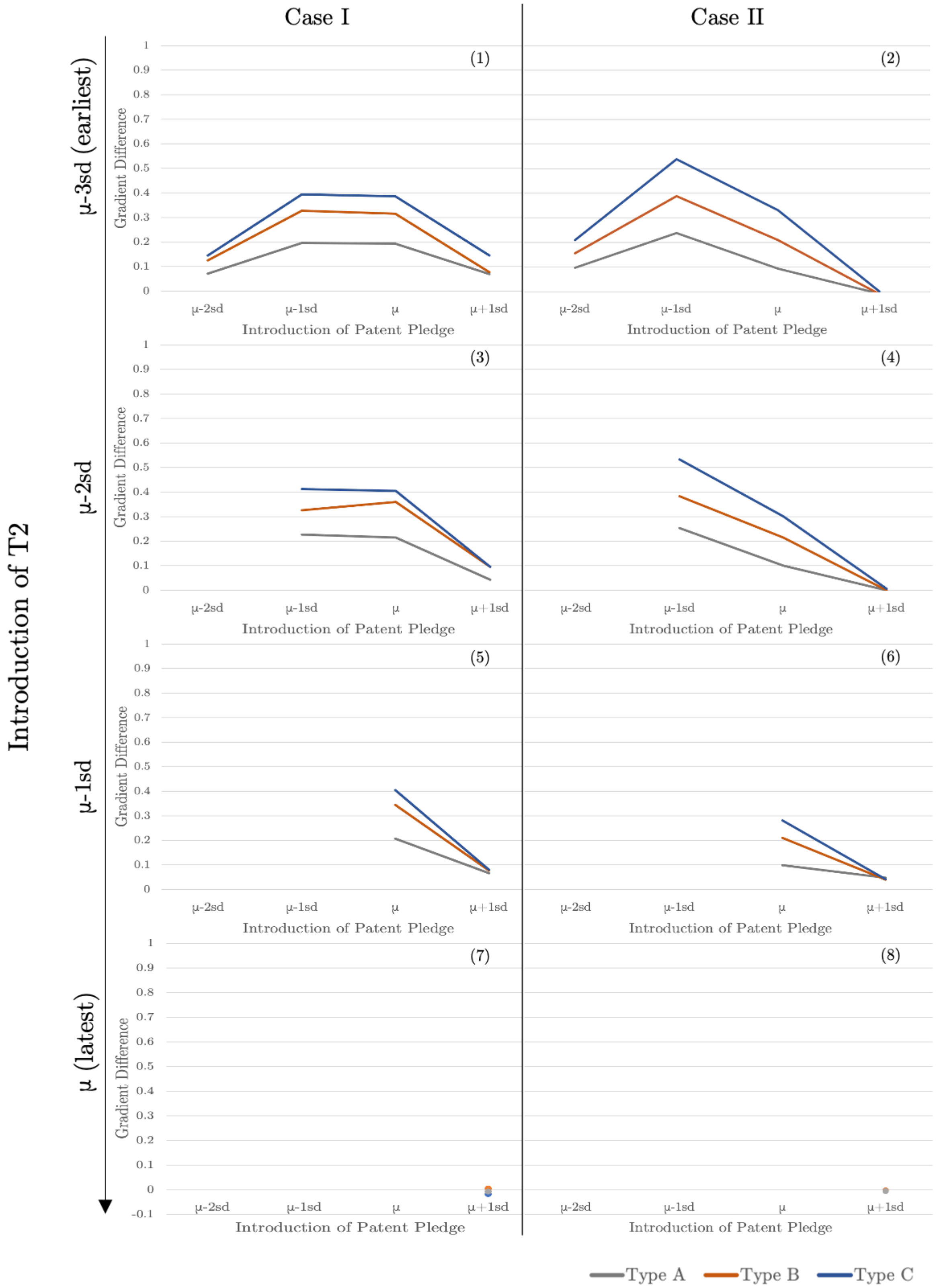


Fig. 6.22 Gradient difference among cases and scenarios.

6.3.3 Borderline scenarios in scheme I of case II

Case II comprised schemes and scenarios in which T2 was inferior to T1. Chapter 6.2.2 showed that even if the technology was inferior, in some scenarios T2 reached a market share of more than 50%. This means that the inferior technology can win the adoption competition against its superior substitute, which poses the question about the latest introduction point of a patent pledge so that an inferior technology still wins the adoption competition. Additional experiment runs with varying patent pledge introduction points were conducted to find such so-called *borderline scenarios*. For this investigation, only scheme I of case II, where both technologies were introduced at the same time and T2 was inferior to T1, was considered. The outcomes show at what time a patent pledge needs to be introduced to win the adoption competition when the pledged technology is inferior and both technologies are introduced at the same time.

Fig. 6.14 in the results section showed that for a strong patent pledge (type C), the equilibrium where T1 and T2 both reached 50% market share was somewhere between the patent pledge introduction points of $\mu - 1\sigma$ and μ. Table 6.15 and fig. 6.23 below expand this scheme by one patent pledge introduction point (highlighted in orange). It is shown that at $\boldsymbol{\mu - 0.837\sigma}$, T2 reached 49.9% market share (mean value) with a strong patent pledge (type C). In the best case, T2 reached 59.3% market share; in the worst case, it reached 36.2%. This indicates that when both T1 and T2 are introduced at the same time and T2 is inferior to T1, a strong patent pledge must be conducted before this point.[10] A medium patent pledge at the same introduction point led to 36.2% market share and a weak patent pledge to 19.9% market share (mean values). Neither of these two patent pledge types led to the adoption competition win of T2 in any experiment run. The medium patent pledge (type B) reached a maximum of 47.1% market share.

[10] $\mu - 0.837\sigma$ translates to 721 time units when all adopters have adopted at 2000 time units.

Table 6.15 Borderline table for patent pledge type C at $\mu - 0.837\sigma$.

Reference		II M(-3sd)_Baseline	II M(-3sd)_-3sd_A	II M(-3sd)_-3sd_B	II M(-3sd)_-3sd_C	II M(-3sd)_-2sd_A	II M(-3sd)_-2sd_B	II M(-3sd)_-2sd_C	II M(-3sd)_-1sd_A	II M(-3sd)_-1sd_B	II M(-3sd)_−1sd_C	II Borderline_A	II Borderline_B	II Borderline_C	II M(-3sd)_0sd_A	II M(-3sd)_0sd_B	II M(-3sd)_0sd_C	II M(-3sd)_+1sd_A	II M(-3sd)_+1sd_B	II M(-3sd)_+1sd_C
Patent Pledge Introduction (PPI)		**Baseline** N/A	**Before Innovators** -3sd			**After Innovators** -2sd			**After Early Adopters** -1sd			**Borderline Case** -0.837			**After Early Majority** 0sd			**After Late Majority** +1sd		
Patent Pledge Type		N/A	A	B	C	A	B	C	A	B	C	A	B	C	A	B	C	A	B	C
Market Share Saturation at time of Patent Pledge (mean)		N/A	0	0	0	**0.021** (0.004) [3.933E-4)]	**0.021** (0.004) [3.891E-4]	**0.021** (0.005) [4.106E-4]	**0.154** (0.012) [0.001]	**0.155** (0.011) [9.877E-4]	**0.155** (0.012) [0.001]	**0.197** (0.013) [0.001]	**0.198** (0.012) [0.001]	**0.199** (0.012) [0.001]	**0.495** (0.016) [0.001]	**0.497** (0.016) [0.001]	**0.496** (0.016) [0.001]	**0.840** (0.012) [0.001]	**0.841** (0.012) [0.001]	**0.840** (0.012) [0.001]
Intercept of T2 at total Market Share {After Mean Time Units}	min	N/A	N/A	0	0	N/A	0.032	0.026	N/A	N/A	0.398	N/A	N/A	0.542	N/A	N/A	N/A	N/A	N/A	N/A
	mean	N/A	N/A	**0.136** (0.184) [0.016] {510.66}	**0.01** (0.014) [0.001] {191.48}	N/A	**0.352** (0.239) [0.022] {864.11}	**0.083** (0.031) [0.003] {535.69}	N/A	N/A	**0.677** (0.129) [0.012] {1173.85}	N/A	N/A	**0.841** (0.106) [0.013] {1381.26}	N/A	N/A	N/A	N/A	N/A	N/A
	max	N/A	N/A	0.976	0.11	N/A	0.998	0.214	N/A	N/A	0.998	N/A	N/A	0.996	N/A	N/A	N/A	N/A	N/A	N/A
Intercept Occurrence in %		0	0	97.4	100	0	89.4	100	0	0	93.0	0	0	51.2	0	0	0	0	0	0
T2 reaches 50% market share at time		N/A	N/A	**1427.696** (100.177) [8.897]	**1192.524** (28.174) [2.47]	N/A	**1497.421** (129.699) [12.024]	**1218.436** (30.605) [2.683]	N/A	N/A	**1496.011** (107.695) [9.789]	N/A	N/A	**1632.703** (129.753) [15.895]	N/A	N/A	N/A	N/A	N/A	N/A
Gradient Difference (mean)		N/A	N/A	N/A	N/A	**0.0982**	**0.1565**	**0.2101**	**0.2386**	**0.3886**	**0.5388**	**0.2440**	**0.4123**	**0.5614**	**0.0952**	**0.2111**	**0.3321**	**0.2634**	**0.2609**	**0.2712**
Final Adopters of T2 in %	min	4.1	22.8	45.5	65.3	21.6	43.4	63.0	15.5	28.6	42.2	12.9	24.0	36.2	6.4	8.0	10.8	4.2	4.2	4.1
	mean	**6.4** (9.37) [0.821]	**31.0** (31.282) [2.742]	**56.7** (35.988) [3.154]	**74.4** (28.094) [2.463]	**29.7** (31.113) [2.727]	**54.2** (36.404) [3.191]	**71.6** (29.614) [2.596]	**21.9** (26.235) [2.300]	**40.2** (36.846) [3.23]	**54.9** (34.833) [3.053]	**19.9** (24.125) [2.115]	**36.2** (35.704) [3.13]	**49.9** (34.956) [3.064]	**10.1** (14.894) [1.306]	**13.8** (21.218) [1.86]	**17.9** (30.673) [2.689]	**6.5** (9.46) [0.829]	**6.4** (9.102) [0.798]	**6.4** (9.363) [0.821]
	max	9.4	40.4	68.2	82.2	39.7	66.5	79.4	30.3	49.5	65.3	28.3	47.1	59.3	15.1	22.7	29.4	9.9	10.7	9.4
Absolute Patent Pledge Effect (APPE)		N/A	**24.621**	**50.361**	**68.058**	**23.304**	**47.928**	**65.267**	**15.492**	**33.850**	**48.533**	**13.525**	**29.865**	**43.516**	**3.708**	**7.455**	**11.522**	**0.101**	**0.05**	**-0.001**
Relative Patent Pledge Effect (RPPE)		N/A	**24.621**	**50.361**	**68.058**	**23.804**	**48.956**	**66.667**	**18.312**	**40.059**	**57.436**	**16.843**	**37.238**	**54.327**	**7.343**	**14.821**	**22.861**	**0.631**	**0.315**	**-0.006**

Note:
- Values in parentheses indicate the standard deviation.
- Values in square brackets indicate the mean confidence interval, assuming that the confidence level equals 95%.
- Standard deviation and mean confidence intervals constitute absolute values with 1000 agents as reference. Adopter values are shown in percentage.
- Values in 'Final Adopters of T2 in %' are rounded to one decimal for illustration purposes. APPE and RPPE are calculated using three decimals.

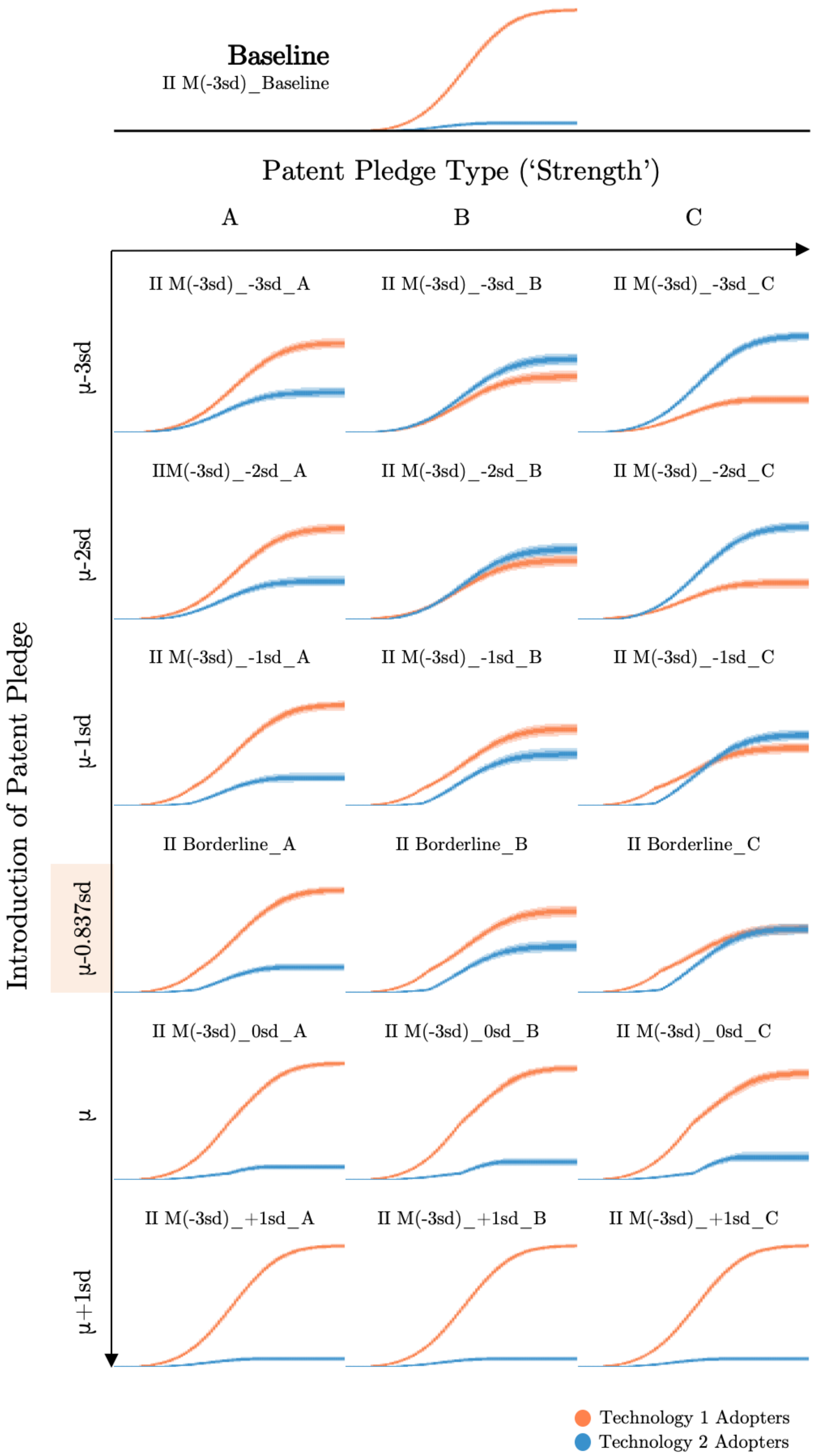


Fig. 6.23 Borderline chart for patent pledge type C at $\mu - 0.837\sigma$.

In a next step, the borderline scenario for a medium patent pledge was investigated. A medium patent pledge (type B) generally needs to be introduced earlier than a strong patent pledge (type C) so that T2 still wins the adoption competition. Through additional experiment runs, it was found that the borderline scenario for a medium patent pledge (type B) occurred at approximately $\boldsymbol{\mu - 1.530\sigma}$.[11] The final adopters of T2 at that time reached 49.9% market share (mean value). In the best case, a medium patent pledge (type B) that was introduced at that time led to a market share of 60.6% for T2; in the worst case, a market share of 37.9% was reached.

The borderline scenarios for a strong and a medium patent pledge indicate that a strong patent pledge (type C) allows to wait for an additional 0.694 standard deviations (or 231 time units when all adopters have adopted at 2000 time units) to still reach 50% market share. This indicates that patent pledgors can wait with the introduction of a strong patent pledge (type C) to still win the adoption competition. They might want to do so to see if a natural preference for their technology occurs and a patent pledge becomes unnecessary. On the other hand, patent pledgors that do not want to introduce a strong patent pledge (type C) because it would be too unrestricted, for instance, should introduce a medium patent pledge before $\mu - 1.530\sigma$ to win the adoption competition. A weak patent pledge (type A) did not lead to a 50% market share for T2 in any scenario of case II. This means there exists no borderline scenario for a weak patent pledge (type A) when T2 is inferior. As a result, patent pledgors that supply an inferior technology and aim to win the adoption competition should consider a medium or strong patent pledge. Further practical implications are given in chapter 6.4.2.

6.4 Study 3 discussion

This section elaborates upon the findings from Study 3 described in the previous section. First, the findings are discussed in light of two literature streams, (i) general technology diffusion and (ii) simulation modeling/aggregate models in areas relating to open innovation. It is shown that patent pledges can help overcome barriers of technology diffusion described in the literature and that the results strongly indicate that patent pledges can serve as a strategic instrument so that inferior technologies can win the adoption competition against superior substitutes. Second, specific practical implications for the utilisation of patent pledges are given. It is described under what conditions patent pledges might be particularly useful and when it might be best not to utilise them.

[11] $\mu - 1.530\sigma$ translates to 490 time units when all adopters have adopted at 2000 time units.

6.4.1 Link to existing theories

6.4.1.1 Technology diffusion

Patent pledges can be seen as strategic instruments to overcome barriers in technology diffusion processes that were described in the literature. Moore (1991), for instance, described a *chasm* between the adopter types *Early Adopters* and *Early Majority*. His prevalent argument was that technology adoption processes do not automatically infer that technologies are adopted by all adopter types. Rather, many technologies fail to transition from one type to another. Moore, who focused on disruptive or discontinuous innovations, argued that the mentality between *Early Adopters* and *Early Majority* is different in the sense that the *Early Adopters* are primarily looking for change, whereas *Early Majority* adopters seek productivity improvement. The challenge, according to Moore, lies in transitioning between these two adopter categories. He called this transitioning '*crossing the chasm*'.

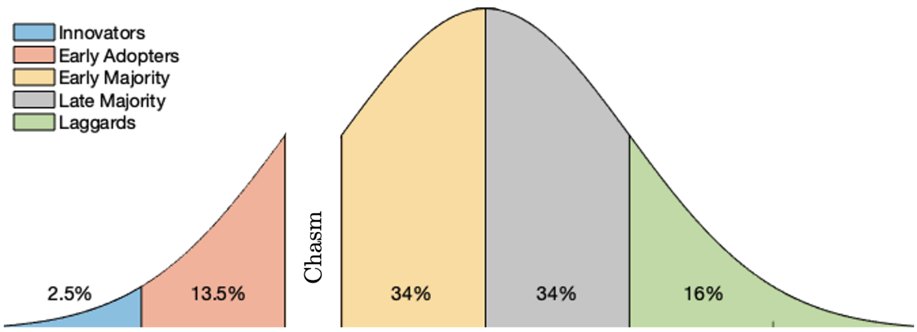


Fig. 6.24 The 'chasm' between Early Adopters and Early Majority described by Moore (1991).

Moore (1991) described several techniques to facilitate this transition, such as specific marketing strategies, incorporating a whole product model, and the right choice of pricing. Patent pledges, too, can constitute a measure to facilitate this transition. The use of patent strategies to 'cross the chasm' was also described by Grzegorczyk (2020). Grzegorczyk mentioned Monsanto as an example for a firm that successfully opened up its IP strategies to overcome the chasm described by Moore. Monsanto licensed-out a specific technology that was then adopted and refined by other firms (Grzegorczyk, 2020). In a similar manner, the previous section showed that when a patent pledge is introduced before the adopter category *Early Majority*, large effects on the adoption rates can occur. The results showed that in some scenarios, more than 60 percentage points in market share could be gained through a patent pledge (see fig. 6.20). Even if that figure would be much lower in reality, say 20 percentage points, this would still constitute a substantial gain. Katz and Shapiro (1986) also showed in their study that *sponsored* technologies can have a positive effect on technology diffusion.

Their study is discussed in more detail below, because they primarily address diffusion in the context of competing technologies. Generally, the findings of Study 3 support prior studies that found a positive correlation between patent pledges and technology diffusion (Wen et al., 2016). A detailed comparison with the studies of Wen et al. (2016), Sundaresan et al. (2017), and Contreras et al. (2019) remains difficult, however, because these studies collected empirical data for one specific scenario to measure the effect of patent pledges on technology diffusion. Study 3, in contrast, simulated multiple, hypothetical scenarios. Study 3 should therefore not be compared to the studies of Wen et al. (2016), Sundaresan et al. (2017), and Contreras et al. (2019), but should rather be seen as a blueprint under what settings patent pledges can lead to large effects on adoption rates.

The conclusion that patent pledges lead to higher adoption rates appears to be also true for inferior technologies that might inherit problems to be adopted by the *Early Majority*. As Moore (1991) noted, these adopters are looking for productivity improvement rather than change. Scheme I of case II illustrates this. In this scheme, the inferior technology failed to be widely adopted without a patent pledge. Its adoption curve stagnated approximately from the beginning of the *Early Majority* (see the baseline scenario in fig. 6.14) and the technology arguably failed to 'cross the chasm'. When a strong patent pledge for this inferior technology was introduced early on, however, a clear preference for this technology occurred. The average market share for the inferior technology in these settings reached more than 70% with maximum values of more than 80%. Patent pledges in this scenario enabled the inferior technology to 'cross the chasm'. The same seemed to be true for scheme II of case II, where an inferior technology was introduced after the *Innovators* have already adopted a superior substitute. An early patent pledge led to the adoption competition win of the inferior technology, but when no patent pledge was introduced, the technology failed to 'cross the chasm'. Study 3 therefore adds to the early work of Moore (1991) and the broad realm of technology diffusion. Specifically, the simulation results support literature that described IP mechanisms to overcome the chasm (see for instance Grzegorczyk (2020)).

The findings from the simulation model of Study 3 furthermore supplement existing research about competing technologies. Katz and Shapiro (1986), for instance, investigated technology adoption of competing technologies under different settings. The authors called a technology *sponsored* when property rights for it are controlled by a firm so that the firm can offer initially low prices for this technology. This investment can then be recouped later on. The firm offers the technology on initially low prices to establish it in the market and to gain an advantage over a competing technology. Katz and Shapiro investigated three different scenarios (both technologies are unsponsored, one technology is sponsored, and both technologies are sponsored) and found that a sponsored technology may be adopted even if it is inferior to an unsponsored substitute. Sponsored technologies described by Katz and Shapiro (1986) seem to clearly relate to the patent pledges discussed in this research. In Study 3, patent pledges, among other influences, reduced the price of a technology. This appears comparable to what Katz and Shapiro called the initial price reduction of a sponsored technology. The authors only mentioned one possibility that could lead to the presence of one unsponsored and one sponsored, competing technology: when '*an emerging technology, B, could be patented while the older technology, A, is no longer subject to effective patent protection*' (Katz and Shapiro, 1986, p. 833). It is argued that patent pledges pose a further possibility that could lead to a sponsored technology. When both technologies are patented but only one is subject to a patent pledge, this could lead to a reduced price for the pledged technology. The finding of Katz and Shapiro (1986) that a sponsored inferior technology may be adopted over a superior, unsponsored substitute is strongly supported by Study 3. The simulation model showed that an inferior technology can win the adoption competition even if its patent pledge is only introduced after the *Early Adopters* have already adopted (see for instance scenario II M(-2sd)_-1sd_C in fig. 6.15). The characteristics that might qualify a technology as being 'superior' or 'inferior' to competing alternatives are not always clear. Nevertheless, it is generally acknowledged that technologies are compared with regards to their performance (Nainwal, 2018). A prominent example is the replacement of sailing ships through steamships, which appeared in a similar realm as the patent pledges of Tesla and Toyota (Nainwal, 2018; Rosenberg, 1972). Their patents relate to technologies that aim to replace gasoline powered vehicles with more efficient and sustainable alternatives.

Patent pledges can be used as a strategic instrument that is comparable to what Katz and Shapiro (1986) called a 'sponsored technology'. It is also conceivable to take on a less price-focused perspective than Katz and Shapiro and to not necessarily see patent pledges as ways to sponsor a technology. Patent pledges could also be seen as 'insignificant events' as described by Arthur (1989). Arthur explored the adoption of two competing technologies under the influence of 'insignificant events', such as political events or unexpected successes of a technology. The author showed that these events can lead to a 'lock-in' of an inferior technology over a superior alternative, similar to the results provided by Katz and Shapiro (1986) in the context of sponsored technologies. Examples for the 'lock-in' of inferior technologies over superior alternatives include the gauge of British railways, the US colour television system, the programming language FORTRAN, and the QWERTY-keyboard (Arthur, 1989; David, 1985; Kindleberger, 1983). While it appears difficult to attribute similar effects to the relatively new phenomenon of patent pledges, Study 3 suggests that a 'lock-in' from patent pledges can occur. This is particularly true when patent pledges are perceived as insignificant events' described by Arthur (1989). In scheme II of case I, for instance, both technologies were similar but T2 was introduced after the *Innovators* have already adopted T1 (see fig. 6.11). Without a patent pledge, both technologies followed approximately the same adoption curve and their market share was almost equal. A medium patent pledge (type B) introduced together with T2, however, led to a lock-in of T2 and a market share of almost 90% for this pledged technology. From fig. 6.11 it can be seen that the adoption curve of T1 stagnated - the technology became locked out. Similar observations can be made from scheme I of case II where T2 was inferior to T1. Whether patent pledges are seen as ways to sponsor a technology as described by Katz and Shapiro (1986) or as insignificant events according to Arthur (1989), Study 3 supports the findings that inferior technologies can win the adoption competition against superior alternatives. Furthermore, the collection of preliminary industry feedback for the suggestibility of technology attributes through patent pledges strengthens the predictive value of the simulation model. The studies of Katz and Shapiro (1986) and Arthur (1989) inherited several limitations that were overcome by the simulation model of Study 3. These limitations are, for instance, the strong focus on technology prices and the assumption that the adopters are homogeneous. The ABM of Study 3 implemented the costs of a technology as one out of 16 technology attributes and therefore simulated a more comprehensive adoption behaviour. A more realistic behaviour of the agents was also achieved through the simulation of heterogeneous agents. It can be concluded that the simulation model of Study 3 expands the studies of Katz and Shapiro (1986) and Arthur (1989) by simulating several introduction points for both T2 and its patent pledge. The conclusion of Study 3 is that even when simulating a more comprehensive adoption behaviour than was the case in the early studies of Katz and Shapiro (1986) and Arthur (1989), their conclusions that inferior technologies can win the adoption competition over superior alternatives hold true. Results from Study 3 showed under what specific settings this is the case. For instance, take an inferior technology that is introduced at about the same time as a superior substitute. In order to win the adoption competition, this inferior technology must be subject to a strong patent pledge that is introduced before the *Early Majority* begins to adopt. Otherwise, no large patent pledge effects and a lock-out of the inferior technology should be expected (see fig. 6.14). The studies of Katz and Shapiro (1986) and Arthur (1989) constituted seminal, early studies in the field of technology diffusion of competing technologies. Newer studies in the area investigated further reasons why an inferior technology might eventually become dominant. Lehmberg et al. (2019), for instance, investigated the flat panel display industry and argued that the initially inferior liquid crystal displays emerged as the dominant design because of its suitability for adjacent markets. The authors argued that network externalities as described by Katz and Shapiro (1986) did not play a role in this specific case. Rather, the set of market opportunities for each technology played a crucial role in its diffusion, which Lehmberg et al. called *application market adjacency*. While Study 3 did not simulate adoption processes in adjacent markets, this might pose an interesting avenue for future research. This is particularly true when patent pledges are not restricted to specific applications, but when they allow the patent utilisation in adjacent areas. It is conceivable that patent pledges facilitate *application market adjacency* as described by Lehmberg et al. (2019) and thereby further support the diffusion of an inferior technology.

To conclude, Study 3 supports findings from previous studies that an inferior technology can win the adoption competition against a superior substitute. Existing literature identified several factors that facilitate this competition win, such as positive network externalities (Katz and Shapiro, 1986), increasing returns (Arthur, 1989), or application market adjacency (Lehmberg et al., 2019). Study 3 adds to these studies by reporting that patent pledges, too, can lead to the adoption competition win of an inferior technology against a superior substitute.

6.4.1.2 Simulation modeling and aggregate models in the context of open innovation

Study 3 also adds to existing research in the broad realm of open innovation, specifically to the few studies that approached this topic with simulation modeling. Study 3 is comparable to the study of Bonaccorsi and Rossi (2003), who developed an abstract simulation model to investigate open-source software diffusion. Even though the focus of Study 3 was on patent pledges, it relates to the study of Bonaccorsi and Rossi (2003) because they compared the adoption rates between a proprietary and an open-source software. They therefore simulated the adoption behaviour of products that differed in their '*openness*'. While the study of Bonaccorsi and Rossi (2003) had a similar approach to Study 3, it reported findings only on an aggregate level. The simulation model of Study 3 depicted multiple diffusion curves and introduced several indicators such as the absolute and the relative patent pledge effects. Study 3 therefore supplements the findings of Bonaccorsi and Rossi (2003) and its indicators can serve as a guideline for future enquiries. Specifically, the APPE/RPPE and the gradient difference can be used by future studies to report findings about diffusion rates under patent pledges. Furthermore, the simulation model of Study 3 relates to the aggregate model proposed by Harhoff et al. (2003). The authors developed a game-theoretic model to investigate incentives to freely reveal proprietary innovations. Harhoff et al. defined freely revealing similar to patent pledges in this research. The ABM of Study 3 supports the findings of Harhoff et al. (2003), because it also concluded that revealing proprietary rights can result in higher adoption rates. The simulation model of Study 3 thereby overcame the usual limitations that aggregate models inherit (see table 3.5). In a more recent study, Alexy et al. (2018) investigated similar to Harhoff et al. (2003) scenarios where *strategic openness*, that is the voluntary forfeiture of control over resources, maximises the profitability of firms. The authors developed a mathematical model and found that a firm's performance improved when (i) their cost base was reduced through the opening of resources while (ii) the demand for their proprietary resources was strongly increased (Alexy et al., 2018). Even though the model of Alexy et al. did not specifically focus on technology diffusion but generally on a firm's performance, their study is related to Study 3. This is because the authors mentioned past patent pledges of IBM and Computer Associates as strategies to forfeit control over proprietary resources. Study 3 therefore complements the study of Alexy et al. (2018) by investigating the effect of such strategies specifically on adoption rates of technologies and adds insights about when forfeiting control can have large effects on technology diffusion.

To conclude, Study 3 complements existing research that combines simulation modeling or aggregate models with open innovation practices. It serves as a blueprint for how to investigate different scenarios and report findings with novel indicators, which was missing in previous simulation models in related areas (see for instance Bonaccorsi and Rossi (2003)). The ABM supports the finding of Bonaccorsi and Rossi (2003) that open innovation practices can result in higher adoption rates. Study 3 further complements aggregate models in the realm of open innovation, specifically the studies of Harhoff et al. (2003) and Alexy et al. (2018). The former study dealt with adoption processes without a focus on patent pledges, the latter study concerned patent pledges (among other open innovation practices), but focused on a firm's general performance. The simulation model of Study 3 connects the two studies by investigating technology diffusion under patent pledges and also overcomes their limitations as aggregate models (see table 3.5).

6.4.2 Practical implications

The findings from Study 3 lead to specific practical recommendations. This section describes these implications from (i) the perspective of technology suppliers and (ii) from the perspective of technology adopters.

6.4.2.1 Implications for technology suppliers

Technology suppliers can use the insights from Study 3 to make informed decisions when confronted with patent pledges in two situations: (i) when they consider conducting a patent pledge themselves and (ii) when they provide a technology whose competing substitute is subject to a patent pledge.

Technology suppliers that intend to conduct a patent pledge to drive adoption of their supplied technology can infer from the findings of Study 3 that early and strong patent pledges usually exhibit the largest effects. This holds true for both cases, when the technology and its competing substitute are similar as well as when the supplied technology is inferior. It was shown, however, that the effect size is not linearly dependent on the timing of a patent pledge. An interesting observation was that in many scenarios, the patent pledge did not need to be introduced with the beginning of the adoption to still have a lasting effect. When the pledge was introduced immediately at the beginning of the adoption process (i.e. before the *Innovators* started to adopt), it only achieved marginally higher effects on technology adoption rates than when it was introduced after the *Innovators*. In this context, it is conceivable that technology suppliers can take this marginal loss and wait to see the adoption process unfold instead of committing to a patent pledge right at the beginning of the adoption period. The results showed that patent pledges that happen before the *Early Majority* started to adopt were often sufficient to win the adoption competition against a competing technology, even when the competing technology was superior.[12] Table 6.7, for instance, showed that a strong patent pledge that was introduced before the *Early Majority* started to adopt led, on average, to the adoption competition win of the pledged, inferior technology. When the same patent pledge was introduced before the *Early Adopters*, the pledged, inferior technology always won the competition. When the adopter category *Early Majority* has already adopted, however, patent pledges led to significantly lower adoption results (up to a decrease of 37 percentage points in market share, see table 6.13). It is therefore recommended to conduct patent pledges before the *Early Majority* begins to adopt. Patent pledges generally did not show large effects on adoption rates when they were introduced after the *Late Majority*.

To make a recommendation regarding the patent pledge strengths, technology suppliers need to evaluate their technology against the competing substitute. When both technologies are perceived as being similar, a weak patent pledge that is introduced when the *Early Majority* begins to adopt can lead to a market share gain of up to 80% for the pledged technology. This value further increases the earlier the patent pledge is introduced. The technology supplier therefore can retain some restrictions on his patent pledge and can still reach a high market share. She can, for instance, offer the patent pledge to the restricted instead of the unrestricted public and thereby keep some competitive advantages (see fig. 6.2). The non-linear relationship between the patent pledge strength and the number of final adopters

[12] This assumes that both technologies are introduced at the same time.

of the pledged technology further indicates that a weak and medium patent pledge are often sufficient to gain large effects on the adoption rates. When the technology is perceived as being inferior, however, a strong patent pledge that is available to the unrestricted public without any monetary compensation is recommended. In this case, weak or medium patent pledges in the simulation were often not sufficient to win the adoption competition and the pledged technology became locked-out of the market. Fig. 6.25 summarises practical patent pledge recommendations and insights for different introduction points of a technology that is competing with a substitute technology. This summary can serve as a management tool, specifically as a matrix-based table as discussed by Phaal et al. (2006), to decide on specific actions when technology suppliers face the decision to conduct a patent pledge.

Technology	Before Innovators (at μ - 3σ)	Before Early Adopters (at μ - 2σ)	Before Early Majority (at μ - 1σ)	Before Late Majority (at μ)
is similar to a competing substitute	• Patent pledges lead to higher adoption rates and are recommended. • Strong patent pledges before the Early Majority can lead to 90% market share of the technology. • Weak and medium pledges after the Early Majority are often sufficient, because they can still lead to a market share of 60%. • The introduction of patent pledges after the Innovators (compared to before the Innovators) only results in a small loss of patent pledge effects.	• Most patent pledges that are introduced before the Late Majority lead to a market share of more than 50%. • Weak patent pledges can reach 75% market share when introduced before the Early Adopters (medium patent pledges can reach 87%). • Patent pledges after the Late Majority only have small effects on adoption rates.	• Medium and strong patent pledges before the Early Majority still lead to the competition win of the technology (weak patent pledges do so in 87% of cases). • After the Early Majority, medium and strong patent pledges are recommended, but do not always result in the competition win. • Weak patent pledges are not recommended after the Early Majority, because they lead to the competition win in only 0.4% of cases.	• Patent pledges do not lead to the competition win of the technology. • In the best case, a strong patent pledge that is introduced before the Late Majority leads to a market share of about 31.5%. • Medium and strong patent pledges can be used to gain between 9 and 14 percentage points in market share. • Weak patent pledges after the Early Majority only lead to a market share gain of 3.9 percentage points.
is inferior to a competing substitute	• Strong patent pledges before the Early Adopters are recommended to win the competition, but medium pledges can accomplish this, too. • After the Early Adopters, only strong patent pledges are recommended. • Weak patent pledges do not lead to the competition win and are not recommended. • Patent pledges after the Late Majority have no effect on adoption rates.	• Strong patent pledges (and often medium patent pledges) before the Early Adopters are recommended to win the adoption competition. • After the Early Adopters, strong patent pledges lead to the competition win in 88% of cases, whereas medium patent pledges do so in 0%. Here, medium patent pledges are not recommended. • Weak patent pledges do not lead to the competition win.	• The competition win can only be achieved with a strong patent pledge before the Early Majority, but only in 46% of cases. • Medium patent pledges before the Early Majority do not lead to the competition win, but can still result in a market share gain of 31 percentage points (14 for a weak patent pledge). • Strong patent pledges after the Early Majority can still be used to increase the market share by 9.1 percentage points.	• Patent pledges do not lead to the adoption competition win of the inferior technology. • Patent pledges are only recommended when the goal is to achieve market share gains up to 6.7 percentage points. • The cost of conducting a patent pledge must be balanced against the small effects on adoption rates.

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Fig. 6.25 Practitioner summary for conducting patent pledges in the realm of competing technologies.

Some practical implications can be given for a technology supplier who herself does not intend to conduct a patent pledge. Even though she does not conduct a pledge, the technology supplier of a competing technology could do so. In this hypothetical scenario, the recommendations from the previous paragraph are reversed. When the adopter category *Early Majority* has already adopted, the patent pledge of the competing supplier cannot unfold its full effect on the adoption rates. Nevertheless, when both technologies are (i) perceived as being similar, (ii) the technologies were introduced at the same time, and (iii) the patent pledge is strong, the competing technology can still reach 70% market share in this setting. When the competing technology is inferior, however, the same patent pledge in the same setting only leads to about 18% market share. This implies that technology suppliers should evaluate how their technology compares to the pledged substitute. When the substitute is perceived as being similar, the technology supplier might want to initiate countermeasures to weaken the patent pledge effects. Such countermeasures could be penetration pricing strategies as described by Katz and Shapiro (1986), or, if applicable, own 'counter patent pledges'. Such complex hypothetical scenarios that simulate reactions to patent pledges go beyond the scope of Study 3, but pose an interesting topic for future research.

6.4.2.2 Implications for technology adopters

Some implications for technology adopters can be derived from the findings of Study 3. It is assumed that technology adopters have an incentive to adopt the technology that will be utilised by most adopters in the future. This is because the '*benefit that a consumer derives from the use of a good often depends on the number of other consumers purchasing compatible items*' (Katz and Shapiro, 1986, p. 822). This benefit was referred to as *positive network externalities* by Katz and Shapiro (1986) and is related to the concept of *increasing returns* described by Arthur (1989). Technology adopters that face the decision between two competing technologies can use the insights from Study 3 to estimate the prospective adoption rates of the technologies and, therefore, their positive network externalities. When an inferior technology is subject to an early, strong patent pledge and both technologies were introduced at the same time, for instance, the findings suggest that the inferior technology wins the adoption competition in most cases (see for instance scheme I of case II in fig. 6.14). When the goal in this hypothetical scenario is to maximise positive network externalities and to choose the technology that wins the adoption competition, the technology adopter should choose the pledged technology that is inferior today over the unpledged, superior technology. When the technology supplier of the inferior technology conducts the patent pledge in this scenario later on, say after the *Early Majority* has already adopted, the technology adopters should expect that the unpledged, superior technology wins the adoption competition and choose this technology to maximise network externalities. In case both technologies are similar, the pledged technology seems to be the best choice for the adopter as long as the technology and its patent pledge are introduced before the *Early Majority* starts to adopt. When the pledged technology is introduced later, the unpledged technology that is on the market for longer is likely to be the optimal choice. Difficulties arise when technology adopters want to maximise network externalities and need to decide between two competing technologies, but do not know if a technology will be subject to a patent pledge in the future. While this cannot be predicted with certainty, some indicators could point towards future patent pledges. When patent rights for a technology are held by multiple technology suppliers, the patent pledge of one firm might not be very useful to a technology adopter. This is because she still needs to acquire licenses or negotiate use with the remaining suppliers to utilise the technology.[13] When the patent rights are held by one technology supplier only, however, a patent pledge would give immediate access to the related technology. The problem is that in this case where all patent rights are held by one supplier, the patent owner could also exclude others from the use and retain revenues through a proprietary business model. Here it is important to look at both the characteristics of the supplier as well as the general market trend. If the supplier has engaged in open innovation practices in the past, this might be an indication that she is inclined to conduct patent pledges in the future. Many of the patent pledgors from Study 1, such as RedHat and Microsoft, had a history of supporting open-source practices and devoting themselves to FRAND-licensing agreements. Apart from the technology supplier herself, the market trend can also give an indication if a technology might be subject to a patent pledge in the future. Take the patent pledge of Tesla as an example. The firm initially patented their technologies relating to electric vehicles to defend themselves against large competitors (Musk, 2014). The market for electric vehicles grew slower than the firm had expected, however, forcing the automaker to find ways to drive growth in this area. Similarly, technology adopters have reasons to expect patent pledges for emerging technologies that exhibit slower than expected growth in their early stages.

[13] The possibility of standard setting in this context is left aside.

Chapter 7

Conclusions

The three previous chapters addressed the research objectives of this thesis. Question-specific discussions were made at the end of each chapter. This chapter first summarises the main findings from the previous chapters, describes theoretical and practical contributions, addresses limitations, and suggests future research directions. The chapter ends with a final conclusion.

7.1 Summary of Findings

7.1.1 Study 1: definition and taxonomy of patent pledges

The literature review showed that many different notions of patent pledges exist (see chapter 2.1). This leads to contorted results of further studies, such as results of studies that investigate motives for patent pledges. The collection of patent pledges and abductive analysis in chapter 4.3.1 led to an empirical definition of patent pledges. The coding process comprised *conventional content analysis* and *pattern coding*. Twelve first order concepts from the coding process led to six second order concepts, which in turn resulted in three aggregate dimensions. The patent pledge definition consisted of the dimensions *Accessibility*, *Compensation*, and *Conditions*. Each dimension took one of two values (the second order concepts), which resulted in a total of eight patent pledge types. The values were mutually exclusive and collectively exhaustive, which qualified the resulting patent pledge model as a *taxonomy* according to Nickerson et al. (2013). Table 4.1 provided a summary of conditions and their prevalence in patent pledges. It was found that the most frequent patent pledges are of the types *conditional, public free* (32%), *conditional, public priced* (20%), and *conditional, semi-public free* (18%). Most patent pledges were subject to certain conditions, because they were often limited to specific applications and/or territories or made use of a non-assertion clause.

The taxonomy development did not end with the eight patent pledge types. Nickerson et al. (2013) argued that 'useful' taxonomies are extendible. The dimensions *Accessibility* and *Compensation* from the patent pledge taxonomy were extended by three values respectively. The result was a comprehensive patent licensing taxonomy that depicts all common patent licensing approaches. The patent licensing taxonomy can act as a further instrument to bring clarity into the 'thicket' of terminologies around the subject (Ehrnsperger and Tietze, 2019). The distinction between patent pools, patent donations, and patent pledges, for instance, was often confused in the literature (see for instance the study by Ziegler et al. (2014)). The patent licensing taxonomy allows for a better distinction between different licensing approaches and enables a more consistent use of terminologies. It was further shown that, drawing on previous literature, patent owners transitioned through the patent licensing taxonomy and did not necessarily remain in their initial position. Changes in their competitive environment as well as legal requirements, for instance, spurred these transitions. The patent licensing taxonomy can also serve as a strategic instrument to facilitate decision processes within firms (Phaal et al., 2006, 2012). Specifically, it was shown that the taxonomy allows for the visualisation of the patent licensing landscape for technologies of interest (see fig. 4.6).

7.1.2 Study 2: motives for patent pledges

Chapter 2.2 showed that previous studies speculated about the motives for patent pledges. Study 2 approached this topic by (i) conducting a pilot study consisting of eight semi-structured interviews with local firms, (ii) conducting a main study consisting of 22 semi-structured interviews with IP experts, and (iii) analysing 50 patent pledge statements that served as secondary data. The study gained access to renowned IP experts with an average professional IP experience of more than 21 years, including the former president of a large national patent office and the president of the patent department at one of the largest tech-companies to date. The interviews of the main study were analysed in three coding cycles, the patent pledge statements in two coding cycles. The first coding cycle comprised *initial coding*, the second one *pattern coding*, and the third one *latent content analysis*. The reliability of the results was ensured through the external review and code allocation of an independent, postdoctoral IP researcher. Thirteen motives belonging to three categories were identified. These categories were *economic motives* (five motives), *perceptional motives* (six motives), and *technological motives* (two motives). Ten out of the 13 motives were mentioned in both, the primary and the secondary data. It was found that 80% of pledging interviewees showed strong evidence that the main motive for patent pledges is to drive technology diffusion. The second and third most prominent motives were '*Decreasing uncertainty and patent threats*' and '*Building reputation and PR*'. The interviews revealed some further insights apart from the motives for patent pledges, such as information about their design and the tracking of users.

As mentioned above, driving technology diffusion was found to be the primary motive for patent pledges. By drawing upon a proven framework from the literature, the TASC model by Asare et al. (2016), it was shown that most remaining motives, too, link to technology diffusion. These motives addressed specific attributes of the TASC model that ultimately influence the decision to adopt a technology. For instance, the motive '*Standard setting and fostering interoperability*' linked to the '*Systems Compatibility*' attribute of the TASC model. It was further shown that patent pledges are particularly prevalent in the realm of competing technologies. Patent pledges aim to drive technology diffusion when there exist substitute technologies to the pledged technology. One interviewee explained that his firm conducted a patent pledge to incentivise the utilisation of his firm's technology over other firm's competing technologies. This posed the question if patent pledges have a measurable effect on technology diffusion rates, specifically in the context of competing technologies.

7.1.3 Study 3: effect of patent pledges on technology diffusion

The effect of patent pledges on technology diffusion was part of an academic debate and different studies found contradictory results (see chapter 2.3). Study 3 was the first to develop an abstract simulation model to investigate this effect. Three patent pledge types, weak, medium, and strong, were simulated. These types were derived from the patent pledge taxonomy and followed findings from Study 1 (see fig. 4.3). The study simulated the adoption competition between a technology T1 and a competing technology T2. Only T2 was subject to a patent pledge. Adopters in Study 3 were 1000 firms that either adopted T1 or T2. Different introduction points for T2 and its patent pledge, following the adopter distribution of Rogers (1962), were simulated. Two cases were considered: in case I, T2 was similar to T1; in case II, T2 was inferior to T1. Approximately 50,000 experiment runs were conducted. The decision rules of the adopters and the simulation parameters were reviewed and verified by industry experts.

Novel indicators that measured the absolute and the relative effect of patent pledges, the APPE and the RPPE, were introduced. While the APPE calculated the difference of final adopters as a result of the patent pledge, the RPPE normalised this difference to the market share of the remaining potential adopters at the time of the patent pledge. It was found that the relationship between these indicators and the patent pledge types is not linear, even though the types (or strengths) were evenly graduated. The effect growth rate of the median from type A to type B averaged around 72.5% for case I and 102% for case II, whereas the growth rate from type B to type C was about 18.9% and 54.18% respectively. Another finding was that the dispersion of the effect is larger the stronger the patent pledge is. The patent pledge effect depends to a large extend on the timing of the introduction of the technology and its patent pledge. This is why in the next step the dependence of this effect on the timing of patent pledges was investigated.

It was shown that the difference of the patent pledge effect is relatively small in the beginning of the adoption curve, while the adopter category *Early Majority*, as described by Rogers (1962), seems to be critical for the effect. This was found to be particularly true when the pledged technology is inferior to a competing substitute. When the competing technologies are similar, the largest change in the relative patent pledge effect occurs between the time periods μ and $\mu + 1\sigma$, which translates to the adopter category *Late Majority*. This was only true for the relative effect, however. The absolute effect still exhibited the largest decrease in the adopter category *Early Majority*. The APPE and the RPPE both considered the final number of adopters and therefore measured the slow effect of patent pledges. The fast effect was measured by the gradient difference of the adoption curve in an interval of $\pm 1\sigma$ at the time of the patent pledge. It was shown that this fast effect exhibited similar characteristics to the slow effect. Finally, the latest possible entry points to conduct a patent pledge that results in a market share of 50% when the pledged technology is inferior was investigated. These specific scenarios were called *borderline scenarios*. It was shown that only medium and strong patent pledges can result in a 50% market share when both technologies are introduced at the same time and the pledged technology is inferior. This tipping point was found to range around the time $\mu - 0.837\sigma$ for a strong patent pledge and at $\mu - 1.53\sigma$ for a medium patent pledge.

7.2 Contributions

7.2.1 Theoretical contributions

This research contributes to knowledge and existing theories in several ways. Study 1 enables the distinction to other forms of patent sharing through the empirically derived definition of patent pledges and the developed taxonomies. Existing literature confused patent pledges with other sharing mechanisms (see for instance Ziegler et al. (2014)), which hindered the comparison of results. The fact that patent pledges were discussed in a variety of fields, such as law and management studies, further complicated a uniform understanding. The definition of patent pledges in Study 1 built upon the patent pledge collection of Contreras (2019) and is the first definition that was empirically derived through qualitative coding. It thereby supplements the early work of Contreras (2019) and his unparalleled collection of patent pledges. The definition and the patent pledge taxonomy lay the groundwork for future research in this area. Part of the problem of an inconsistent view and different notions about patent pledges was arguably the existence of different types. The patent pledge taxonomy poses a general framework that comprises all patent pledges from the sample, which makes it possible for future studies to relate their study to others in the field. This is not only true for patent pledges, but also for all common types of patent licensing approaches. The patent licensing taxonomy that extended the patent pledge taxonomy followed the taxonomy development of Nickerson et al. (2013) and used standardised dimensions to depict all common forms of patent licensing. Study 1 therefore adds to existing theories that develop taxonomies, specifically from textual data. Scholars in the field can use the patent licensing taxonomy as a reference to clarify the subject of their studies. They can classify their investigated patent licensing approach by assigning values to the dimensions *Accessibility*, *Compensation*, and *Conditions*, which facilitates the comparison to other patent licensing approaches. It was also shown that the patent licensing taxonomy contributes to existing theories by enabling the illustration of patent licensing approaches described in previous studies. Prior to the taxonomy, transitions in patent licensing were mainly described in textual form. In Study 1, the licensing practices of firms described by Fosfuri (2006) and Grindley and Teece (1997), for instance, were illustrated in the patent licensing taxonomy to facilitate the comparison between them (see fig. 4.5). This makes it easier to comprehend the described licensing approaches and to gain an aggregated view when investigating several studies or licensing practices. The taxonomy also adds a strategic instrument to the literature about technology management tools, specifically a matrix- or grid-based tool as described by Phaal et al. (2006).

Study 2 strongly supports the main motive for patent pledges suggested in the literature. Contreras (2017a), for instance, mentioned the motive to induce other market participants to adopt a certain technology as a major motive for patent pledges. The exchange with renowned IP experts through case study research poses a complement to the empirical derivation of motives by Contreras et al. (2019) and overcomes limitations of studies that relied on secondary data. Ziegler et al. (2014), for instance, were not able to gain access to people directly involved in patent pledges and relied on press releases or firm reports, among others. This obstacle of gaining access to qualified interview participants might be one of the reasons why earlier studies followed motives from other open innovation models (see Schweisfurth et al. (2011) for an overview). Study 2 therefore adds an explicit view, because 13 motives solely for patent pledges were identified. It further adds to the literature about motives in a managerial context, for instance to the studies of Bansal and Roth (2000) and Belal and Owen (2007). A specific theoretical contribution lies in the connection of patent pledge motives with the literature about technology diffusion. It was shown that the identified motives relate to technology adoption attributes of the TASC model described by Asare et al. (2016), which highlighted the prevalent goal of patent pledges to drive technology diffusion. Specifically, fig. 5.3 illustrated the primary influence of the motive categories on the individual technology attributes of the TASC model. Asare et al. (2016) focused on inter-firm diffusion processes, which is why Study 2 particularly strengthens the link between patent pledges and technology diffusion on an organisational level. Study 2 furthermore links motives for patent pledges to the general theory of motivation, because the identified motives appeared to be extrinsic rather than intrinsic (Becker, 1976; Frey, 1997). The findings therefore complement previous studies that found primarily extrinsic motives for engaging in open innovation activities (Chesbrough, 2006a; Lakhani and Wolf, 2003; Nuvolari, 2004). The exchange with IP experts also allows for the guidance of future academic literature. One interview participant, for instance, criticised the methodology of several quantitative studies that addressed patent pledges and emphasised the importance of qualitative studies similar to Study 2.

Study 3 adds to the literature about technology diffusion, specifically in the realm of open innovation. A detailed description of the link of Study 3 to existing theories was given in chapter 6.4.1. The study built a simulation model to investigate technology adoption rates and thereby overcame major limitations of traditional aggregate diffusion models. Study 3 was the first to simulate the effect of different patent pledge types on technology diffusion and pioneers future studies in this area. It contributes to theories about inter-firm diffusion as a subject that, compared to the large body of diffusion literature, is seldom investigated (Asare et al., 2016; Oliveira and Martins, 2011). Study 3 also builds upon and strengthens the understanding of the TASC model described by Asare et al. (2016). For instance, it was shown that specifically three technology attributes of the TASC model are influenced by patent pledges: *Costs*, *Industry Support*, and *Management Support*. This allows a more concise use of the TASC model in the context of patent pledges and serves as a first guidance on what technology attributes might be influenced by other open innovation models. Study 3 also adds to the understanding of the adopter types introduced by Rogers (1962) and its implications for technology diffusion. Specifically, it was shown how the introduction of patent pledges at the transition between different adopter types relates to the effects on technology diffusion. This further complements findings about how to overcome the *chasm* between adopter types described by Moore (1991), specifically through IP mechanisms as mentioned by Grzegorczyk (2020). The description of several indicators to measure the patent pledge effects, among others, further constitute tools that can be used by future scholars interested in the field.

7.2.2 Practical contributions

Practitioners can benefit from this research in multiple ways, either through specific insights or through strategic tools as described by Phaal et al. (2006).

First, practitioners can use the patent pledge taxonomy and the patent licensing taxonomy to distinguish and visualise patent strategies for multiple technologies. These can concern their patents or the ones from other units of interest such as competitors. They can also illustrate entire patent licensing landscapes for specific technological areas by depicting patent holders and their patents' importance in the taxonomy, for instance (see fig. 4.6). By using the patent licensing taxonomy as a strategic tool, firms can gain an overview of the characteristics (the importance, the accessibility, the price, and the conditions) of patent licenses from multiple patent owners, which can support them in making informed decisions when choosing between technologies. This way, the taxonomies pose managerial tools that add to available models used in the decision making processes of practitioners (Phaal et al., 2006). For a more detailed description of the use of the patent licensing taxonomy as a strategic tool, see chapter 4.4.2. The taxonomies further facilitate the knowledge transfer in organisations, because terms such as *patent pledges* and *patent pools* are visualised and easier to understand. Particularly the patent licensing taxonomy finds a remedy for the knowledge transfer to people not trained in IP. It is therefore also conceivable to use the taxonomies for educational purposes.

Second, this study helps practitioners to better understand patent pledges. It was shown, through both the literature review and the interviews of Study 2, that patent pledges are a phenomenon that is poorly understood. One highly experienced interview participant, for instance, said that his firm did not use any of Tesla's pledged patents because they did not trust these announcements, even Tesla laid out the conditions on its website. Organisations need to understand why patent owners conduct patent pledges. The identification of the motives supports firms to better comprehend the actions of patent pledgors and to understand their rationales. It is also possible that the revelation of the motives leads to increased utilisation of patent pledges because patent owners that would not have conducted patent pledges before now might use them with the intention to disseminate their technology.

Third, practitioners can benefit from the insights of the simulation study in different ways. This was described in detail in chapter 6.4.2. From the perspective of a technology provider, Study 3 provides guidelines in the decision making process whether or not to conduct a patent pledge and what adoption rates to expect. The investigated cases, schemes, and scenarios pose a blueprint for many real-world scenarios. Through the insights of Study 3, technology providers can estimate the effect a patent pledge can have on their supplied technology. They can appraise what patent pledge type (or strength) would be required to help them achieve a specific goal. This is applicable for both cases, in case competing technologies are similar and in case the pledged technology is inferior. Firms can use the insights from this study to also choose the correct patent pledge introduction points. The results indicate that the difference in final adopters is relatively small when the pledge occurs within the first adopter category, but is often large when the pledge occurs within the third adopter category after Rogers (1962). This can help potential patent pledgors to estimate the importance of the right timing in their decision. A framework with practical insights and recommendations for technology suppliers was given in fig. 6.25. Technology providers that compete with other providers that have conducted a patent pledge can benefit from Study 3, too. They can estimate the adoption rates of their technology and the ones of the competing, pledged technology and make informed decisions. From the perspective of prospective technology adopters, the estimation of the adoption rates of different technologies can also be useful. They can balance the current disadvantages against future prospects when intending to adopt an inferior, pledged technology over an unpledged substitute.

7.3 Future research directions

The mixed-method investigation of patent pledges in this research points towards several future research avenues. The collection of patent pledges that was used to answer Study 1 and supported the investigation of Study 2 asks for a continuous inclusion of future patent pledges. This will alter the distribution of pledges across industries and the occurrence of specific patent pledge types and conditions, which will ultimately lead to a more comprehensive view of the subject matter. It might be necessary to modify the patent pledge taxonomy and the patent licensing taxonomy to fit types that are not yet known. Another important point for future research to consider is an investigation of patent pledges by emphasising the distinction between industries. The relatively small number of patent pledges in certain industries and the limited number of IP experts experienced in the area did not allow for an industry comparison. Future research should aim to collect patent pledges in specific industries and to gain access to experts in those realms specifically. This will enable the further distinction of motives between specific patent pledge types in certain industries. Results from Study 2 furthermore showed that existing best-practices for patent pledges described in the literature were not fully sufficient to convince third parties of the credibility of patent pledges. More work on the optimal design of patent pledges should therefore be conducted.

The simulation of patent pledges and their effect on technology diffusion lay the groundwork for several future inquiries. Due to the time constraints of Study 3, only two cases, one case with equal technologies and one case with an inferior technology, could be simulated. Many more scenarios are possible, however. One interesting case would be a 'hybrid' of the two cases investigated in this research. Specifically, it might be worthwhile to examine the absolute and the relative patent pledge effects in a setting in which one technology is inferior to another technology only in some attributes, not in all of them as simulated in Study 3. This would add another case that could serve as an additional blueprint for practitioners. Another aspect is the adaptation of the decision rules of the simulation model. Study 3 applied a utility-maximisation-approach because it appeared as the most suitable approach to simulate firms' decision making processes. Other decision rules, such as the theory of planned behaviour, should also be investigated, as this would help to gain an understanding of how the decision rules influence the patent pledge effects. The simulation model furthermore assumed that there exist only two competing technologies and that only one of them is being pledged. Future simulation models should aim to simulate the competition between several technologies, all of which could be subject to a patent pledge. A more complex simulation model should also include specific reactions of technology providers in response to the pledge of a competing technology, as discussed in chapter 6.4.2.1. Furthermore, the simulation of multiple products that utilise patent pledges but do not compete with each other is an interesting topic for future research. This relates to the concept of *application market adjacency* described by Lehmberg et al. (2019) (see chapter 6.4.1.1). In this context, it would be interesting to know how the utilisation of patent pledges in adjacent markets supports technology adoption processes and under what conditions this could lead to the adoption competition win of an inferior technology. Lastly, the collection of empirical data for the initialisation and the derivation of input parameters poses an important research topic for future inquiries. Study 3 developed an abstract simulation model to concur with the exploratory nature of this research and to gain insights that are as general as possible. Only some provisional industry feedback to estimate reasonable parameter values was collected. Future studies should focus on specific industries and apply large-scale data collections that allow for comprehensive parameter derivations. Analytical hierarchy processing and discrete choice models are only some tools that can be used to estimate parameters for simulation models. This focus on specific industries and the thorough parameter derivation will enable a more accurate prediction of technology diffusion under patent pledges.

7.4 Limitations

This research inherits several limitations. They are described in a consecutive order from Studies 1-3 in the following paragraphs.

The definition of patent pledges and its taxonomy were derived from secondary data of organisations. It is not assumed that these data contain misinformation, because the patent pledges serve as statements on which third parties need to be able to rely on. The data, however, can inherit some bias in the sense that they palliate situations or exaggerate their usefulness. While the collection of 60 patent pledges appears to be comprehensive, the sample comprised primarily patent pledges that were made through media announcements or press releases and did not distinguish between coordinated and unilateral patent pledges (Contreras, 2017a). In general, many more patent pledges that were not considered in Study 1 might exist. Another point to be aware of is the existing notion of patent pledges that guided the data collection process. This was a result of the abductive research approach and was discussed in more detail in chapter 4.1. The results of Study 1 therefore originated from existing theories and are not entirely inductive. Specifically, Study 1 relied to a large extent on the data set of Contreras (2019) and on notions about patent pledges described by Contreras (2017a) and Valz (2017), among others. Other studies that use different inclusion criteria for their samples might arrive at a different patent pledge taxonomy and a different number of patent pledge types. This also extends to the patent licensing taxonomy, as it is built upon the patent pledge taxonomy.

The motives for patent pledges were investigated through case study research with both primary and secondary data. Study 2 therefore inherits the usual limitations of case study research. Due to the high quality of the interviewees, it is assumed that the results are valid and reliable. This is also consolidated by the anonymity of the participants as well as the external review of codes and their allocation to categories through an independent IP researcher. Although not all participants fell into the category of *pledging interviewees*, the results were separated to allow for a full transparency. Despite the triangulation of the results through two sources of evidence, Study 2 lacks data from multiple participants from the same organisation and from different organisational levels. The 22 interview participants were part of 16 distinct organisations, and 11 participants solely represented their organisation (see table 5.1). Further interviews with participants from the same organisation and preferably from different hierarchical levels might lead to additional insights or other results. Similarly, the limited number of respondents did not allow for a distinction of motives between industries and patent pledge types. This also poses questions about the external validity, i.e. the generalisabiliy of the results (Yin, 2009). The motives constitute broad motives for patent pledges and are limited in the sense that they do not apply to every patent pledge. Study 2 in parts linked respective patent pledge types to specific motives, for instance, the motive *promoting additional monetisation* only applies to patent pledges that require monetary compensation. Such a distinction between patent pledge types could not be given for all motives, however. The secondary data, which were the same used for Study 1, inherit the same risk as described in the previous paragraph. Patent owners publishing these secondary data might palliate their stated motives to achieve the best possible public response. To mitigate the risk of bias in the secondary data, they were only used as supporting data for the analysis of Study 2. A risk of bias remains, however.

The simulation model of Study 3 faces specific limitations, some of which relate to the assumptions that were described previously. For a detailed description, see chapter 6.1.3. The simulation of only two technologies and the non-responsiveness of competing technology providers to patent pledges, for instance, limit the explanatory power of the model. Furthermore, the introduction of T2 and its patent pledge only in between different adopter types is an assumption that is unlikely to be observed in reality.[1] Similarly, the assumption that both technology providers hold all patents for their respective technology seems unrealistic. Also, the shift of the mean values of attributes that were found to be influenced by patent pledges, particularly for patent pledges type C, might be too large. These shifts were chosen to explore the entire parameter range of the attributes and to provide holistic results, but the real influence of patent pledges on technology attributes might be less pronounced. The study developed an abstract simulation model to explore the topic and to remain as general as possible. This can be interpreted as a limitation as well because its ability to estimate future diffusion rates in specific industries might depend on empirical data. While some industry feedback was collected to verify the decision rules and to estimate parameter values, the relatively small number of respondents (five) did not allow conclusive results. Four out of the five respondents worked in the German automotive industry, which inherits the risk of bias towards this industry. While the respondents verified the decision process and some parameter values, it is possible that respondents from other industries would deliver different results. Similar to the case study research of Study 2, questions about the external validity and the generalisability remain (Yin, 2009). One specific limitation to point out is

[1] Nevertheless, the simulation of different schemes in Study 3 allows for an estimate of diffusion rates when T2 and its patent pledge are introduced at other points in time.

the reliability on the studies of Rogers (1962) and Asare et al. (2016). The study is valid only as long as the adopter type distribution of Rogers and the TASC model of Asare et al. apply. Furthermore, the simulation study primarily addresses patent pledges of specific categories described in the literature, specifically the 'platform leadership'-type within the 'inducement' category described by Contreras (2017a). Other types, such as the 'interoperability'-type, are not considered in the simulation model. This is because some patent pledges, particularly the ones that address specific standards, often occur in areas where no competing technologies exist.

7.5 Conclusion

This research set out to explore the phenomenon of patent pledges by answering three questions: (i) *What is the definition of patent pledges and what different types exist?*, (ii) *Why do patent owners pledge their patents?*, and (iii) *How do patent pledges affect the diffusion and adoption of technologies?* Patent pledges are poorly understood and challenge existing theories and practitioners alike. The main objective was to provide an exploratory investigation into the topic that provides clarification and lays the groundwork for future studies. The research set out to achieve its objectives through different approaches: (i) through the qualitative analysis of 60 patent pledges and the conceptualisation of two taxonomies, the patent pledge and the patent licensing taxonomy; (ii) through the exchange with 22 renowned IP experts supported by the analysis of 50 patent pledge statements; and (iii) through the development of a simulation model that enabled the investigation of several scenarios between competing technologies, only one of which was subject to a patent pledge.

This research contributes to knowledge specifically in the realms of IP management, technology and innovation management, and technology diffusion. Patent pledges were diversely discussed in the literature, however, which is why this research to some extent also adds to licensing studies, motivational studies in an organisational context, and the open innovation literature. By developing an agent-based model and suggesting key indicators to interpret its results, this research further consolidates the use of simulation modeling as a research method in management studies. Finally, this research adds to the strategic technology management toolkit by providing practical instruments to facilitate firms' decision-making processes. The results of this research are a foundation for further inquiries on the emerging phenomenon of patent pledges.

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Appendix A

Supporting information for Study 1

Table A.1 Collected patent pledges (1/3).

Organisation(s)	Country (Headquarter of organisation)	Date of press release	Number of patents	Technology area	Patent pledge type
Blackboard	United States	13.03.2010	10	Internet based support systems	Conditional, public free
Blockstream	Canada	19.07.2016	N/A	Blockchain / Bitcoin	Conditional, public free
Eco-Patent Commons	N/A	N/A	284	'Green' technology	Conditional, public free
Google open patent non-assertion pledge (OPN)	United States	Status: 02.2019	202	Information technology	Conditional, public free
GreenXchange (research non-exempt option)	N/A	N/A	N/A	'Green' technology	Conditional, public free
GreenXchange (standard plus option / conditions only)	N/A	N/A	N/A	'Green' technology	Conditional, public free
iBiquity (free license)	United States	13.04.2005	N/A	Standards for transmission equipment that implements NRSC-5	Conditional, public free
IBM	United States	11.01.2005	500+	Information technology	Conditional, public free
IBM	United States	13.07.2007	N/A	Specific specifications	Conditional, public free
IBM	United States	24.10.2005	N/A	Healthcare / Education	Conditional, public free
Microsoft	United States	11.2005	N/A	Microsoft Office 2003 XML reference schemas	Conditional, public free
Microsoft	United States	12.09.2006	N/A	Various specifications	Conditional, public free
Nokia	Finland	25.05.2005	N/A	Linux technology	Conditional, public free
Open Invention Network (OIN)	United States	Status: 02.2019	750+	Linux technology	Conditional, public free
Open Web Foundation (OWF) 1.0	United States	Status: 11.2018	N/A	Emerging web technologies	Conditional, public free
RedHat	United States	29.05.2002	N/A	Software	Conditional, public free
Southern California Edison	United States	2008	1	Method of communicating between a utility and its customer locations	Conditional, public free
Sun Microsystems	United States	30.09.2005	N/A	Open document standards	Conditional, public free
Tesla Motors	United States	06.2014 Status: 02.2019	361	Electric vehicles and related technology	Conditional, public free
Apple	United States	11.11.2011	N/A	Cellular technology	Conditional, public priced
Google	United States	08.02.2012	N/A	All existing licenses after the acquisition of Motorola Mobility Holdings, Inc.	Conditional, public priced

Table A.2 Collected patent pledges (2/3).

Organisation(s)	Country (Headquarter of organisation)	Date of press release	Number of patents	Technology area	Patent pledge type
GreenXchange (standard plus option/payment and conditions)	N/A	N/A	N/A	'Green' technology	Conditional, public priced
Intel	United States	17.02.2018	N/A	'Industry Standards'	Conditional, public priced
Microsoft	United States	07.2006	N/A	Operating system inventions	Conditional, public priced
Microsoft	United States	08.02.2012	N/A	Standard technologies	Conditional, public priced
Microsoft (Interoperability commitment general provisions)	United States	16.12.2009	N/A	Public standards in Microsoft's relevant software products	Conditional, public priced
Nokia	Finland	08.05.2002	N/A	W-CDMA technology	Conditional, public priced
Nokia	Finland	2010	N/A	Standards around long-term evolution and service architecture evolution	Conditional, public priced
Qualcomm	United States	12.2008	N/A	Standards for CDMA-based telecommunication	Conditional, public priced
Samsung	South Korea	27.09.2013	N/A	UMTS standards	Conditional, public priced
Vodafone	United Kingdom	2017	N/A	Mobile network technologies	Conditional, public priced
iBiquity (FRAND-license)	United States	13.04.2005	N/A	Transmission equipment that implements NRSC-5 (no standard)	Semi-public priced
Computer Associates, International	United States	09.2005	14	Information Technology	Conditional, semi-public free
Consumer and Merchant Awareness Foundation (CMAF)	N/A	2013	1	Fraud protection method	Conditional, semi-public free
Max-Planck-Gesellschaft zur Förderung der Wissenschaften e.V.	Germany	2006	2	RNA interference mediating small RNA molecules	Conditional, semi-public free
Microsoft (Interoperability commitment Subject D.)	United States	16.12.2009	N/A	Interoperability information	Conditional, semi-public free
Microsoft	United States	21.02.2008	N/A	Technology relating to open source compatibility	Conditional, semi-public free
Microsoft (Open Specification / Community Promise)	United States	30.09.2013	N/A	Specifications for protocols that are used by Windows server operating systems to interoperate with Windows client operating systems	Conditional, semi-public free
Microsoft (Commitment to Academia)	United States	03.12.2003	N/A	Technology relating to web standards	Conditional, semi-public free
MIT, Max-Planck-Gesellschaft zur Förderung der Wissenschaften e. V., The Whitehead Institute for Biomedical Research, University of Massachusetts,	N/A	2006	11	RNA sequence-specific mediators of RNA interference	Conditional, semi-public free
Monsanto	United States	2014	N/A	Patented seed and traits	Conditional, semi-public free

Table A.3 Collected patent pledges (3/3).

Organisation(s)	Country (Headquarter of organisation)	Date of press release	Number of patents	Technology area	Patent pledge type
Myriad Genetics	United States	2014	N/A	Healthcare	Conditional, semi-public free
Toyota	Japan	2015	5680	Fuel cell stacks, high-pressure hydrogen tanks, fuel cell system software control, hydrogen production and supply	Conditional, semi-public free
Organisations contributing to QR-Code technology	N/A	N/A	9	QR-Code technology	Public free
Gatespace Telematics, IBM, Nokia, ProSyst Software, Samsung	N/A	26.07.2006	N/A	OSGi Service Platform Release 4	Public free
GreenXchange (standard option)	N/A	N/A	N/A	'Green' technology	Public free
IBM	United States	26.09.2006	100+	Business-methods	Public free
OpenPOWER foundation (RF-mode)	N/A	06.08.2013	N/A	Instruction Set Architecture	Public free
Alcatel-Lucent, Ericsson, NEC, NextWave Wireless, Nokia, Nokia Siemens Networks and Sony Ericsson	N/A	14.04.2008	N/A	3GPP Long Term Evolution and Service Architecture Evolution (LTE/SAE)	Public priced
OpenPOWER foundation (RAND-mode)	N/A	06.08.2013	N/A	Instruction Set Architecture	Public priced
Ericsson	Sweden	12.01.2012	N/A	Mainly wireless technology	Public priced
Ericsson	Sweden	27.11.2012	N/A	Information technology	Public priced
Ford	United States	28.05.2015	1650	Electric vehicles and related technologies	Public priced
GreenXchange (standard plus option / payment only)	N/A	N/A	N/A	'Green' technology	Public priced
Microsoft	United States	03.12.2003	N/A	Clear Type Technology and FAT File system	Public priced
Microsoft (Open Source Compatibility)	United States	21.02.2008	N/A	Technologies relating to Microsoft's 'Open Protocols'	Public priced
NTT DoCoMo, Ericsson, Nokia, Siemens, Fujitsu, Matsushita Communication Industrial (Panasonic), Mitsubishi Electric, NEC and Sony Corporation	N/A	06.11.2002	N/A	W-CDMA technology	Public priced
Microsoft	United States	03.12.2003	N/A	Microsoft Office 2003 XML reference schemas	Semi-public free
Sun Microsystems	United States	31.01.2005	1600	Technology relating to Sun OpenSolaris	Semi-public free
www.thepatentpledge.org	N/A	Status: 11.2018	N/A	Software	Semi-public free

Appendix B

Supporting information for Study 2

Fig. B.1 Interview guideline for the main study.

Part A: Patent pledge(s) of the interviewees organisation[1]

- How did you select the patents?
- Why did you choose this specific technological area?
- What was your motivation to conduct this patent pledge?
- Have you experienced any problems/resistance with the preparation?
- Who had the idea to initiate this patent pledge?

Part B: Patent pledges in general

- What is the general motive to conduct patent pledges?
- Why do patent pledgors retain their rights on the pledged patents?
- Would you use / Have you used pledged patents of competitors?
- Would you conduct a patent pledge in the future?[2]
- Do you think that patent pledges will become more prevalent in the future?

Part C: Patent pledge effects

- Do you have evidence that your organisation's patent pledge helped fostering the related technology? What is your personal opinion?[1]
- Do you think patent pledges foster ther related technologies?[2]
- How did competitors react to your patent pledge?[1]
- How did potential adopters react to your patent pledge?[1]
- Were there any other effects?[1]

Key:
[1] Pledging interviewees only.
[2] Non-pledging interviewees only.

Note: The questions varied to include specific characteristics of interviewees (e.g. specific details of a patent pledge).

Fig. B.2 Interview guideline for the pilot study.

- What are your most important IP assets?
- What are your inbound and outbound IP strategies?
- Have your IP strategies worked for you? What impacts have been created?
- What are the motives behind the choice of your current IP strategies?
- Would you consider applying a more open IP strategy in the future? If yes, under what conditions?
- How many patents have you licensed out? (To how many parties? Do you have cross-licensing agreements?)
- Have you licensed out patents for free? If yes, under what conditions/terms and why have you done so? If no, under which circumstances would you do so, if at all?
- Would you be interested in utilising patents that your competitors gave away for free?

Table B.1 Coding counts from the interviews.

	Motives												
	Economical					Perceptional						Technological	
Participant No.	Driving technology diffusion and ecosystem and infrastructure building	Fostering collaboration, open Innovation, and recource pooling	Fostering network effects and economies of scale	Promoting additional monetization	Encouraging competition	Decreasing uncertainty and patent threats	Building reputation and PR	Showing social responsibility	Attracting attention and providing clarification	Fostering sustainability	Fostering integrity	Improving and fostering technology and innovation	Standard setting and fostering interoperability
1	9*	0	0	0	0	0	1	2*	1*	2*	0	0	0
2	1*	0	0	0	0	0	0	0	0	0	0	0	0
3	9*	0	1*	0	0	2*	0	3*	1*	1*	0	0	0
4	1	1*	1*	0	0	2*	6*	1	0	0	0	0	0
5	0	1*	0	0	0	1*	1*	0	0	0	0	1*	0
6	3*	0	0	0	0	0	0	0	0	0	0	0	0
7	3*	1*	0	0	0	2*	1	1*	0	0	0	0	0
8	2*	0	0	0	0	1	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0
10	4*	0	0	0	0	1*	1*	0	0	0	0	1*	0
11	1*	0	0	0	0	4*	0	1*	0	0	0	1*	0
12	0	0	0	0	0	1*	1*	0	0	1	0	0	0
13	1*	0	0	0	0	0	1	0	0	0	0	0	0
14	2*	0	0	0	0	0	0	0	0	0	0	0	0
15	3*	0	0	0	0	2*	0	1*	0	0	0	2*	0
16	4*	0	2*	0	0	1*	0	0	0	0	0	0	1
17	8*	0	0	0	0	0	7*	1	0	0	0	0	0
18	10*	0	0	0	0	6*	1*	0	0	0	0	0	0
19	1*	1*	0	0	0	0	1*	0	0	0	0	0	0
20	1*	2*	0	0	0	0	0	0	0	0	0	0	2*
21	0	0	0	0	0	0	4*	0	2*	0	0	0	0
22	0	0	1*	1*	0	0	1	1	0	0	0	0	0
Total count	63	6	5	1	0	23	26	11	4	4	0	5	3
Share of participants showing strong evidence: All	73%	23%	18%	5%	0%	45%	36%	23%	14%	9%	0%	18%	5%
Pledging only	80%	20%	13%	7%	0%	47%	40%	27%	13%	7%	0%	20%	7%
Non-pledging only	57%	29%	29%	0%	0%	43%	29%	14%	14%	14%	0%	14%	0%

*Participant shows strong evidence.
Highlighted participants represent pledging interviewees.
Numbers represent coding counts.

Table B.2 Coding counts from the patent pledge statements.

		Motives												
		Economical					Perceptional						Technological	
Pledging Organisation(s)	Date	Driving technology diffusion and ecosystem and infrastructure building	Fostering collaboration, open Innovation, and recource pooling	Fostering network effects and economies of scale	Promoting additional monetization	Encouraging competition	Decreasing uncertainty and patent threats	Building reputation and PR	Showing social responsibility	Attracting attention and providing clarification	Fostering sustainability	Fostering integrity	Improving and fostering technology and innovation	Standard setting and fostering interoperability
Alcatel-Lucent et al.[1]	2008	8	0	1	0	0	4	0	1	0	0	1	0	0
Apple[1]	2011	0	0	0	0	0	1	0	0	0	0	0	0	0
Blackboard[1]	2010	0	0	0	0	0	0	0	0	0	0	0	0	0
Blockstream[1]	N/A	1	1	0	0	0	3	0	1	0	0	0	1	0
CMAF[1]	N/A	3	0	0	0	0	1	0	1	0	0	1	0	0
Computer Associates[1]	2005	1	0	0	0	0	0	0	0	0	0	0	3	0
Eco-Patent Commons[3]	N/A	5	0	0	0	0	0	0	2	0	2	1	1	0
Ericsson[1]	11.2012	4	0	1	0	0	1	0	0	0	0	0	0	1
Ericsson[1]	1.2012	1	1	0	2	0	0	0	0	0	0	0	0	1
Ford Motor[2]	2015	1	1	0	0	0	0	0	0	0	0	0	5	0
Google - OPN[1]	N/A	1	0	0	0	0	2	0	0	0	0	0	1	0
Google[1]	2012	0	0	0	0	0	0	0	0	0	0	0	0	1
GreenXchange[3]	N/A	0	3	0	0	0	0	0	0	0	5	0	4	0
iBiquity[1]	2005	1	0	0	0	0	0	0	0	0	0	1	0	0
IBM[1]	10.2005	1	0	0	0	0	0	0	0	0	0	1	1	1
IBM[1]	2006	0	1	0	0	0	3	0	1	0	0	1	3	0
IBM[1]	1.2005	1	0	0	0	0	0	0	0	0	0	0	3	0
IBM[1]	2007	1	0	0	0	0	0	0	0	0	0	0	0	0
Intel[1]	N/A	2	0	0	0	0	0	0	0	0	0	1	1	0
Max Planck Gesellschaft[4]	N/A	2	0	0	0	0	0	0	0	0	0	0	0	0
Microsoft[1]	7.2006	1	0	0	0	1	0	0	0	0	0	0	0	1
Microsoft[1]	2005	0	0	0	0	0	0	0	0	0	0	0	0	0
Microsoft[1]	2009	0	0	0	0	0	1	0	0	0	0	0	0	3
Microsoft[1]	2003	6	2	0	0	0	0	0	0	0	0	3	5	4
Microsoft[1]	2012	1	0	0	0	0	0	0	1	0	0	0	0	1
Microsoft[1]	2008	0	0	0	0	0	0	0	0	0	0	0	0	3
Microsoft[1]	2013	0	0	0	0	0	0	0	0	0	0	0	0	0
Microsoft[1]	2006	0	0	0	0	0	0	0	0	0	0	0	0	0
MIT et al.[4]	N/A	2	0	0	0	0	0	0	0	0	0	0	0	0
Monsanto[4]	N/A	0	0	0	0	0	0	0	0	0	0	1	0	0
Myriad Genetics[4]	N/A	0	0	0	0	0	0	0	1	0	0	1	1	0
Nokia[1]	2010	1	0	0	0	1	2	0	1	0	0	0	1	0
Nokia[1]	2005	2	0	0	0	0	1	0	0	0	0	0	2	0
Nokia[1]	2002	2	0	0	0	1	0	0	0	0	0	0	2	0
NTT et al.[1]	2002	2	0	0	0	0	0	0	0	0	0	0	2	0
OIN[1]	2012	0	0	0	0	0	0	0	0	0	0	0	0	0
Open POWER Foundation[1]	N/A	0	0	0	0	0	0	0	0	0	0	0	0	0
OSGi et al.[1]	2006	4	0	0	0	1	0	0	1	0	0	0	4	1
OWF CAgreement 1.0[1]	N/A	0	0	0	0	0	0	0	0	0	0	0	0	0
QR Code[1]	N/A	0	0	0	0	0	0	0	0	0	0	0	0	0
Qualcomm[1]	2008	1	0	0	1	1	1	0	0	0	0	1	0	0
Red Hat[1]	2002	1	0	0	0	0	0	0	0	0	0	1	0	0
Samsung[1]	2013	0	0	0	0	0	0	0	0	0	0	0	0	0
SCE[1]	2008	0	0	0	0	1	0	0	0	0	0	0	1	0
Sun Microsystems[1]	9.2005	0	0	0	0	0	9	0	0	0	0	0	0	0
Sun Microsystems[1]	1.2005	3	1	0	0	0	5	0	0	0	0	2	4	0
Tesla Motors[2]	2014	1	0	0	0	0	0	0	1	0	1	0	1	0
ThePatentPledge.org[1]	N/A	0	0	0	0	0	1	0	0	0	0	0	0	0
Toyota[2]	2015	5	1	0	0	0	0	0	0	0	0	2	2	0
Vodafone[1]	N/A	0	0	0	0	0	0	0	0	0	0	0	1	0
Total count		65	11	2	3	6	35	0	11	0	8	18	49	17
ICT count		49	6	2	3	6	35	0	7	0	0	13	35	17
Sustainability count		5	3	0	0	0	0	0	2	0	7	1	5	0
Automotive count		7	2	0	0	0	0	0	1	0	1	2	8	0
Life Science count		4	0	0	0	0	0	0	1	0	0	2	1	0

Industry key:
1=ICT 2=Automotive 3=Sustainability 4=Life Science
Numbers represent coding counts.

Table B.3 Exemplary quotes for the main motives (quotes from the patent pledge statements were obtained from Ehrnsperger (2019)).

Motive	Source	Quotes
Driving technology diffusion and ecosystem and infrastructure building	Participants	*'View the world as a pie and I want to take the biggest slice. But if the whole world grows, your slice becomes bigger, too.'* Source: Participant no. 10
		'We are in a very competitive marketplace where we have a […] and we are competing against […]. We want when customers are thinking about which one to choose, we have this additional benefit. We want customers to put value on that and we want to let them know that, when they choose our platform, they are gonna get this benefit from it.' Source: Participant no. 17
		'It has to do with adoption of your technologies and your programs and surveys that show favorability of customers.' Source: Participant no. 17
		'We wanted to disseminate […] technology.' Source: Participant no. 17
		'… in the world of […], you want to encourage the industry to grow in tandem together.' Source: Participant no. 15
		'Encourage other […] companies to enter […] space.' Source: Participant no. 14
		'The situation […] drives […] to open patents. […] need new infrastructures, so we`d like to motivate them.' Source: Participant no. 13
	Patent Pledge Statements	*'Our goal at Blockstream is to accelerate technological innovation in Bitcoin, building infrastructure and innovative tools to support its secure, trustless, decentralized nature. We believe that open innovation is necessary for the long-term success of Bitcoin, and because of this we intend for all of the technology developed at Blockstream to be freely available for the benefit of the Bitcoin community and the world. But we operate in an environment where good intentions are not enough, and must be backed by mechanisms that ensure those intentions are carried out.'* Source: Blockstream Patent Pledge (2017)
		'By sharing our research with other companies, we will accelerate the growth of electrified vehicle technology and deliver even better products to customers.' Source: Ford Patent Pledge (2015)
		'IBM wants to encourage broad adoption of the Covered Specifications….' Source: IBM (2007)
		'Tesla was created to accelerate the advent of sustainable transport, and this policy is intended to encourage the advancement of a common, rapidly evolving platform for electric…' Source: Tesla Motors' patent pledge (2014)
		'As part of the efforts to popularise FCVs, Toyota Motor Corporation is allowing royalty-free se of about 5,680 of the FCV related patent licenses […]. To facilitate faster expansion of hydrogen station networks, Toyota will also provide royalty-free use of approximately 70 hydrogen station-related patent licenses indefinitely for those installing and operating hydrogen stations.' Source: Toyota patent pledge (2015)
Decreasing uncertainty and patent threats	Participants	*'… we knew that we would not get in any legal fight with any of the competitors ….'* Source: Participant no. 15
		'You are trying to send messages in addition to reconciling actual or perceived issues. You take tension out in places where tension is perceived. Whether you believe there is tension, if others believe there is, you have to deal with that.' Source: Participant no. 3
	Patent Pledge Statements	*'The OPN Pledge is designed to supplement existing OSS licensing alternatives, providing patent holders who care about reducing threats to OSS a more robust defensive capability against incoming patent aggression.'* Source: Google Open Patent Non-Assertion pledge (2013)
		'We will actively monitor for patent-related threats to Linux and adjacent open source technologies and encourage open source community intellectual property-related initiatives.' Source: Open Invention Network (2019)
Building reputation and PR	Participants	*The optics that it looks good when you say 'You can use our patents for free'. When you end up in patent litigation with them, they can also wave this pledge in front of the jury and say 'But we said they can use our patents for free, and they are being really mean by trying to sue us'. It is about making other people look bad.'* Source: Participant no. 21
		'… move to position yourself as a white knight and being anti-patent and being free innovation and all that.' Source: Participant no. 17

Table B.4 Exemplary quotes for non-main motives (1/2) (quotes from the patent pledge statements were obtained from Ehrnsperger (2019)).

	Motive	Source	Quotes
Economic motives	Fostering collaboration, open innovation, and resource pooling	Participants	*'[Company name] perceived this as a positive signal to cooperate....'* Source: Participant no. 5 (translated)
		Patent Pledge Statements	*'As an industry, we need to collaborate while we continue to challenge each other.'* Source: Ford (2015)
	Fostering network effects and economies of scale	Participants	*'These companies understand the power of network effects. OIN, GPL and of the open source licenses they are not about giving up your IP. They are about using your IP to strengthen the ecosystem.'* Source: Participant no. 3
		Patent Pledge Statements	*'In order to connect 5 billion people and deal with 100-fold traffic at lowest cost of ownership we need to create economies of scale'*. Source: Alcatel-Lucent et al. (2008)
	Promoting additional monetization	Participants	*'But we also think that companies that are heavily investing in R&D [...] it is important that the companies that put a lot of resources, a lot of money in R&D, get a reasonable amount back. And this money enables new R&D, which is some kind of a positive wheel. You invest in R&D and you get money back from your technology, but also from IPRs.'* Source: Participant no. 22
		Patent Pledge Statements	'...*Qualcomm relies heavily upon licensing revenues to obtain a fair return on its enabling innovations and to fuel its industry-leading R&D investments that continue to drive the industry forward with enhancements of 3G CDMA standards and the development of OFDMA-based 4G standards.'* Source: Qualcomm (2008)
	Encouraging competition	Patent Pledge Statements	*'Open standards provide an industry framework for effectively advancing the development and deployment of new technologies, and encouraging competition, which ultimately benefits consumers.'* Source: Nokia (2010)

Table B.5 Exemplary quotes for non-main motives (2/2) (quotes from the patent pledge statements were obtained from Ehrnsperger (2019)).

	Motive	Source	Quotes
Perceptional motives	Showing social responsibility	Participants	*'It was not really to support any one company or a group of companies, the members did this really for the benefits of the entire community. Not because they wanted to get some benefits uniquely themselves.'* Source: Participant no. 7
		Patent Pledge Statements	*'Mobile broadband implementation using technologies with a predictable, transparent maximum aggregate costs for licensing intellectual property rights will drive global adoption and foster social and economical growth.'* Source: Alcatel-Lucent et al. (2008)
	Attracting attention and providing clarification	Participants	*'The [patent pledge] had the idea to attract attention.'* Source: Participant no. 3
		Patent Pledge Statements	*'We will continue to promote and educate our community on complementary defensive intellectual property strategies and support key open source projects.'* Source: Open Invention Network (2020)
	Fostering sustainability	Participants	*'Yes it was a good thing and yes it was about helping the environment but it is really more than that.'* Source: Participant no. 3
		Patent Pledge Statements	*'New mechanisms for collaborative innovation are required to foster the green technology sector.'* Source: GreenXchange (research non-exempt option) (published in 2015)
	Fostering integrity	Patent Pledge Statements	*'The worldwide policy, built on IBM's long-standing practices of high quality patents and transparency of ownership, is designed to foster integrity, a healthier environment for innovation, and mutual respect for intellectual property rights.'* Source: IBM (2006)
Technological motives	Improving and fostering technology and innovation	Participants	*'It encouraged people to develop open source software that read on the functionality of the patents that [company name] pledged.'* Source: Participant no. 11
		Patent Pledge Statements	*'Computer Associates is committed to promoting innovation for the benefit of our customers and for the overall growth and advancement of the information technology field.'* Source: Computer Associates (2005)
	Standard setting and fostering interoperability	Participants	*'They want it to get standardized.'* Source: Participant no. 20
		Patent Pledge Statements	*'To promote such interoperability and ensure the continued appeal of its products to developers and customers, Microsoft is committed to designing these high-volume products, and to running its business, in accordance with the following principles addressed to open connections to its products, support for industry standards and data portability.'* Source: Microsoft (2008)

Appendix C

Supporting information for Study 3

Fig. C.1 Survey for collecting feedback for Study 3 (1/8).

-PART A-

BACKGROUND AND EXPLANATION:
In the tables below, you find a list of attributes that have been identified as factors influencing the adoption decision of a technology (e.g. costs, relative advantage, etc.). Take on the perspective of a firm that needs to decide to adopt one of two competing technologies. For instance, you might need to decide whether to produce electric or fuel-cell vehicles, or whether to use a light-water reactor or a molten-salt reactor to produce electricity. You evaluate the utility of any technology by considering the listed attributes.
Please answer generally while NOT focusing on specific technologies or industries.

INSTRUCTIONS:

1. Complete the red column (to be completed before moving on to the green column)
When you face the decision to choose a technology, which attributes play, to what degree, a role in your decision process. Evaluate how important each attribute is in your decision process. Please fill in the entire red column for each attribute, before continuing with the green column.

2. Complete the green column
Imagine that you have not yet decided what technology to adopt. Now, third parties that own essential patents for one of the technologies have announced a ‘patent pledge’. A patent pledge is a publicly announced intervention by patent owning entities (‘pledgers’) to out-license active patents to the restricted or unrestricted public free from or bound to certain conditions for a reasonable or no monetary compensation using standardised written or social contracts’. **Assume that for this concrete example, the patents for the technology are now freely available, without any restrictions or conditions.** Does this patent pledge influence your adoption decision? Please specify to what degree this patent pledge influences each attribute.

3. Complete the yellow column
Evaluate if the influence from the green column is either positive (ie the attribute is changed so that the probability of adoption will increase) or negative (ie the attribute is changed so that the probability of adoption will decrease). **Please answer only if you have NOT selected ‘*No influence at all*’ in the green column.**

*Questions marked with an asterisk (*) are required.

Fig. C.2 Survey for collecting feedback for Study 3 (2/8).

	ATTRIBUTE	**IMPORTANCE*** (How important is this attribute in your adoption decision process?)	**DOES A PATENT PLEDGE INFLUENCE THIS ATTRIBUTE?**		**COMMENTS** (optional)
			To what degree is this attribute being influenced by a patent pledge regarding the specific technology?*	Is this influence positive (ie the attribute is changed so that the probability of adoption will increase) or negative (ie the attribute is changed so that the probability of adoption will decrease)? **Please answer only if you have NOT selected 'No influence at all' in the green column**	
Characteristics of technology	**Relative Advantage** (the degree to which an innovation is perceived as being better than the technology/idea that it replaces)	Choose an item	Choose an item	N/A (no influence in green column)	Write your comments here...
	Complexity (the degree to which an innovation is difficult to implement, use and understand)	Choose an item	Choose an item	N/A (no influence in green column)	Write your comments here...
	Organisational Compatibility (compatibility between the innovation and the adopter's internal culture, business processes and management practices)	Choose an item	Choose an item	N/A (no influence in green column)	Write your comments here...
	Systems Compatibility (compatibility between the technology and the organization's existing software, hardware, back office computer systems and other technology systems and resources)	Choose an item	Choose an item	N/A (no influence in green column)	Write your comments here...
	Testability (the degree to which an innovation can be experienced on a limited basis before adoption)	Choose an item	Choose an item	N/A (no influence in green column)	Write your comments here...
	Observability (can the results of the adopted technology be easily demonstrated or quantified, eg increased sales, return on investment, ...)	Choose an item	Choose an item	N/A (no influence in green column)	Write your comments here...
	Direct Costs (costs associated with acquiring the technology)	Choose an item	Choose an item	N/A (no influence in green column)	Write your comments here...
	Indirect Costs (costs associated with implementing, using, and maintaining the technology)	Choose an item	Choose an item	N/A (no influence in green column)	Write your comments here...

Fig. C.3 Survey for collecting feedback for Study 3 (3/8).

	ATTRIBUTE	**IMPORTANCE*** (How important is this attribute in your adoption decision process?)	**DOES A PATENT PLEDGE INFLUENCE THIS ATTRIBUTE?**		**COMMENTS** (optional)
			To what degree is this attribute being influenced by a patent pledge regarding the specific technology?*	Is this influence positive (ie the attribute is changed so that the probability of adoption will increase) or negative (ie the attribute is changed so that the probability of adoption will decrease)? **Please answer only if you have not selected 'no influence at all' in the green column**	
External environment	**Environmental Uncertainty** (uncertain environments make companies feel vulnerable and more willing to adopt technologies that they believe could help them perform better. These vulnerable companies continuously scan the environment, looking for technologies that could help them perform better)	Choose an item	Choose an item	N/A (no influence in green column)	Write your comments here...
	Competitive Pressure (companies are under pressure to adopt technologies when their competitors or trading partners have either adopted that technology or have the capability and desire to adopt it)	Choose an item	Choose an item	N/A (no influence in green column)	Write your comments here...
	Industry Support + Reputation (support from industry associations, availability of industry-wide standards and other industry-wide initiatives aimed at managing and promoting the new technology. This also includes the reputation of the technology, for instance if it has a good reputation because of its sustainability, ...)	Choose an item	Choose an item	N/A (no influence in green column)	Write your comments here...

Fig. C.4 Survey for collecting feedback for Study 3 (4/8).

	ATTRIBUTE	**IMPORTANCE*** (How important is this attribute in your adoption decision process?)	**COULD A PATENT PLEDGE INFLUENCE THIS ATTRIBUTE?**		**COMMENTS** (optional)
			To what degree is this attribute being influenced by a patent pledge regarding the specific technology?*	Is this influence positive (ie the attribute is changed so that the probability of adoption will increase) or negative (ie the attribute is changed so that the probability of adoption will decrease)? **Please answer only if you have not selected 'no influence at all' in the green column**	
Organisational characteristics	**Size of the Organisation** (large organisations usually have more resources that they can use to adopt technologies)	Choose an item	Choose an item	N/A (no influence in green column)	Write your comments here...
	Centralisation (extent to which decision-making authority is limited in an organization. Lower-level managers in different functional areas are more likely to possess greater knowledge of the technology, operational-level problems and the business processes than the higher-level executives. Organizations with decentralized structures are expected to adopt more innovative and cutting-edge technologies. In organizations where lower-level managers are not empowered to make important decisions, new ideas and innovations are less likely to be encouraged)	Choose an item	Choose an item	N/A (no influence in green column)	Write your comments here...
	Management Support (extent to which senior executives of an organization support an innovation. Management support does not refer to mere approval from top management but requires active and enthusiastic support that can be transmitted through the whole organization)	Choose an item	Choose an item	N/A (no influence in green column)	Write your comments here...
	IT Readiness (the level of sophistication of IT management. Companies that have sophisticated IT environments adopt technologies easier than those with less sophisticated IT environments since sophisticated IT firms are more likely to have the necessary expertise and resources in-house to adopt and implement the technology)	Choose an item	Choose an item	N/A (no influence in green column)	Write your comments here...

Fig. C.5 Survey for collecting feedback for Study 3 (5/8).

	ATTRIBUTE	IMPORTANCE* (How important is this attribute in your adoption decision process?)	COULD A PATENT PLEDGE INFLUENCE THIS ATTRIBUTE?		COMMENTS (optional)
			To what degree is this attribute being influenced by a patent pledge regarding the specific technology?*	Is this influence positive (ie the attribute is changed so that the probability of adoption will increase) or negative (ie the attribute is changed so that the probability of adoption will decrease)? **Please answer only if you have not selected 'no influence at all' in the green column**	
Inter-firm relationships	**Power** (power is defined as the ability of a firm to exert influence on another firm. Since inter-firm technology adoption usually involves one company trying to influence the other to adopt the technology, the amount of power that the initiating company has is an important factor in the decision to adopt technology. A persuasive approach could be used to convince the adopting firms of the benefits of adopting technology, or a more coercive approach could be used in which threats and punishments instead of inducements are used). In short, to what degree does the power of an initiating firm influence your decision to adopt a technology?	Choose an item	Choose an item	N/A (no influence in green column)	Write your comments here...
	Justice (in inter-firm technology adoption, the adoption process is frequently initiated by a larger firm asking their trading partners to adopt a technology that may be of limited value to the firms being asked to adopt it. When this happens, the target companies may consider it unfair and resist the adoption of the technology. To ensure that their trading partners adopt the technology, the initiating companies frequently threaten those who are reluctant to adopt the technology with punishments like fines or termination of their contracts. For fear of the consequences of not adopting the technology, the target companies may only partially adopt the technology or even buy the technology at the request of their trading partner but not implement it. Some companies will use alternative and less-efficient methods in their back-end systems	Choose an item	Choose an item	N/A (no influence in green column)	Write your comments here...

Fig. C.6 Survey for collecting feedback for Study 3 (6/8).

	while making their larger partners believe that they are using the newly adopted innovation. Because the companies might not be using the new technology, the trading partner will, in the long run, not get the efficiencies that they thought they had planned for. Because companies are being forced to adopt technologies that they do not find particularly beneficial to them, issues of fairness and justice are important in inter-firm technology adoption. Researchers have identified three distinct dimensions to justice – distributive, procedural and interactional. In short, to what degree does the prospect of justice in the case of 'unfair' relationships between firms play a role in your decision to adopt a technology?				
	Trust (trust is important in the adoption of collaborative B2B technologies since the use of inter-firm technologies introduces collaborations that entail more sharing and access to important confidential information, leading to increased vulnerability and interdependence. Trust between partners is also necessary for a company to ensure its partner will commit resource to the technology adoption and not act opportunistically in this adoption. To manage these vulnerabilities and uncertainties, it is important for trust to exist between trading partners. Without trust, the trading partners will be reluctant to adopt technology that will enable their trading partners to access sensitive trade information)	Choose an item	Choose an item	N/A (no influence in green column)	Write your comments here...

Fig. C.7 Survey for collecting feedback for Study 3 (7/8).

-PART B-

To the right, you see the preliminary technology adoption decision process for a firm, as implemented in our computer simulation. While it might look complicated, the process is straightforward and follows simple calculations:

Decision 1)
The first decision is whether to adopt a technology at all. It is assumed that not all firms decide to adopt a new technology at the same time. Rather, following the academic literature, they follow a normal probability density function over time, which results in a cumulated S-shaped curve. The implementation and the code for this decision result in a normal distribution of adopters over time.

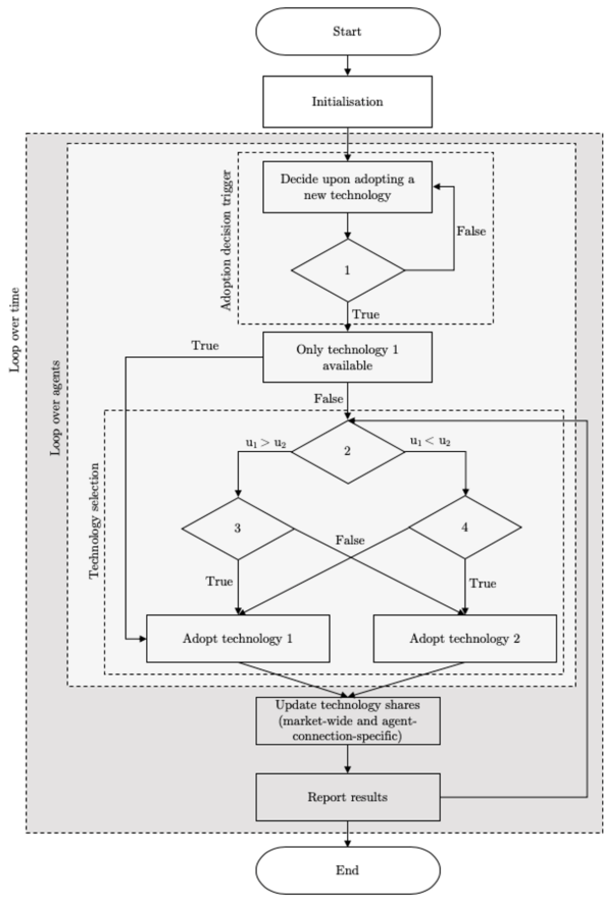
Decision 2)
When more than one technology is available to fulfil the same purpose, each firm *j* calculates the utility of each technology *k* and chooses the one with the higher value. The importance of the red column from part A is thereby multiplied with the respective value of the attribute.

$$u_{k,j,t} = \sum_{i=1}^{16} w_i \times att_{k,i}$$

where
w = weight of attribute, where $0 \leq w_i \leq 1$ and $\sum_{i=1}^{16} w_i = 1$

att = attribute, where $0 \leq att_i \leq 10$.

Decisions 3/4
Firms change their technology decisions when
1) The other technology has reached a critical market share of adopters (80% of all firms)
OR
2) A predefined share of connected firms of the focal firm has adopted the other technology (80% of the connections.



Decisions

1	Each agent inherits a constant parameter ('adoptionParameter'), which is drawn from the assumed technology adoption function. Therefore, the conditional transition `adoptionParameter < time()` results in the assumed adoption function.
2	The utility for each technology *k* at time *t* is calculated. The agent chooses the path with the higher utility.
3, 4	The agent changes his technology preference after the utility calculation if • a predefined percentage value ('criticalMarketShare') of all agents ('market') has already adopted the other technology or • a predefined percentage value ('criticalConncectionShare') of the agent's network connections has already adopted the other technology. The Java code is as follows: For 3: `(get_Main().shareTechnology2Users <= get_Main().criticalMarketShare) && (shareTechnology2Connections <= get_Main().criticalConnectionShare)` For 4: `(get_Main().shareTechnology1Users <= get_Main().criticalMarketShare) && (shareTechnology1Connections <= get_Main().criticalConnectionShare)`

Fig. C.8 Survey for collecting feedback for Study 3 (8/8).

Please provide any feedback that you have regarding the decision process or implementation.

General feedback
Write your feedback here...

Feedback for decision 1
Write your feedback here...

Feedback for decision 2
Write your feedback here...

Utility function in decision 2
Write your feedback here...

Feedback for decisions 3/4
Write your feedback here...

Do you think the critical market share in decisions 3/4 of 80% is realistic? Should the threshold be higher/lower?
Write your feedback here...

Do you think the critical connection share in decisions 3/4 of 80% is realistic? Should the threshold be higher/lower?
Write your feedback here...

Do you have any other thoughts/comments? Any feedback is helpful!
Write your feedback here...