Essays on the relationship between standardization and intellectual property rights

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Introduction

Standards may be defined as "documents that provide requirements, specifications, guidelines or characteristics that can be used consistently to ensure that materials, products, processes and services are fit for their purpose."[1] They aim at insuring interoperability between product components and make a selection between competing technologies for a given technical issue (Tassey 2000, Blind and Jungmittag 2008). Unlike regulations, standards are rules with no compulsory character, whose success depends solely on whether companies voluntarily decide to adopt them or not. Standards, therefore, can be understood as self-regulatory actions of an industry (Rysman and Simcoe 2008).

Technology standards play an important role in our daily lives and in the economy we live in. The Information and Communication Technology (ICT) industry, for example, represents an interesting case for the need of standardization and its evolution over time. In this fast growing industry, which is characterized by high product fragmentation and rapid technological change, standardization plays a crucial role. Standards also play an important role for globalization by harmonizing products and norms across countries and by allowing for market expansion through greater economies of scale, better division of labor, reduced transaction costs and network effects (Hallikas et al. 2008, Biddle et al. 2012, Chiao, Lerner, and Tirole 2007, Swann 2010). Despite its importance, the standardization process receives still little attention in the public discussion and has been picked up by the economic literature rather recently. Yet, it represents an interesting interplay between different actors of society.

The standardization system is closely linked to the patent system due to the implementation of proprietary technologies in standards and the standards potential impact on innovation and patenting itself. While standardization aims at facilitating the diffusion of knowledge, the patent system is designed to incentivize innovation by according a temporary property right to innovators, usually of up

[1] International Organization for Standardization (ISO), What is a standard?, `http://www.iso.org/iso/home/standards.htm`

to 20 years. For standardization to be efficient, these two principles must be balanced such that innovation can diffuse while technology owners are sufficiently compensated for their investment. However, the licensing of patents relevant to a standard, so called standard essential patents or SEPs, is prone to market failures such as externalities, information problems, market power and free-riding. One problem of the standardization process with regard to patents is the lack of transparency. Patent owners might try to withhold information about patents relevant to a standard project until the standard is adopted or bundle them with patents that are not relevant to the standard in order to increase licensing incomes and/or increase their market power. Another problem arises when technology owners and implementers are not the same, especially if patent ownership is very fragmented. These problems raise transaction costs and inefficiencies on the market (Bekkers et al. 2014a).

Standard development is by itself an innovative process that builds, on the one hand, on available technologies and adds, on the other hand, to the existing technological knowledge. Blind and Jungmittag 2008 show furthermore that standards have a positive impact on economic growth, especially in less R&D intensive sectors. Standardization projects are often followed by increased patenting of the participating entities in the process. Ex-post patenting can be due to opportunistic behavior of firms that seek to increase their market power by strategically patenting technologies that have been implemented in a standard once it has passed the ballot. However, Layne-Farrar, Padilla, and Schmalensee 2007 argue that part of the ex-post patenting reflects innovation. Bekkers, Bongard, and Nuvolari 2011 show also that SEPs tend to be more valuable than comparable patents, even though the participation in standard development affects the probability of a patent to become a SEP more strongly. Standardization can trigger innovation not only directly through the standard development process, but also by reducing uncertainty over technology selection in the market.

In this thesis I investigate the close connection between standards and patents from different angles. I analyze how standardization affects the development of new patents and what effect the introduction of patented technologies in standards has on the patent owner's revenues. I also study how a country's patent stock can affect its willingness to harmonize standards with other countries. Before giving an overview of the different chapters of this thesis, I will describe the ecosystem of standardization more in detail with a special emphasis on the role of firms in the process of standard development. I will also outline some international aspects of standardization and discuss the patent and standards data used throughout the thesis.

The ecosystem of standard setting organizations

Since standards are voluntary rules, they can be established by any company or group of companies. In practice, one can distinguish between four types of agents that establish standards. First, single companies might develop a standard on their own. Standards developed by single companies are referred to as "proprietary specifications" (Bekkers et al. 2014c). The firm retains full control over the specification and its evolution, and the specification typically serves the particular interests of the firm. When the specification gains market success, it is referred to as a "de facto standard". An example here is the Video Home Standard (VHS) developed by the JVC.

More commonly, standards are established by formal standard setting organizations (SSOs). Depending on the scope of their standards, formal SSOs can be national or international. National SSOs are entities that are formally recognized by the regulators as standard developing organizations (Bekkers et al. 2014a). They are "membership-driven bodies that bring together standardization experts - often from competing companies and from governments, academia and civil society - to develop standards in response to priorities determined by public- or private-sector members" (Bekkers et al. 2014c). An example for a formal national SSO is the German Institute for Standardization (DIN). Standards can also be established by quasi-formal SSOs, which are very similar in terms of structure and status to the formal SSOs but do not have a formal recognition by the regulators. An example here is the the World Wide Web Consortium (W3C). Finally, standards can be developed also by informal industry organizations called consortia (also fora or Special Interest Groups (SIGs)). A consortium consists of private sector members that share a common interest. It may limit the number of participants in order to achieve a more efficient and quick standard development process. Consortia may be formed for developing a single standard or for a broader scope.

In this thesis, I study standards issued by formal SSOs. SSOs provide platforms for different market participants to collaborate in order to produce interoperable components for technology systems. SSOs can be seen as industrial networks where firms bring together their competencies in order to meet the needs of customers and to reconcile the benefits of all participants (Rysman and Simcoe 2008,Hallikas et al. 2008). Yet, there is also competition between the different actors who pursue their private objectives and try, therefore, to influence the standardization process in their favor. In its role of a benevolent social planner, the SSO has to find an equilibrium between interoperability, market competition and optimal technology selection. As a membership based organization, however, it has to take into account the benefit maximizing behavior of its participants. This conflict of interests raises questions about the strategic behavior of participants in the standardization process that leads to deviations from the social optimum.

Developing and adopting a standard is a complex process that may take up to several years. Although the characteristics for this process exhibit a substantial heterogeneity across different SSOs, there are also common features. As an example, a consensus among the members of the SSO on the standard's scope and context must be reached before a standard is released. Thus, typically, a standard must pass some sort of ballot. Voting rules of different SSOs differ in the approval requirements, but also in the distribution of votes across members (Baron and Spulber 2015). Baron, Ménière, and Pohlmann 2014 model the conflict of interest in the SSOs technology selection by letting the SSO members' profits depend on the industry's joint profits, as well as the single firm's revenues from SEP ownership. Simcoe 2010 models a game where SSO members vote upon whether or not to accept an offer from the member with the best technology. The firms' profits depend on whether or not their technology is selected for the standard and on the concessions made by the winner. Both models show that the technology selection in SSOs is biased towards private incentives of the members.

In addition, most of the SSOs have (formal or informal) rules that concern intellectual property rights (IPR) on technologies necessary for the adoption of the standard (the most prominent example being here standard essential patents (SEPs)). These policies aim at ensuring fair conditions for SEP holders and applicants once the standard is adopted. Examples for such policies are ensuring transparency about and licences for SEPs, preventing patent hold ups, preventing too high cumulative fees, and many more (see Bekkers et al. 2014a for a detailed discussion). SSOs generally require of their members to disclose SEPs before a standard is formally adopted. Firms might, however, be reluctant to do so, since disclosure could expose information on their technological strategies and the application spectrum of the patented technologies (Chiao, Lerner, and Tirole 2007). SSOs might demand free or reasonable licensing arrangements for SEPs from their members.

Firms' participation in the standardization process

Firms participate in the standardization process by offering their technological knowledge. They interact in regular meetings and working groups where they have the possibility to propose their technological knowledge to a standardization project. The different solutions are discussed by the members and selected through consensus. Firms compete for having their IPR included in the standards in order to ensure future licensing revenues. Therefore, they might invest in proprietary technologies in advance and try to include them in the standard (Ménière 2015). Firms also devote a lot of effort to the standardization process by making important investments in R&D (Chiao, Lerner, and Tirole 2007). The costs often have to be born ex-ante, while benefits are uncertain and can arise with a time delay. Yet, benefits can be considerable and persist over time for certain technology standards. First, standards can serve as a positive signal for the firm's products (Lerner and Tirole 2006). Second, the inclusion of a firm's intellectual property rights (IPR) in a technology standard can guarantee a steady future flow of royalties to the firm.

In order to influence the standard setting process and successfully implement their technologies in standards, many firms develop their patent portfolios (Chiao, Lerner, and Tirole 2007). Chiao, Lerner, and Tirole 2007 describe standard development as a process which often takes place at an early stage of the technology development. IPR accumulation efforts can occur in the lead time to SSO entry with the objective to gain negotiation power in the standard setting process and to include their technologies in the standards. Bekkers, Bongard, and Nuvolari 2011 analyze the firms' strategic behavior on patent inclusion in the standards, however, they note that their paper does not take into account strategic behavior such as the creation of patent portfolios, cross-licensing, licensing of patent bundles, agreements on future patents, etc. Yet, patent portfolios can serve as a negotiation tool in cross-licensing agreements and presumably as a motivation for the formation of alliances in the standard voting process. In their paper on transfers of standard essential patents (SEPs), Baron and Ciaramella 2017 show that prior to the declaration date buyers of SEPs are more likely to be SSO members.

The decision to participate in a SSO is a strategic one. Competing firms might decide to cooperate in standard development for several reasons. One reason is to gain certainty about different aspects. Standard development by its nature reveals information to the market. Firms can learn, on the one hand, about technological needs in their respective markets and might be able to influence the market's response to these needs by influencing the standardization process. On the other hand, they also gain insights in the market strategies of their competitors. The standardization process can lay open the technological know-how and R&D strategy of the participants. The timing of SSO entry represents therefore a trade-off between the ability to influence a standard, which might be higher in the early stages of standard development, and a possible second-mover advantage by gaining valuable information about competitors and the standard itself while protecting own information a bit longer (Kauffman, Shao, and Tsai 2010).

One important driver for the firms' willingness to influence a standard and therefore to participate in its development is the prospect of a potential increase in revenues. Patents have been shown to be an indicator of a firm's market value (Belenzon and Patacconi 2013, Hall, Thoma, and Torrisi 2007) and SEPs tend to be more valuable than other patents (Bekkers, Bongard, and Nuvolari 2011). Yet, the ownership of a SEP does not necessarily come along with an increase in revenues, since standardization facilitates market competition (Aggarwal, Dai, and Walden 2011) and some SSOs require their members to license SEPs royalty free. The participation in standard setting can be both risky and rewarding for firms. The strategic composition of firms' patent portfolios can affect the direction of the effect (Pohlmann, Neuhäusler, and Blind 2015).

International aspects of standardization

From an international point of view, standardization can lead to either cooperative or competitive behavior between nations. Many standards are developed by SSOs from different countries that work together on a specific standardization problem. Many SSOs are international organizations which develop by definition international standards. Standardization is a promoter of international trade by harmonizing functionalities and product components and, hence, facilitate interoperability between products from different countries. The WHO therefore explicitly encourages the harmonization of standards across countries with the aim to decrease barriers to international trade. However, the distribution of the benefits from international standard harmonization is debatable and notably less developed countries act often as opponents to harmonization attempts arguing that benefits are skewed towards developed countries. One argument is that intellectual property rights related to international standards are mainly owned by developed countries' firms which makes standard compliance very costly for less developed countries and puts them in a less advantageous market position (Gibson 2007). Thus, standardization bodies are often confronted with the choice between endorsing a standard of a different SSO or developing a competing standard (Chiao, Lerner, and Tirole 2007).

Benefits and flaws of standards and patent data

The empirical analyses in this thesis are conducted with the help of different datasets on standards, patents, firms and countries. One very time-intensive task was the preparation and combination of these datasets for the purpose of each chapter. It was time-intensive for two reasons. First, standards and patent data are quite complex and, more importantly, incomplete. For example, standards have often several versions, but the identification of these standard groups is not necessarily an easy task due to the erroneous documentation of standard identifiers. A very common problem that researchers encounter with patent data is the flawed documentation of patent owner names. Second, the different datasets are quite large and contain many string variables which makes computation very long.

The datasets used are very rich and represent therefore the most used data in the related literature. However, they also have certain drawbacks which are related to the nature of the data collection. I will discuss the benefits and limitations of the data in the following, in order to give the reader clarity over the scope of the conclusions that can be drawn from the empirical analyses.

Throughout the thesis I use the Perinorm[2] database for information on standards. I enrich this data with data on SEPs and SSOs from the Searle Center database Database on Technology Standards and Standard Setting Organizations[3]. Standards are documented on the basis of document identifiers chosen by the SSO. However, one standard can be described by several documents due to amendments and replacements done by the standard's issuing body, but also due to standard adoption by other SSOs. All of these events can, but do not have to, be accompanied by the publication of a standard document. As described in chapter 3, the adoption of a standard developed by a different SSO should go along with the publication of a document referring to the adopted standard and indicating a similarity category. Yet, this is not always the case. The same is true for amendments and replacements. Also, for those cases where the reference is made, document identifiers might be incomplete and hence difficult to assign. Furthermore, some standards are developed by more than one SSO and therefore published as distinct documents by the different cooperating SSOs. It was therefore necessary to group documents that constitute the same technology standard. Such a group might contain amendments and equivalent adoptions of the same standard. Replacements and not equivalent adoptions, however, cannot be classified as the same standard, even though the latter is rather rare, presumable due to a deficient reporting of such events. The link between the Perinorm and the SEP data was made using the standard identifiers.

The SEP database has been created by retrieving publicly available SEP declarations from patent owners to the SSOs. Due to the diverging policies of SSOs

[2] https://www.perinorm.com
[3] see Baron and Spulber 2018

regarding SEP declarations and their publications, the data is highly skewed towards specific SSOs. If applicable, the SEP database contains information on the standard and the patent in question. Yet, many letters to different SSOs contain blank declarations, i.e. the standard and/or patents of interest are not necessarily specified. The number of SEPs is therefore much higher than represented by the data available (Bekkers et al. 2014b). On the other hand, it has been shown that firms tend to over-declare patents as standard essential out of precaution or strategic reasons, even though an essentiality declaration is still a strong indicator for actual standard essentiality of a patent (Stitzing et al. 2017a).

Data on patents come from the Patstat[4] database of the EPO. This database has two important advantages. First, it combines patent data from 38 patent authorities all over the world, which makes it the most complete cross-country patent database. Second, the EPO puts a lot of effort in harmonizing and structuring the data as much as possible. One possible drawback is linked to the accurateness with which patent offices report their data to the EPO. A more delicate issue arises from the complexity of the patent system itself which makes data collection challenging. Though, what is more striking is the presumably voluntary insertion of mistakes and ambiguousness by the patent applicants. This is especially problematic when analysing the ownership structure of patents, when firm names are not harmonized and often varied on purpose. Furthermore, the allocation of patent ownership to a country becomes difficult when patent owners are multinational companies. It was therefore necessary to conduct an algorithmic harmonization of firm names. Also the matching between patent owners and other firm level data has been achieve through an algorithmic matching. Due to its algorithmic nature, the result cannot be determinate. The aim was to minimize miss-allocations as much as possible. In order to solve the problem of multinational firms, all patents were allocated to the global ultimate owner of each firm as defined by the database Orbis[5], where additional data on firms is gathered.

Thesis overview

This thesis contributes to the research on several aspects of the relationship between standards and patents. Each of the chapters of this thesis deals with an independent research question, and can be read separately. The first two chapters discuss the role of firms in the standardization process. I therefore first present a simple theoretical model that describes the interplay between a firm's patent portfolio and its willingness to participate in SSOs. I also demonstrate the trade-

[4] https://www.epo.org/searching-for-patents/business/patstat.html
[5] https://www.bvdinfo.com/en-gb/our-products/data/international/orbis

off SSOs face between striving for socially optimal standards versus satisfying its members. This is an attempt to present the motivation for the research questions treated in this thesis from a theoretical point of view.

In Chapter 1, I study the effect of standardization on innovation. I develop a novel empirical approach in order to deal with the endogeneity between innovation an standardization. I apply machine learning methods in order to test the predictability of a standardization event and predict a counterfactual innovation path for non-anticipated standards. This chapter is an attempt to provide a method for causal analysis between two variables that suffer from a complicated endogeneity problem and to give a first insight in the direction of the causal effect of standardization on innovation. The empirical method developed in this chapter contributes also to the econometric literature on causal inference using machine learning methods. Chapter 1 is co-authored with Petyo Bonev (Univeristy of St. Gallen).

In Chapter 2, I investigate the effect of SEP ownership on firm revenue empirically. Again, I focus on thoroughly creating counterfactual outcomes in order to estimating a causal effect. I emphasis on firms' market performance rather than financial performance in order to enrich the existing literature on the subject. This topic is important, because SEPs can be a substantial source of revenue for firms. Chapter 2 is an attempt to measure this effect. Chapter 2 is a single authored paper.

In Chapter 3, I take an international perspective on the interplay between patents and standards. This chapter studies the international standard harmonization and the role of patents and international trade in this context. I particularly shine a light on the differences between developed and developing countries regarding standard harmonization and therefore contribute to the discussion about the distribution of benefits from standard harmonization. Chapter 3 is a signle authored paper.

Chapitre 1

L'effet de la standardisation sur l'innovation

Dans ce chapitre, j'analyse l'effet de la standardisation sur l'innovation. Afin de résoudre le problème d'endogénéité de cette relation, j'applique des méthodes d'apprentissage artificielle pour prédire des trajectoires d'innovation contrefactuelles. Cette méthode d'identification est basée sur l'exploitation des normes imprédictibles par le marché. Pour ces normes imprédictibles, j'utilise les données de brevets historiques pour faire des prédictions de l'innovation future. Ces prédictions servent de situation contrefactuelle dans le calcul de l'effet causal. Je trouve un effet positif de la standardisation sur le nombre de nouveaux brevets, mais pas d'effet sur la qualité des brevets.

Chapter 1

The effect of standardization on innovation: A machine learning approach

Abstract. In this study, we estimate the effect of standardization on innovation. A major difficulty arises because innovation itself potentially impacts standardization, which leads to reverse causality. To deal with the resulting endogeneity, we apply machine learning methods to predict counterfactual innovation paths. Our identification strategy exploits unpredictable standards, i.e. standards that could not be foreseen by the market. For the corresponding technologies, we use innovation history to predict what the amount of patents would have been in the case of no standards. We use these predictions as counterfactual (no-treatment) outcomes to estimate the effect of the standards. We find a positive effect of standardization on subsequent patenting activity, but no effect on patent quality.

1.1 Introduction

We evaluate the effect of technology standards on innovation in their technological area. This question is of importance, because standards might have two very opposed effects on innovation. Standard development is an innovative process by itself and can enhance further innovation in the field by reducing uncertainty on the market, by facilitating component interoperability and by making technological knowledge publicly available. Standardization can also have the opposite effect. Since standards make a technology selection and aim at a widespread adoption of the selected technological solution, they can freeze innovation by locking the market in one technology and therefore reducing the incentives for innovative investments in alternative solutions. We use SEPs to link standards and patent technology classes and apply a novel econometric approach in order to estimate the effect of a standard event on subsequent innovation in the related technology classes. Our results indicate a positive effect of standardization on subsequent patenting activity, but no effect on patent quality. Furthermore, our results do not support the technology selection theory of standards at the level of the economy.

Despite the close interrelatedness between innovation and standardization, the identification of causality between these two dimensions has not been addressed rigorously by the economic literature. It has been argued repeatedly that standardization plays an important role for innovation, yet, very little empirical evidence exists as of today on this subject matter. Shin, Kim, and Hwang 2015 noted that the relationship between standardization and innovation has received too little attention and still today we can cite only a few economic studies that have investigated the effect of standardization on innovation. However, since standards represent a choice of one technology among competing ones, it is likely that they affect innovation. When a standard becomes accepted by the market, it can be costly to deviate from the standard and innovate in a different direction. Therefore, it is plausible that the introduction of a new technology standard a) reduces the variety of RD efforts, and b) determines the path of future innovation.

Tassey 2000 describes the reduction of variety as one of the functions of standardization and argues that this category of standards is the most difficult to analyze since it can either enhance innovation through the realization of economies of scale or hamper it by increasing market concentration and, therefore, excluding small, innovative firms. Other qualitative arguments for the positive effect of standardization on innovation have been made, for example, by Blind 2013 who describes standardization as a knowledge sharing and producing process through the interaction of actors with heterogeneous backgrounds, capacities and knowledge. Blind and Jungmittag 2008 mention that variety reduction through standards is a necessary condition for the development of new technologies, because the selection of a dominant technology makes investment in and the use of the technology attractive.

Few empirical analysis exists as of today. Some scholars have used data from the Community Innovation Survey (CIS), a harmonized survey on the innovative activities of enterprises in EU member countries. This survey contains, among others, two questions related to standards: first, to what extent standards are a relevant source of information for the enterprises, and second, to what extent they constrain them in their innovative activities. Both questions have been found to be positively correlated, i.e. firms that use standards as a source of information feel also constrained by them. There is also some evidence for a non-linear relationship between innovative activity and standard age, which is found to be increasing up to a certain age and decreasing afterwards. Yet, this result has found to be less robust. The empirical evidence is based on two separate ordered logit models for the two survey questions of the CIS and including them respectively as explanatory variables (DTI 2005; Swann 2010). It is, however, not clear to what extent the use of standards as an information source actually translates into innovation. The survey questions are also framed such that the information source question refers to standards and regulations (mandatory rules), while the question on constraints mentions only regulations. It is likely that regulations represent both, an information source and a constraint, since they are by definition an obligatory information source. Standards, on the other hand, might be less of a constraint given their voluntary character.

Another paper by Layne-Farrar 2013 investigates the short-run effect of standards on innovation by SSO members. In the short-run, standards often lead to follow-up innovations and, therefore, to amendments or replacements of existing standards. The paper analyzes patenting behavior of SSO members after the first publication of a standard. She argues that two possible effects can explain the raise in patenting in the early stage of a standard's life. First, it can be related to opportunistic behavior of firms that try to enhance their market power by patenting technologies embedded in the standard. Second, new innovations occur due to follow-up R&D that aims to refine the standard in its preliminary stage, but also due to implementation details of the standard. By comparing the value of SSO members' patents filed before and after standard publication, she concludes that post-publication patenting is a mixture of opportunistic and innovative patenting. Her argument is that patents filed after standardization are still of value, but less then those filed before. However, standards might have short- and long-term effects on innovation, as well as inside and outside the SSO, for reasons mentioned before. Also, her econometric model does not account for several potential sources of bias, such as a mutual causal relationship between the quality of the SSO members' patent portfolios and the timing of standardization or the fact that patenting takes time and patent applications are published only 180 days after filing. Furthermore, it is possible that firms file patents for simultaneous inventions at different times, potentially starting with the most valuable ones.

Baron and Schmidt 2017 have used standards as a measure for technological shocks. Technological progress is described to be crucial for the business cycle, where firms first conduct R&D which leads to the emergence of new technologies. Standardization intervenes then as a selection mechanism among competing technologies. This reduces uncertainty and leads to technology adoption which is then followed by implementation and commercialization of the newly adopted technology. Using a Baysian vector auto-regression model, they investigate the impact of standardization events on macroeconomic parameters: output, investment, total factor productivity (TFP) and stock market indices. The stock market reacts immediately, while TFP and output decline at first and increase after some years. They explain this phenomenons through the informative character of standards about future macroeconomic movements, which leads to the quick and positive reaction of stock markets, and the need for adoption to the new technology, which causes TFP and output to decrease temporarily. The authors also show that the responses of output and TFP do not change when including the stock market indices in the model which might suggest that standardization is not necessarily predicted by the markets.

Other studies have looked at the emergence of new technologies. The categorization of an emerging technology is hereby often related to high quality patents or new combinations of technology classes or a combination of both. Joung and Kim 2017 try to identify emerging technologies using keyword analysis of patent documents and creating clusters of keyword pairs. Kim and Bae 2017 analyze patent clusters created through the cooperative patent classification (CPC) and evaluate whether they are promising using patent quality measures, including forward citations, triadic patent families and independent claims. Their method has the drawback that it can evaluate new clusters only with a time delay and is dependent on the scope of existing technology classes. Recently, studies have also employed machine learning methods in order to predict emerging technologies. Lee et al. 2018 apply a feed-forward multilayer neural network for predicting the value of a patent (measured by forward citations). They then cluster patents into predicted value categories in order to identify emerging technologies. Kyebambe et al. 2017 categorize patent clusters as either containing an emerging technology or not using backward citations and applying a supervised learning approach. All these studies define emerging technologies based on characteristics of patents, i.e. inventions. Using standards, as stated before, allows to measure technology adoption instead and, according to the definition of technology shocks by Gali 1999, positive productivity shocks through technological change imply not only invention, but also the implementation of the invention.

The reason for the scarcity of empirical evidence is that identifying the causal effect of standardization on innovation is a non-trivial task. The major problem is the reverse causality relationship between standardization and innovation. In particular, standards might arise precisely due to already existing innovation in a certain technology area.

We establish a novel identification approach to the deal with the endogeneity of standards. Our approach consists of three steps. In a first step, we build a prediction of whether a standard will be established in a given period, a given country, and a given technological class. The objective of this first step is to mimic the expectation formation of the firms using market information on the uncertain future events of establishing a standard.

In a second step, we construct predictions of counterfactual post-treatment (i.e. post standard release) innovation paths. An innovation path in a certain technology class is defined in this paper as the number of patent applications within the technology class followed over time. We restrict our attention to those technology categories, for which a standard is established in a given period despite a high predicted probability from our first step of no standard establishment. The intuition for this choice is the following. Consider a technology group, for which firms anticipate a high probability that no standard will be released. Then their innovation activities just prior to the event of the standard will correspond to those that firms would have exerted in the counterfactual no-standard scenario. The event of establishing a standard in that technology class can be viewed as a shock to the market. Thus, for those technology classes, we can use pre-treatment (i.e. prior to the standard) information to predict the future, post-treatment innovation path for the counterfactual no-treatment case. In particular, the pre-treatment information does not contain anticipation effects.

Steps 1 and 2 are generic in the sense that they can be constructed with prediction approach. In our empirical evaluation, we use machine learning methods - neural networks and random forests, respectively. These methods have been shown to deal well with large number of covariates and nonlinear model functions.

In a third step, we compare the actual innovation paths in the "shocked" technology categories to the predicted innovation paths. This comparison allows us to estimate the treatment effect of the technology shocks (the standards). The treatment effect is local in the sense that this is a treatment effect on a particular group of treated units: those, where no anticipation effects took place.

Our three-step approach complements existing econometric techniques. It relies on the assumption is that the information contained in our dataset correctly accounts for anticipation of standardization events. This assumption underlies the validity of the first step. The assumption is related to CIA- and conditioning-on-the-propensity-score-type assumptions (e.g. as in matching estimation). The major advantage of our approach is that we do not require common support in the covariates. Each (technology) unit serves as its own counterfactual match. The second step of our approach draws on the paper of Burlig et al. 2017 who also use past histories to construct counterfactuals. Our method accounts for the complex nature in which innovation activities are planned and implemented at the level of the firm. In particular, anticipation effects are likely to shift the paths of innovation already prior to treatment, invalidating the approach of Burlig et al. 2017. Our initial prediction step accounts for the anticipation of the firms and ensures an unbiased prediction in the second step.

The paper is structured as follows. Section 2.4 describes the institutional backgroud of standardization and the data, and section 2.2 our empirical strategy. Section 2.5 shows the results and is divided in two subsections. In section 1.4.1, we present the results of the first step of our methodology, the prediction of standard events, while in section 1.4.2, we create the counterfactual innovation path for unpredicted standards and estimate the effect of standardization on innovation. Section 2.7 concludes.

1.2 Institutional background and data description

In many cases there is a substantial uncertainty in the process of developing a standard. Although often a working group is setup by the SSOs to elaborate a draft proposal, the final outcome might not be foreseeable to the participants until the very end. One rather amusing example is the development of the Computer Graphics Reference Model by the International Standardization Organization (ISO), (ISO 1992). An ad hoc group was set up by ISO to investigate the feasibility of creating a standard, and a year later, two competing approaches were established (see Rada et al. 1994 for a detailed description of this case). It took the working group three further years to realise that the first approach was a process-oriented view and the second a data-oriented one. The two approaches were subsequently merged into one.

Even after a draft is established, a substantial uncertainty still resides in the subsequent standard setting phase. One part of it is related to the negotiation process that reflects the complex interplay of (often conflicting) interests. An unsatisfactory ballot can result in a subsequent refinement of the standard before a final consensus is achieved. A second part of the uncertainty is due to the disclosure of SEPs by the patent holders. In particular, it may be the case, that even the SEP holders are not aware of all of their standard-relevant patents. Such a patent might however be discovered ex post. In addition, participants might not be aware of patents owned by third parties that have been disclosed. Finally, a participant might simply realize that a known SEP has a much higher value for the firm. All of these cases might lead to a revision of the standard (e.g. by using an alternative technology) or to a withdrawal of the standard altogether if the former is not feasible (Bekkers et al. 2014a).

All these aspects of the standard setting procedure can make its outcome uncertain even for involved participants. Our empirical strategy relies on identifying this uncertainty.

1.2.1 Data sources

Data used for prediction of standards

To predict the timing of a release of a standard, as described in section 1.3.3, we use data from several sources.

First, we retrieve data on standards from the database Perinom. It contains information on national standards from 27 countries, as well as on European and global standards. We dispose of information on the publication date, the issuing SSO, the country, information on the content of the standards (such as the title, the abstract, the language), as well as the technological classification according to the International Classification for Standards (ICS) (a given standard can be categorised with a combination of several ICS classes). We can also track international relationships between standards, i.e. to which extent standards from different SSO's are related to each other and how similar they are. In particular, when releasing a standard, a SSO should publicly disclose if the standard is equivalent to some already existing one (or a modified version of it), a process which, ironically, is itself standardized by an ISO standard (ISO/IEC Guide 21). We use this information to determine which countries have implemented international and European standards, and to distinguish whether a country has developed or adopted a standard. We only use newly developed standards and exclude adopted ones in our analysis since we are interested in the effect of technological shocks to the market. Standard adoption can also affect innovation, however, the effect might not be comparable to the implementation of a new and unexpected standard. Furthermore, expectations about standard development and adoption might follow different patterns.

Second, for each of the 27 countries in the Perinom database, we extract GDP per capita, total population, R&D expenditure as a percentage of GDP, the mean tariff rate, the natural resource rent as a percentage of GDP, and the categorization of countries in high vs. low income countries (time varying) for each year from the World Bank's World Development Indicators (WDI) database. In addition, we also obtain trade data on country and product level from the United Nation's UNCTAD database.

The choice of these variables is motivated in section 1.2.4.

Patent data

We extract patent data from Patstat, a database of the European Patent Office (EPO) that collects and structures information on patents from 38 patent authorities worldwide. We observe detailed characteristics for each patent such as technology category, owner, inventor, filing date, and all kinds of changes in the patent's life time (renewal, withdrawal, etc.).[1] Our main dependent variable is the number of patent applications in a given period, country and technology area. This variable can be interpreted as a proxy for innovation. To account for patent quality, we also calculate the average number of forward citations to patents of a technology category.[2]

1.2.2 Linking data sources and sample definition

Standards and patents are classified with different technology classification systems. In particular, patents are typically classified according to the International Patent Classification (IPC) system and/or according to the Cooperative Patent Classification (CPC), whereas standards are classified according to their own system (the ICS). As of today, there exists no publicly available concordance table that links the IPC (or CPC) to the ICS categories. In order to identify the relevant patent technology classes for a standard, we use data on declared SEPs from the Searle Center database Database on Technology Standards and Standard Setting Organizations. This database combines data on standards similar to Perinorm with information on the SSOs themselves. A major advantage of this database is that it contains information on SEP declarations and reports the patent identification numbers of the SEPs. These declarations make it possible to link the ICS classes of the standards to the International Patent Classification (IPC) numbers

[1] For a detailed description of the database see European Patent Office 2018.

[2] For patent counts and citations as proxies for innovative activities see for example Acs and Audretsch 1989, Hagedoorn and Cloodt 2003.

of the patents. SEP declarations do not exist for all standards, either because the standard does not include patented technologies or because the relevant patents are not declared publicly as SEPs. Furthermore, some argue that firms tend to over-declare, i.e. declare patents that are not really essential to the standard (Stitzing et al. 2017a). This limits our sample of standards to those where information on SEPs is available.

We only consider newly developed standards and exclude adopted standards. We use international relationships in order to link international or European standards to countries. The developing country is then the country that first adopted an international or European standard.

In order to link trade to technology classes, we use the concordance table provided by Lybbert and Zolas 2014. This table links product categories from the Standard International Trade Classification (SITC) (used also in the UNCTAD database) to IPC classes. The matching is done through keyword searches in the patent documents and allocates probability weights to each SITC-IPC pair. We obtain trade data on the technology level by weighting exports and imports from the UCTAD database with these probability weights and linking them to standards through the ICS-IPC matches.

1.2.3 Descriptive statistics

Our final dataset contains 143,451 observations and 253 technologies (i.e. ICS combinations). Every observation is defined as a combination of a technology, a country and a year. We count 13,244 standardization events, i.e. about 9% of the observations. The scarcity of standard events makes prediction particularly challenging. A naive prediction of no standardization event for all years would already result in a prediction accuracy of 91%, i.e. 91% of cases are predicted accurately. Our data represents only a fraction of all available standards in Perinorm. This is mainly due to the ICS-IPC matching using SEP data which was not possible for all technologies. We also loose some standardization events by considering the period of observation from 1995 to 2015 which excludes older and some more recent standards. Figures 1.1 and 1.2 show the distribution of standardization events over the available years and countries. Figures 1.8 and 1.9 in the appendix show the same distributions for the whole set of standards in Perinorm for the same time period. These exclude international and European standards which have bee allocated to countries as described in section 1.2.2.

Figure 1.1: Number of standards over years
13,244 standards

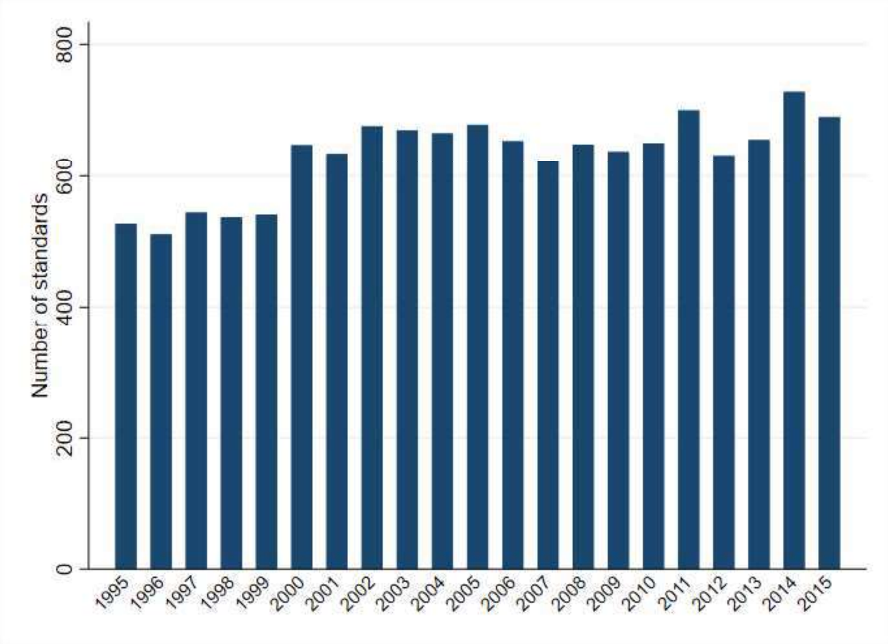


Figure 1.2: Number of standards over countries
13,244 standards

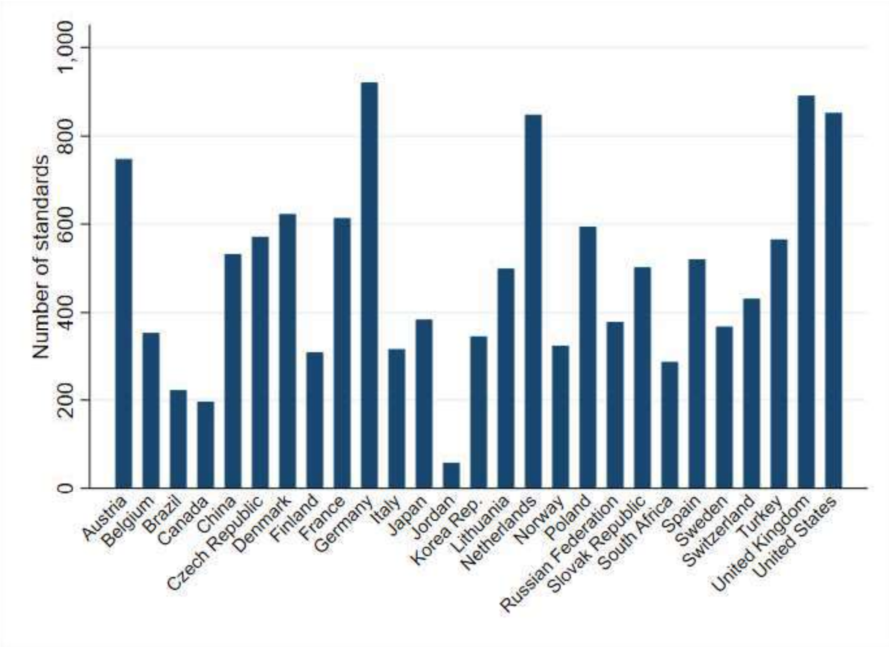


Table 1.1 presents descriptive statistics of all input variables for standard prediction as well as of the standardization event variable itself and our variables of interest, the number of patent applications and the average number of 5-years forward citations, which serve as our proxy for innovation. Furthermore, we show average values of all vairables by country in tables 1.15 and 1.16 in the appendix.

Table 1.1: Descriptive statistics

	Mean	Standard dev.	Min.	Max.	No. of observations
Standard event (0/1)	.0923	.2895	0	1	143451
Exports in tech. (mio. USD)	253	575	.0003	8784	143451
Imports in tech. (mio. USD)	234	500	.0025	6631	143451
Patent stock in tech. (thous.)	38	111	0	1049	143451
Total patent stock (mio.)	11	41	0	621	143451
GDP per capita (thous. USD)	32	21	1	92	143451
Total population (mio.)	99	244	3	1371	143451
Standard stock in tech. (thous.)	.6527	3	0	43	143451
R&D expenditure (% GDP)	.0179	.0088	-.0026	.0429	143451
Mean tariff rate	.0438	.0399	0	.2382	143451
Natural resource rent (% GDP)	.0179	.034	.0001	.2175	143451
Number of patents in tech. (thous.)	8	21	0	186	143451
Total number of patents (mio.)	2	8	0	108	143451
Number of patent citations	7	71	0	2880	132825
Cumulative number of patent citations	35	323	0	11776	132825
Average number of 5 years citations	91	499	0	7101	132825

Note: The unit of observation is on the country - technology category - year level.

Table 1.2 compares descriptive statistics of all input variables of years where a standardization event occurs in the following years with years where without standardization. Years preceding a standardization event are characterized on average by less exports and imports, smaller total and technology related patent stocks, a lower mean tariff rate and a lower natural resource rent. GDP per capita, population size, standard stocks within the technology area and national R&D expenditure are higher for these years. T-statistics for the mean comparisons are reported in the table. All differences are significant at the 95% confidence level.

Table 1.2: Descriptive statistics by standard and no-standard years

	Standard		No standard				
2-5	Mean	Standard deviation	Mean	Standard deviation	Difference in means	t-statistic	No. of observations
Exports in tech. (mio. USD)	171	475	254	561	-82	-16	143451
Imports in tech. (mio. USD)	165	445	235	489	-69	-15	143451
Patent stock in tech. (thous.)	30	99	38	111	-9	-9	143451
Total patent stock (mio.)	8	35	11	41	-3	-9	143451
GDP per capita (thous. USD)	34	19	32	21	2	10	143451
Total population (mio.)	109	255	98	242	11	5	143451
Standard stock in tech. (thous.)	4	6	.2524	2	4	181	143451
R&D expenditure (% GDP)	.0182	.0084	.0177	.0089	.0005	6	143451
Mean tariff rate	.0358	.032	.0452	.041	-.0095	-25	143451
Natural resource rent (% GDP)	.0145	.0301	.0186	.0348	-.0041	-13	143451
Number of patent citations	6	60	7	74	-.6669	-.9661	143451
Cumulative number of patent citations	25	220	30	282	-5	-2	143451
Average number of 5 years citations	77	412	92	508	-16	-3	143451

1.2

In table 1.3, we compare our output variables by years with and without standardization event. More precisely, the table reports the average increase of patent applications and citations one to five years after the year of observation compared to the average number of patent applications and citations of the preceding five years. The number of patent applications increases for both, years with and without standard. However, the increase is on average higher if no standardization event happened. This naive comparison between treated and untreated years would lead to the conclusion that standardization reduces innovation. No difference can be found for patent citation. The differences are small and not significant at the 95% confidence interval. As we will see in section 2.5, our estimation method, which accounts for predictability of standards, suggests a positive relationship between standardization and patent applications. The simple comparison of means between treated and untreated is therefore misleading.

Table 1.3: Patent applications and citations - Before-after and Diff-diff

	Standard		No standard				
2-5 Years after treatment	Mean	Standard deviation	Mean	Standard deviation	Difference in means	t-statistic	No. of observations
Patent applications							
1 year	242	4938	414	5986	-171	3	129789
2 years	356	5612	614	6701	-258	4	122958
3 years	463	6219	803	7460	-341	5	116127
4 years	562	6858	1001	8271	-439	5	109296
5 years	678	7616	1181	9010	-503	5	102465
Patent citations							
1-year lead	3	61	2	67	.6945	1	132825
2-years lead	4	64	4	71	.3941	.587	126500
3-years lead	6	69	5	73	.5482	.7668	120175
4-years lead	7	70	6	74	.3908	.5209	113850
5-years lead	7	71	7	76	.0525	.0663	107525

Note: The table reports the difference between the average patent count 1-5 years after the treatment period and the lagged patent counts averaged over the 5 years preceding the treatment period.

1.2

1.2.4 Variable selection for standard prediction

To our knowledge, the likelihood of standardization has not been studied empirically yet. In order to discuss the predictability of standards, it is important to understand how standards are created. The first step of standardization emerges from the idea of one or more market participants. The initiators then have to find enough support for their idea and a standardization body to sponsor it. Standards are built on the beliefs and understanding of its authors about the market and are either created in anticipation of market changes or based on current practice. Anticipatory standards are especially implemented in sectors with short product life cycles such as the ICT sector (Cargill 2011). Chiao, Lerner, and Tirole 2007 describe standard development as a process which often takes place at an early stage of the technology development. Firms can seek to obtain a comparative advantage by initiating the standardization process at this early stage. Cargill 2011 examines sources of standardization failure at different stages of standardization and argues that in the very early stage standardization can fail due to a lack of interest of market participants to standardize or to bear the costs of standardization. Another early source of failure is disagreements between different parties, notably about intellectual property rights. Furthermore, standardization is influenced by the innovative activity within the technology area. Chiao, Lerner, and Tirole 2007 indicate, for example, that firms devote a lot of effort to the standardization process by making important investments in R&D.

Loyka and Powers 2003 discuss factors influencing global product standards and relate it to market, industry and company factors. Market factors describe country specific aspects such as consumer characteristics, economic development and infrastructure. Industry factors include market structure, product and production particularities, competition and technological aspects. Company factors relate rather to the adoption of product standards within the companies. He also argues that standardization becomes necessary as an economy develops due to the increasing complexity of the society and the industrialization of the economy.

Moreover, the international trade literature has identified standards as potential barriers or promoters of international trade (2008, 2012, Chiao, Lerner, and Tirole 2007, Swann 2010, *Technical Information on Technical barriers to trade*). Standards are often implemented in response to the countries' position in the international market space and frequently create tensions between the developed and the developing world due to differences in adoption costs and an unequal distribution of intellectual property rights (Gibson 2007, Ernst 2011). It is also worth noting that standardization is a costly process and requires a certain institutional structure. Only very few low income countries dispose of a standardization body.

Our input variables for standard prediction include technology related exports and imports in order to capture international trade effects on standardization. Macroeconomic development is captured by GDP per capita, population and a high income dummy. Technology related and total patent stocks as well as R&D expenditure as a percentage of GDP capture the importance of intellectual property rights and innovation for standardization. We furthermore include the age of the technology and the number of existing standards worldwide within the technology category in order to control for the anticipatory character of the standards. Finally, we include country and year dummies in order to capture trends in time and space.

1.3 Empirical strategy

1.3.1 Microeconomic foundations

We use a standard on the (ethical) use of Artificial Intelligence (AI) in industrial application to motivate the first approach of our empirical strategy. A proposal for such a standard is currently under development by an expert committee of ISO (the ISO/IEC JTC1 committee). Consider a firm that can spend in period $t = 0$ a total of 1 on R&D activities. The firm can adopt a technology that optimally prepares the firm for a standardization event in $t = 1$. As an example, the firm could hire researchers trained in developing certain types of algorithms. Or it can change those of its current models that use a certain type of information (e.g. race) in order to make them "more ethical". Adopting this technology is costly and the cost equals $C \in [0, 1]$. When a standardization event occurs in $t = 1$ and the firm is properly prepared, the R&D activities of the firm yield a return of ρ_1. When there is no standardization event in $t = 1$ and the firm prepares in $t = 0$, the R&D activities yield a return of ρ_2. Finally, when the firm does not prepare and there is an event, the R&D activities yield a return ρ_3. We assume that $\rho_1 > \rho_2 > \rho_3$ and set $\eta_i := 1 + \rho_i$ for $i = 1, 2, 3$. The motivation behind this assumption is that if the firm correctly predicts a standardization event, its preparation might give it an early-adopter advantage, e.g through developing patents on standard-based algorithms.[3] Let the firm-specific discount rate be τ and the (possibly subjective) probability for a standardization event in $t = 1$ (as seen from $t = 0$) be p. When the firm adopts a technology as a preparation for a future standard, its expected profit in $t = 0$ is

$$\Pi_{0,S} = -C + \frac{p(1 - C)\eta_1 + (1 - p)(1 - C)\eta_2}{1 + \tau}. \tag{1.1}$$

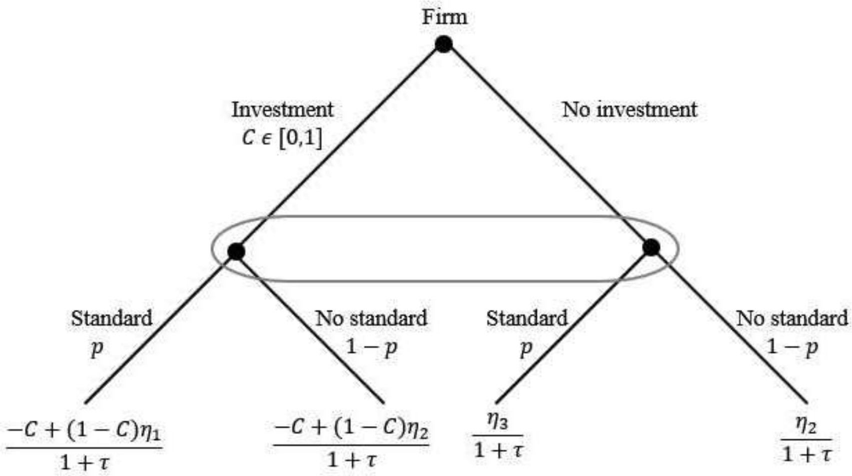
In the case of no preparation, the expected profit of the firm in $t = 0$ is

$$\Pi_{0,N} = \frac{p\eta_3 + (1 - p)\eta_2}{1 + \tau}. \tag{1.2}$$

[3] In Europe, an algorithm can be patented only if it is a part of mixed-type invention, which also solves a technical problem in an innovative way (IAM 2018).

The decision tree in figure 1.3 illustrates the firm's decision graphically.

Figure 1.3: Firm's investment decision



The firms adopts a standardization technology iff

$$\Pi_{0,S} > \Pi_{0,N}, \tag{1.3}$$

which is equivalent to

$$p > \frac{C(1+\tau+\eta_2)}{(1-C)\eta_1 + C\eta_2 - \eta_3} =: \bar{p} \tag{1.4}$$

Thus, if the probability for a standard is lower than a threshold $\bar{p}$, the firm behaves in $t = 0$ as if there will be no standard in $t = 1$ (namely, it does not invest in a future standard). We refer to this case as "No anticipation".

The idea of our identification strategy is to exploit this decision rule in the following way. Suppose that we can estimate the probability p. If we knew $\bar{p}$, then we could isolate all the cases in which there was a surprise for the firm, i.e. it decided not to invest in standardization technology and there was a standard or vice versa. Using these surprises yields a source of identifying variation. In particular, one can use the non-prepared trajectory of patents until $t = 0$ in order to predict how many patents there would have been in $t = 1$ had there been no standardization event. This prediction can be interpreted as a counterfactual post-treatment patent trajectory.

There are two pitfalls related to this strategy. First, in our paper we consider innovation on a national level, and not on a firm level. This problem could be solved by considering all firms in the given technological area of the national market. In particular, if we knew all thresholds of the firms operating on this market, we could either aggregate the procedure firm by firm, or simply pick the highest threshold in a given period (and use considerations identical to those in the previous paragraph applied to this highest threshold).

Second, $\bar{p}$ is not known to the researcher. Estimating it would involve substantial assumptions on the future profits of the firm, which are hard to be elicited from the data particularly in the case of standardization. We therefore choose the threshold $\bar{p}$ with the highest prediction accuracy in our main results and analyze the sensitivity of our results with respect to changes in $\bar{p}$.

1.3.2 Econometric framework

We cast our econometric problem in the Rubin Causal Model framework (Rubin 1974). Denote by D_{it} the random standardization indicator for time t and technology category i, $i = 1, \dots, n$, $t = 1, \dots .T$, where $D_{it} = 1$ denotes the event "A standard is introduced" (we omit the country index for simplicity). Define $Y_{i,t}(d)$ to be the potential outcome of interest in period t and technology i when the treatment is equal to $d \in \{0, 1\}$. For simplicity of exposition, assume that the standards are introduced at the beginning of a period and the outcome is realized at the end of the same period. The notation can be generalized to a multi-period gap between treatment and outcome in a straightforward way.

We are interested in estimating the average causal effect

$$ATE = \mathbb{E}[Y_{i,t}(1) - Y_{i,t}(0)]. \tag{1.5}$$

However, for each t and i, only one of $Y_{i,t}(1), Y_{i,t}(0)$ is observed. This problem is referred to as the Fundamental Problem of Causal Inference (Holland 1986).

Our approach identifies a conditional version of equation (1.5) in three steps. The first step aims at isolating those standards that surprised the market. We pursue this step by using a rich dataset to predict whether a standard will be released or not. In particular, let $\mathbb{F}_l$ be the information at some point in time l that agents can use to estimate the propensity score $p_{i,t} = P\{D_{i,t} = 1\}$ for technology i at time t. Denote the estimate with $\hat{p}_{i,t}$. We assume that market participants form a prediction $\hat{D}_{i,t}$ for $D_{i,t}$ using a simple Bayes classifier:

$$\text{Set} \quad \hat{D}_{i,t} = 0 \quad \text{if} \quad \hat{p}_{i,t} \leq \bar{p} \quad \text{and} \quad \hat{D}_{i,t} = 1 \quad \text{if} \quad \hat{p}_{i,t} > \bar{p}, \tag{1.6}$$

where $\bar{p}$ is a threshold probability.[4] We define the set of standards with $\hat{D}_{i,t} = 0, D_{i,t} = 1$ to be the Non-Anticipated standards (NA).

This definition of NA-standards has two advantages. First, the actual implementation is straightforward. The researcher can use either standard econometric classification approaches such as logit or Machine Learning techniques. We discuss the empirical implementation in subsection 1.3.3 below. Second, this definition of a missclassified standard is closely related to the microeconomic discussion from the previous section. Market participants are "surprised" by the standard, in the sense, that prior to the standard they behave as if no standard will be released.

In a second step, we predict the outcome variable for all standards in the NA group using only pre-treatment (i.e. pre-standard) characteristics, including pre-treatment outcomes. This step and the following step are borrowed from the paper by Burlig et al. 2017. Denote the predicted outcome for technology i and period t by $\hat{Y}_{i,t}(0)$. The motivation for this step is that for the NA-set of standards, the history $(Y_{i,l}, X_{i,l})_{l \leq t-}$ does not contain anticipatory effects and can be used to construct an unbiased prediction for the counterfactual non-treatment outcome. The notation of the prediction reflects this assumption by including an indicator for the potential outcome.

In a final third step, each outcome in the NA-group is compared to its predicted counterfactual. The resulting estimator is defined as

$$\hat{\beta}^T = \mathbb{E}[Y_{i,t}(1) - \hat{Y}_{i,t}(0) \mid NA] = \mid NA \mid^{-1} \sum_{i,t} (Y_{i,t} - \hat{Y}_{i,t}(0)), \tag{1.7}$$

where $\mid NA \mid$ is the number of observations in the NA group.

Before we discuss the actual implementation of steps 1-3, we briefly discuss the main underlying assumptions through a comparison of the estimator to the standard matching on the propensity score. Both, equation (**??**) and the matching estimator rely on estimating the propensity score. However, the matching estimator crucially relies on a common support assumption, which ensures finding similar treated and non-treated units. Our approach, on the contrary, builds for each unit in the NA group its own counterfactual prediction. The two crucial

[4]The standard Bayes classifier uses $\bar{p} = 0.5$.

assumptions behind our estimation approach are (i) that the information available to the econometrician is sufficient to identify the NA group and (ii) the counterfactual predictions for this group are unbiased. Assumption (i) is similar in spirit to the CIA assumption invoked by the matching estimator. It is a non-testable assumption. Assumption (ii) can be defended in a way similar to defending the parallel trend assumption used in a DID estimator: by predicting pre-treatment outcomes based on their histories

Predictions might not follow the exact same pre-treatment path as actual outcomes, but follow a parallel trend. In order to take this into account, the prediction error on pre-treatment innovation can be subtracted:

$$\hat{\beta}^{TD} = \mathbb{E}[Y_{i,t}(1) - \hat{Y}_{i,t}(0) \mid NA] - \mathbb{E}[Y_{i,t-\epsilon}(1) - \hat{Y}_{i,t-\epsilon}(0) \mid NA] \ , \tag{1.8}$$

where $t - \epsilon$ denotes some pre-treatment period.

Although our estimation method does not depend on the selection of an untreated control group, i.e. a comparable sample without standardization, we follow Burlig et al. 2017 in randomly selecting untreated observations. Untreated means that no standard has been released, but also that no standard was predicted by the model. Yet, the timing of a standard event cannot be defined for untreated units. Burlig et al. 2017 propose a solution that consists of randomly assigning a treatment date to those units. We decided to repeat the random selection of untreated years 100 times and use average counterfactual outcomes in order to avoid that the estimated effects are due to the specific random sample. The comparison with this control group allows us to control for global trends and shocks that could lead to prediction errors in the whole sample. Just as in equations (1.7) and (1.8), we can calculate $\hat{\beta}^{U}$ and $\hat{\beta}^{UD}$ for this control group. We obtain two additional measures of the treatment effect that account for general trends across country-technology pairs, the difference-in-differences estimator

$$\hat{\beta}^{DD} = \hat{\beta}^{T} - \hat{\beta}^{U} \tag{1.9}$$

and the triple difference estimator

$$\hat{\beta}^{3D} = \hat{\beta}^{TD} - \hat{\beta}^{UD} \ . \tag{1.10}$$

1.3.3 Empirical implementation

For the first step, we use a neural network with one hidden layer in order to predict the occurrence of a standard in technology category i at time t in a given country.

It has been shown that in many cases one hidden layer is sufficient for an accurate prediction due to the universal approximation theorem that states that any continuous function can be approximated using a feed-forward neural network with a single hidden layer and a finite number of neurons under mild assumptions on the activation function. Neural networks have been used increasingly for classification problems. One advantage of neural networks is that they allow for complex non-linear relationships between the input variables and the output without imposing a specific functional form ex-ante. The neural network implicitly selects the most useful variables for prediction among the input variables by allocating weights to each variable in the input layer. Furthermore, each neuron in the hidden layer obtains also a weight which can introduce non-linearity in the prediction model. There is a trade-off between the number of neurons in the hidden layer and the calculation time until convergence. We vary the number of neurons in the hidden layer in order to evaluate the sensitivity of our prediction results with respect to the number of neurons. The model issues a prediction value between zero and one which can be understood as the probability of a standardization event to occur in t. Prediction accuracy is defined as the ratio between correctly predicted realization to the number of realizations. Correctly predicted events include true positives, i.e. years with a standard event that have been predicted correctly, and true negatives, i.e. years without a standard event which have been predicted as zeros. False positives and negatives represent false predictions. In order to decide whether the prediction of a standard event is set to zero or one, we have to decide on the threshold $\bar{p}$. We choose the threshold that leads to the highest prediction accuracy as a baseline and conduct a sensitivity analysis relative to the choice of the threshold. In particular, we compare our results with a the ones of a very low threshold which we arbitrarily set to 10%. With a very low threshold NA-standards are considered extremely unlikely by the prediction model and can therefore be considered more confidently as actual shocks to the market.

In the second step, we use random forests in order to construct counterfactual innovation paths. Random forests are increasingly popular methods for both, classification and regression problems. They combine a multitude of decision trees in order to improve out-of-sample predictions. Decision trees are prone to overfitting, i.e. to match training samples to closely and can therefore lead to poor out-of-sample predictions. In other words, they lead to low-bias, but high-variance predictions. Random forests reduce variance by randomly selecting a subset of input variables for each tree (therefore reducing the risk of growing too strongly correlated decision trees) and averaging the predictions of the different trees. In our model, we set the number of decision trees to 100. Our random forest uses a bagging algorithm for model averaging, i.e. the algorithm generates a number random subsamples with replacement and averages prediction output over these samples. Decision trees are grown deep, i.e. potentially fit the data in the respective subsample very well. The reduction in variance is achieved through bagging and the random selection of input variables in each decision tree.

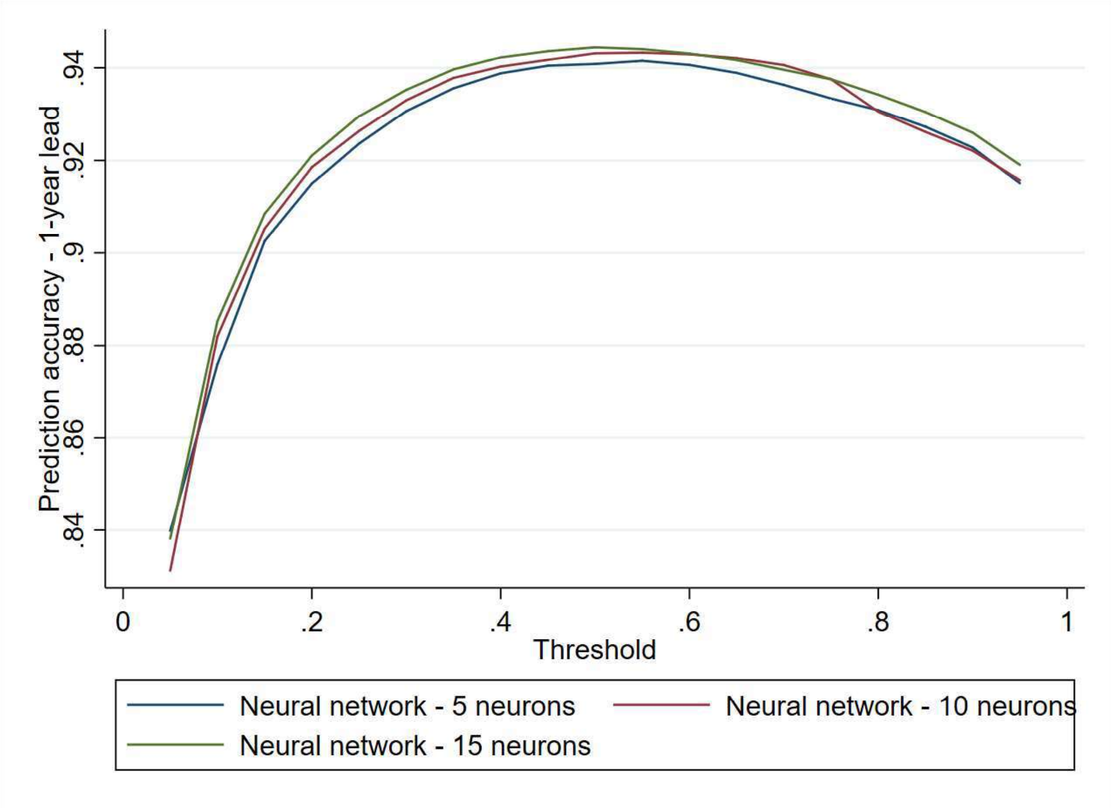
1.4 Results

1.4.1 Standard prediction

We randomly select 20 percent of our data as the training sample and 80 percent as the validation sample. Standardization events are predicted one to five years ahead. The dataset consists of a panel of 253 technology groups and 27 countries between 1995 and 2015 and contains 143,451 observations.

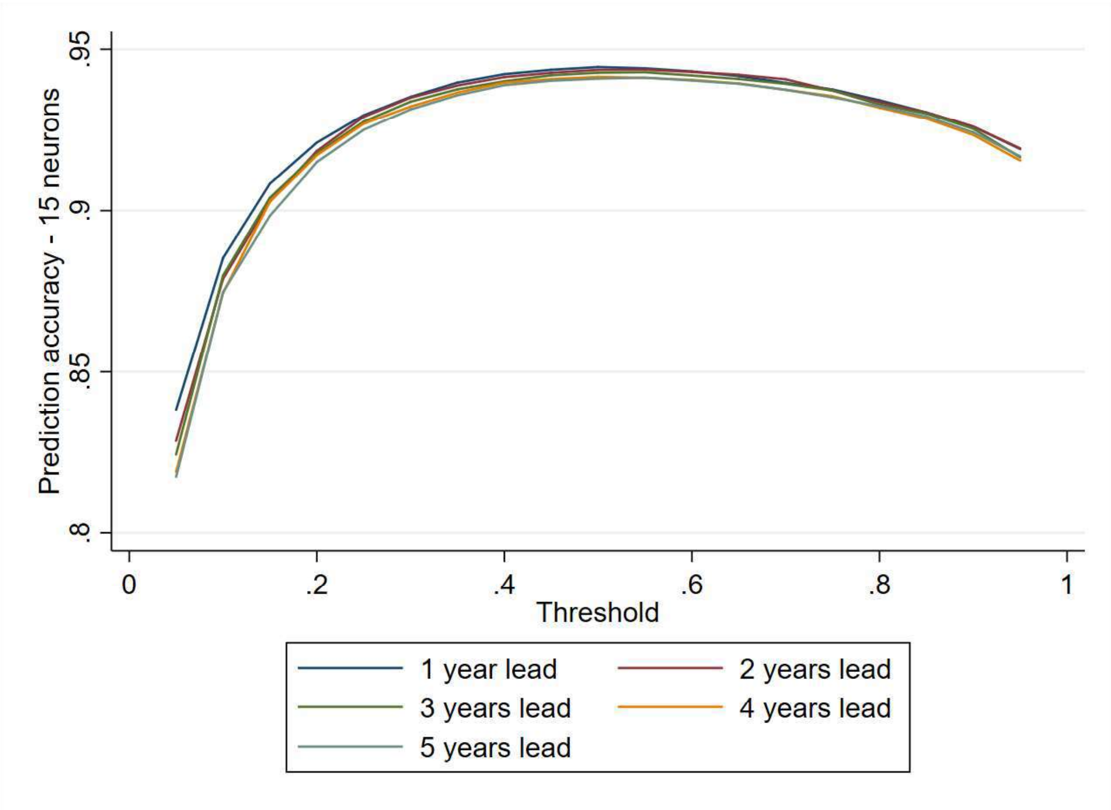
Figure 1.4 shows the prediction accuracy for the different number of neurons in the hidden layer of the neural network (predictions from period -1). A higher number of neurons in the hidden layer leads to a better prediction accuracy. This is the case for all prediction leads. This reflects the complex non-linear relationship between the input variables and the output. In figure 1.5 we show the prediction accuracy by prediction lead, i.e. for how many years ahead the standardization event has been predicted. The maximum accuracy is 94.4% (the values of figure 1.5 are presented in table 1.17 in the appendix). Here, we use predictions made with 15 neurons in the hidden layer, since they lead to the highest prediction accuracy. The prediction accuracy is very similar for the different leads, but becomes slightly better closer to the standardization event. The prediction accuracy is generally the highest at a prediction threshold of 0.5-0.55. The predictions are better than a naive predictor of setting predictions to 0 for all periods which would lead to a prediction accuracy of 90.8% because of the scarcity of standardization events. Using a prediction lead of 1 year, 15 neurons in the hidden layer and a threshold of 0.5, we are able to correctly predict 98.1% of all non-standardization events (true negatives), and 57.9% of standardization events (true positives). Compared to the naive predictor, we loose 1.5% of possible true negative predictions, but are therefore able to predict more than half of the standardization events correctly.

Figure 1.4: Accuracy of standard prediction by number of neurons



Note: Neural network with 1 hidden layer for prediction. Standard prediction is set to 1 if the prediction value of the neural network is larger than threshold. Predictions 1 year ahead, i.e. using inputs from $t-1$. Accuracy = true predictions/number of observations.

Figure 1.5: Accuracy of standard prediction by prediction lead



Note: Neural network with 1 hidden layer with 15 neurons for prediction. Standard prediction is set to 1 if the prediction value of the neural network is larger than threshold. Predictions x=1,...,5 years ahead, i.e. using inputs from $t - x$. Accuracy = true predictions/number of observations.

Table 1.4 reports the prediction accuracy as well as the share of true positives and negatives with a decision threshold of 0.5. More than half of all standards are predicted accurately. As shown in table 1.18 in the appendix, the prediction accuracy is very similar for the training and test samples. Our neural network outperforms predictions obtained by simple regression, probit or logit models. The results are presented in tables 1.19 to 1.21 in the appendix. Figure 1.10 plots the prediction accuracy of the logit model for the different prediction leads. The prediction accuracy and the number of correctly predicted negatives are only slightly lower, but all models do worse in predicting standard events (true positives) then the neural network. The share of correctly predicted positives ranges from 29 to 43 percent depending on the model, while it ranges from 55 to 58 percent for the neural network.

Table 1.4: Accuracy of standard prediction by treatment outcome

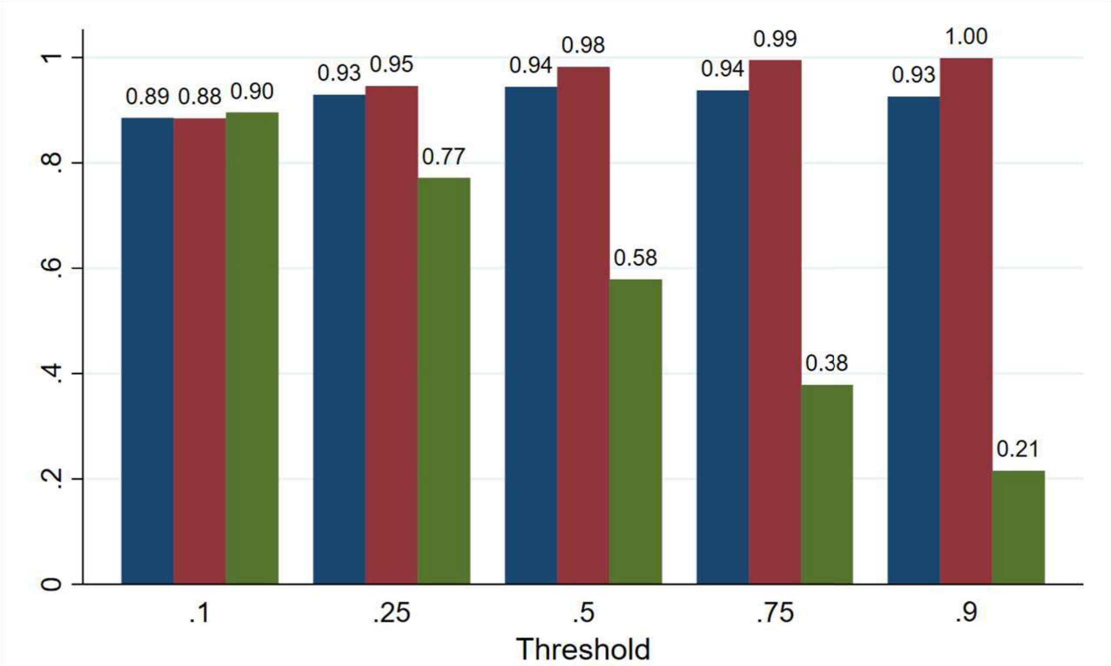
		Full sample		
Prediction lead	Accuracy	True positives	True negatives	Number of obs.
1 year	.944	.579	.982	136620
2 years	.944	.569	.982	129789
3 years	.943	.562	.983	122958
4 years	.941	.562	.982	116127
5 years	.941	.548	.983	109296

Note: Neural network with 1 hidden layer with 15 neurons for prediction. Standard prediction is set to 1 if the prediction value of the neural network is larger than threshold. Predictions x=1,...,5 years ahead, i.e. using inputs from $t-x$. Accuracy = true predictions/number of observations.

Prediction accuracy is maximal at a threshold of 0.5. However, the choice of the threshold is arbitrary and implies an assumption about how market participants make predictions about standard events. Prediction accuracy measures the total share of correct predictions, i.e. gives the same weight to correct predictions of the occurrence and the absence of standardization events. Risk-averse market participants who want to avoid investing in the wrong technology might fear false positive predictions more than false negatives and might, therefore, choose a higher threshold. On the other hand, our analysis is based on the assumption that the selected standards are truly unpredictable by the market. This might especially be the case for very unlikely standardization events, i.e. where the predicted probability of a standard to occur is very low.

For these reasons, we conduct a sensitivity analysis when constructing the innovation counterfactual with respect to the decision threshold above which a standardization event is assumed. Figure 1.6 illustrates the prediction accuracy (share of correctly predicted events), as well as the percentage of correctly predicted positives and negatives by decision threshold. The percentage of correct positive (negative) predictions decreases (increases) mechanically with the threshold.

Figure 1.6: Standard prediction by decision threshold



Note: Neural network with 1 hidden layer with 15 neurons for prediction. Standard prediction is set to 1 if the prediction value of the neural network is larger than threshold. Predictions 1 year ahead, i.e. using inputs from $t-1$. Accuracy = true predictions/number of observations. Well classified positives = correctly predicted years *with* standardization event. Well classified negatives = correctly predicted years *without* standardization event.

For the following analysis of the causal effect of standardization on innovation we use standard predictions from the neural network with 15 neurons in the hidden layer which led to the best prediction results.

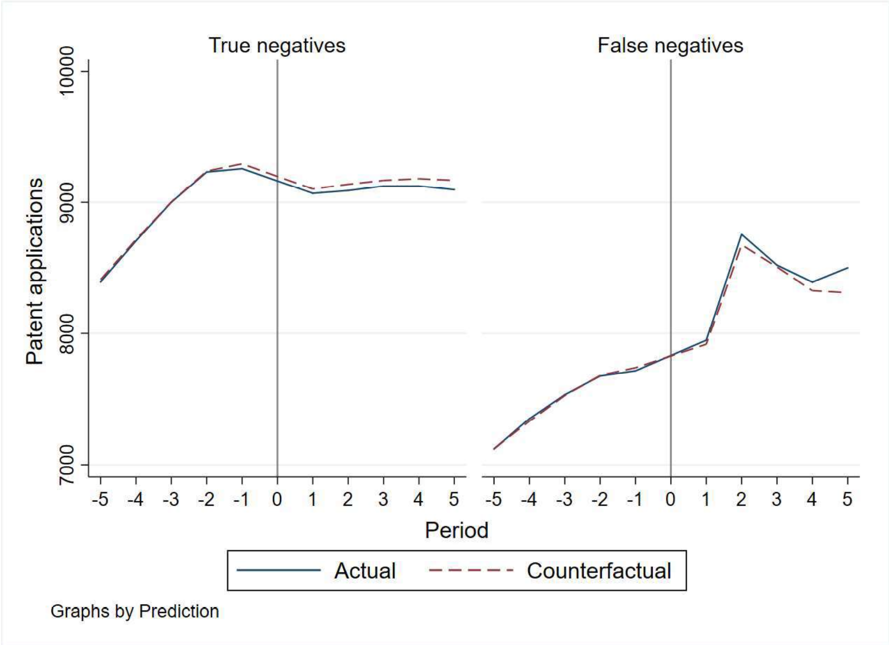
1.4.2 Counterfactual innovation and the causal effect of standardization on innovation

In this section, we present our findings on the effect of standardization on innovation. We use patent application counts to proxy innovative activity and compare our findings with the standards' effect on forward citations to patents of a technology and the share of a technology's patent applications in the country's total applications in order to measure different aspects of innovation. Patent counts measure the overall patenting activity within a technology class. Forward citations are often used to measure patent quality, since patents can be of very different quality and importance to an industry. The technology's share of patent applications refers to its importance in the national market and shows whether innovation efforts are shifted towards or away from a standardized technology.

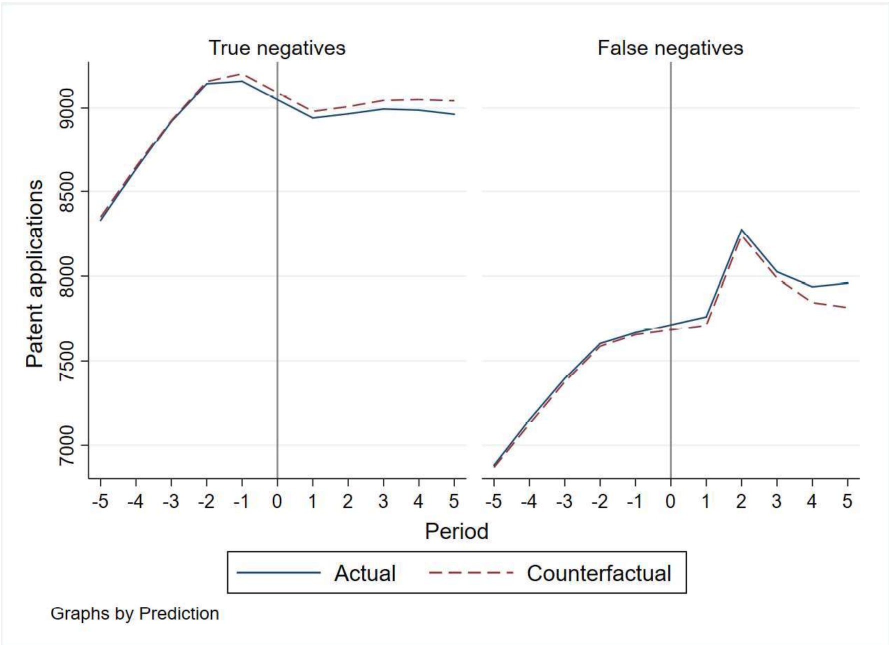
We predict counterfactual innovation paths for five years before and after the treatment period and compare them with actual innovation paths. We also test for differences and parallel trends in pre-treatment counterfactual and actual innovation paths. Predictions are made for false negatives and a control group that consists of average predictions of 100 random untreated samples, i.e. true negatives (see section 1.3.2). We identify all years with an unexpected standard, i.e. all years where no standard has been predicted, but a standardization event occurred (false negatives), as our treatment group. We use the same pre-treatment variables to create the counterfactual innovation path as have been used for standard prediction. Since our prediction model was not able to predict these standards, those variables do not contain information on the standard itself and can therefore be used to create a counterfactual situation of innovation without standardization. Only pre-treatment (i.e. pre-standard) information is used, i.e. prediction inputs from periods -1 to -5. Period 0 represents the year of the standardization event for false negatives and the randomly selected pseudo-treatment period for the control group. The results below use standard predictions one year ahead (i.e. standard predictions made with inputs from period -1). Results are similar for other prediction leads.

Figure 1.7 shows average actual and counterfactual patent application counts for the thresholds 0.5 and 0.1. The latter represents a very low threshold, i.e. false negatives include only very unlikely standards. The lower the threshold, the more unlikely have been the unexpected standards, i.e. the bigger the surprise of a standardization event to happen. The figure shows that pre-treatment patent applications follow a very similar path as the counterfactual predictions, while post-treatment counterfactuals deviate from actual outcomes.

Figure 1.7: Actual vs. counterfactual patent application counts



(a) Threshold = 0.1



(b) Threshold = 0.5

Note: Estimation of counterfactual patent counts using random forest with 100 decision trees. Period 0 = treatment or pseudo-treatment period. For false negatives, predictions are averaged over 100 random control group draws.

The figures suggest that patent applications are higher after an unexpected standardization event than the would have been without the standard. For true negatives the counterfactual patent application path seems to be slightly higher than the actual path after the pseudo-treatment period. In tables 1.5 and 1.6 we calculate the different treatment effects discussed in section 1.3.2. The treatment group (T) refers to all years with false negative predictions, i.e. years with a NA-standard. The control group consists of the randomly selected false negatives, i.e. years without standardization where no standard has been predicted by the model (U). β^T and β^U are the simple differences between actual and counterfactual patent application counts. β^{TD} and β^{UD} represent the DID estimators within each group where pre-treatment outcomes are averaged over the five years preceding the treatment period 0. β^{DD} and β^{3D} calculate the difference in the post-treatment differences as well as the triple-differences estimator between false and true negatives. The columns refer to the years after the treatment period. The results show that patent applications are higher than they would have been without standardization. However, for true negatives the treatment effects are negative, which suggests that our prediction model does not perfectly predict patent applications for the control group. The difference in post-treatment differences and the triple-differences estimators show that ignoring the prediction error in the control group would lead to an underestimation of the positive effect of standardization on patent applications.

Table 1.5: Treatment effects of standardization on patent applications (threshold 0.1)

	Post-treatment period in years					
2-6	1	2	3	4	5	Average
β^{T}	30.74	79.29	14.49	65.18	188.99	75.74
β^{TD}	31.55	80.1	15.3	65.99	189.8	76.55
β^{U}	-32.83	-47.14	-43.21	-56.19	-70.47	-49.97
β^{UD}	-18.5	-32.8	-28.88	-41.86	-56.13	-35.63
β^{DD}	63.57	126.43	57.71	121.37	259.46	125.71
β^{3D}	50.05	112.91	44.18	107.85	245.93	112.18

Note: Estimation of counterfactual patent application counts using random forest with 100 decision trees. Treatment period = year of standardization event for false negatives or pseudo-treatment period for true negatives. For false negatives, predictions are averaged over 100 random control group draws. Prediction errors for pre-treatment periods are averaged over the 5 years preceding the treatment period for β^{TD}, β^{UD} and β^{3D}. In column 6, post-treatment errors are averaged over 5 years following the treatment period.

Table 1.6: Treatment effects of standardization on patent applications (threshold 0.5)

	Post-treatment period in years					
2-6	1	2	3	4	5	Average
β^{T}	49.96	34.39	36.96	92.82	143.45	71.52
β^{TD}	32.79	17.22	19.8	75.66	126.29	54.35
β^{U}	-38.79	-42.82	-51.16	-62.43	-80.19	-55.08
β^{UD}	-19.79	-23.81	-32.15	-43.42	-61.18	-36.07
β^{DD}	88.75	77.2	88.12	155.25	223.64	126.59
β^{3D}	52.58	41.03	51.95	119.08	187.47	90.42

Note: Estimation of counterfactual patent application counts using random forest with 100 decision trees. Treatment period = year of standardization event for false negatives or pseudo-treatment period for true negatives. For false negatives, predictions are averaged over 100 random control group draws. Prediction errors for pre-treatment periods are averaged over the 5 years preceding the treatment period for β^{TD}, β^{UD} and β^{3D}. In column 6, post-treatment errors are averaged over 5 years following the treatment period.

The above calculated treatment effects do not tell us anything about the significance of the effects. Furthermore, the DID estimators rely on a crucial assumption, the assumption of pre-treatment parallel trends. In order to test this, we estimate a DID regression model where we regress patent applications on the period, the treatment and their interactions (see Pischke 2005). The periods refer to the years around the standardization event or the pseudo-treatment period, where 0 represents the treatment period. We use the year before treatment (period -1) as our reference period. The treatment indicator is 1 for actual realizations of patent applications and 0 for their predicted counterfactuals. This setting allows us to test for two things. First, we are able to test whether pre-treatment counterfactual paths are parallel to actual paths. If pre-treatment trends are parallel, the interaction terms between the treatment indicator and the pre-treatment periods should be insignificant, i.e. the difference between actual and counterfactual outcomes does not vary over time before treatment, or in other words, is not significantly different from the reference period. Second, we can test whether there is a significant difference in trends after treatment, i.e. whether the DID estimator is significant. Since we have several post-treatment periods, we are also able to evaluate how the effect of standardization on patent applications evolves over time. Note that the coefficients of the interaction terms correspond to $\hat{\beta}^{TD}$ and $\hat{\beta}^{UD}$ (see section 1.3.2).

Tables 1.7 and 1.8 present the regression results for true and false negatives. Pre-treatment trends are parallel for false negatives, but not for true negatives. For false negatives, the DID estimator is significant and positive in period 5. This means that patent applications are higher five years after the unexpected standardization event than they would have been had no standard occurred. Depending on the threshold, they exceed the counterfactual by 213 or 132 patent applications. The DID estimator for false negatives is valid since pre-treatment trends are parallel. However, it cannot account for eventual global prediction errors that affect our whole data sample, i.e. also true negative predictions. A prediction model that only excludes information of the standardization event itself should show parallel trends before and after treatment for true negatives. Since counterfactual predictions deviate from actual patent applications for true negatives, we have to account for this when calculating the effect of standardization on patent applications. Since pre-treatment trends are not parallel for true negatives, the DID estimator is not correct for this sample. However, for our triple-difference estimator it is important that the trends in the difference between actual and counterfactual patent applications of false and true negatives are parallel before treatment.

Table 1.7: DID estimation for patent applications within groups (threshold of 0.1)

	False negatives		True negatives	
T	-24	-24	-37***	-37***
Period -5	-616***	870	-881***	53***
Period -4	-406***	612	-577***	30***
Period -3	-210*	323	-292***	10
Period -2	-58	50	-56***	3
Period 1	178	335	-192***	-63***
Period 2	938**	9	-157***	-68***
Period 3	770	-173	-127***	-80***
Period 4	591	-303	-114***	-77***
Period 5	575	-355	-126***	-78***
T × Period -5	22	22	19***	19***
T × Period -4	43	43	27***	27***
T × Period -3	29	29	36***	36***
T × Period -2	20	20	30***	30***
T × Period 1	54	54	4	4
T × Period 2	103	103	-10*	-10*
T × Period 3	38	38	-6	-6
T × Period 4	89	89	-19***	-19***
T × Period 5	213**	213**	-34***	-34***
Year dummies	No	Yes	No	Yes
Country dummies	No	Yes	No	Yes
Technology dummies	No	Yes	No	Yes
Observations	9906	9906	1328326	1328326

Standard errors are clustered at the country - technology level

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Linear least-squares regression with patent applications (flow) as depend variable. T = 1 if actual, 0 if counterfactual outcome. Period 0 = treatment or pseudo-treatment period. False negatives = unpredicted standardization events. True negatives = correctly predicted years without standardization. For false negatives, predictions are averaged over 100 random control group draws. Standard prediction 1 year ahead.

Table 1.8: DID estimation for patent applications within groups (threshold of 0.5)

	False negatives		True negatives	
T	12	12	-44***	-44***
Period -5	-787***	756	-854***	41***
Period -4	-530***	504	-557***	21***
Period -3	-281***	287	-276***	4
Period -2	-69	73	-45***	0
Period 1	56	230	-222***	-61***
Period 2	583*	-324	-193***	-68***
Period 3	332	-506	-157***	-68***
Period 4	189	-470	-152***	-68***
Period 5	160	-605	-159***	-61***
T × Period -5	1	1	25***	25***
T × Period -4	14	14	31***	31***
T × Period -3	8	8	38***	38***
T × Period -2	5	5	31***	31***
T × Period 1	38	38	5	5
T × Period 2	23	23	1	1
T × Period 3	25	25	-7	-7
T × Period 4	81	81	-19***	-19***
T × Period 5	132**	132**	-36***	-36***
Year dummies	No	Yes	No	Yes
Country dummies	No	Yes	No	Yes
Technology dummies	No	Yes	No	Yes
Observations	15042	15042	1410334	1410334

Standard errors are clustered at the country - technology level

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Linear least-squares regression with patent applications (flow) as depend variable. T = 1 if actual, 0 if counterfactual outcome. Period 0 = treatment or pseudo-treatment period. False negatives = unpredicted standardization events. True negatives = correctly predicted years without standardization. For false negatives, predictions are averaged over 100 random control group draws. Standard prediction 1 year ahead.

In tables 1.9 and 1.10 we regress the difference between actual and counterfactual patent applications on the period, an indicator variable which is 1 for false negatives and 0 for true negatives, and their interactions. The differences are parallel for pre-treatment periods since their interaction terms with the false negatives indicator (FN) are insignificant. The assumption of pre-treatment parallel trends between false and true negatives holds. We find a positive and significant difference in the fifth post-treatment period, i.e. the difference between actual and counterfactual patent applications in period 5 experienced a significantly higher increase with respect to the pre-treatment reference period for false negatives than for true negatives. Depending on the threshold, this difference amounts to 158 or 113 more patent applications when controlling for year, country and technology fixed effects. This confirms our finding using only within-group treatment effects for false negatives.

Table 1.9: DID estimation for treatment effects on patent applications across groups (threshold of 0.1)

	(1)	(2)
FN	13	76
Period -5	19***	178***
Period -4	27***	142***
Period -3	36***	111***
Period -2	30***	69***
Period 1	4	-21***
Period 2	-10*	-13**
Period 3	-6	9*
Period 4	-19***	16***
Period 5	-34***	20***
FN × Period -5	2	-39
FN × Period -4	16	-16
FN × Period -3	-7	-39
FN × Period -2	-10	-38
FN × Period 1	50	44
FN × Period 2	113	45
FN × Period 3	44	-12
FN × Period 4	108	49
FN × Period 5	246***	158*
Year dummies	No	Yes
Country dummies	No	Yes
Technology dummies	No	Yes
Observations	669116	669116

Standard errors are clustered at the country - technology level
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Linear least-squares regression with the difference between actual and counterfactual patent applications as depend variable. FN = 1 if false negatives, 0 if true negatives. Period 0 = treatment or pseudo-treatment period. False negatives = unpredicted standardization events. True negatives = correctly predicted years without standardization. For false negatives, predictions are averaged over 100 random control group draws. Standard prediction 1 year ahead.

Table 1.10: DID estimation for treatment effects on patent applications across groups (threshold of 0.5)

	(1)	(2)
FN	56*	62*
Period -5	25***	170***
Period -4	31***	135***
Period -3	38***	105***
Period -2	31***	66***
Period 1	5	-18***
Period 2	1	-4
Period 3	-7	5
Period 4	-19***	11**
Period 5	-36***	9
FN × Period -5	-24	-59**
FN × Period -4	-17	-43
FN × Period -3	-30	-56**
FN × Period -2	-26	-46*
FN × Period 1	33	34
FN × Period 2	22	-23
FN × Period 3	33	-4
FN × Period 4	100	62
FN × Period 5	168***	113*
Year dummies	No	Yes
Country dummies	No	Yes
Technology dummies	No	Yes
Observations	712688	712688

Standard errors are clustered at the country - technology level

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Linear least-squares regression with the difference between actual and counterfactual patent applications as depend variable. FN = 1 if false negatives, 0 if true negatives. Period 0 = treatment or pseudo-treatment period. False negatives = unpredicted standardization events. True negatives = correctly predicted years without standardization. For false negatives, predictions are averaged over 100 random control group draws. Standard prediction 1 year ahead.

In the following, we calculate treatment effects for different innovation measures and different country groups.

Patent quality

Patents can be of very different quality and importance to the industry. Therefore, patent counts are often adjusted for quality. The literature has identified different measures for patent quality, each with their advantages and inconveniences. One of the most used ones is the number citations towards the patents, so-called forward citations. This measure captures the use of a patent for other inventions and can, therefore, proxy the patent's technological importance. Since patents are of different age, it is common to use only forward citations within the first years of the patent's life. Here, we use the average number of forward citations a patent application of a given technology has received in the first 5 years after the application filing year.

Table 1.11: Treatment effects of standardization on average 5-years citation counts

	Post-treatment period in years					
2-6	1	2	3	4	5	Average
β^T	-1.56	-1.38	-2	-2.02	-1.64	-1.72
β^U	-.11	.21	-.13	-.12	-.39	-.11
β^{DD}	-1.45	-1.59	-1.87	-1.9	-1.25	-1.61
β^{TD}	0	.18	-.43	-.46	-.08	-.16
β^{UD}	0	.32	-.02	-.01	-.29	0
β^{3D}	0	-.14	-.41	-.44	.21	-.16

Note: Estimation of the counterfactual using random forest with 100 decision trees. Treatment period = year of standardization event for false negatives or pseudo-treatment period for true negatives. For false negatives, predictions are averaged over 100 random control group draws. Prediction errors for pre-treatment periods are averaged over the 5 years preceding the treatment period for β^{TD}, β^{UD} and β^{3D}. In column 6, post-treatment errors are averaged over 5 years following the treatment period.

Table 1.11 shows that the effect of standardization on early patent life citations is very small, almost zero. This suggests that standardization leads to an increase in patent applications within the technology area of the standard, but not to an increase in the average number of citations to the technology class, thus, the average quality of the patents. One possible explanation could be that standard implementation and diffusion takes time and related patents might gain importance later in their life.

Technology selection

The introduction of this thesis mentioned the technology selection function of standards. Here, we make a first attempt to test this hypothesis. To do so, we use the share of a technology's patent applications in the total number of patent applications in a given country and year as output variable of our random forest model. This measures the degree of patenting within a technology compared to all other technologies and proxies its relative R&D intensity.

Table 1.12: Treatment effects of standardization on the share of standard related patent counts in total patent counts

	Post-treatment period in years					
2-6	1	2	3	4	5	Average
β^T	-.0065	-.0114	-.0093	-.0111	-.0159	-.0108
β^U	.0022	.0028	.0013	.0009	.0028	.002
β^{DD}	-.0088	-.0142	-.0106	-.012	-.0187	-.0129
β^{TD}	.0044	-.0004	.0016	-.0002	-.0049	.0001
β^{UD}	.0004	.001	-.0005	-.0009	.001	.0002
β^{3D}	.004	-.0015	.0021	.0007	-.0059	-.0001

Note: Estimation of the counterfactual using random forest with 100 decision trees. Treatment period = year of standardization event for false negatives or pseudo-treatment period for true negatives. For false negatives, predictions are averaged over 100 random control group draws. Prediction errors for pre-treatment periods are averaged over the 5 years preceding the treatment period for β^{TD}, β^{UD} and β^{3D}. In column 6, post-treatment errors are averaged over 5 years following the treatment period.

The variable ranges from 0 to 100, thus, represents percentage points. Table 1.12 shows an effect very close to zero, hence, does not suggest that standardization leads to technology selection in terms of patenting concentration within the standard's technology area. However, our measure of technology selection refers only to the economy as a whole and cannot reveal selection mechanisms within the technology fields. It also does not take into account standardization patterns in other technology fields. Hence, the technology selection theory of standards demands further research.

Country income groups

Tables 1.13 and 1.14 show the treatment effects on patent applications for high income and low income countries separately. The average positive effects found above seem to be driven by the high income countries, while treatment effects are generally negative for low income countries. Standards frequently create tensions between the developed and the developing world due to differences in adoption costs and an unequal distribution of intellectual property rights (Gibson 2007, Ernst 2011). Low income countries might benefit less from standardization due to their second mover disadvantage on global markets and intellectual property right distribution. It is therefore possible that firms in low income countries try to innovate around standardized technologies.

Table 1.13: Treatment effects of standardization on patent applications for high income countries (threshold 0.5)

	Post-treatment period in years					
2-6	1	2	3	4	5	Average
β^{T}	66.4	53.41	60.24	120.38	174.54	94.99
β^{TD}	43.93	30.95	37.78	97.92	152.08	72.53
β^{U}	-45.87	-51.7	-65.64	-77.71	-98.17	-67.82
β^{UD}	-23.28	-29.11	-43.04	-55.11	-75.58	-45.22
β^{DD}	112.27	105.11	125.88	198.09	272.71	162.81
β^{3D}	67.21	60.06	80.82	153.03	227.65	117.76

Note: Estimation of the counterfactual using random forest with 100 decision trees. Treatment period = year of standardization event for false negatives or pseudo-treatment period for true negatives. For false negatives, predictions are averaged over 100 random control group draws. Prediction errors for pre-treatment periods are averaged over the 5 years preceding the treatment period for β^{TD}, β^{UD} and β^{3D}. In column 6, post-treatment errors are averaged over 5 years following the treatment period. Income groups according to the WDI database.

Table 1.14: Treatment effects of standardization on patent applications for low income countries (threshold 0.5)

	Post-treatment period in years					
2-6	1	2	3	4	5	Average
β^{T}	-20.59	-48.44	-63.97	-25.07	2.23	-31.17
β^{TD}	-14.57	-42.43	-57.96	-19.05	8.24	-25.15
β^{U}	-16.85	-15.27	-6.27	-15.07	-24.45	-15.58
β^{UD}	-8.96	-7.39	1.61	-7.19	-16.57	-7.7
β^{DD}	-3.74	-33.16	-57.7	-10	26.68	-15.58
β^{3D}	-5.61	-35.03	-59.57	-11.86	24.81	-17.45

Note: Estimation of the counterfactual using random forest with 100 decision trees. Treatment period = year of standardization event for false negatives or pseudo-treatment period for true negatives. For false negatives, predictions are averaged over 100 random control group draws. Prediction errors for pre-treatment periods are averaged over the 5 years preceding the treatment period for β^{TD}, β^{UD} and β^{3D}. In column 6, post-treatment errors are averaged over 5 years following the treatment period. Income groups according to the WDI database.

1.5 Conclusion

In this paper, we investigated the causal effect of standardization on innovation. This is a non-trivial task due to the complex causal relationship between standardization and innovation. In order to solve this problem, we developed a novel methodology which accounts for anticipatory effects of standardization. First, we predict standards using a feed-forward neural network. Subsequently, we use pre-standard data in a random forest to create a counterfactual innovation path for non-anticipated standards. For this set of standards, we are able to estimate the causal effect of standardization on innovation, since pre-standard data do not contain information on the standard itself and are therefore not able to predict the standard.

We estimate the effect of standardization for our set of non-anticipated standards on the number of patent applications within a technology field, the average number of 5-years citations to patents from the technology and on the technology's share in total patent applications of a country. We find a positive but insignificant (or close to insignificant) effect of standardization on patent applications. We find no significant effect on patent citations and application shares.

This paper contributes to the literature by estimating the causal effect of standardization on innovation. Former studies have struggled to identify the causal effect properly due to the reverse causality relationship between standardization and innovation. We are able to identify this effect by excluding anticipation of standardization. We also provide a novel identification strategy which may be used in other settings. Finally, we contribute to the literature on technology shocks by predicting standardization events. It is important to keep in mind that our treatment effect is local, i.e. valid for the set of non-anticipated standards in our sample.

Further research is necessary on the effect of standardization on the quality and distribution of innovation. An additional topic is the effect of standard adoption rather than standard development on innovation. Our current work focuses on providing empirical evidence for the unpredictability of our non-anticipated standards which represents the crucial assumption of our identification strategy.

1.6 Appendix

1.6.1 Figures

Figure 1.8: Total number of standards over years in Perinorm between 1995 and 2015
1,208,663 standards

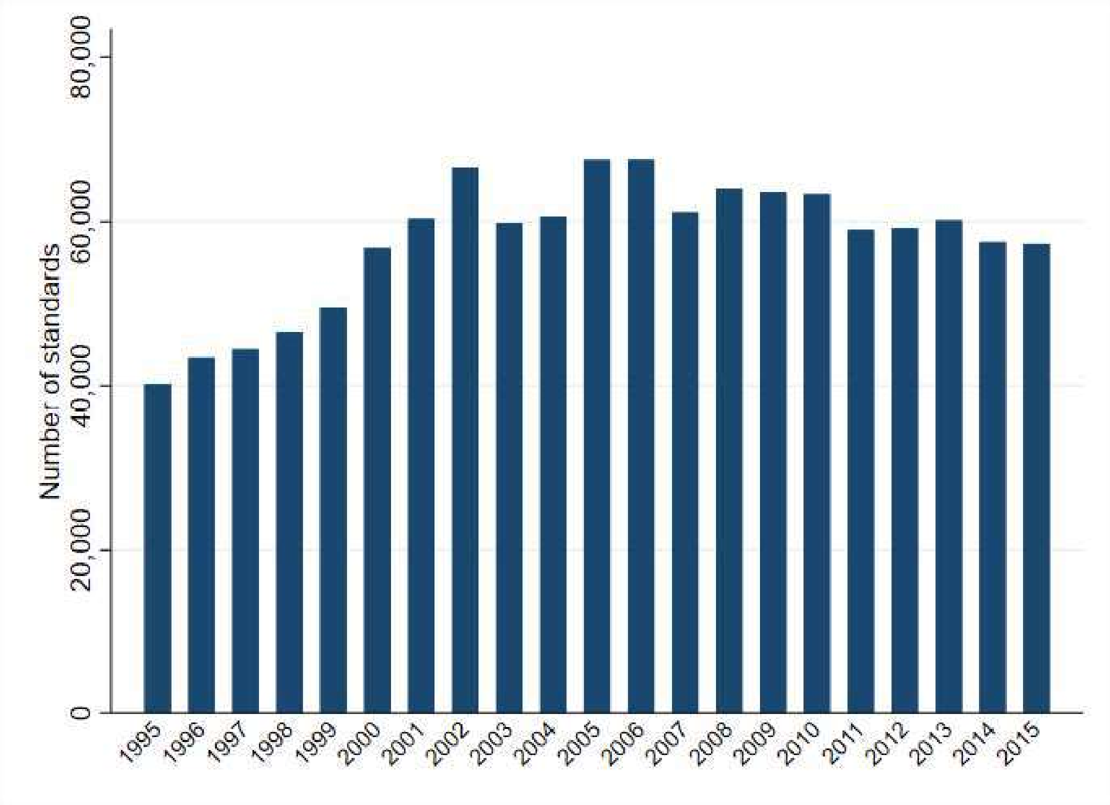
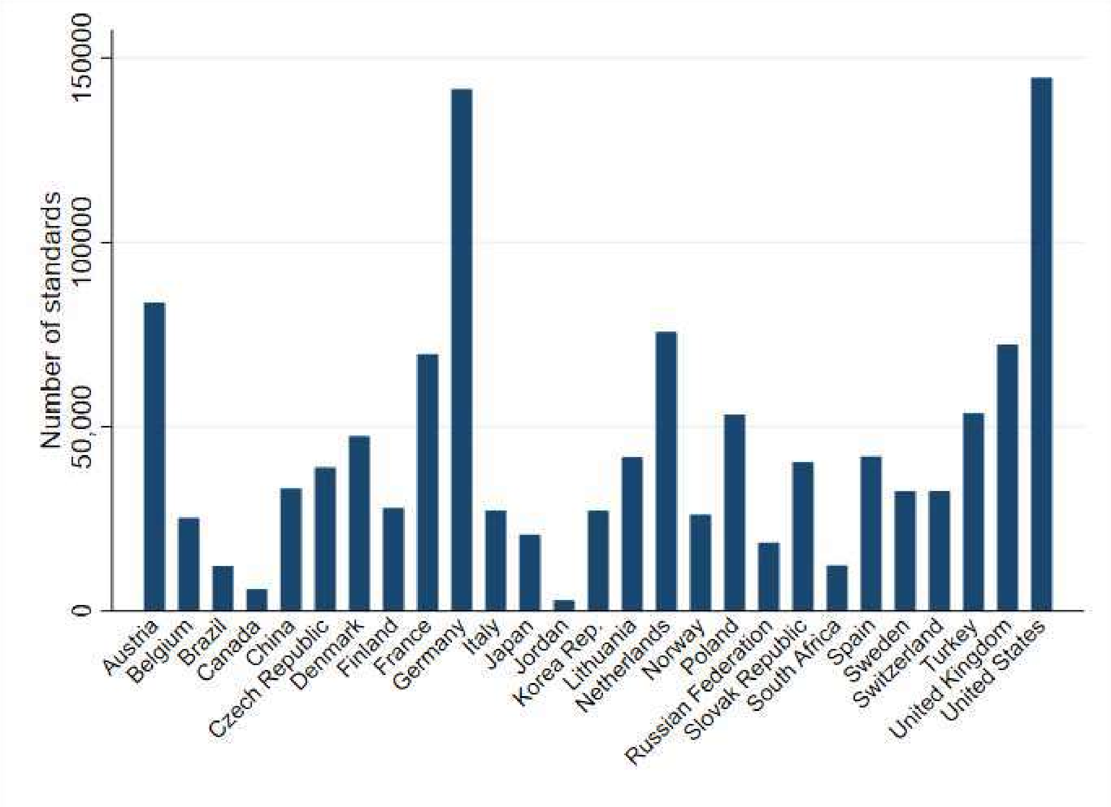


Figure 1.9: Total number of standards over countries in Perinorm between 1995 and 2015
1,208,663 standards



1.6.2 Tables

Table 1.15: Descriptive statistics by country

	Mean											
3-13	Total number of standards	Exports in tech. (mio. USD)	Imports in tech. (mio. USD)	Patent stock in tech. (thous.)	Total patent stock (mio.)	GDP per capita (thous. USD)	Total population (mio.)	R&D expenditure (% GDP)	Mean tariff rate	Natural resource rent (% GDP)	No. of patent applications in tech. (thous.)	Total no. of patent applications (mio.)
Austria	748	104	96	6	2	44	8	.023	.024	.0017	1	.3644
Belgium	352	204	192	8	2	42	11	.02	.024	.0002	1	.3514
Brazil	222	65	106	1	.2067	10	187	.0124	.1407	.0342	.2373	.0443
Canada	196	220	272	19	5	45	32	.0187	.0467	.0332	4	1
China	532	1107	769	15	4	3	1298	.0128	.1166	.0388	4	.9048
Czech Republic	571	80	72	.5113	.0657	17	10	.0132	.024	.0066	.1095	.0144
Denmark	622	56	56	7	2	56	5	.0254	.024	.0114	1	.3274
Finland	308	74	50	11	3	43	5	.0315	.024	.0049	2	.4875
France	613	408	408	50	15	39	63	.0214	.024	.0005	10	3
Germany	921	870	657	116	39	40	82	.025	.024	.0012	22	8
Italy	315	300	239	17	6	36	58	.0121	.024	.001	3	1
Japan	384	604	359	251	74	44	127	.0313	.0283	.0002	50	15
Jordan	58	2	8	.0274	.0003	4	6	.0118	.1195	.0107	.0061	.0001
Korea Rep.	344	382	237	55	14	19	48	.028	.0851	.0002	12	3
Lithuania	499	9	9	.0254	.0005	10	3	.0079	.024	.007	.0066	.0002
Netherlands	848	307	294	27	7	47	16	.0188	.024	.0065	5	1
Norway	323	39	46	3	.723	85	5	.0188	.0134	.0827	.6101	.1419
Poland	594	84	95	.4497	.0602	10	38	.0072	.024	.0114	.1048	.0152
Russian Federation	379	58	120	1	.2181	9	145	.0109	.1004	.1451	.2728	.0467
Slovak Republic	502	30	33	.1218	.0053	14	5	.0073	.024	.0034	.0242	.0011
South Africa	286	23	47	.9698	.159	7	47	.0062	.0824	.0539	.1864	.0303
Spain	520	131	188	5	1	29	43	.0116	.024	.0006	.9834	.2586
Sweden	368	133	92	20	5	48	9	.0304	.024	.0053	4	1
Switzerland	431	142	112	28	9	70	8	.0273	.0114	.0002	6	2
Turkey	565	41	82	.4077	.0483	9	68	.0069	.043	.0038	.0982	.0122
United Kingdom	891	308	390	37	11	37	61	.0174	.024	.0078	7	2
United States	852	1039	1284	348	101	47	295	.0258	.0332	.0099	71	21

Table 1.16: Descriptive statistics by country

	Mean											
2-13	Number of patent citations	C number of patent citations	A number of 5 years citations	Average operating revenue per firm in tech. (thous.)	Average number of employees per firm in tech. (thous.)	Number of firms in tech. (thous.)	Share of biggest firm's operating revenue	Share of biggest firm's number of employees	Country's share in global operating revenue in tech.	Country's share in global number of employees in tech.	Tech.'s share in total country's operating revenue	Tech.'s share in total country's number of employees
Austria	.2916	2	5	725	2	.0066	.2912	.2767	.0011	.001	.0003	.0003
Belgium	.7944	5	13	108	.066	2	.2465	.2178	.0115	.0058	.0003	.0003
Brazil	.0634	.2967	.8261	0	0	0	0	0	0	0	0	0
Canada	2	11	29	0	0	0	0	0	0	0	0	0
China	.767	4	13	293	2	.4902	.1496	.0951	.0283	.0563	.0002	.0002
Czech Republic	.04	.1496	.8394	14	.0903	2	.1708	.153	.0097	.0206	.0003	.0003
Denmark	.662	4	3	401	1	.0101	.196	.1958	.0009	.0009	.0002	.0002
Finland	.4171	3	6	103	.2311	.3999	.4497	.4022	.0111	.008	.0003	.0003
France	2	17	30	441	2	.8188	.2776	.2806	.0581	.0512	.0003	.0003
Germany	5	31	62	389	.5747	2	.2295	.2185	.1661	.117	.0003	.0003
Italy	1	10	17	41	.1098	6	.2034	.2089	.0598	.0351	.0003	.0003
Japan	5	49	67	2180	5	.3844	.4021	.3242	.1957	.1257	.0003	.0003
Jordan				76	.3705	.0012	.3649	.3404	0	0	.0002	.0002
Korea Rep.	1	7	18	19	.0556	2	.1846	.137	.0104	.0077	.0003	.0003
Lithuania				3	.0326	.6434	.2839	.2351	.0002	.0009	.0004	.0003
Netherlands	1	8	15	937	.2947	.8629	.4038	.3727	.0225	.0221	.0003	.0003
Norway	.1673	.7558	2	745	2	.01	.1959	.1993	.002	.0016	.0001	.0001
Poland	.0124	.0796	0	44	.2372	.0352	.4889	.2966	.0013	.0027	.0003	.0003
Russian Federation	.0582	.1942	1	9	.1683	6	.2259	.1852	.0133	.0601	.0003	.0003
Slovak Republic	.0116	.1124	.1357	49	.1237	.8693	.3771	.2435	.0055	.005	.0003	.0003
South Africa	.0951	.6504	1	822	4	.0034	.3536	.2758	.0006	.001	.0002	.0002
Spain	.386	2	6	15	.0387	10	.1292	.0828	.0699	.0481	.0003	.0003
Sweden	.8089	4	13	20	.054	3	.2452	.2198	.0153	.013	.0003	.0003
Switzerland	2	12	19	357	.8211	3	.2258	.2525	.0141	.0119	.0003	.0003
Turkey	.0302	.1592	.6347	1155	4	.0018	.1398	.1583	.0005	.0005	.0002	.0002
United Kingdom	4	21	45	229	.4708	1	.2663	.1754	.0704	.0466	.0003	.0003
United States	145	675	1900	1091	3	.1103	.2499	.211	.1267	.0804	.0003	.0003

Table 1.17: Prediction accuracy by lead

	Prediction lead				
Threshold	1 year	2 years	3 years	4 years	5 years
0.05	.838	.829	.824	.819	.817
0.1	.885	.879	.88	.875	.875
0.15	.908	.903	.904	.903	.898
0.2	.921	.918	.918	.917	.915
0.25	.93	.929	.928	.927	.925
0.3	.935	.935	.934	.932	.931
0.35	.94	.939	.938	.937	.936
0.4	.942	.941	.94	.94	.939
0.45	.944	.943	.942	.941	.94
0.5	.944	.944	.943	.941	.941
0.55	.944	.944	.943	.941	.941
0.6	.943	.943	.942	.94	.94
0.65	.942	.942	.941	.939	.939
0.7	.94	.941	.939	.937	.937
0.75	.938	.937	.937	.935	.935
0.8	.934	.934	.933	.932	.932
0.85	.93	.93	.93	.928	.929
0.9	.926	.926	.925	.923	.924
0.95	.919	.919	.917	.916	.917
Number of observations	136,620	129,789	122,958	116,127	109,296

Note: Neural network with 1 hidden layer and 15 nodes for prediction. Standard prediction is set to 1 if the prediction value of the neural network is larger than threshold. Predictions are made 1 to 5 years ahead, i.e. inputs in period t are used for predictions in $t+x$, where $x \in \{1, ..., 5\}$. Accuracy = true predictions/number of observations.

Table 1.18: Accuracy of standard prediction for training and test samples

		Full sample		
Prediction lead	Training sample	Number of obs.	Test sample	Number of obs.
1 year	.944	114761	.946	21859
2 years	.943	107930	.945	21859
3 years	.942	101099	.946	21859
4 years	.941	94268	.942	21859
5 years	.942	87437	.935	21859

Note: Neural network with 1 hidden layer with 15 neurons for prediction. Standard prediction is set to 1 if the prediction value of the neural network is larger than threshold. Predictions x=1,...,5 years ahead, i.e. using inputs from $t - x$. Accuracy = true predictions/number of observations. The restricted sample includes firm data from Orbis for prediction. Training/test sample contains 80/20 percent of the observations.

Table 1.19: Prediction accuracy of simple regression

Prediction lead	Accuracy	True positives	True negatives	Number of obs.
1 year	.9276	.2927	.9927	136620
2 years	.9271	.2963	.9926	129789
3 years	.9266	.2999	.9923	122958
4 years	.926	.3042	.9919	116127
5 years	.9256	.3104	.9915	109296

Note: Standard prediction using a linear prediction model. Prediction of a standard event for prediction values larger than 0.5.

Table 1.20: Prediction accuracy of probit

Prediction lead	Accuracy	True positives	True negatives	Number of obs.
1 year	.9305	.4237	.9825	136620
2 years	.9299	.4247	.9824	129789
3 years	.9292	.4251	.982	122958
4 years	.9282	.4251	.9815	116127
5 years	.9272	.4253	.981	109296

Note: Standard prediction using a probit model. Prediction of a standard event for prediction values larger than 0.5.

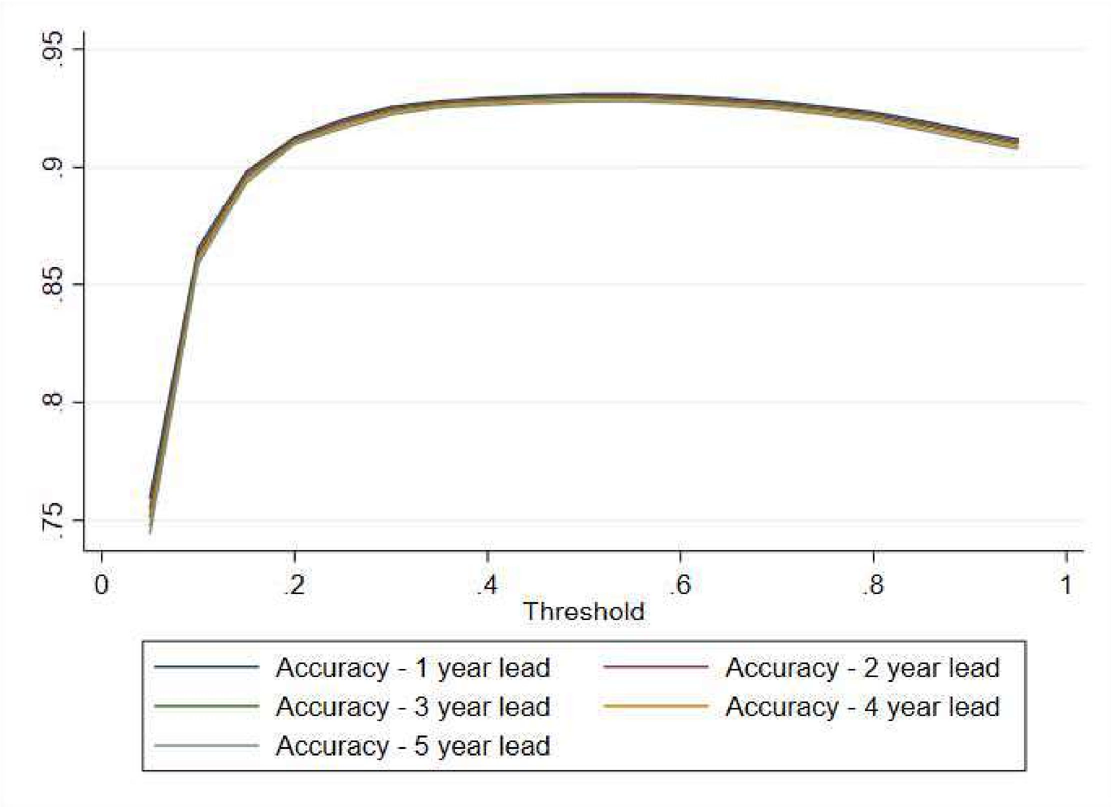
Table 1.21: Prediction accuracy of logit

Prediction lead	Accuracy	True positives	True negatives	Number of obs.
1 year	.931	.4344	.982	136620
2 years	.9301	.4328	.9817	129789
3 years	.9295	.4353	.9813	122958
4 years	.9284	.4339	.9808	116127
5 years	.9277	.4361	.9804	109296

** Prediction of a standard event for prediction values larger than 0.5

Note: Standard prediction using a logit model. Prediction of a standard event for prediction values larger than 0.5.

Figure 1.10: Prediction accuracy of logit



Chapitre 2

L’effet de la propriété de SEP sur le revenu des entreprises

Dans ce chapitre, j’analyse l’effet de la propriété de SEP (standard essential patents, brevets essentiels aux normes techniques) sur le revenu opérationnel des entreprises. Plusieurs études ont analysé la valeur des SEP et leur effet sur la performance financière, mais peu d’étude ont traité leur effet sur la performance sur le marché. J’applique la méthode à contrôle synthétique avec multiples unités de traitement afin de créer des trajectoires de revenue contrefactuelles. Les résultats suggèrent un effet positif de la propriété de SEP sur le revenu opérationnel, mais uniquement pour les membres d’organismes de standardisation.

Chapter 2

The treatment effect of declared SEP ownership on firm revenue

Abstract. This paper evaluates the effect of declared SEP ownership on firms' operating revenue. While several studies have analyzed the value of standard essential patents and their effect on their owners' financial performance, little is known on their effect on the firms' market performance. I use a synthetic control method with multiple treated units in order to create counterfactual revenue paths for firms that declared patents as standard essential. My findings suggest that declared SEP ownership affects operating revenues positively for members of standard setting organizations.

2.1 Introduction

This paper analysis the effect of declared standard essentiality of patents on firm revenue using a synthetic control approach with multiple treated units. Standard essential patents (SEPs) are patents that protect a technology which is necessary for the implementation of a technology standard. Technology standards are norms and requirements of technological systems which assure interoperability across products. The adoption of standards is voluntary, but the deviation from an accepted standard can be costly (REF). Standards also represent technological restrictions which can discourage their implementation (REF). Therefore, the inclusion of a patented technology in a standard can have an important impact on the use of the technology and, thus, on its owner's revenues and market advantages.

The literature has looked at the importance of patents on firm value from different angles (Belenzon and Patacconi 2013, Hall, Thoma, and Torrisi 2007, Hall, Jaffe, and Trajtenberg 2005, Lerne 1994). Standardization can come with great costs and benefits for firms that participate in standard setting. However, through the public good character of standards, the benefits of standardization do not only benefit those firms that invested in standard development. One way of recovering these investments is through proprietary technologies that are implemented in the standards. Owning SEPs for successful technology standards can result in important revenue gains for firms through licensing revenues and an increase in market power. SEP ownership can affect firm revenues in different ways. Pohlmann, Neuhäusler, and Blind 2015 note that the effect of SEP ownership on firms' financial performance could go in both directions. It could be positive, since firms that own standardized technologies gain control over whole markets. Also, SEPs have shown to be more valuable than other comparable patents (Bekkers, Bongard, and Nuvolari 2011) and have therefore a positive effect on the firm value (Hall, Thoma, and Torrisi 2007). On the other hand, SEP ownership could negatively affect firm revenue since standard setting organizations (SSOs) often require their members to license SEPs under free/reasonable and non-discriminatory (F/RAND) terms, and because standardization might reduce the firm's competitive advantage on the market due to a harmonization of technological knowledge (Pohlmann, Neuhäusler, and Blind 2015, Aggarwal, Dai, and Walden 2011).

Pohlmann, Neuhäusler, and Blind 2015 note that, while different measures of patent value have been studied by the literature, the standard essentiality of patents has not received much attention with regard to firms' financial performance. Yet, standards indicate the use of technologies on the market. In their paper, they analyze the effect of SEP ownership on a firm's financial performance and find a curvilinear relationship between the two variables using a simple panel data regression model. SEP ownership and financial performance of firms could, however, be linked through time-varying confounding factors or reversed causality which are not taken into account in their estimation model.

One difficulty of estimating the effect of patents' standard essentiality on firm revenue is given by a potential reverse causality relationship. Firm revenue impacts innovation and therefore patenting which can impact the likelihood of SEP ownership (Bekkers, Bongard, and Nuvolari 2011). Furthermore, it has been shown that the participation of firms in standardization bodies is related to their size and financial possibilities (Cargill 2011, Baron Li?) and that the participation in the standardization process increases the firms' influence on the technologies selected for a standard (Bekkers, Bongard, and Nuvolari 2011). I use a synthetic control approach with multiple treated units in order to create counterfactual firm revenues for each SEP declaration (treatment). For each treated firm, the synthetic control method allocates weights to untreated units (firms without declared SEPs) such that pre-treatment revenues of the counterfactual match those of the treated unit. The average treatment effect of declared SEP ownership on firm revenue is the difference between post-treatment (post-declaration) actual and counterfactual firm revenue. I show that this method performs better than a differences-in-differences (DID) approach, since pre-treatment revenues in the DID regression are not parallel between firms with and without SEP declarations.

I combine a comprehensive dataset on SEP declarations with firm information of the SEP owners. SEP declarations are voluntary statements of patent owners to the standard issuing body about their (supposed) SEPs. The requirements on SEP declarations differ across standardization bodies (Bekkers et al. 2014a, Chiao, Lerner, and Tirole 2007). The literature has found evidence for overdeclaration of SEPs, i.e. patents which are not essential to a standard are declared as such, due to strategic firm behavior (Stitzing et al. 2017b) or differences in disclosure rules of standard setting organizations (Bekkers et al. 2019).

This paper contributes to the literature by identifying the treatment effect of declared SEPs on firm revenue, i.e. their effect on the firms' market performance rather than financial performance. I apply a synthetic control approach which allows for a flexible estimation of both, individual and average treatment effects, and therefore for the evaluation of heterogeneous effects across different firm dimensions.

The paper is structured as follows. In section 2.2, I explain the methods used to estimate the treatment effect and in section 2.3, I derive hypotheses about the expected results from a simple theoretical framework. Section 2.4 describes the data. Section 2.5 shows the estimation results and section 2.6 robustness checks and effect heterogeneity. Section 2.7 concludes.

2.2 Empirical approach

This paper aims to evaluate the average treatment effect (ATT) of declared SEP ownership on firm revenue. Consider a firm i over the periods $t = 1, ..., T$ that declares a SEP in T_0, where $1 < T_0 < T$. Let us denote declared SEP ownership with $D_{it} \in \{0, 1\}$. The individual treatment effect of SEP declaration on firm revenue Y_{it} is

$$ITE_{it} = Y_{it}\Big(D_{it} = 1\Big) - Y_{it}\Big(D_{it} = 0\Big) \ , \tag{2.1}$$

where $t \in \{T_0, T_0 + 1, ..., T\}$. Yet, $Y_{it}\Big(D_{it} = 0\Big)$ cannot be observed. In the case of multiple SEP owners, the average treatment effect would be

$$ATT_t = N^{-1} \sum_{i=1}^{N} \Big[Y_{it}\Big(D_{it} = 1\Big) - Y_{it}\Big(D_{it} = 0\Big)\Big] \ , \tag{2.2}$$

for SEP owners $i = 1, ..., N$.

2.2.1 Differences-in-differences

The differences-in-differences (DID) estimator assumes that

$$Y_{it}\Big(D_{it} = 1\Big) = Y_{it}\Big(D_{it} = 0\Big) + \triangle Y_{it} \times D_{it} \ , \tag{2.3}$$

where $\triangle Y_{it} = Y_{it}\Big(D_{it} = 1\Big) - Y_{it}\Big(D_{it} = 0\Big)$, and that the counterfactual is determined by

$$Y_{it}\Big(D_{it} = 0\Big) = \delta_i + \delta_t + \varepsilon_{it} \ . \tag{2.4}$$

Consider a treatment and a control group, i.e. firms who own SEPs ($S = 1$) and firms who do not ($S = 0$). The DID estimator assumes furthermore that

$$\triangle_t \mathbb{E}\Big[Y_{it}\Big(D_{it} = 0, S = 1\Big)\Big] - \triangle_t \mathbb{E}\Big[Y_{it}\Big(D_{it} = 0, S = 0\Big)\Big] = 0 \ , \tag{2.5}$$

i.e. in the absence of treatment, the difference in the average values between post- and pre-treatment periods of the treated would match the controls, or put differently, that pre-treatment trends Y_{it} are parallel between the treated and the controls. Under these assumptions, the average treatment effect can be estimated with

$$Y_{it} = \delta_i + \delta_t + \beta D_{it} + \varepsilon_{it} \tag{2.6}$$

and corresponds to

$$ATT_t^{DID} = \hat{\beta} \ . \tag{2.7}$$

If the assumptions in equations 2.4 and 2.5 are not met, the DID estimator does not provide an unbiased estimate of the treatment effect.

2.2.2 Synthetic control

The synthetic control (SC) estimator, also called case study synthetic control (CSSC) estimator, has been developed to create data driven counterfactuals for situations with few treated units and a sufficiently large number of untreated units (Abadie, Diamond, and Hainmueller 2010). It aims at creating a control group that satisfies

$$Y_{it}\Big(D_{it} = 0, S = 1\Big) = Y_{it}\Big(D_{it} = 0, S = 0\Big) \ . \tag{2.8}$$

Consider $I + 1$ units and T time periods where unit 1 has been treated ($S = 1$ for $i = 1$), while the others have not ($S = 0 \ \ \forall i > 1$). The treatment period is given by T_0, where $1 < T_0 < T$. The SC method assumes that that $Y_{it}\Big(D_{1t} = 0\Big)$ is given by the linear model

$$Y_{it}\Big(D_{1t} = 0\Big) = \delta_t + \theta_t Z_i + \lambda_t \mu_i + \varepsilon_{it} \ , \tag{2.9}$$

where δ_t is an unknown common factor, Z_i is a vector of observed covariates, θ_t is a vector of unknown parameters, λ_t is a vector of unobserved common factors, μ_i is a vector of unknown factor loadings, and the error term ε_{it} represents unobserved shocks with zero mean. Contrary to equation 2.4, this assumption allows for unobserved time-varying individual-specific heterogeneity ($\lambda_t \mu_i$).

Suppose there is a vector of weights $W = (w_2^*, ..., w_{I+1}^*)$ such that

$$\sum_{i=2}^{I+1} w_i^* Y_{it} = Y_{1t} \quad \forall \quad t < T_0 \ , \tag{2.10}$$

where

$$\sum_{i=2}^{I+1} w_i^* Y_{it} = \delta_t + \theta_t \sum_{i=2}^{I+1} w_i^* Z_{it} + \lambda_t \sum_{i=2}^{I+1} w_i^* \mu_{it} + \sum_{i=2}^{I+1} w_i^* \varepsilon_{it} \ . \tag{2.11}$$

Then, the treatment effect for unit 1 can be estimated by

$$ITE_{it}^{SC} = Y_{1t} - \sum_{i=2}^{I+1} w_i^* Y_{it} \ , \tag{2.12}$$

for $t > T_0$. The SC estimator assumes that the treatment has no effect on the control units $2, ..., I+1$ and before the treatment period T_0. If the latter is the case, Abadie, Diamond, and Hainmueller 2010 suggest that T_0 corresponds to the first period where the outcome reacts to the treatment.

With multiple treated units $j = 1, ..., N^T$, the average treatment effect can be obtained by

$$ATT_t^{SC} = \sum_{j=1}^{N^T} ITE_{jt}^{SC} \ . \tag{2.13}$$

Another advantage of the SC over DID is that allows to analyze the heterogeneity of the treatment effect across different dimensions and to exclude treated units for which the assumptions do not hold.

2.3 Simple theoretical framework

Consider a duopolistic market with firms $i = 1, 2$ and a demand function

$$P(q_1 + q_2) = a - (q_1 + q_2) \ , \tag{2.14}$$

where q_i is the produced quantity of a certain good by firm i and P the market price. The firms' profit function is given by

$$\pi_i = Pq_i - C_i(q_i^{\delta_i}) \ , \tag{2.15}$$

where $\frac{\partial C_i}{\partial q_i} > 0$. The cost function $C_i(q_i^{\delta_i})$ depends on the production quantity q_i and the technology used for production T, with $\delta_i = f(T)$. Both firms set their production quantities simultaneously (Cournot competition) by maximizing their profit.

Each firm i can own a technology t_i. The production technology T can be fixed by a standard. If T is set by a standard, the firm has no choice over T. The standard can be built on a technology owned by a firm, t_1 or t_2, or a non-proprietary technology t_{NP}.

Suppose that

$$\delta_i(T = t_i) < \delta_i(T \neq t_i) \ , \tag{2.16}$$

i.e. the firm produces more efficiently if it uses its own technology, whereas for simplicity $\delta_i(T = t_j) = \delta_i(T = t_k) \ \forall \ j, k \neq i$. Then

$$\frac{\partial C_i}{\partial q_i}\bigg| T = t_i < \frac{\partial C_i}{\partial q_i}\bigg| T \neq t_i \ . \tag{2.17}$$

By symmetry, the optimal production quantity of each firm i is

$$q_i^* = \frac{\frac{\partial C_j}{\partial q_j} - 2\frac{\partial C_i}{\partial q_i} - a}{3} \ . \tag{2.18}$$

The equilibrium market price is then

$$P^* = a - \frac{\frac{\partial C_2}{\partial q_2} - 2\frac{\partial C_1}{\partial q_1} - a}{3} - \frac{\frac{\partial C_1}{\partial q_1} - 2\frac{\partial C_2}{\partial q_2} - a}{3} \tag{2.19}$$

$$= \frac{5a + \frac{\partial C_1}{\partial q_1} + \frac{\partial C_2}{\partial q_2}}{3} \tag{2.20}$$

and the firm i's operating revenue

$$P^* q_i^* = \left[\frac{5a + \frac{\partial C_1}{\partial q_1} + \frac{\partial C_2}{\partial q_2}}{3}\right]\left[\frac{\frac{\partial C_j}{\partial q_j} - 2\frac{\partial C_i}{\partial q_i} - a}{3}\right] \ . \tag{2.21}$$

Due to assumption 2.16, the production quantity of firm i in equilibrium is larger if $T = t_i$ than if $T \neq t_i$, i.e. $q_i^*(T = t_i) > q_i^*(T \neq t_i)$. The effect of the technology choice on the equilibrium market price depends on its effect on the other firm's production cost and the alternative technology choice. Compared to t_{NP}, firm i's operating revenue increases if $T = t_i$.

From that, I derive the following hypothesis:

A. The ATT of SEP ownership on the firms' operating revenue is positive.

Firms that participate in standard setting have been shown to have more influence on the technology choice T (see Bekkers, Bongard, and Nuvolari 2011). They might not only be more likely to own technologies implemented in the standard, but also to choose those that benefit them most. Therefore, I establish my second hypothesis:

B. The ATT of SEP ownership on the firms' operating revenue is higher for SSO members.

2.4 Data

2.4.1 Data sources

I use data on SEP declarations and SSO membership from the Searle Center Database on Technology Standards and Standard Setting Organizations (see Baron and Spulber 2018 for a detailed description). The database contains information on 598 SSOs, thereof 195 with information on institutional membership and 36 with information on SSO rules including rules on standard essential patents (SEPs), openness, participation and standard adoption procedures. Information on patents are taken from the worldwide patent statistical database of the European Patent Office (EPO), Patstat. This database allows me to match SEPs to their owners and to information on the patents themselves. Furthermore, I retrieve information on patent applications and patent stocks for the firms in the sample. Firm level data are retrieved from the Bureau van Dijk database Orbis. I group firms with the same global ultimate owner. Orbis reports firm data for a period of 10 years.

Since firm names are not harmonized within and between the different databases, I use string matching methods to relate patent owners from Patstat to the firms in Orbis. Therefore, I use the SearchEngine, a string matching tool developed by Thorsten Doherr (Doherr 2017). I first undertook some basic string cleaning and eliminated legal control names (e.g. "Corp."). Then I used the SearchEngine to match firm names based on the n-gram method. Matches are ranked by n-gram overlap and word frequency, where more frequent words receive a lower weight. Based on these results, I apply a fairly strict selection rule in order to avoid false positives. Finally, I use the global ultimate owner of firms from Orbis instead of the single firm matches, since the matching method often generates matches with several subsidiaries of one global firm. When a SEP is owned by several firms, I count one SEP per firm.

2.4.2 Data description

The Searle Center database reports SEP declarations between 1967 and 2017. The final dataset of this analysis contains 63,720 observations. I observe 6,372 firms between 2004 to 2016. For each firm, Orbis reports data over a 10-year period (depending on the firm, the periods vary slightly). The synthetic control method requires pre- and post-treatment periods around the SEP declaration year. I only keep SEP declaration years with at least 3 pre- and post-treatment years. Therefore, I capture SEP declarations between 2007 and 2013. During this period, 504 firms from 30 countries declared SEPs to the SSOs in the sample. The dataset contains 1,116 treated units, i.e. firm-year combinations with at least one SEP declaration, and 21,289 SEPs. The SEPs in my sample have been declared at 9 SSOs. The original database on SEP declarations from the Searle Center contains 30 SSOs. The number of SSOs and SEP declarations is reduced in my sample due to the matching with firms in Orbis and because I excluded blank SEP declarations, i.e. without specific patent identification number. The restricted time horizon in Orbis also limits the period of observation, since firm data is only available over 10 years. The sample contains firms from 19 1-digit NACE codes (Statistical Classification of Economic Activities in the European Community) with about half of them classified in manufacturing and 13% in the information and communication technology (ICT) sector. Tabe 2.1 shows that firms that declare SEPs are very concentrated in manufacturing. Tables 2.2 and 2.3 show that most SEP declaration in the sample come from the European Telecommunications Standards Institute (ETSI).

Table 2.1: NACE categories

NACE category	Number of firms	Number of SEP declarations
A	1	2
B	18	1797
C	234	10879
D	17	453
E	4	9
F	28	606
G	71	1599
H	20	2458
I	11	60
J	51	1643
K	5	21
L	10	37
M	15	1596
N	9	48
P	1	59
Q	1	1
R	5	14
S	3	7

A: Agriculture, forestry and Fishing; B: Mining and Quarrying; C: Manufacturing; D: Electricity, Gas, Steam and Air Conditioning Supply; E: Water Supply, Sewerage, Waste Management and Remediation Activities; F: Construction; G: Wholesale and Retail Trade, Repair of Motor Vehicles and Motorcycles; H: Transportation and Storage; I: Accommodation and Food Service Activities; J: Information and Communication; K: Financial and Insurance Activities; L: Real Estate Activities; M: Professional, Scientific and Technical Activities; N: Administrative and Support Service Activities; P: Education; Q: Human Health and Social Work Activities; R: Arts, Entertainment and Recreation; S: Other Service Activities

Table 2.2: Number of declared SEPs by SSO

	ARIB	ATIS	Broadband Forum	ETSI	IEEE	IETF	ISO	ITUT	OMA
2007				4					
2008		8		69					
2009		10		79					
2010	4	966	5	6493	3	13		46	
2011	4	704	2	6126	1	30	3	19	
2012		309		3151		15	3	39	2
2013		183		2862	4	27	5	100	
Total	8	2180	7	18784	8	85	11	204	2

Table 2.3: Number of firms declaring SEPs by SSO

	ARIB	ATIS	Broadband Forum	ETSI	IEEE	IETF	ISO	ITUT	OMA
2007				3					
2008		4		9					
2009		6		13					
2010	3	146	4	314	3	13		33	
2011	4	104	2	317	1	16	3	17	
2012		71		216		11	2	24	2
2013		52		192	4	21	5	3	

The dependent variable is the firm's operating revenue, i.e. the revenue the firm gains from its primary business activities. I use different input variables on the firm and country level in order to create the synthetic control groups. On the firm level, I dispose of the number of employees, net profits, R&D expenditure over net sales, net sales over the number of employees, the number of patent applications in the current year, the firm's patent stock in 2000 and the number of SSOs where the firm is member. Furthermore, I include GDP per capita, population size and R&D expenditure as a percentage of GDP for the firm's country of residence. Table 2.4 shows descriptive statistics of all variables for firms that declared SEPs during the period of observations and firms that did not. Except for the residence country's R&D expenditure, all variables have higher means for firms with SEP declarations. SEP declaring firms declare on average 8.2 SEPs per declaration year.

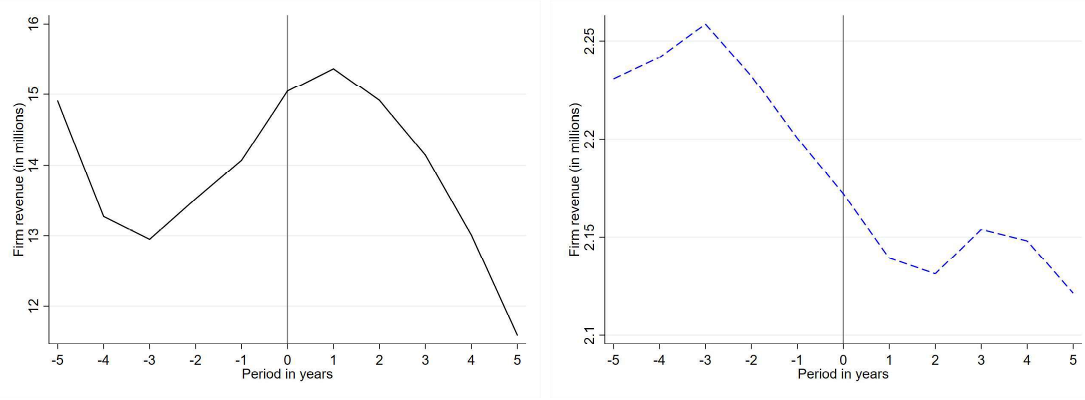
Table 2.4: Descriptive statistics

	With SEP declarations		No SEP declarations	
	Mean	SD	Mean	SD
Operating revenue (thous. USD)	8023.26	26872.88	1965.94	9777.27
Number of employees (thous.)	21.57	59.6	5.99	25.18
Net profit (thous. USD)	425.52	1868.5	81.9	784.63
R&D expenditure/net sales	.04	.47	.25	22.23
Net sales/number of employees	1287.65	20946.93	522.16	1812.84
Number of SSO memberships	3.42	11.62	.09	1.63
Number of patent applications	92.74	655.43	24.75	274.68
Patent stock in 2000	3132.08	27389.02	707.54	9124.75
GDP per capita (USD)	40577.57	11738.97	40438.2	11814.62
Population of firm's country (thous.)	146181.7	269874.1	127343.9	238321.5
R&D expenditure (% GDP)	2.44	.88	2.44	.9
Number of SEPs	8.2	71.31		

Note: Means for firms that declared SEPs during the period of observation vs. firms that did not.

In figure 2.1, we can observe the evolution of the average firm revenue around years with SEP declaration and without. This figure is a very naive comparison of firm revenues, but firm revenues seem to be higher on average if a SEP is declared. The aim of of this paper is to find a valid control pattern for the revenue path in figure 2.1a.

Figure 2.1: Actual firm revenue around years with and without SEP declaration



(a) SEP declaration in period 0

(b) No SEP declaration in period 0

2.5 Results

In this section, I present the results of the DID and synthetic control estimations of the treatment effect of declared SEP ownership on firm revenue.

2.5.1 Differences-in-differences

In order to obtain ATT_t^{DID}, I estimate the following equation

$$Y_{it} = \delta_i + \delta_t + \beta_t D_{it} + \gamma X_{it} + \varepsilon_{it} \ , \tag{2.22}$$

where X_{it} res presents a vector of covariates. The DID estimator depends crucially on the parallel trend assumption. The estimation model 2.22 allows to test whether this assumption holds. I denote the period of treatment, i.e. of SEP declaration, with $t = 0$. Negative periods are pre-treatment periods, positive periods post-treatment. Every β_t must be interpreted relatively to the reference period (dummy variable trap) which I set to period -9, i.e. 9 years before SEP declaration. In the case of pre-treatment parallel trends, the estimated coefficients $\hat{\beta}_t$ should be statistically insignificant for pre-treatment periods $t \in \{-8, ..., -1\}$. The ATT_t^{DID} is given by the coefficients $\hat{\beta}_t$ for $t \geq 0$. Table 2.5 shows the estimates of equation 2.22.

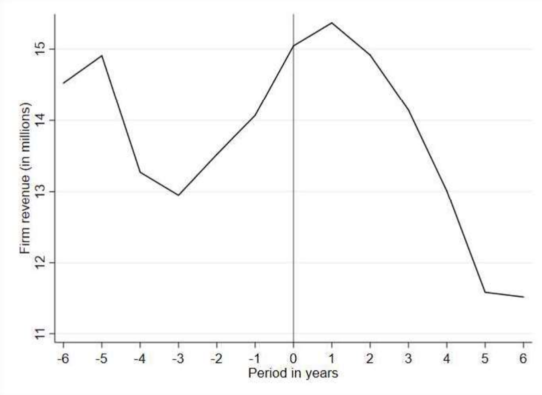
Table 2.5: DID estimation for firm revenues

	Operating revenue (Turnover) th USD	Operating revenue (Turnover) th USD
Treatment	-72012***	-54355***
Period -8	-994	-4
Period -7	-676	116
Period -6	-1070	147
Period -5	-1674	36
Period -4	-2236	-262
Period -3	-3022	-823
Period -2	-3135	-672
Period -1	-4147	-611
Period 0	-6188*	-367
Period 1	-6540*	-67
Period 2	-6948*	66
Period 3	-7604*	242
Period 4	-8172**	533
Period 5	-9071**	561
Period 6	-10874***	403
Period 7	-14542***	-362
Period 8	-19461***	-400
Period 9	-26490***	-367
Treatment × Period -6	70621***	51485**
Treatment × Period -5	78443***	59782***
Treatment × Period -4	90174***	71338***
Treatment × Period -3	107868***	89115***
Treatment × Period -2	103407***	85285***
Treatment × Period -1	102339***	83530***
Treatment × Period 0	91297***	70973***
Treatment × Period 1	74074***	53492***
Treatment × Period 2	66696***	47034***
Treatment × Period 3	53493***	38361**
Treatment × Period 4	35772*	22982
Treatment × Period 5	22178	14997
Constant	27337***	-9899
Covariates	Yes	Yes
Year dummies	No	Yes
Country dummies	No	Yes
Observations	637200	637200

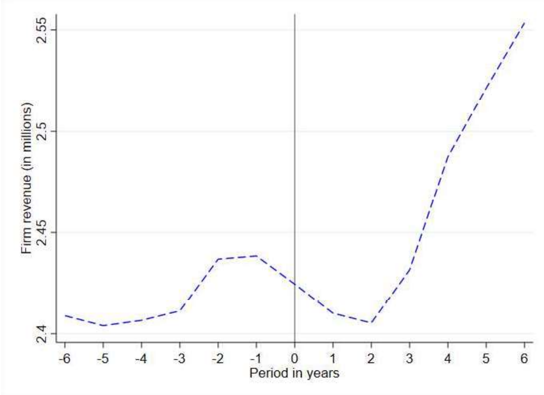
Revenues in thousand USD???

Table 2.5 shows that pre-treatment revenue trends are not parallel between the treated and control units. The interaction terms between the treatment and the periods represent D_{it}. The treatment variable and the coefficients of the interaction terms with pre-treatment periods are all highly significant, suggesting that the difference between the revenues of treated and untreated firms is not constant over time prior to SEP declaration. This can also be observed graphically in figure 2.2, where 2.2a shows the average prediction of firm revenues by the DID regression for the treated and 2.2b for the controls.

Figure 2.2: DID prediction of firm revenue for treated and untreated



(a) Treated



(b) Control

Since the parallel trend assumption does not hold for the DID model, the estimates for ATT_{it}^{DID} are not valid.

2.5.2 Synthetic control

I created a synthetic control for each treated unit, i.e. each firm-year pair with at least one SEP declaration. Table 2.6 shows the distribution of the number of control units per treated unit. Yet, the number of control units is not crucial as long as assumption 2.10 holds. For about half of the treated units, the synthetic control is averaged over at least 10 control units. About 14% of the treated units dispose of 500 control units.

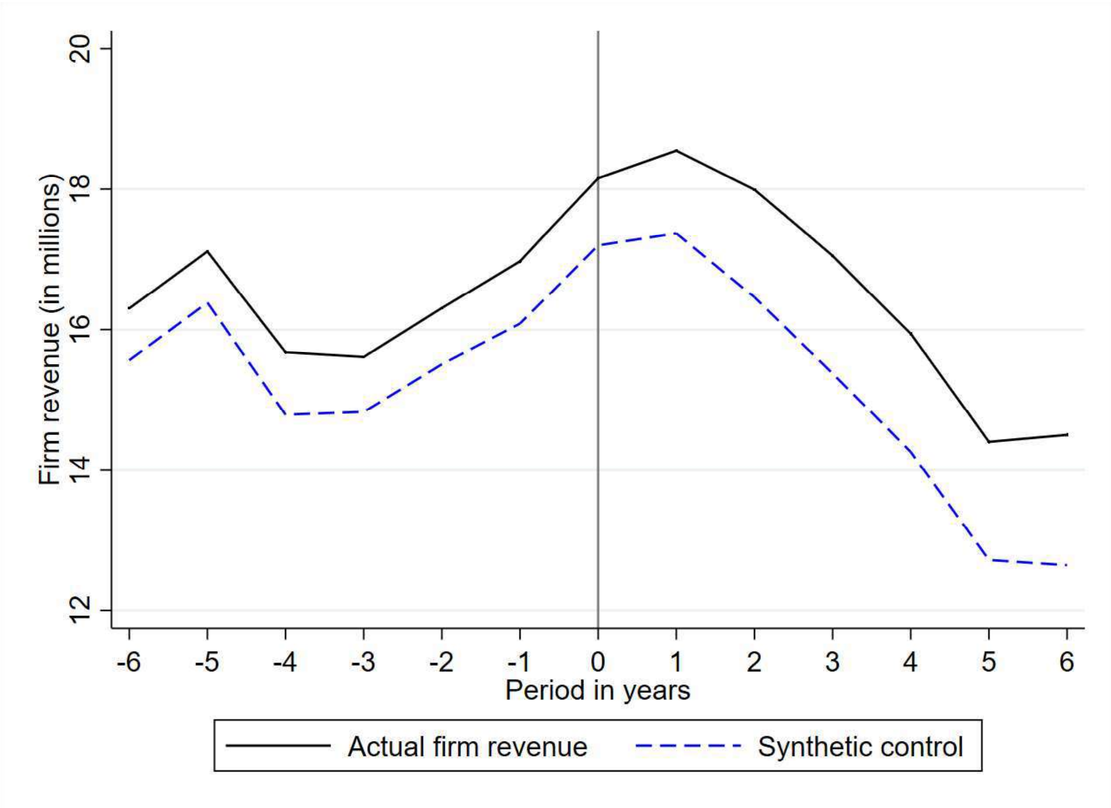
Table 2.6: Distribution of the number of control units

	Mean	Median	Standard dev.	Minimum	Maximum
Number of control units	84	10	172	1	500

Figure 2.3 shows the average firm revenue of the treated and the corresponding synthetic controls. My synthetic control model was not able to create an accurate

synthetic control for all treated units, since pre-treatment revenues are not equal on average. This is confirmed in table 2.11 which shows the results of the t-test for differences in means between the treatend and the synthetic controls. All differences are positive and significant at the 5% confidence level for periods -4 to 5. Abadie, Diamond, and Hainmueller 2010 suggest to exclude those units for which equation 2.10 does not hold. This is possible since for each treated unit an individual synthetic control is estimated. Then, the internal validity of the ATT_t^{SC} for the selected sample of treated units holds.

Figure 2.3: Average operating revenue - actual vs. synthetic control



Note: The figure shows the average actual and counterfactual operating revenue of all firm-years with a SEP declaration. Period 0 denotes the year of the SEP declaration.

Table 2.7: Difference between actual and SC operating revenue by period

[t]Period in years from treatment	Average actual revenue	Average counterfactual revenue	Difference	p-value	Number of observations
-6	16302	15565	738	.352	187
-5	17111	16385	726	.158	386
-4	15679	14788	891	.015	650
-3	15612	14828	783	.015	910
-2	16307	15508	799	.011	910
-1	16971	16086	885	.005	910
0	18155	17197	958	.008	910
1	18546	17367	1178	.004	910
2	17992	16462	1529	.001	910
3	17049	15376	1673	0	910
4	15942	14261	1681	.003	723
5	14404	12722	1682	.013	524
6	14503	12649	1854	.054	260

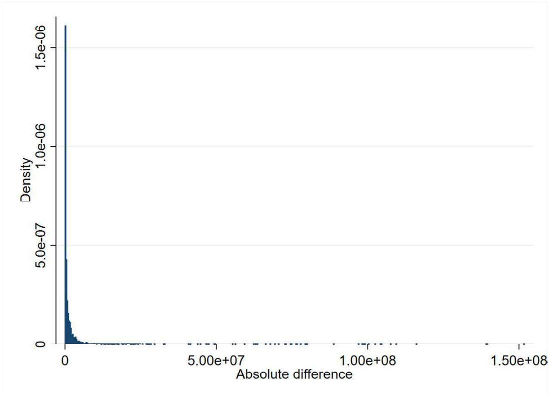
Note: Revenues in thousand USD. Period 0 = treatment period. p-value of two-sided t-test for difference in means.

Exclude treated with ”bad” synthetic controls

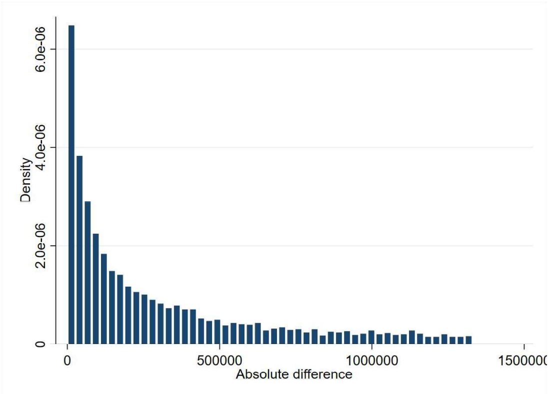
In order to exclude treated units for which equation 2.10 does not hold, I compare pre-treatment firm revenues between the treated and their synthetic controls. Figure 2.4 shows the absolute and relative difference between actual and SC firm revenues for pre-treatment periods. The relative difference consists of the absolute difference divided by the revenue of the synthetic control group. Subfigures 2.4a and 2.4c show that the difference in revenues is highly skewed towards zero. In subfigures 2.4b and 2.4d, I show the same distributions only up to the 75th percentile of the distribution. This shows that for most treated units the pre-treatment revenue differences to their synthetic control group are very small, especially in relative terms.

Figure 2.4: Distribution of difference between actual and SC firm revenue

Absolute difference

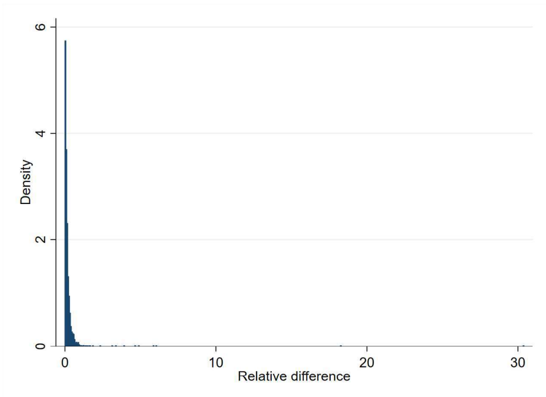


(a) All

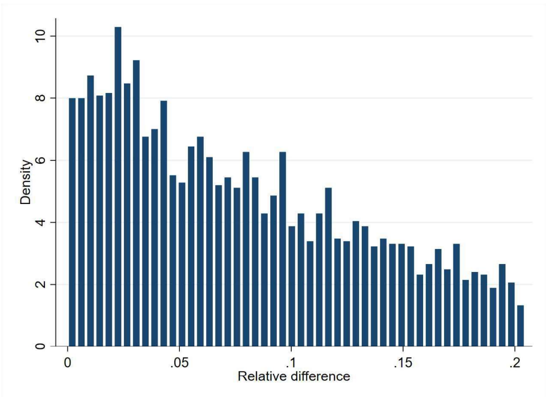


(b) Difference ≤ 75th percentile

Relative difference



(c) All

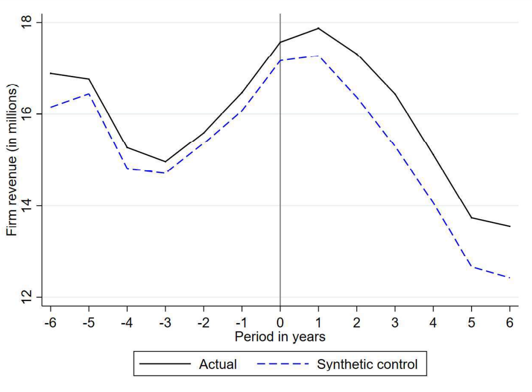


(d) Difference ≤ 75th percentile

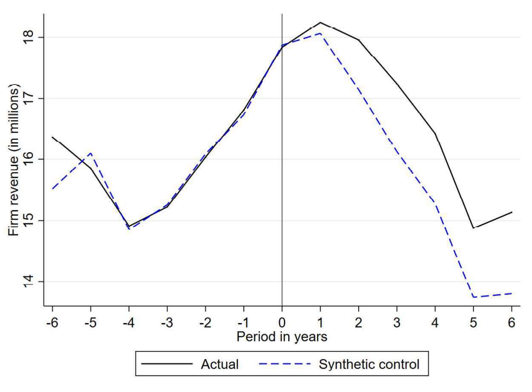
Figure 2.5 shows the evolution of average actual and SC firm revenues when treated units with "bad" synthetic controls are excluded. In figure 2.5a, I exclude those with an average difference in pre-treatment revenues above the 75th percentile of the distribution (78 treated units). Figure 2.5b shows the same for an even lower threshold for the relative difference of 0.05 (299 treated units). The lines of pre-treatment revenue paths become closer as the threshold for the relative difference decreases. Table 2.8 shows that the excluded treated units with an average difference in pre-treatment revenues above the 75th percentile represent those with a very high number of control units (500 control units) or with only one control unit. This suggests that for these units no optimal weights could be found such that weighted pre-treatment revenues of the control units corresponds to the revenues of the treated (or the pre-treatement revenue of the treated is not located in the convex hull of the controls). Too many control units might be an indicator that the algorithm was not able to find optimal weights with the given potential control units.

In table 2.9, I test for a difference between actual and SC revenues for the different samples: all treated, treated with a relative difference in revenues within the 75th percentile, and treated with a relative difference up to 0.05. For the last two samples, pre-treatment revenues are not significantly different between the treated and their synthetic controls. The lower the threshold for the relative difference in pre-treatment revenues, the higher the p-values of the t-tests. The positive differences in revenues in post-treatment periods stay significant at the 5% confidence level. The ATT_t^{SC} is positive and significant for most post-treatment periods.

Figure 2.5: Average operating revenue - actual vs. synthetic control excluding "bad" synthetic controls



(a) Relative difference $\leq$ 75th percentile



(b) Relative difference ≤ 0.05

Table 2.8: Distribution of the number of control units excluding treated units with an average difference in pre-treatment revenues above the 75th percentile

	Mean	Median	Standard dev.	Minimum	Maximum
Number of control units	11	9	13	2	136

Table 2.9: Difference between actual and SC operating revenue by period

	All		75th percentile		0.05	
Period	Diff.	p-value	Diff.	p-value	Diff.	p-value
-6	738	.352	739	.382	849	.257
-5	726	.158	321	.459	-247	.385
-4	891	.015	456	.115	58	.787
-3	783	.015	247	.241	-35	.794
-2	799	.011	232	.217	-52	.632
-1	885	.005	399	.094	74	.643
0	958	.008	402	.133	-35	.872
1	1178	.004	588	.049	182	.54
2	1529	.001	948	.009	813	.056
3	1673	0	1147	.005	1118	.027
4	1681	.003	1041	.025	1152	.05
5	1682	.013	1068	.051	1136	.112
6	1854	.054	1125	.127	1336	.177
Number of treated		910		832		611

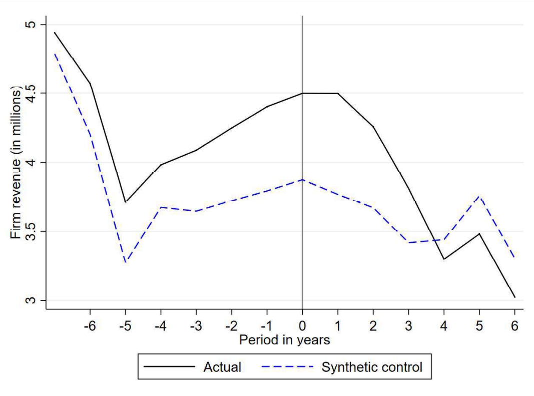
2.6 Robustness checks and heterogeneity of the ATT

Placebo test

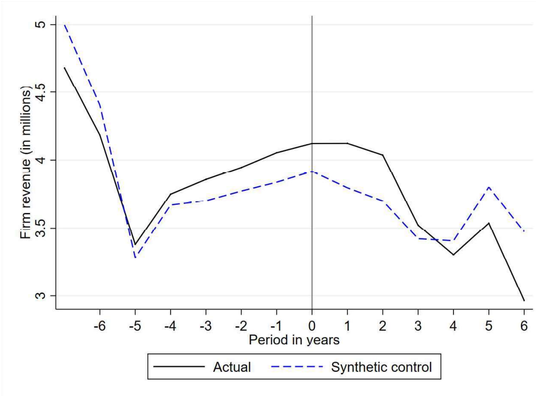
The restriction of the set of treated by excluding those where pre-treatment revenues are significantly different could raise concerns. It could notably be argued that treatment effects occur by pure chance. In order to verify whether similar treatment effects could be obtained with any set of firm-year pairs, I conduct a placebo test. To do so, I select a random sample of firm-years without SEP declaration and use them as pseudo-treated units. In order to have a similar number of observations, I select 1% of all untreated units. Then, I create a synthetic control for each pseudo-treated unit using the same model as before. Finally, as before, I exclude those pseudo-treated for which relative differences in revenues before the pseudo-treatment are very high (exclude ”bad” synthetic controls), so that equation 2.10 holds for the remaining units.

Figure 2.6 shows the average firm revenue per period. For all pseudo-treated, actual and SC revenues seem to differ in the four to five years around the pseudo-treatment period. When excluding units with "bad" synthetic controls, the lines approach before and after the pseudo-treatment period. This is confirmed in table 2.10, where differences in means become mostly insignificant before and after the pseudo-treatment period when excluding outliers.

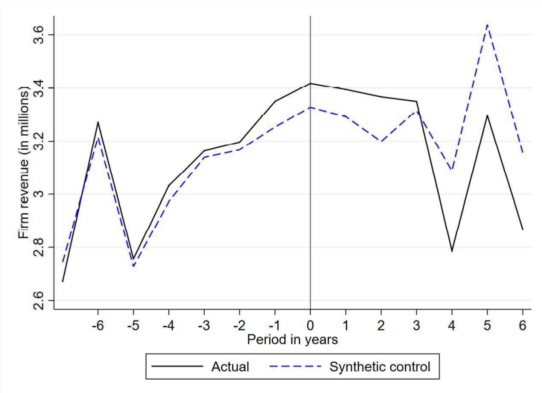
Figure 2.6: Average operating revenue - pseudo-treated vs. synthetic control



(a) All



(b) Relative difference ≤ 75th percentile



(c) Relative difference ≤ 0.05

Table 2.10: Difference between actual and SC operating revenue by period

	All		75th percentile		0.05	
Period	Diff.	p-value	Diff.	p-value	Diff.	p-value
-6	371842	.328	-220128	.43	55721	.721
-5	439232	.091	97740	.313	28930	.527
-4	306978	.158	80139	.383	59808	.251
-3	438576	.086	154823	.31	24320	.495
-2	523809	.11	171922	.31	28976	.41
-1	607916	.079	216449	.093	96702	.073
0	624150	.091	204426	.146	90384	.282
1	727253	.047	325278	.027	102531	.383
2	584631	.024	335061	.045	168149	.274
3	392501	.214	99651	.552	34305	.842
4	-141251	.545	-102731	.632	-301855	.055
5	-278734	.278	-265152	.2	-341086	.156
6	-281728	.485	-508061	.224	-287049	.356
Number of pseudo-treated		1386		1223		701

Note: Randomly selected 1% of years without SEP declaration

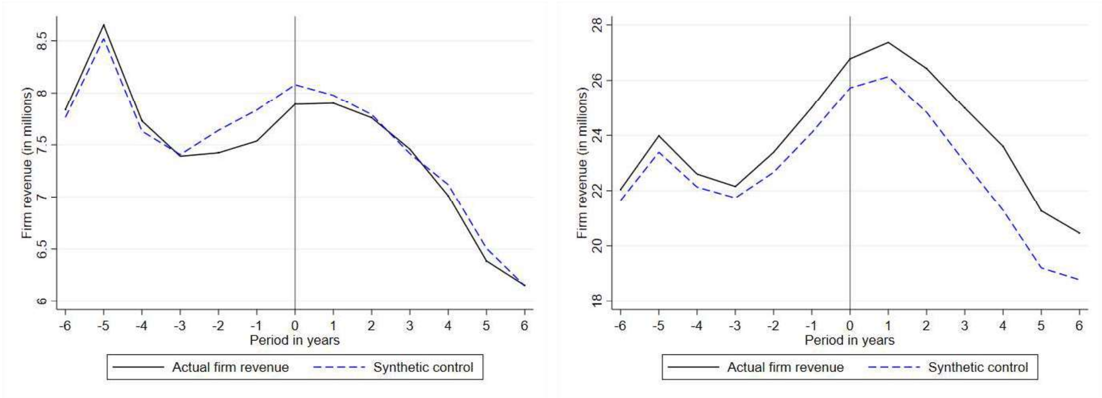
SSO membership

The synthetic control method allows to evaluate the heterogeneity of the ATT, since treatment effects are estimated on the individual level. One important dimension of the effect of SEP ownership on firm revenues is SSO membership. SSO members have a higher influence on standardization outcomes then non-members and are therefore more likely to own SEPs. Members might also be more interested in the standards they participate to develop and therefore benefit more from SEP ownership. I derive average treatment effects by membership status, by averaging individual treatment effects within the two groups. As before, I exclude treated units with "bad" synthetic controls. I keep treated units where the relative difference between pre-treatment revenues falls within the 75th percentile of the distribution.

Figure 2.7 shows the average firm revenues of the treated and their controls by SSO membership. SSO membership is set to 1 if the firm is member of any SSO during the five years before or after the SEP declaration year. The SC revenues follow actual revenues quite closely for non-members, while for SSO members we observe the a similar pattern as in section 2.5.2.

In table 2.11, I present the average treatment effects by period and SSO membership status. For non-members, all differences in means are insignificant except for periods -1 and -2, where the differences are negative and significant at the 5% confidence level. SSO members experience a significant increase in revenues after declaring SEPs, which reflects the ATT found in section 2.5.2. The treatment effects for SSO members in the two periods before SEP declaration are close to significance, which might suggest some anticipation effect.

Figure 2.7: Average operating revenue - treated vs. synthetic control



(a) No SSO member

(b) SSO member

Table 2.11: Difference between actual and counterfactual operating revenue by period

	No SSO member		SSO member		
[t]Period in years from treatment	Difference	p-value	Difference	p-value	Number of observations
-6	74	.866	400	.741	158
-5	130	.608	591	.476	315
-4	98	.468	471	.395	540
-3	-16	.859	417	.305	750
-2	-215	.009	720	.076	750
-1	-298	.042	910	.053	750
0	-190	.408	1052	.041	750
1	-78	.777	1241	.023	750
2	-30	.923	1598	.008	750
3	43	.892	1962	.004	750
4	-107	.775	2316	.006	592
5	-121	.785	2060	.05	435
6	5	.994	1686	.246	210

Note: Revenues in thousand USD. Relative difference $\leq$ 75th percentile. Period 0 = treatment period. p-value of two-sided t-test for difference in means.

2.7 Conclusion

This paper analyzed the effect of declared SEP ownership on firms' operating revenue. I compare the estimates of a conventional differences-in-differences (DID) approach with a synthetic control method that creates counterfactual revenue paths for each SEP declaration. I show that DID is not applicable due to the violation of the parallel trends hypothesis. The synthetic control method allows to estimate a local average treatment effect for those SEP declarations where the pre-treatment revenues are in the convex hull of the control units. The estimated effect is positive and significant for the observed post-declaration periods. Conducting a placebo test using the same synthetic control method, I show that my method does not lead to similar results when no SEP has been declared. When comparing SSO members and non-members, I show that this positive effect comes from the SSO members which seem to benefit more from SEP ownership in terms of operating revenues compared to non-members. This could be explained by the fact that SSO members have more influence on the technology choice of a standard.

The paper contributes to the literature by analysing the effect of declared SEP ownership on the firms' market performance rather than their financial performance. Further research must be conducted on the relationship between SEP ownership and the firms' cost structure in order to evaluate the profitability of SEP ownership. One downside of the study is that I observe only declared SEP ownership rather than actual standard essentiality. Not all declared SEPs are actually standard essential, however, a SEP declaration has been shown to be an important indicator for standard essentiality. Future work will also involve varying the treatment period from the declaration date to the standard release date.

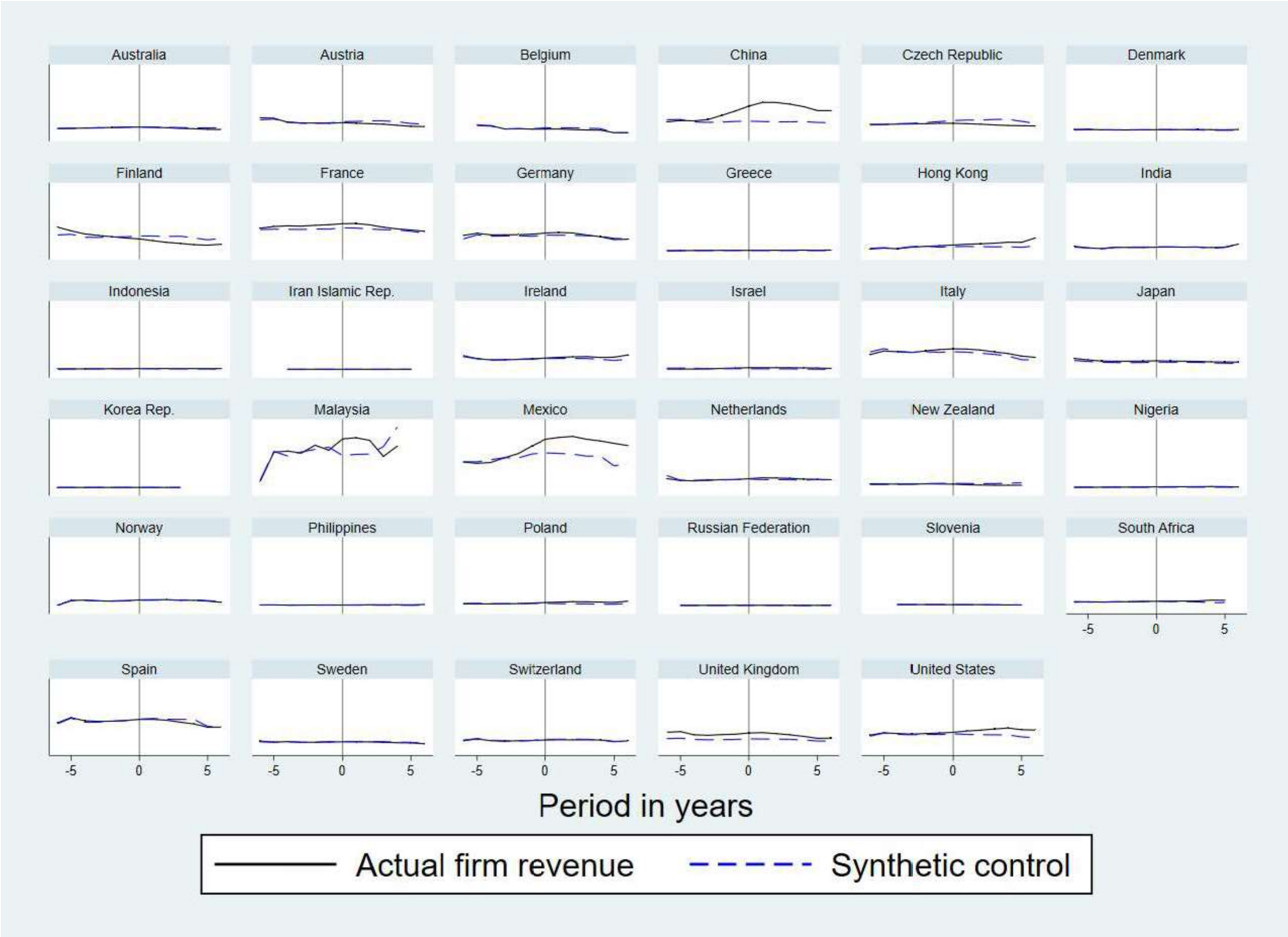
2.8 Appendix

Table 2.12: differences-in-differences estimator of SEP revenue by country

Country	Number of observations	Mean diff-diff	Standard deviation
Australia	40	-860	697
Austria	60	-3123	2324
Belgium	20	-1581	1680
China	550	13592	37685
Czech Republic	40	-3629	1876
Denmark	100	403	841
Finland	220	-7012	12239
France	910	-103	9664
Germany	710	571	8780
Greece	40	234	218
Hong Kong SAR China	260	3083	7525
India	80	184	1387
Indonesia	90	262	245
Iran Islamic Rep.	20	-14	0
Ireland	120	1812	3256
Israel	60	929	965
Italy	220	2022	5904
Japan	4110	-394	4098
Korea Rep.	20	6	0
Malaysia	20	7660	8236
Mexico	40	14340	4854
Netherlands	210	1736	5692
New Zealand	30	-1313	269
Nigeria	30	469	327
Norway	150	378	2742
Philippines	70	270	334
Poland	50	2019	1220
Russian Federation	50	30	106
Slovenia	10	36	0
South Africa	40	615	2523
Spain	220	-2124	9890
Sweden	430	-435	2677
Switzerland	290	-595	3622
United Kingdom	1980	625	11891
United States	740	4074	15614

Note: differences-in-differences estimator by country. Revenues in thousand USD. Per-treatment revenue = average operating revenue of periods -1 to -3. Post-treatment revenue averaged over periods 1-3.

Figure 2.8: Average operating revenue by country - actual vs. synthetic control



Note: The figure shows the average actual and counterfactual operating revenue of all firm-years with a SEP declaration. Period 0 denotes the year of the SEP declaration.

Table 2.13: Diff-diff estimator of SEP revenue by country and NACE code

	A	B	C	E	F	G	H	I	J	K	L	M	N	O	Q	R	S	T
Australia			-124															
Austria			-78					-265										
Belgium										-1595								
China		13180	523	1307		-42		2689				227		127			2	
Czech Republic				-1611														
Denmark			108				10	82										
Finland			-2906	-304			-1437			-182								
France	297	539	-12	2139	-5520		-2233	255		37	-259			674				
Germany			-111	18173		-720	-2483	-857		257			156					-3
Greece							95											
Hong Kong SAR China			304					459	387	6773		492		-114			1159	
India			684							-12								
Indonesia	269	-51	27				198											
Iran Islamic Rep			-14															
Ireland		-3	201					680					12					
Israel			38							142								
Italy			322	934		239			-1020									
Japan			-46	-12	393	-623	187	31	-66	-2063	-58	159	25	-78	-73		-508	
Korea Rep			6							7								
Malaysia		7844		-367														
Mexico										4081								
Netherlands		1799	-398			-19		415					346					
New Zealand										-1313								
Nigeria			383															
Norway		1534	-315							321		21						
Philippines			201															
Poland			-29				411											
Russian Federation			-40	38														
Slovenia										36								
South Africa										784	-3640							
Spain			-693	-76		15246	-3472			-1719				1032				
Sweden		-476	67				241			-205	-816		8	-68			205	
Switzerland			220					158		-41		263	200					
United Kingdom		-1836	161	-1115	-136	280	590	206	-79	180	10	42	251	495	636	33		97
United States			263	-1154		-252	26750			161			31					

Note: Revenues in thousand USD. Sectors: A - Agriculture, forestry and Fishing; B - Mining and Quarrying; C - Manufacturing; D - Electricity, Gas, Steam and Air Conditioning Supply; E - Water Supply; Sewerage, Waste Management and Remediation Activities; F - Construction; G - Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles; H - Transportation and Storage; I - Accommodation and Food Service Activities; J - Information and Communication; K - Financial and Insurance Activities; L - Real Estate Activities; M - Professional, Scientific and Technical Activities; N - Administrative and Support Service Activities; O - Public Administration and Defence; Compulsory Social Security; P

Chapitre 3

Harmonisation stratégique des normes techniques

Dans ce chapitre, j'analyse la relation entre la propriété intellectuelle, le commerce international et l'adoption de normes technique entre pays. La standardisation est devenue de plus en plus importante sur le niveau international avec l'avancement de la globalisation et la fragmentation de la production, mais les stratégies de standardisation diffèrent entre pays. Les normes techniques sont souvent basées sur des technologies protégées par des brevets. Des pays en développement en argumenté que l'adoption de ces normes techniques favorise principalement des entreprises basées dans les pays développés. Je montre que l'influence des pays dans les organismes de standardisation est liée à leurs volumes de propriété intellectuelle et leur position sur les marchés internationaux.

Chapter 3

Strategic Harmonization of ICT Standards: A Duration Data Analysis

Abstract. This study analyzes the relationship between intellectual property rights, international trade, and the adoption of international standards across countries in the Information and Communication Technology (ICT) sector. International standardization has become increasingly important with the rise of globalization and the fragmentation of the production of product components, particularly in the ICT sector. However, standardization strategies differ between countries. Standards often build on technologies that are protected by intellectual property rights, and developing countries in particular have argued that the adoption of such standards usually involves a transfer to firms based in relatively rich countries. I argue that the bargaining power of countries in the international standard setting process is related to their ownership of intellectual property rights and their involvement in international trade, which in turn affects incentives to harmonize their standards.

3.1 Introduction

The Agreement on Technical Barriers to Trade (TBT) aims to avoid all "unnecessary obstacles to trade." Given the high number of technical regulations and standards and their presumed negative impact on trade costs, all member countries of the World Trade Organization (WTO) are required to harmonize their standards in the absence of "legitimate divergences of taste, income, geographical and other factors between countries" (*Technical Information on Technical barriers to trade*). The literature has indeed found a generally positive effect of internationally harmonized standards on trade (Swann 2010; Portugal-Perez, Reyes, and Wilson 2010; Li-Juan 2013; Mangelsdorf, Portugal-Perez, and Wilson 2012). However, regulations in developed countries can have a restrictive effect on less developed countries' exports due to their weaker capacity to fulfill these standards (Czubala, Shepherd, and Wilson 2009; Essaji 2008). Gibson 2007 describes the tensions between developed and less developed countries with the specific example of China, which is often criticized for using national standards as barriers to trade in order to promote domestic industries. China argues that, because intellectual property rights (IPRs) embedded in international standards are mostly owned by Western firms, the adoption of such standards disadvantages developing countries and reduces their participation in international trade (Gibson 2007). China is a particularly interesting case in this context, because standardization is highly monitored by the government and represents an essential tool for improving the country's innovative capacity and for helping it to make the transition from being a standard taker to becoming a co-shaper of international standards. The country's goal is not only to create patent-worthy technology essential to global standards in order to strengthen its bargaining power and reduce its exposure to high royalty fees, but also to increase China's geopolitical influence and promote new rules of international standardization (Ernst 2011). The conflict between developed and emerging economies is documented in the WTO TBT Information Management System, where 60% of the concerns about TBTs submitted to the WTO have been raised between developed and emerging economies.

International standard setting can be compared to a network where the benefit of entering the network depends on the number of participants. At the same time, participants vary in the benefits of adoption, because of differences in technological endowment and integration in global markets. International standardization can lead to conflicting interests between agenda-setting first movers and second movers who may face switching costs. Yet, as more countries adopt international standards, the opportunity costs of national standards increase (Mattli and Büthe 2003). International standard setting is a strategic interplay of participants who maximize their benefits (or minimize their costs) from harmonization and are constrained by their bargaining power.

This study examines the different motivations of international standard harmonization across countries. I assume that harmonization of national standards with international and foreign standards succeeds the attainment of a specific threshold of accumulated IPR while taking into account the countries' relative position on international markets, as well as the network effects of international standardization. A large literature has examined the impact of IPRs on development and innovation in emerging markets. In general, IPRs are associated with increased FDI and technology transfer (Branstetter, Fisman, and Foley 2006), Keller 2002b,Keller 2002a), increased exports to developing countries (Ivus 2010), and increased trade in IP-intensive products (Delgado et al. 2013). However, McCalman 2001 argues that developed countries, particularly the US, are the main beneficiaries of international patent harmonization, as significant income is transferred from developing countries to those where IPR owners are located. Less attention has been paid to the relationship between standards and trade. A recent exception is Schmidt and Steingress 2017, who find that standard harmonization increases bilateral trade. This paper focuses on the incentives for countries to adopt international standards, and in particular, how this varies with their ownership of international IPRs rather than the effect of domestic changes to IPR policy. To my knowledge, this is the first study which relates the cross-country distribution of IPR to the dynamics in the international standard setting process using detailed data on standard and patent documents.

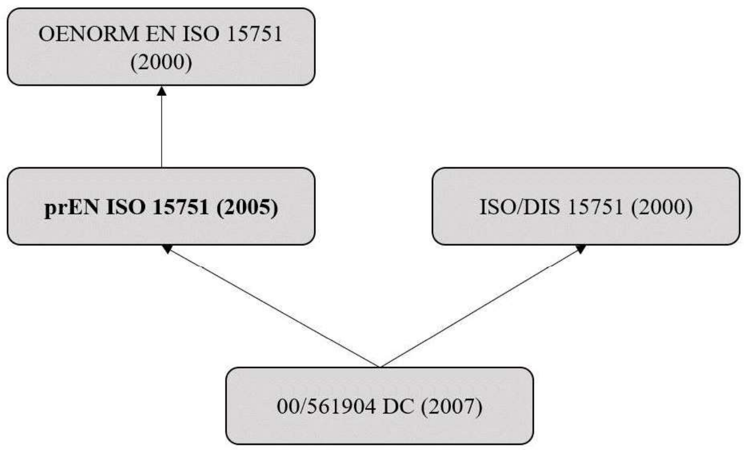
3.2 Data

Data on standards are taken from the Perinorm database, which contains information on the origin country of a standard setting organization that issued the standard, the technology class (International Classification for Standards, ICS), the publication date, the issuing body, as well as the international relationships between standards. I also exploit information on the similarity between related standards, which takes the values "identical", "equivalent" and "not equivalent" (following the standard "ISO/IEC Guide 21" on the adoption of international standards as regional or national standards, see WTO 2005). Some regional and national specification exist as well: related (CEN and CENELEC), modified (ISONET), necessary and useful (ASI). I use this information to measure the adoption of a standard issued by different standard setting organizations.

This approach has a number of limitations. First, the information on international relationships is missing for some origin codes in the Perinorm database

(Canada, Norway, Lithuania, French and European regulations) and the records about international relationships are not necessarily complete (WTO 2005). However, Perinorm represents the most exhaustive database on standards and is, therefore, the most widely used data source on standardization in the literature. Another issue arises from the fact that international relationships are recorded at the time of publication of a standard (direct backward relations). I use network theory in order to account for forward relationships. Furthermore, international relationship records are not always exhaustive. A standard's international relationships might refer to other standards which are not referred to by the standard itself, but which are equivalent to this standard (indirect backward relations). Network theory also helps us to identify these "standard families." Thereby, I increase the number of observed international relationships between standards. The example below demonstrates this issue.

Figure 3.1: Direct vs. indirect relations between standards



The resulting international relationships for this example would then look as follows.

Standard	International relationship
00/561904 DC (2007)	ISO/DIS 15751 (2000)
00/561904 DC (2007)	prEN ISO 15751 (2005)
00/561904 DC (2007)	OENORM EN ISO 15751 (2000)
prEN ISO 15751 (2005)	OENORM EN ISO 15751 (2000)
prEN ISO 15751 (2005)	ISO/DIS 15751 (2000)

Unfortunately, the document identifiers in the international relationships variable contain errors and abbreviations, so that it was necessary to undertake some cleaning in order match them with the information of the standard documents. I use string cleaning methods and compare standard documents by title and technology class in order to exclude wrong matches. Very short abbreviation have been excluded since they would match too many different standard documents. I also exclude all matches with standards from sectors other than ICT. Standards from different technological fields can refer to each other. However, since I am interested in the adoption of equivalent standards, this selection method seems to be accurate. The same reasoning allows us to exclude standards with very different titles which I determine using the Levenshtein distance. I am confident that the remaining matches represent truly related standards. Due to the lack of exhaustive documentation of international relationships by some standard setting organizations and the strictness of my matching method, my results can be interpreted as a lower bound to international standard adoption. My sample period goes from 1995 to 2015. I exclude standards that have been published after 2014.

The two-digit ICS classes for ICT are 33 and 35. The importance of international interoperability in the ICT sector is reflected in the high number of standards and an above-average number of shared standards. Figure 2 graphs the total number of standard documents world wide by sector. The sector of ICT technologies shows by far the highest standardization activity, followed by health, environment and safety, electronics, transportation and construction technologies. My dataset contains 203,411 ICT standards from 27 national, 13 international and 12 European standard setting organizations. Figure 3 displays the number of standard documents by origin code of the issuing body. Standards from European and international standard setting organizations account for almost half of all ICT standards recorded in Perinorm. The average duration until adoption (if adopted) is 3.66 years. The figures 4 and 5 show that countries differ in there average adoption speed as well as in there average tendency to adopt foreign or international standards.

Figure 3.2: Number of standard documents by sector

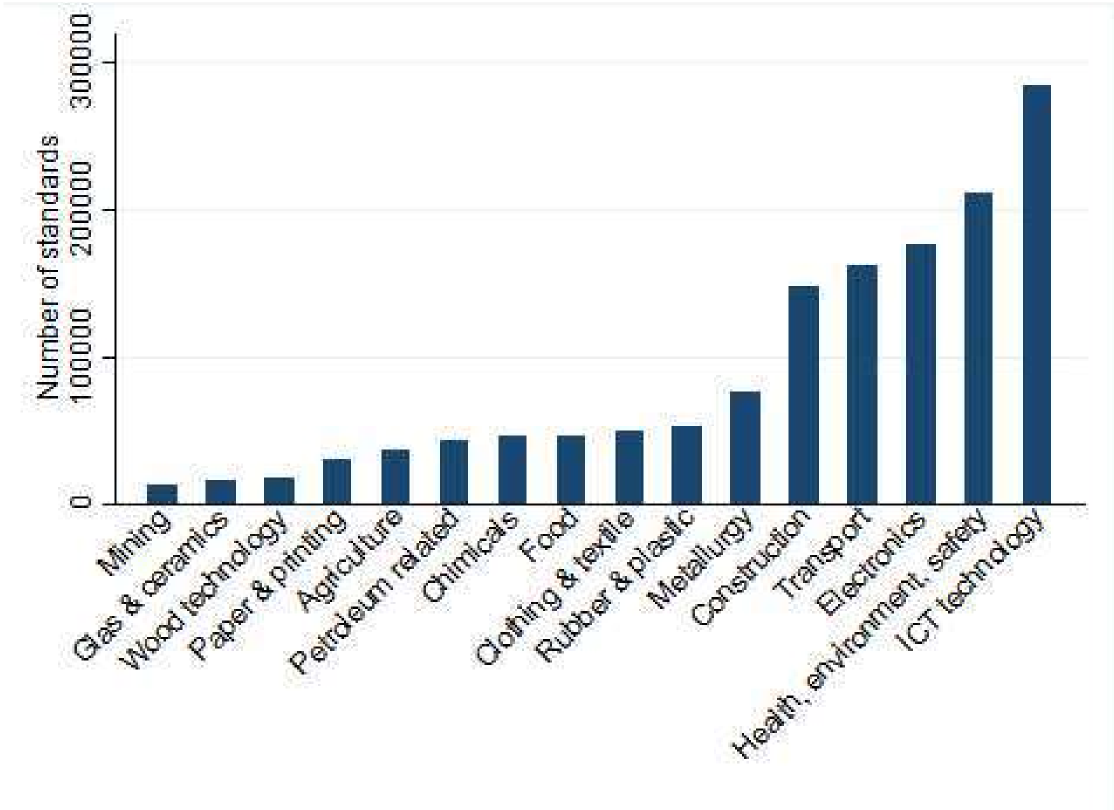


Figure 3.3: Publication of ICT standards by origin code

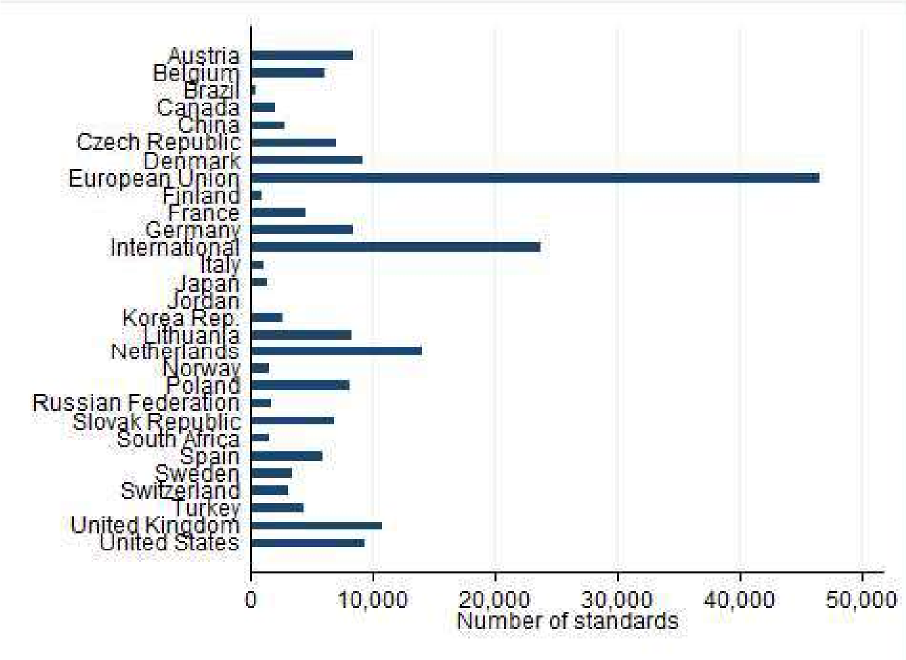


Figure 3.4: Average number of years before adoption

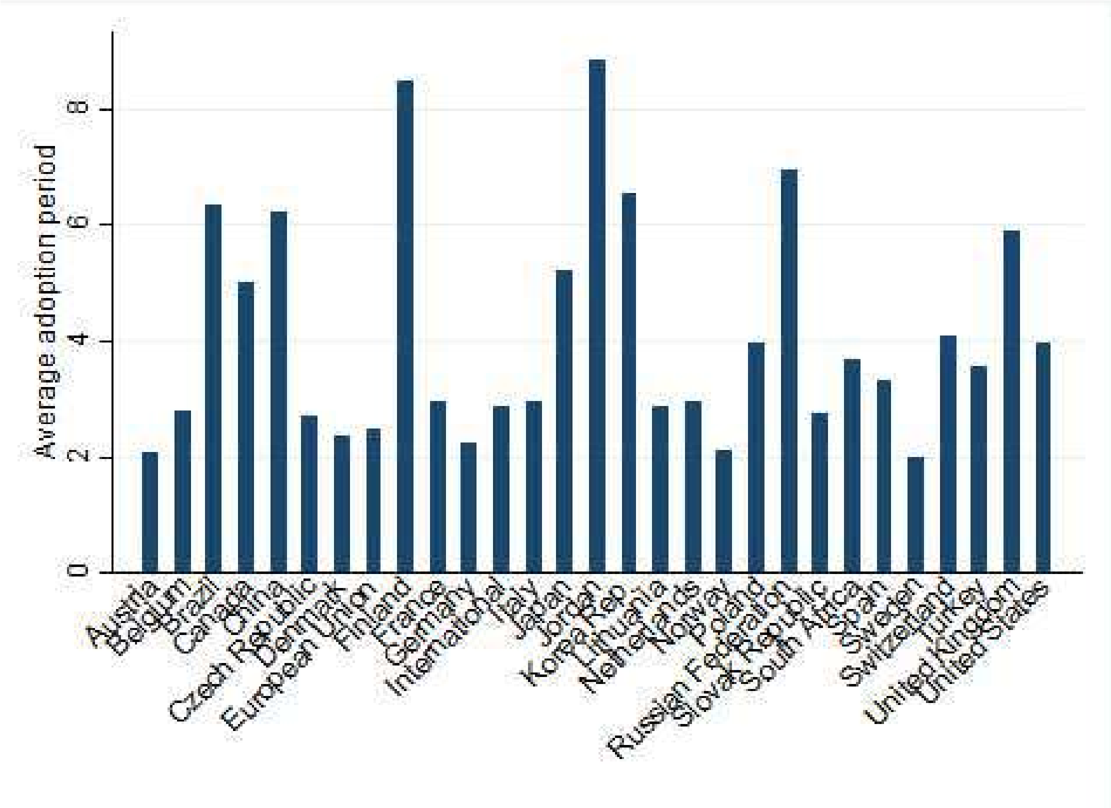
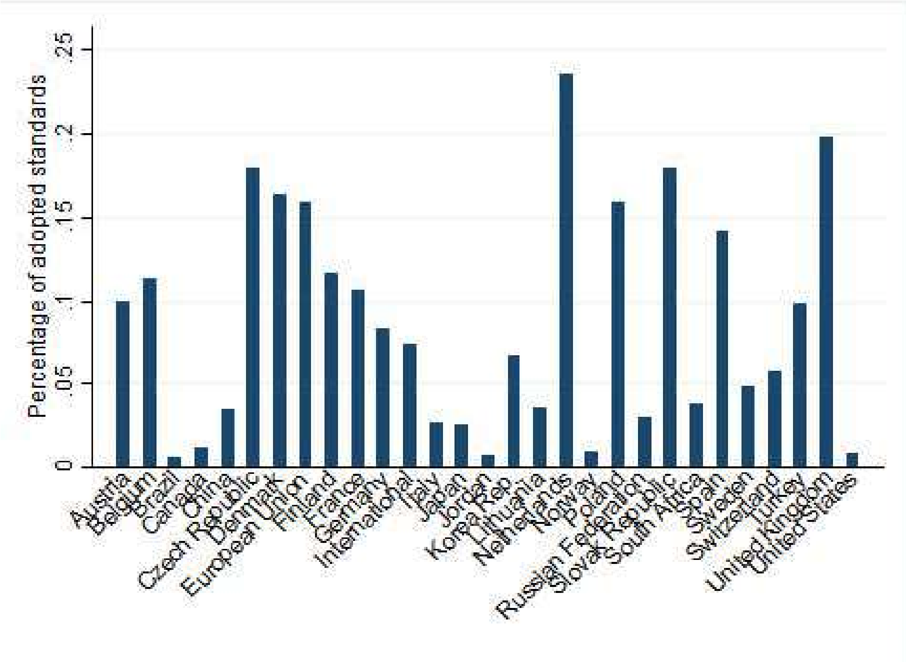


Figure 3.5: Percentage of standards adopted



I use ICT patent stocks extracted from the PATSTAT database (European Patent Office, EPO) to measure a country's (*current*) stock of domestically owned intellectual property rights. Patents are assumed to expire 20 years after the filing year. PATSTAT contains information on patent families, i.e. patents which protect the same invention (2009) in different countries. In order to avoid double counting of the same inventions, I only keep first priority patents. The International Patent Classification (IPC) categorizes ICT patents in the three-digit class "H04." I directly match these patents to the data on ICT standards.[1] In order to control for level effects, I also include the ICT patent stock in 1995, the first year of observation in my data. The *current* patent stock counts only patent applications filed after 1995 in order to avoid to confound the effects of new and initial patent stocks.

The UNCTAD Data Center provides data on bilateral trade flows on the product level. I use bilateral export data (value in U.S. dollars) to identify the countries' overall position on the global market place, as well as their relative strength in the ICT market. Product classifications follow the Standard International Trade Classification, Revision 3. In order to match patent and trade, I use the method of Lybbert and Zolas 2014 which consists of generating a list of keywords for each

[1] To date, there does not exist a convincing concordance between the IPC and ICS classes. The development of such a concordance between the two technology classifications is a subject for future research.

product class that are then compared with each patent document. The algorithm then allocates a similarity weight to each patent-product class pair. Export values are then weighted by these similarity weights. I replace all missing values for all possible country pairs with zeros.

I retrieved further control variables from the World Bank database on World Development Indicators (WDI) such as GDP (constant U.S. dollars), total labor force, total population, urban population (percentage of total). The table below shows descriptive statistics of the variables used in the estimation models.

Table 3.1: Descriptive statistics

	Mean	Standard deviation	Count
Patent stock since 1995, thous.	25.54272	53.31402	5349666
Patent stock in 1995, thous.	5.179689	11.42207	5349666
Total imports (L1), mil.	391.379	469.0721	5349666
Total exports (L1), mil.	411.5105	504.3863	5349666
ICT export share (L1)	0.0632037	0.0238539	5349666
ICT import share (L1)	0.0579021	0.0672441	5349666
Average tariff rate	0.0321288	0.0270037	5349666
Number of adopters	2.032881	3.09401	5349666
GDP , mil	2105.999	3415.355	5349666
Labor force, mil.	2.154022	27.89586	5349666
Population, mil.	106.021	259.2705	5349666
Urban population share	0.7699644	0.107433	5349666

The unit of observations of my final dataset is defined by standard, year and (potentially) adopting country. I estimate the hazard of standard adoption as described in the following section.

3.3 Empirical model

Let T be the event of standard adoption in a given period, i.e. a binary variable that takes the value 1 if country i has published a national standard in period t which is equivalent to the international or foreign standard s, and 0 otherwise. I estimate a hazard rate model with yearly grouped duration data (see Wooldridge 2010, Cleves et al. 2008). Hazard rate models estimate the probability of switching from one state to another given that the unit of observation has been in the initial state up to this point in time. They are widely used to analyze adoption behavior with censored duration data (e.g. Saloner and Shepard 1992). My data is right censored and the starting points differ between the international standards according to their publication dates.

Assuming time to be continuous, the hazard rate can be expressed as the time elasticity of the probability of survival past time t, $S(t) = 1 - F(t)$, where $F(t)$ represents the probability of adopting a standard before time t:

$$F(t, X) = 1 - exp[-\int_0^t \lambda(x, X) \ dx]$$

with density function

$$f(t, X) = \lambda(t, X) \ exp[-\int_0^t \lambda(x, X) \ dx]$$

$$X = \{X_{it}, X_{it_0^s}, X_{st}, t_0^s\}$$

where X is a vector of control variables, t_0^s is the publication date of standard s and $\lambda(.)$ is the hazard rate function. For the parametric model, I assume a Weibull distribution of the survival probability which can then be written as

$$S(t, X) = exp(-\gamma t^{\alpha}),$$

where $\alpha > 0$ and $\gamma = exp(X\beta)$ for the proportional hazard rate model. With the density function given by

$$f(t, X) = \alpha t^{\alpha-1} exp(-t^{\alpha} exp(X\beta) + X\beta)$$

the underlying hazard rate is therefore

$$\lambda(t, X) = \alpha t^{\alpha-1} exp(X\beta) \ .$$

The link between the hazard rate and the probability of an event occurring is the following:

$$\lambda(t, X) = \lim_{h \to 0} \tfrac{P(t \leq T < t+h | T \geq t)}{h} \ ,$$

i.e. it represents the probability of an event T to occur during a time interval $[t, t+h]$ relatively to the length of the time interval h, given that it has not occurred up to time t. If h is sufficiently small,

$$P(t \leq T < t + h | T \geq t) \approx \lambda(t, X)h.$$

The Weibull proportional hazard model allows us also to test whether the underlying probability of adoption is time-dependent by estimating the parameter α. If $\alpha > 1$, the hazard rate increases with time.

The main explanatory variables are IPR stocks in and since 1995 and trade in the ICT secotr of country i in period t which are defined as described in section 3. The vector of time-varying country-specific control variables, X_{it}, includes the gross domestic product in constant U.S. dollars, total labor force, total population and the share of urban population. Covariates on trade contain the adopting countries' one-year lagged total imports and exports as well as their ICT import and export shares in $t-1$ and the overall average tariff rate. I control for opportunity costs of purely national standards by integrating the number of countries that have officially adopted the standard s at period t (X_{st}). I also include fixed effects for the publication year, t_0^s, of the international standard s (such that $t = t_0^s + \Delta$, where Δ is the duration) in order to control for a potential correlation between t_0^s and Δ. Finally, I integrate information on the initial IPR position of country i in period t_0^s in order to control for level effects ($X_{it_0^s}$).

3.4 Results

3.4.1 Estimation results

Table 2 displays the coefficient estimates (β_k) of the covariates on the hazard rate of the Weibull model. The first column pools standard documents issued by all standard setting organization in my sample. In column 2, I only keep standards that have been adopted by at least two countries, which I refer to as global standards. The literature often refers to international standards as standards issued by international standard setting organization (e.g. Portugal-Perez, Reyes, and Wilson 2010), but standards from national standard setting organizations can become de facto global standards, while it is possible that standards from international standard setting organizations are not adopted in any country. Column 3 and 4 show the estimates if only standards from EU or international standard setting organizations are kept. Continuous variables have been logged and trade variables have been lagged by one year (L1).

Table 3.2: Weibull hazard model for standard adoption

	All	Global	EU	International
Patent stock since 1995, thou. (log)	-0.0458***	-0.0455***	-0.0421***	-0.146***
Patent stock in 1995, thou. (log)	0.0483***	0.0477***	0.0404***	0.324***
ICT export share (L1)	4.962***	4.757***	1.640***	10.07***
ICT import share (L1)	2.228***	2.172***	0.502***	4.009***
Total imports, mil. (log, L1)	-1.748***	-1.781***	-1.305***	-2.707***
Total exports, mil. (log, L1)	0.780***	0.798***	0.647***	1.751***
WTO member	0.425***	0.419***	0.240***	0.507***
Average tariff rate	-0.793***	-0.868***	12.71***	-3.889***
Number of adopters	-0.116***	-0.134***	-0.159***	-0.0569***
Upper middle income country	0.174***	0.138***	-0.0749**	0.582***
Lower middle and low income country	0.348***	0.306***	0.154***	0.562***
GDP, bil. (log)	0.758***	0.737***	0.797***	0.333***
Labor force, mil. (log)	0.228***	0.195***	0.286***	0.193***
Population, mil (log)	-0.463***	-0.398***	-0.679***	-0.198***
Urban population share	0.0805**	0.143***	0.188***	-1.282***
Constant	-3.045***	-2.828***	-3.529***	-1.461***
Ancillary parameter (α)	0.600***	0.611***	0.626***	0.704***
T0 dummies	Yes	Yes	Yes	Yes
Issuing country dummies	Yes	Yes	Yes	Yes
Observations	5349666	2439903	1254152	642287

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The Weibull proportional hazard model makes an assumption about the distribution of the baseline hazard, i.e. of the hazard function which is not explained by the covariates. As a robustness check, I estimate a semi-parametric Cox proportional hazard model which allows to estimate the coefficients without making an assumtion on the distribution of the underlying hazard function. The coefficient estimates are generally in line with the results from the Weibull model.

Table 3.3: Cox hazard model for standard adoption

	All	Global	EU	International
Patent stock since 1995, thou. (log)	-0.0372***	-0.0368***	-0.0282***	-0.132***
Patent stock in 1995, thou. (log)	0.0394***	0.0388***	0.0294***	0.253***
ICT export share (L1)	3.615***	3.436***	0.973***	7.380***
ICT import share (L1)	1.602***	1.563***	0.336***	3.448***
Total imports, mil. (log, L1)	-1.271***	-1.289***	-0.622***	-1.936***
Total exports, mil. (log, L1)	0.582***	0.589***	0.308***	1.224***
WTO member	0.309***	0.302***	0.115	0.315***
Average tariff rate	-0.613***	-0.704***	9.242***	-2.621***
Number of adopters	-0.0862***	-0.102***	-0.104***	-0.0417***
Upper middle income country	0.0805***	0.0516***	-0.0842**	0.393***
Lower middle and low income country	0.234***	0.201***	0.148***	0.446***
GDP, bil. (log)	0.513***	0.495***	0.430***	0.253***
Labor force, mil. (log)	0.213***	0.183***	0.254***	0.180***
Population, mil (log)	-0.355***	-0.302***	-0.508***	-0.177***
Urban population share	0.142***	0.189***	-0.00102	-0.763***
T0 dummies	Yes	Yes	Yes	Yes
Issuing country dummies	Yes	Yes	Yes	Yes
Observations	5349666	2439903	1254152	642287

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Ownership of IPRs

I expected patent stocks to have a positive effect on standard harmonization, as a strong position in IPRs related to ICT should allow a country to participate in the international standard-setting process as both a producer of technology as well as a consumer. This is to some extent validated by the positive coefficient of the initial IPR position in 1995. However, the coefficient of the *current* patent stock is negative across all specifications. There are several possible explanations for this finding. First, current patents may be of lower quality. It is important to note that patent counts are not adjusted for patent quality, since I are interested in IPR rather than innovation, and patent quality is difficult to capture. However, more recent patents may rely on the foundational technology embodied in pre-1995 patents, for example. Alternatively, the observed time period is characterized by a large increase in patenting in less developed countries, notably in China. Although these patents accord IP rights, the protected technology might not be relevant for current standards, depending on how quickly standards reflect new patenting.

Trade

The coefficients on the trade variables are intuitive. Since members of the WTO are required to remove unnecessary barriers to trade, the positive coefficient was expected. Export-dependent countries depend on foreign consumer tastes and standards, while import-dependent countries might want to protect their domestic markets. This could explain why the coefficients of total exports and imports go in opposite directions. ICT export and import share, however, show both positive coefficients. This could be due to the particularity of the ICT sector, in which products are built on many different components manufactured across many countries.

Other coefficients

The coefficients of GDP and total population are as expected. Richer countries tend to have a relative technological advantage, which translates in a willingness to implement new standards. A bigger population has the opposite relationship. All else equal, small countries may see greater benefits from harmonization, as the alternative (using a country-specific standard, for example) allows for fewer economies of scale. In addition, controlling for GDP, a large population implies lower GDP per capita and perhaps less demand for international technologies. The share of urban population has a positive coefficient in most models. It is likely that people living in cities are more educated and more connected on the international level and might therefore have a higher demand for international products.

I find that $\alpha < 1$, i.e. the probability of adoption decreases over time. Since I included the number of adopters at time t and therefore control for the opportunity cost of non-adoption, this is not surprising. The benefits of adopting a relatively old standard are likely to be low, as the technology may have subsequently been replaced by later standards. When the number of adopters is excluded from the estimation, the estimated α is greater than 1. Yet, surprisingly the coefficient of the number of adopters is negative, suggesting that I are unable to separately identify the benefits of joining a larger network (which grows over time) from technological obsolescence.

3.4.2 Patent quality

As mentioned above, the models in table 2 do not account for patent quality. In order to address this limitation, I ran my models using only patents which have been filed at the patent offices of the ‘”triadic”’ patent families: the European Patent Office (EPO), the United States Patent and Trademark Office (USPTO) and the Japan Patent Office (JPO). Table 4 shows the coefficient estimates. Triadic patents are patents which have been filed at all three of these patent offices. Since the number of triadic patents is relatively small, I also show the estimates for patents that have been filed at at least one (column 1) or at at least two of the three patent offices (column 2). Column 3 contains the estimates for patents filed at all three of them. As before, I calculated patent stocks in and since 1995. The signs of the coefficients of current and initial patent stocks do not change, though their magnitude becomes smaller the stricter the definition of quality patents.

Table 3.4: Weibull hazard model for standard adoption

	(1)	(2)	(3)
Patent stock since 1995, thous., at least 1 (log)	-0.0407***		
Patent stock in 1995, thous., at least 1 (log)	0.0196***		
Patent stock since 1995, thous., at least 2 (log)		-0.0350***	
Patent stock in 1995, thous., at least 2 (log)		0.0221***	
Triadic patent stock since 1995, thous. (log)			-0.0140***
Triadic patent stock in 1995, thous. (log)			0.00823***
ICT export share (L1)	5.232***	4.391***	5.365***
ICT import share (L1)	2.718***	2.765***	1.834***
Total imports, mil. (log, L1)	-2.074***	-1.974***	-1.872***
Total exports, mil. (log, L1)	1.138***	1.015***	0.920***
WTO member	0.599***	0.463***	0.401***
Average tariff rate	-0.691***	-0.570***	1.142***
Number of adopters	-0.117***	-0.117***	-0.118***
Upper middle income country	0.199***	0.0459***	0.194***
Lower middle and low income country	0.177***	0.0648***	0.194***
GDP, bil. (log)	0.653***	0.593***	0.891***
Labor force, mil. (log)	0.230***	0.230***	0.231***
Population, mil (log)	-0.312***	-0.259***	-0.547***
Urban population share	-0.251***	-0.541***	-0.412***
Constant	-2.746***	-1.973***	-3.198***
Ancillary parameter (α)	0.604***	0.607***	0.591***
T0 dummies	Yes	Yes	Yes
Issuing country dummies	Yes	Yes	Yes
Observations	5349666	5349666	5349666

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3.4.3 Heterogeneous effects across income groups

In table 5, I distinguish between standards issued in high income countries (HIC, columns 1 and 3) versus standards issued in low to middle income countries, hereafter referred to as developing countries (DC, columns 2 and 4). I still find a negative coefficient for current and a positive coefficient for initial patent accumulation. The coefficients in column 1 and 2 suggest that these effects are stronger for standards issued by developing countries. In column 3 and 4, I seperate the effect of patent stocks by the potentially adopting countries' income groups: high income countries (HIC, reference group) and developing countries (DC). The results show that the absolute values of the IPR coefficients are smaller for developing countries than for high income countries. In the case of standards issued by developing countries, the coefficients are almost equal to 0 for developing countries.

Table 3.5: Weibull hazard model for standard adoption

	HIC	DC	HIC	DC
Patent stock since 1995, thou. (log)	-0.0386***	-0.0570***	-0.876***	-1.093***
Patent stock in 1995, thou. (log)	0.0405***	0.0666***	0.977***	1.318***
Patent stock since 1995 * DC, thou. (log)			0.841***	1.047***
Patent stock in 1995 * DC, thou. (log)			-0.920***	-1.239***
ICT export share (L1)	4.868***	4.887***	5.067***	6.581***
ICT import share (L1)	2.467***	1.913***	3.112***	3.140***
WTO member	0.320***	0.433***	0.838***	0.898***
Total imports, mil. (log, L1)	-1.791***	-1.721***	-3.187***	-3.351***
Total exports, mil. (log, L1)	0.734***	0.871***	2.118***	2.421***
Number of adopters	-0.130***	-0.0961***	-0.113***	-0.0718***
Average tariff rate	-2.144***	1.206***	-6.081***	-3.900***
DC dummy	0.149***	0.198***	-2.061***	-2.760***
GDP, bil. (log)	0.681***	0.820***	-1.070***	-1.617***
Labor force, mil. (log)	0.223***	0.233***	0.218***	0.226***
Population, mil (log)	-0.340***	-0.574***	1.001***	1.269***
Urban population share	0.584***	-0.397***	3.093***	2.726***
Constant	-3.447***	-3.937***	1.394***	2.991***
Ancillary parameter (α)	0.624***	0.608***	0.778***	0.836***
T0 dummies	Yes	Yes	Yes	Yes
Observations	3161799	2187867	3161799	2187867

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3.5 Conclusion

In this study, I examine the effect of trade and intellectual property ownership on the countries' probability to harmonize technology standards in the ICT sector. This analysis is motivated by the fact that standards can be used strategically to increase market shares and profits from intellectual property or to protect and expand domestic markets by creating technological barriers to trade. I empirically analyze this issue using a survival data approach. I find a positive effect of overall export dependency and a negative effect of import dependency on standard harmonization. Both, imports and exports in the ICT sector have a positive effect on standard harmonization. This is not surprising for this market where products consist of many different components and are highly dependent on interoperability. My findings on IPR ownership indicate that a country's initial technological position drives the willingness to harmonize standards, while *current* IPR accumulation has the opposite effect. The results hold even after accounting for patent quality, but the absolute values of the coefficients become smaller. Separating the effects between income groups, find that IPRs have a stronger effect for developed countries. Even though my results are very preliminary, they give a promising new insight in the mechanisms that lead to conflicts about technical barriers to trade between countries. Yet, further research has to be conducted, particularly with regard to potential reversed causal effects of standard harmonization on trade and patenting.

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RÉSUMÉ

Cette thèse analyse la relation entre les normes techniques et les brevets. Le chapitre 1 étudie l'impact des normes techniques sur le développement de nouveaux brevets. Le chapitre 2 analyse l'effet de la possession de technologies breveté introduites dans les normes techniques sur les revenus de leurs propriétaires. Chapitre 3 traite la relation entre le stock de brevets au niveau national et la volonté des pays de harmoniser leurs normes techniques.

MOTS CLÉS

Normes techniques, brevets, innovation, économie, industrie

ABSTRACT

In this thesis I investigate the close connection between standards and patents from different angles. I analyze how standardization affects the development of new patents and what effect the introduction of patented technologies in standards has on the patent owner's revenues. I also study how a country's patent stock can affect its willingness to harmonize standards with other countries.

KEYWORDS

Standards, patents, innovation, economics, industry