Cooperation and Competition: The Case of Innovation in the Telecommunications Sector *

Tatiana Rosa †

This draft: April 11, 2023

Abstract

This paper proposes a novel framework for analyzing collaborative innovation that captures both competition and cooperation among firms, and examines the impact of private appropriation through IP rights licensing on firms' incentives to innovate and on the overall outcome. I show that when developing technology together firms compete and cooperate, and that the intensity of each force depends on their technological similarity and business model. To study the net effect of these forces in equilibrium, I focus on the standardization of mobile telecommunications technologies and use a novel dataset on the development of 3G and 4G standards to estimate my model. I show that enforcing royalty-free clauses reduces the participation and contributions of firms, delaying the completion of the initial release of 4G by almost one year beyond the almost 3 years it took to develop.

JEL Codes: O3, L1, L2
Keywords: Innovation in teams, Telecommunications standards, Innovation, Interfirm collaboration, Patents, Complementarities, Competition.

*I am deeply grateful to my supervisor Gerard Llobet for his patience, guidance, constant encouragement, and invaluable advice, and to Manuel Arellano for his advice, enlightening comments, and continuous support. I also thank Justus Baron, for kindly helping me to understand the development of technology standards, and Dante Amengual, Dmitry Arkhangelsky, Guillermo Caruana, Despina Doneva, Susanna Esteban, Nicolás Figueroa, Ariel Gomez, Aija Leiponen, Jorge Lemus, Gastón Llanes, Pedro Mira, Jorge Padilla, Ariel Pakes, Claudia Robles, Marc Rysman, Timothy Simcoe, and Emanuelle Tarantino for all their help and suggestions. I would also like to thank participants at the NBER Summer Institute Productivity/Innovation meeting, the CEMFI seminar, the Searle Center Roundtables on Patents and Technology Standards, EPFL, TILEC Workshop on the Economics of Patents and Standards, and the First Annual Empirical Workshop on Standardization organized by the Searle Center of Northwestern University for very useful comments and suggestions. I particularly thank industry practitioners attending these meetings who were very generous in sharing their knowledge of the market. The paper uses data from the Center of Law, Business and Economics from Northwestern University that was provided under a data-access agreement for research purposes. Funding from the Fundación Ramón Areces and from Spain's Ministerio de Economía, Industria y Competitividad (María de Maeztu Programme for Units of Excellence in R&D, MDM-2016-0684) and Agencia Nacional de Investigaciòn y Desarrollo (FONDECYT-11220506) is gratefully acknowledged. All errors are my own.

†tatiana.rosa@uc.cl

1 Introduction

Modern innovations often require the collaboration of firms with diverse technological knowledge. This is particularly true for the development of industry standards, which have been crucial to some of the most significant innovations of the century, including Internet protocols and mobile communication networks as 4G and 5G, technologies projected to contribute around 600 billion to the global GDP by 2030 (GSMA, 2022). However, firms are interested in steering a standard towards their patented technologies to appropriate rents through licensing fees from subsequent users. With the expansion of 5G and other advanced technologies like the Internet of Things and connected cars, the licensing of standard patents has become increasingly complicated. As a result, several major jurisdictions are now considering regulatory actions to address the issue (EC, 2022).[1] Moreover firms may be reluctant to contribute to the development of a standard unless they can appropriate most of the value of their contributions. For instance, they may wish to avoid free-riding by other participating firms or competing technologies that may undermine the potential value of their contributions. As a result when considering regulatory measures related to standard-related patents, it is critical to evaluate their impact on firms' incentives to innovate.

I study firms' incentives to contribute to the development of a standard, considering that free-riding and the competition for the inclusion of patented technologies might compromise the development of the innovation. I provide empirical evidence illustrating the relationship between technological diversity among firms participating in a standard and the intensity of their cooperation and competition. Furthermore, I develop a structural model to study firms' participation decisions, the extent of their contributions to a standard, and to quantify the effect of private appropriation through patent licensing on firms incentives to innovate and the common outcome.

My analysis focuses on the development of 3G and 4G standards. I combine several data sources. I use a novel dataset developed by the Center of Law, Business and Economics of Northwestern University, which contains information on the participating firms, the contributions made by each firm to the development of each component of the technol-

[1]The US launched two public consultations in December 2021 and April 2022, while UK launched a public consultation in December 2021. Japan adopted guidelines in 2018, 2020 and 2022, while in Europe the European Commission released a Communication in 2017 "Setting out the EU approach to Standard Essential Patents" and the 2020 action plan on intellectual property

ogy, and which firms claim to have Intellectual Property (IP) rights over the technologies included in the 3G and 4G standards. I merge these data with information on the firm's patent portfolio, which I obtained from the United States Patent and Trademark Office, and information on the standards themselves, which I scraped from the corresponding standards-setting organization's webpage.

The descriptive analysis reveals three key findings. First, there is an inverted-U relationship between the number of contributions a firm provides to the standard and the average knowledge similarity between the firm and the other contributing firms. The knowledge of firms is inferred from the technological classification of their patents. Second, standards develop faster when firms work together and even faster when firms' knowledge is similar. I call this the cooperation effect. Third, I provide evidence suggesting that firms compete within standardization groups to have their own technology included in the standards. I call this the competition effect.[2]

More specifically, regarding the cooperation effect, when contributions come from firms with a knowledge similarity in the top 20% of the distribution, a 10% increase in contributions reduces the time to develop the standards by 1.4%. By contrast, if contributions come from firms with a knowledge similarity in the bottom 20%, this decrease in time is reduced to 0.05% and is not statistically different from 0 at a 5% significance level. Regarding the competition effect, working with other firms that are on average 1% more similar reduces the firms' claims of Standard Essential Patents (SEPs) by 1.3%.

Motivated by this empirical evidence, I develop and estimate a two-stage model to examine the incentives that firms face when collaborating to develop telecommunications standards. The profit-maximizing firms make two decisions: (1) which standardization group(s) to participate in, and (2) how many "contributions" (technological alternatives) to provide within each group. Firms profit from the production of goods using the standards as inputs, which depends on their exogenous business model, and the (cross) licensing of SEPs, which is an endogenous variable modeled as a function of firms' characteristics, the standard characteristics and the knowledge similarity between participating firms (hereafter, SEP function). Both sources of profits are negatively impacted by the time required to develop the set of standards in a given release, which is an endogenous variable in the model and depends on the observed and unobserved characteristics of the

[2]Competition between firms to include their preferred technologies has been documented also by Simcoe (2012), Spulber (2013) and Spulber (2016).

standards, the contributions provided by participating firms, and the complementarities between those contributions, modeled altogether as a time production function. The firms are characterized by their technological knowledge and business models, while the standardization groups are heterogeneous in terms of the technological complexity. The technology components that need to be standardized are taken as exogenously given.

When deciding how many contributions to provide, firms know their marginal cost of contributing and the characteristics of other participating firms in the group (including their knowledge similarity and marginal cost). Firms compute expected profits based on the number of contributions submitted and their expectation on others firms participation and submissions. Participation costs depends on the match between a firms' technological expertise and that required to develop the standards.

I identify key parameters of the model by exploiting the exogenous nature of firms' technological knowledge prior to their participation in standardization groups, their business model, and the technology requirements for each component in each generation of mobile networks. This exogenous match determines the firms' participation decisions and, in turn, their similarity within standardization groups. In addition, I exploit the panel structure of the data, which allows me to account for firms' and standards' time-invariant unobservable heterogeneity, and the variation in firms' contribution decisions in different standardization groups in a same version of technology. Furthermore, I construct an instrument to identify the cooperation parameter associated with firms' contributions and the time required to develop a standard. This instrument is based on the size of each firm's patent portfolio prior to joining the group and the expected probability of each firm's participation, estimated using the exogenous characteristics of firms and standards.

To estimate the parameters , I rely on a three-stage procedure in which I first estimate the parameters in the time production function and the SEP equation using standard withing group estimators. Second, I use these estimates and the equilibrium equations of the model to calculate some moment conditions, which I then match to key moments in the data. I rely on a minimum distance estimator to back out this last set of structural parameters. A novel feature of this approach is that it does not require any proprietary data on royalty revenues, profits from standardization, or prices of intermediate goods to estimate the model. Finally, I compute the difference between the profits of the observed participation decision and those of the unobserved ones, imposing a parametric distribution on the participation shock, and estimate the participation parameters by maximum likelihood.

Results indicate that in the 4G standards development, SEP licensing accounts for over 20% of firms' expected standardization profits. Before 4G launch, SEP licensing accounted for 5% of intermediary firms' and less than 10% of vendors' total profits.[3] As a robustness check, I compare my results with those from Qualcomm's earnings reports, which show that from 2010-2016, licensing profits constituted between 63-73% of their total profits, aligning with my model's estimate of 60-66%.[4] [5]

In this context, the impact of enforcing a royalty-free licensing scheme is ambiguous.[6] On the one hand, it would shut down the competition effect, by aligning firms' private and common incentives and encouraging similar firms to cooperate more in order to take full advantage of their complementarities and develop the standards in less time. On the other hand, it would also shut down one of the potential revenue streams, by disincentivizing firms from participating and providing contributions. This second channel is particularly important for firms that do not profit from selling products. To quantify this trade-off, I compare the predictions my economic model, using the estimated parameters against those of a model in which patents are licensed for free. In my counterfactual scenario, I allow the number of contributions and participation decisions to vary with the new licensing policies.

I find that, despite an increase of almost 5% in the average similarity between firms in the same standardization group, which boosts the cooperation effect, the overall impact of a change in the licensing rules would be an increase in the time it takes to develop the technology. This result can be explained by a decrease of 7% and 18% in average participation and average number of contributions made, respectively. The change in the licensing rules would also change the composition of firms interested in developing common standards. Pure upstream firms would hardly ever participate in this counterfactual scenario, representing less than 1% of overall participants, while vendors would be the ones taking over the standardization of mobile network technologies. Intermediary firms would be the second most affected group, since their participation would be reduced by

[3]This share is not relevant in the case of pure upstream firms and telecommunications operators, since by assumption of the model it would be 100% and 0%, respectively.

[4]See https://investor.Qualcomm.com/financial-information/quarterly-results.

[5]4G was commercially launched in 2010.

[6]Under royalty-free clauses, firms must license their patents at no cost.

10%, while the participation of telecommunications operators would remain unchanged.

The results are heterogeneous across standards' versions, called releases. In the case of the first release of 4G, which took 3 years to develop, forcing firms to license their patents for free would have delayed completion of the first release of 4G by one year. I also calculate the final impact of removing royalties in the downstream part of the market. The final price of mobile handsets would fall by around 11–20 USD, representing between 3%–5% of the average price in 2012.

Contributions to the literature. While the cooperation and competition aspects as well as the inclusion of patented technologies in public standards has been studied theoretically or through reduced form empirical analysis, this paper is the first one to put them together and provide an empirical framework for analyzing the incentives firms face in developing common innovations, quantify the importance of licensing revenues with respect to market revenues, and provide an empirical model that can be used to evaluate counterfactual policies, such as changes in licensing agreements. This paper also makes an empirical contribution to a longstanding academic and policy debate regarding the effect on IPR policy of standards organizations.

Licensing of standards' patents has been mostly analyzed from a theoretical point of view. Shapiro (2000) discusses whether the patent system slows down the commercialization of new technologies, recommending the use of cross-licensing agreements and patent pools. In a similar vein, Lerner and Tirole (2015) study the inefficiencies arising from the lack of price commitments and show how structured price commitments restore competition. Layne-Farrar, Llobet and Padilla (2014) assess the effects of different licensing rules on firms' participation in standardization processes and R&D investment. On the empirical side of this literature, using data from W3C and IEEE, two standardization bodies in the ICT sector Simcoe and Zhang (2021) find little evidence that changes in the licensing policies caused a decline in participation by patent licensors or reduced innovation in patent-intensive parts of either SSOs. Rysman and Simcoe (2008) show that when a patented technology is included in a technological standard, the standard-related patents increase their returns. Consistent with the view that inclusion increases a patent's value, Simcoe, Graham and Feldman (2009) show that patents disclosed by a Standard-Setting Organization (SSO) have higher litigation rates, particularly if these patents are issued by small firms. Bekkers et al. (2017) study differences in the rules used by different SSOs and how these influence which patents are disclosed, the terms of licensing commitments, and ultimately long-run citation and litigation rates for the underlying patents.

Baron and Pohlmann (2013) explore how the degree of complementarity and competition between firms participating in the development of ICT standards shapes firms incentives to collaborate. In a similar vein, Bar and Leiponen (2014) find a negative correlation between firms' technological distance and their probability of developing R&D together, and Jones, Leiponen and Vasudeva (2021) show that in innovation ecosystems, cooperation with adversaries persists despite conflict. Using the 3GPP as a case study, Jones, Leiponen and Vasudeva (2021) find evidence of cooperation between competitors by showing that firms contributing to mobile standards tend to cooperate more after a patent litigation event. Exploring cooperation and competition inside SSOs, Leiponen (2008) finds that firms compete and collaborate at the same time using formal and informal structures. Focusing on informal structures in SSOs, Delcamp and Leiponen (2014) find that technologies that are likely to become part of the UMTS telecommunication system tend to build on technologies developed by firm peers who were members of the same informal structure.

My study relates to team production models. Goyal and Joshi (2003), Ballester, Calvó-Armengol and Zenou (2006), and Benlahlou (2019).[7] develop a theoretical framework that accounts for complementarities and substitutions between players' efforts in a team production function. I use a similar production function but I also include competition among team members for a share of the common output. I also estimate effort complementarities in the team production function, while allowing them to depend on the knowledge similarity of participating firms.

2 Institutional setting

2.1 The mobile telecommunications market

The market for mobile telecommunications has an upstream, intermediary, and downstream part. Upstream, firms collaborate to develop the mobile system's technology, while also protecting their individual Intellectual Property (IP) rights. The technology is then used as an input to produce intermediary and final goods, such as semiconductors,

[7]For a survey of the literature on network formation see, e.g., Myerson (1994); Bala and Goyal (2000) and Jackson and Wolinsky (1996).

mobile phones, and telecommunications services.

Most of the firms operating in this market produce goods that comply with the technology standards. These firms can be divided in two groups: final and intermediate goods' producers. I do not consider firms producing intermediate goods as downstream firms, since they do not sell to final consumers, who buy phones and contract with telecommunications operators.

Downstream firms are mainly phone vendors, such as Samsung, Apple, LG, Huawei, and ZTE and telecom operators such as Verizone and Vodafone. The last ones are the ones buying infrastructure equipment to deploy the mobile network.[8] Intermediaries are those producing chips, like Qualcomm, and infrastructure equipment, like Ericsson , Nokia and Huawei.

One of main differences between downstream and intermediary firms is how intensively they use the technology developed upstream for manufacturing their own goods. Vendors need to comply with several technological specifications to produce phones, and therefore must obtain licenses for all patents protecting the corresponding technology. This is not the case of firms producing chips or infrastructure equipment that produce goods compatible with the technology but do not implement it.[9]

Finally, there are pure upstream firms, which I define as those that do not produce any good, but earn most of their revenue by licensing intellectual property. InterDigital, Universities, and research centers such as the Chinese Academy of Telecommunications Technology are examples of such firms.

There are two channels through which firms can profit: (i) producing goods using the technology developed upstream, and (ii) licensing their IP rights. The extent to which firms benefit from each depends on their business model.

Upstream firms and intermediaries license their IP rights to vendors, resulting in royalty revenues. Firms typically license their entire patent portfolio, and the amount they can charge is often set in court.[10]

[8]These firms contribute to the development of the standards but rarely develop technology upstream and therefore hold almost no IP rights.

[9]According to industry practitioners consulted by the author, royalties on standard essential patents are almost exclusively charged to downstream producers. In the 3G and 4G eras most of the downstream producers were mobile devices' manufacturers. With the upcoming 5G technology it is expected that Internet of Things gadgets and smart cars would have also to comply with 5G standards.

[10]The number of ongoing disputes over the licensing of these patents is indicative of the enormous stakes involved. According to Lerner and Tirole (2015), as of May 2014, there were at least 50 lawsuits between Apple and Samsung, and 20 between Apple and Google. Galetovic, Haber and Zaretzki (2018) estimate

For vertically integrated firms, their downstream business model has implications for their licensing revenues, as they are usually engaged in cross-licensing agreements. These are contracts in which each party is granted rights to a piece of technology, product, research, or other intellectual property. Cross-licensing agreements allow a party to use the technology protected by a counterparty's patents without having to pay, in return for allowing the counterparty to use the party's protected technology. They help prevent litigation over patents infringement disputes.[11]

Throughout this paper, I focus mainly on the upstream part of the market, accounting for the downstream activity of firms only when considering the incentives they have to innovate.

2.2 Standards, technology generations, releases, and technological specifications

Mobile telecommunications technology relies on technological standards, that is, rules for building complementary technology. More specifically, a standard is a document that describes a feature of a technology. In telecommunications, this could be a document describing an antenna's attribute required to send a cellular signal. In order to describe the whole system of mobile telecommunications, hundreds or even thousands of standards are required.[12]

Mobile communication technologies evolve over time, and each round or version of standardization is called a *release*. The documents that describe a feature of a technology (component) in each release are called *technical specification* (hereafter, TS). Each release is formed of all the TS necessary to implement a given version of the mobile communication system. Throughout the paper I will refer to a standard as a combination of TS-release, that is, a standard is a TS of a specific release.

Each release belongs to a given generation of the technology. There are five generations of mobile standards. Table E.1 in Appendix E shows the different releases and their corresponding technology generation. Within each generation, there is heterogeneity in the technology used. A change in generations occurs only when there is a major change in

that royalty revenues from SEP licensing in 2016 were around 14,000 million dollars, and represented 3% of the cost of manufacturing a smartphone.

[11] If a firm undertakes activities that are covered by the claims of a patent without having a license for it, they are said to infringe the patent.

[12] For a more comprehensive description of technology standards the interested reader may refer to Baron and Spulber (2018).

the technology, while a minor evolution of the technology gives place to a new release of the standards inside the same generation of technology. Consider the development of 4G. The first release of 4G was Release 8, describing Long-Term Evolution (LTE) technology. Though 4G is still in use, devices can now also connect with LTE advanced Pro, from Release 14.[13]

2.3 Standard Development Organizations

Standard Development Organizations (SDOs) are responsible for developing mobile standards such as Wi-Fi, Bluetooth, and the Internet Protocol. Any organization that plays an active role in standard development can be considered an SDO. Sometimes, an SDO may endorse a standard that it has developed, while in other cases, the standard may be formally endorsed by a Standard Setting Organization (SSO).

SDOs have their own unique standard development procedures, as well as rules that their members must follow in order to participate. These rules typically outline the necessary steps and majorities required for approving a standard, as well as how patent licensing for standard implementation is handled. For a more detailed understanding of the variety of SDO rules, readers can refer to Lerner and Tirole (2006) and Baron and Spulber (2018).

The Third-Generation Partnership Project (3GPP) is the primary SDO responsible for providing mobile telecommunications standards to the industry (see Appendix E for more details).

2.4 Development of standards in 3GPP

Developing standards is a complex and non-linear process. Here is a simplified version of the steps in the 3GPP standard development process. Firstly, a technological goal is defined, proposed by any organization with the support of four 3GPP members. These broad goals are then "broken down" into smaller work items, which can result in the creation of a new technical specification or modification of an existing one.[14] Each work item is assigned to a working group responsible for transforming the idea into a technical

[13] The release of a new version of the technology, such as LTE Advanced, doesn't fully replace the previous one. Usually several technologies coexist in time and their use depends on the deployment of each of them.

[14] Formally, there are many categories of work items: study items, features, building blocks, and work tasks. See ETSI TR 121 900 (p. 26) for more details on work items.

specification (see Figure E.1 on Appendix E for a description of 3GPP's structure).

The first step is to define a technological goal that the system should meet. This goal can be proposed by any organization as long as it has the support of 4 3GPP members. These initial goals are typically broad and must be broken into smaller ideas and parts that are more concrete and actionable in order to ultimately attain the broad goal. Each "part" of this goal, generically called a *work item*[15] in 3GPP language can either result on the creation of a new technical specification (if there is a completely new feature that must be developed in order to accomplish the goal) or the modification of an existing one. Each part of the broad goal is assigned to a working group,[16] which is in charge of transforming the idea into a technical specification.

As an illustrative example, consider a release of only two technical specifications[17] with three goals: (i) allowing network connectivity in densely populated area; (ii) enhancing energy efficiency; and (iii) improving network security. Figure 1 illustrates this example. Goal 1 and 3 are directly assigned to the working groups developing technical specification 1 and 2, Goal 2 is broken down into two parts, each assigned to a different working group. The assignment of ideas/parts into working groups depends on the technological requirements.

Imagine now that goal 1 requires a new type of antenna capable of emitting signals in densely populated cities. Since this is a new feature, it requires a new technical specification to describe it. Then, the chair of the working group sets up a meeting for interested firms.[18] Once there, firms provide documents with their ideas for this new antenna. These documents are called *contributions*. Before providing these technical solutions to the group, firms conduct in-house R&D. Firms developing standards typically have a history of R&D activities that determines their *knowledge*. I define *firm knowledge* as the capacities and know-how acquired through experience and R&D activities.

The process of developing a standard usually requires firms to meet more than once and its approval is accomplished in stages: first the technical specification is approved by the firms actively contributing to the its development and then by all firms in the

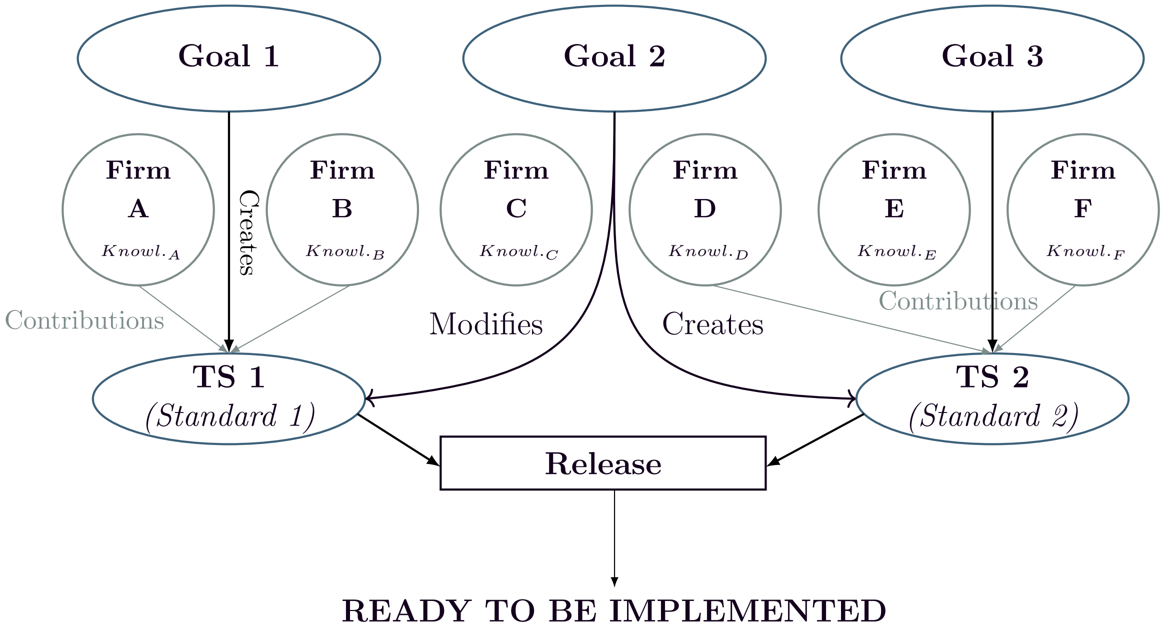
[15] Formally, there are many categories of work items: study items, features, building blocks, and work tasks. See ETSI TR 121 900 (p. 26) for more details on work items.

[16] See Figure E.1 for a description of 3GPP's structure.

[17] Remind that a standard is defined as a technical specification in a given release. That is, the combination technical specification-release.

[18] Working groups have been omitted from Figure 1 to simplify the figure.

Figure 1: Example of the development of a release with 2 technological specifications



corresponding working group. Approval is achieved by consensus.[19] Contributions have different names depending on their type and the stage at which they are submitted: technical reports, discussion documents, change request or proposals.

Consider now goal 2. Suppose that to enhance the energy efficiency of the system, two things must be achieved: modify some feature of the antenna previously developed and develop a new way of transmitting signals. The first part of this goal requires the technical specification. The procedure for modifying an existing standard is the same as the one for creating one.

To conclude my simple example, consider now the third goal. To improve the security of the network, the transmission technology must be modified. This goal only involves modifying technical specification 2.

Goals continue arriving until the chair of the Project Coordination Group judges that most of the work for this release is done. Then, the release is said to be "frozen" and it can be used by implementers. Firms holding IP rights over technologies that are standard-essential have to declare at some point of the standardization process. A technology is considered essential if there is no alternative way to implement the standard without using it. Patents protecting the IP rights of these technologies are called Standard Essential Patents (SEPs).

[19]Consensus in 3GPP is defined as lack of sustained opposition and need not imply that 100% of the members agree with the decision.

3 Data

3.1 Data sources

In this study, I combine several sources of information.

The Searle Center Data Base (SCDB): This novel dataset developed by the Center of Law, Business and Economics of Northwestern University in collaboration with Qualcomm, Perinorm, and IPLytics, consists of three interconnected datasets, as described in Baron and Spulber (2018), Baron and Gupta (2018), and Baron and Pohlmann (2018). The SCDB contains information on the standardization process of mobile networks in 3GPP from 1999 to 2012, covering nine different releases of the technology. It includes details on participating firms, the number of written contributions submitted by firm to each standard, the submission date, and whether it was approved or rejected.[20]

The SCDB also includes information on the claimants of the IP rights for the technologies included in each standard. SEPs data have been used in academic studies to provide insights into the standard-setting process (Bekkers et al., 2017), and in legal proceedings to assess the relative contributions of parties to a standard. Since SEPs are declared by each participating firm, this measure is subject to observation error, a feature that will be considered in the econometric analysis. Another concern with SEPs is the timing of the claim. While firms can declare SEP ownership throughout the standard development period, evidence suggests that a large portion of firms disclose their SEP after the standard is complete, while some do so during development.[21] Finally, assigning patents to standards is not straightforward. Baron and Pohlmann (2018) explain several criteria they used to match SEPs to the standard's documents in the SCDB, all based on the information declared in the letters sent by firms to 3GPP. I use the broadest criterion, which assigns the highest possible number of patents declared to be essential to a

[20]Contributions have different names depending on their type and the stage at which they are submitted: technical reports, discussion documents, change request or proposals. See subsection 2.4 for more details.

[21]In their work, Baron and Pohlmann (2010) analyzed SEP declarations to several SDOs and found that 56% of all declarations were made more than one year after the first standard version was officially released. Slightly less than 35% of all declarations are made ex ante or in the year of standard. In the same vein, Layne-Farrar (2011) analyzed ETSI disclosures and found that 44% of patents were filed after the standard was frozen, meaning that the other 56% of patents were filed before or during the development of the standard. Finally, Kang and Bekkers (2015) studied 'just in time patenting' in telecommunications standards and found that participating firms apply for patents of low technical merit just before a standardization meeting, and then send the patents' inventors to the meeting to negotiate this patented technology into the standard. Finally, Brismark (2021) documents that in the case of 4G standards, more than 90% of disclosures were made after the standard's freeze date.

standard.

Patent data: Patent portfolio data was obtained from the United States Patent and Trade Office (USPTO). I collected data on firms granted patents from the Patentview platform, from 1970 to 2014.[22] Technological classification was also included, based on the International Patent Classification (IPC).

3GPP data: I complement my analysis with data on *work items* affecting each standard, which I scraped from 3GPP's webpage. I will refer to work items as "technology goals", since they are the first steps in incorporating new features into the system.

To merge these datasets together, I rely on firm names and algorithms to match string variables. See Table C.2 and Table C.3 in Appendix C for descriptive statistics on the final sample and subsection C.3 of the same Appendix for details and robustness checks.

3.2 Estimation sample, empirical measures and descriptive statistics

While around 280 firms contributed to the development of telecommunications standards during 1999–2012, the majority contributed very little. 265 of these firms contributed, in total with less than 15% of total contributions. Therefore, and since the goal of this paper is to study strategic interaction between firms, I concentrate my analysis in the top 15 contributors per year, ending up with 35 firms in my sample.[23]

Most of the variables I need to conduct my study are not observed, I therefore construct various empirical proxies.

Standard heterogeneity. Not all standards carry equal weight. Some of them describe broader or more complex parts of the system. I use number of technological goals mentioning a standard to measure its broadness. On average, a standard is mentioned in 7.18 technology goals (see Table C.2 in Appendix C for more details).

Contributions and participation decision. Though there are different types of contributions, I cannot identify the type for most of them; therefore I proceed as if all contributions were equally valuable for the development of the standard.[24] If the contribution is submitted by more than one firm, I give equal weight to all participating firms. I consider any firm that submits at least one contribution as a participant in the standard.

[22]patentsview.org.

[23]To select the top 15 contributions per year I pooled all contributions made in a given year an selected the 15 companies that contributed the most.

[24]Robustness on this assumption are provided when possible and results remained unchanged.

Firms' knowledge similarity. I rely on patented technologies to measure firms' knowledge. Using USPTO data on patents, I construct firms' patent portfolio by counting the number of patents in each technological class, as defined by the International Patent Classification (IPC). Most of the firms in the dataset specialize in Information and Communication Technologies (ICT) and have no patents in classes unrelated to ICT. To avoid false similarities driven by zeros in non-ICT categories, I consider only the 15 most relevant classes for this market as in Leiponen (2008).[25] With the 15 classes for each firm in each year, I follow Jaffe (1986) and use Cosine Similarity (CS) to measure the similarity between any two firms. See Appendix C for more details on the knowledge similarity construction.

Group outcomes. According to the project agreement, one of the goals of 3GPP is to "[use] minimum production time for Technical Specifications and Technical Reports from conception to approval."[26] Given that neither value nor quality is observable at a standard level, the time it takes to develop the standard is the closest observable proxy for the success of the group. I define *time to develop* as the number of days it takes to accomplish 90% of the standardization work.[27]

Standards quality is a very relevant outcome when it comes to study group outcomes in standards development but defining quality at a standard (document) level is not straightforward, and is beyond the scope if this paper. Even assessing the quality of the whole set of standards for a given version of the technology is not straightforward. Nevertheless, Spulber (2019) shows that given the current rules of the SSO, in equilibrium, standards and market outcomes are efficient. This result suggest quality may be assured by SSOs rules on how to select the technology to be included in the standard. Yet, as an attempt to proxy for the quality of the standard, I rely on the panel structure of the data and use the probability of a technical specification to be updated in the next release of the technology as well as the number of times a technical specification is updated in the next 4 releases as a proxy for quality. [28]

[25]These 15 classes cover a little over 85% of all essential patents.

[26]See page 1 of the 3GPP Partnership Project Agreement at https://www.3gpp.org/ftp/Inbox/2008_web_files/3gppagre.pdf.

[27]The utilization of 100% completion is abstained from due to the presence of long tails in the distribution of time required for development. The concluding 10% of the standard development process, leading up to the freeze date, can consume equivalent time as the preceding 90%. This delay primarily stems from formalities associated with standard publication. As robustness check, estimations based on 80% and 85% of contributions are made and can be made available upon solicitation.

[28]The inclusion of these measures in the estimation is constrained by a censoring issue due to the

Payments. Payments in this market comes from the sale products or services complying with the standard and the (cross) licensing of SEP, but neither of these variables are observed.[29]. I therefore use the number of SEPs as a proxy for the private upstream revenues a firm gets from participating in a standardization process. As for the sale of products complying with the standard I assume that they depend on the firm business model which I've got for each firms' webpage.

4 Empirical evidence

I now present empirical evidence documenting the economic trade-off that arises when firms with similar knowledge work together as described in the theoretical framework in Appendix H. I first show the non linear relationship between the number of contributions firms submit and the group's knowledge similarity. I then provide evidence of two effects behind this nonlinearty. I show evidence on the cooperation effect, where firms with similar knowledge speed up the development of a standard due to complementarities in their contributions, as well as on the competition effect, where the competition over IP rights becomes more intense negatively affecting cooperation.

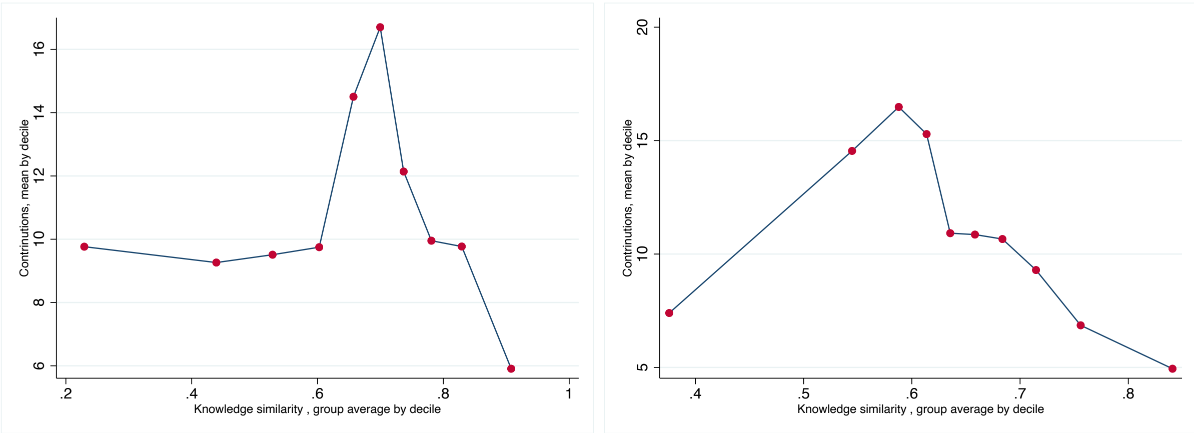
4.1 Inverted U-shaped relationship between contributions and knowledge similarity

I start my analysis by plotting the average number of contributions submitted by firms to a given standard, on the knowledge similarity of contributing firms. To avoid comparing averages with a different number of observations, I discretized the similarity measure in deciles. See Appendix A for other discretizing criteria.

construction of the variables, leading to a reduction in the size of the estimation sample. As a result, I have employed this measure solely as a robustness check.

[29]SEPs have to be licensed under FRAND and most of the royalties are set in court.

Figure 2: Contributions and similarity of firms



(a) Contributions and group knowledge similarity, no controls

(b) Contributions and group knowledge similarity, firm fixed effects

Notes: Figures below show the average number of contributions submitted by firms with respect to the average knowledge similarity of the group without any control (Panel a) and controlling by firm fixed effects (Panel b)

Panel(a) and panel (b) of Figure 2 suggests a nonlinear inverted U-shaped relationship between firms' contributions and their knowledge similarity. That is, firms do not submit their maximum number of contributions when teaming up with other firms that are specialized in the same technological area, nor when cooperating with firms with completely unrelated knowledge. The maximum average number of contributions by decile of knowledge similarity is 16.7 contributions per firm and it is achieved in groups in which firms' knowledge similarity is, on average, 0.7 (decile 6 of the similarity distribution). This lower number of contributions at the extremes of the similarity distribution still holds when controlling by technical specification fixed effect, as shown in Figure A.1, showing evidence that this result is not driven by the unobserved heterogeneity of the technical specification each group is developing. Furthermore, the shape of this relationship is also not inherit from the number of participating firms and its relationship with firms' similarity, as can be seen in Figure A.2 in Appendix A

4.2 Complementarities in contributions and knowledge similarity

It may be intuitive to think that firms must be working together when there are complementarities between their contributions, but it is not obvious that those complementarities are related to the firms' knowledge similarity, neither the sign of this relationship.

To obtain empirical evidence of complementarities in contributions and their association with firms' knowledge similarity, I estimate a translog production function. I use the number of days required by the group to develop the standard, normalized by its broadness as output, and the number of contributions provided by each participating firm as inputs. Groups are defined at a technical specification-release (standard) level.

I estimate the following fixed-effects model:

$$ttd_{t,r} = -\beta_1 \sum^{f \in F} c_{f,t,r} - \frac{\beta_2}{2} \sum^{f \in F} c^2_{i,t,r} - \frac{\phi_c}{2} \sum^{f \in F} \sum^{j \in F} c_{f,t,r} c_{j,t,r} - \mu^S_s - \mu^R_r - \epsilon_{t,r}, \quad (1)$$

where $ttd_{s,r}$ is the time it takes the group to develop technical specification s in release r, normalized by its broadness, in logs.[30] $c_{f,t,r}$ and $c^2_{f,t,r}$ are, respectively, the number of contributions (logs) and the number of contributions squared (logs) that firm f submits. The interaction of firms' contributions is represented by the parameter ϕ_c. A positive ϕ_c means that firms' contributions are complements, negative ϕ_c means that the contributions submitted by different firms are substitutes.

I control for unobserved heterogeneity in technical specification by absorbing a set of fixed-effects at the technical specification level, and include release fixed-effects. As an extra control I include a dummy variable that takes value 1 if the technical specification is developed for the first time and 0 otherwise.

Column 1 of Table 1 presents estimates for Equation 1. After adding controls, I find that:(i) there is a nonlinear and concave relationship between the number of contributions and time (adjusted by the standard broadness); and (ii) contributions submitted by different firms are indeed complements. The estimation of parameter β_1 shows that the linear effect of an increase of 10% in contributions decreases the average time to develop a standard by 2%, other things being equal.[31]We can see that β_2 is negative with a magnitude of about 0.01%, suggesting decreasing returns in the submission of contributions. The positive and significant value of the estimated parameter ϕ_c supports finding (ii).

The cooperation effect implies that firms with similar knowledge face lower coordination costs, such as a common expert language, and therefore, the combination of their contributions will speed up the standardization process more than the contributions provided by dissimilar firms.

[30] I normalize time by dividing it by the broadness of the standard, defined as the number of related technological goals (see Section 3.2 for more details on this measure).Normalization is chosen over controlling for the number of technology goals in order to avoid endogeneity issues.

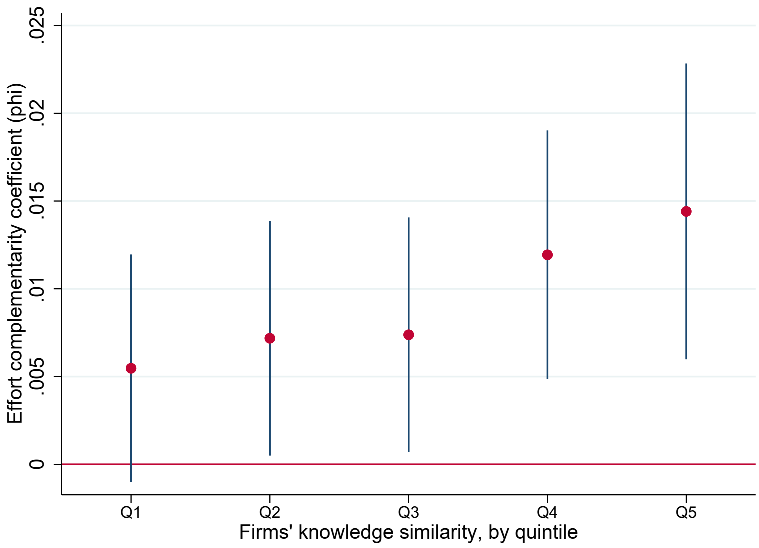
[31] Recall that Equation 1 is defined in terms of $-\beta_1$ and $-\beta_2$.

Table 1: Time production function

	(1) Restricted model	(2) Linear effect	(3) Nonlinear effects
Contributions ($-\beta_1$)	0.200	0.019	0.174
	(0.050)	(0.047)	(0.052)
Squared number of contributions ($\frac{-\beta_2}{2}$)	-0.011	-0.011	-0.011
	(0.005)	(0.004)	(0.005)
Contributions'interaction term :			
All similarity levels ($\frac{-\phi_c}{2}$)	0.007		
	(0.003)		
Contributions x Similarity ($\frac{-\phi_s}{2}$)		0.012	
		(0.005)	
Q1 similarity ($\frac{-\phi_1}{2}$)			0.005
			(0.003)
Q2 similarity ($\frac{-\phi_2}{2}$)			0.007
			(0.003)
Q3 similarity ($\frac{-\phi_3}{2}$)			0.007
			(0.003)
Q4 similarity ($\frac{-\phi_4}{2}$)			0.012
			(0.004)
Q5 similarity ($\frac{-\phi_5}{2}$)			0.014
			(0.004)
Standard first time (dummy)	Yes	Yes	Yes
Standard FE	Yes	Yes	Yes
Release FE	Yes	Yes	Yes
N	1792	1792	1792
adj. R^2	0.541	0.543	0.545

Note: Robust standard errors in parenthesis. All variables are in logs.

Figure 3: Estimates of ϕ_q (95% confidence bands)



To explore this hypothesis I estimate two more flexible versions of Equation 1:

$$ttd_{t,r} = -\beta_1 \sum^{f \in F} c_{f,t,r} - \frac{\beta_2}{2} \sum^{f \in F} c_{f,t,r}^2 - \frac{\phi_s}{2} \sum^{f \in F} \sum^{j \in F} c_{f,t,r} c_{j,t,r} sim_{f,j} - \mu_s^S - \mu_r^R - \epsilon_{t,r}, \qquad (2)$$

where $sim_{f,j}$ is the knowledge similarity between firms f and j and therefore ϕ_s captures the linear effect in the complementarities of contributions done by firms with different levels of similarities. Also I estimate,

$$ttd_{t,r} = -\beta_1 \sum^{f \in F} c_{f,t,r} - \frac{\beta_2}{2} \sum^{f \in F} c_{f,t,r}^2 - \sum_{q=1}^{q=Q} \frac{\phi_q}{2} \sum^{f \in F} \sum^{f \in F} c_{f,t,r} c_{j,t,r} D_{f,j}^q - \mu_s^S - \mu_r^R - \epsilon_{t,s}, \qquad (3)$$

where $D_{f,j}^q$ is a set of dummy variables that take value 1 if the similarity between firm f and j is at the qth percentile of firms' knowledge similarity distribution. Then, the set of parameters ϕ_q represent the complementarities between contributions of firms whose similarity falls in the qth percentile of the distribution. Table 1 and Figure 3 present estimates using quintiles. See Appendix B for robustness checks using other percentiles and variables in levels.

Column 2 of Table 1 presents an estimate of the ϕ_s parameter. The positive and significant estimation of ϕ_s suggests that, given a level of contributions, the more similar the firms providing them, the bigger their complementarities in reducing the time to develop a standard.

Figure 3 shows empirical evidence of a positive relationship between the value of ϕ_q and firms' knowledge similarity when allowing for a more flexible pattern in such relationship. As can be seen in column 3 of Table 1, an increase in the contributions interaction term of 10% decreases the time to develop the standard by 1.4% if the contributions are provided by firms with a knowledge similarity in the top 20% of the distribution. If this same contributions are provided by firms with a knowledge similarity in the bottom 20%, this decrease in time is reduced to 0.05% and it is not statistically different from 0 at a 5% significance level. This evidence and the linear trend estimates, support the hypothesis of a *cooperation effect*, in which contributions are stronger complements the more similar the knowledge of the firms providing them.

For a formal test on the increasing complementarities, I estimate a model including a *quintile trend*, that is, a unique variable that takes the value of the number of contributions made by firms in each quintile of the knowledge similarity distribution. This allows me to see if this trend has a positive coefficient, what will show a positive and increasing relationship between complementarities and similaritiy level. As shown in Appendix B this trend is positive and significant, providing extra evidence supporting the cooperation effect.

4.2.1 Endogenous number of contributions

One concern that might arise from the estimation of the previous model is the potential endogeneity of the number of contributions, and of the knowledge similarity of participating firms.

With respect to the number of contributions, one potential concern can be the reverse causality problem, that is, if time is limited in some way firms are pressured to contribute more and develop the standard faster. To address this concern I instrument the number of contributions provided by a firm with the size of its patent portfolio prior to joining the standardization process. Portfolio size prior to the standard development is a good instrument in this setup because: (i) its exogeneity comes from the difference in time with *ttd* and the fact that the size of a firm's patent portfolio is the result of the firm's IP policy, which is a more general decision than its participation in the development of any specific standard; and (ii) its relevance comes from the fact that the size of such a portfolio can be easily related to the potential to contribute each firm has and it is shown empirically in Appendix B.[32]

As an instrument for the contributions' interaction term, I use the interaction between patent's portfolio size of firms multiplied by firms' knowledge predicted similarity. I construct this last measure in two steps. First, I estimate a probit model for firms' standard participation decision using as independent variables the size of firms' patent portfolio and the broadness of the standard. Since both variables are exogenous in my setup, participation decision predicted by this model, that I name *participation hat* is also exogenous in the *ttd* equation. Secondly, I compute the predicted knowledge similarity between two firms using this predicted participation probability instead of the observed decision. I show in Appendix B that this instrument is also relevant to explain contributions' interaction term.

I then estimate Equation 1 by instrumental variables and compute the Wald coefficient. The results remain unchanged. See subsection B.5 of Appendix B for more details on the estimation and results.

4.2.2 Quality and time to develop.

This paper focuses on standardization time as the main group outcome . The reader might then be concerned that any decrease in time could result in lower quality standards. In an attempt to provide evidence of the relationship between the time taken to develop a standard and its quality, I use the probability of a standard being updated in the next release as a proxy for its quality, as well as the number of times a standard is updated in the following four releases. As shown in subsection B.3 in Appendix B, there is a negative and significant correlation between the time to develop a standard and its quality, which becomes statistically insignificant when controlling for unobserved heterogeneity in firms and technical specifications.

4.3 SEP competition and knowledge similarity

Licensing SEPs is one of the channels through which firms can benefit from participating in the development of standards. Simcoe (2012), Spulber (2013), and Spulber (2016) show

[32] The decision of participating and its correlation with the firms portfolio size does not invalidated the exogeneity argument of the instrument due to the time difference between the moments each decision take place. While firms decide to participate or not in a first stage, they decide how much to contribute in the second one, realizing the time to develop shock at that time. Therefore any potential shock to the time to develop will be uncorrelated with the firm's patent portfolio size not even through the participation decision.

that firms in SDOs compete within standards to include their preferred technology.[33] Firms have private interests in including certain technologies in a standard, since they often have IP rights over them.

The value of a SEP is difficult to assess since firms usually license the entire patent portfolio and since it is defined in court under FRAND conditions.[34] Therefore, one could think that competition in this market is not over prices, but over the number of patented technologies to be included in the standard. This last statement implicitly assumes that all SEPs are equally valuable. Though this may appear to be a strong assumption, it is based on the essentiality of a SEP: if all SEPs are required to implement the innovation, they are then perfect complements. Following a Shapley value approach, it is then reasonable to assume that they have the same value.[35]

My competition effect hypothesis states that firms with similar knowledge, which by definition have similar patents, are closer competitors when it comes to introduce their patented technology in the standard and claim SEPs. As an initial exploration of this hypothesis, in Figure A.3 and Figure A.4 in Appendix A I plot the average number of SEPs firms get in each standardization group (technical specification-release) over the knowledge similarity of contributing firms. Figure A.3 and Figure A.4 show a negative relationship between the two variables, robust to several controls and specifications.

I then formalize my hypothesis and estimate the following fixed-effects model:

$$Numbersep_{f,s,r} = \alpha + \psi gsimil_{f,-f,s,r} + \beta X_{f,s,r} + \omega X_{-f,s,r} + \mu_f^S + \delta_r^S + \gamma_s^S + \epsilon_{f,s,r}, \quad (4)$$

where the variable $NumberSep_{f,s,r}$ is the log of the number of SEPs firm f declared in technical specification s for release r, and $gsimil f, -f, s, r$ is the average cosine similarity between the patent portfolios of firm f and all other firms $-f$ participating in technical specification s in release r, also in logs. I include firm fixed effects to control for unobserved firm heterogeneity, such as experience in standardization and bargaining power, which may also affect the number of SEPs a firm claims. To capture the heterogeneity across releases, which may also affect the number of SEPs, I include release fixed-effects. In the same spirit, I absorb a set of technical specification fixed effects to account for the unobserved heterogeneity in their complexity.

[33] Simcoe (2012) studies the development of Internet standards.

[34] Some of the most well-known cases are Microsoft Corp. vs. Motorola, Inc. and Ericsson, Inc. vs. D-Link Sys.

[35] See Roth (1988) for a detailed description of the Shapley value.

Covariates $X_{f,s,r}$ control for the number of contributors in the specification-release, for the broadness of the specification-release, a dummy variable that takes value 1 if the standard is developed for the first time in that release, and for the portfolio size of the firm and its expenditure in R&D activities. The value of these last two variables is computed in the year prior to joining the standard, as joining the standardization process might impact firms' patent portfolios and their R&D activities. In some specifications, I also control for the average characteristics of other firms in the group, $X_{-f,s,r}$, to account for the portfolio size and R&D expenditures of the competing firms.

The number of contributions submitted by firms in developing the standard are not included in the main specifications. In this I was guided by anecdotal evidence from engineers attending standardization meetings and previous research, such as Rysman and Simcoe (2008) who show that the technology finally included in standards developed in SSOs are promising technologies and not the result of vested interests. As a robustness check for my analysis, I estimated the SEP equation including the number of contributions provided by firms to a standard. To overcome contributions' endogeneity problem I propose an instrument and estimate by Instrumental Variables. I find that once instrumented, the number of contributions a firm makes to a standardization group is statistically insignificant in explaining the number of SEPs a firm claims in that standard. The full analysis and results are presented in subsection B.4 in Appendix B.

Firms do not always get SEPs when participating in the development of a standard. In fact, in the sample of standards on which I have information, 43% of the time firms participate they do not get any SEPs. Given the significant number of zeros in my sample, I also estimate a tobit model for Equation 4.

Table 2 shows the estimates of ψ in Equation 4. See Appendix B for the complete table including all estimates in Equation 4 and other robustness checks for this analysis. Controlling for firm, release and technical specification unobserved heterogeneity , an increase of 1% in the average knowledge similarity of firms participating in the development of standard decreases the average number of SEPs obtained by firms in that group between by 2.47% and 0.875% depending on the model specification. The negative and significant relationship between a firm's number of SEPs and a firm's knowledge similarity in the group is robust to the several sets of controls detailed in the previous paragraph. This evidence supports the hypothesis of a competition effect, according to which firms with

Table 2: SEPs and firms' knowledge similarity

	(1) Baseline	(2) Controls	(3) Other firms controls	(4) Tobit
Firms' knowledge similarity (group average)	-1.723	-0.875	-1.286	-2.470
	(0.418)	(0.520)	(0.528)	(0.693)
Firm's characteristics (Portfolio, R&D)	No	Yes	Yes	Yes
Other firms' characteristics	No	No	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Release FE	Yes	Yes	Yes	Yes
Tech. specification FE	Yes	Yes	Yes	No
Standard characteristics (Number of firms, Broadness, First time)	No	Yes	Yes	Yes
Average number of SEPs per firm in a standard	1.5	1.5	1.5	1.5
Firms' average knowledge similarity	0.64	0.64	0.64	0.64
N	2059	2059	2059	2059
adj. R^2	0.137	0.286	0.300	

Robust standard errors in parentheses. All values are in logs.

similar knowledge are closer competitors when it comes to obtaining SEPs.

5 A model for firms' contributions and participation decisions

5.1 The setup

I now develop and estimate a model that captures the most relevant trade-offs firms face when deciding whether to participate and how many contributions to submit in each standardization group. I later use it to simulate counterfactual policy analysis.

The model focus on the participation and contributions' decisions taken by *firms* in each standardization *group* and how their *knowledge similarity* shapes those decisions. A *group* is defined by the standard (technical specification(s)-release(r)) its members are there to develop. The goal of the group is to develop the standard "[using] minimum production time."[36] The value of the common innovation is then modeled as a negative

[36] 3GPP Partnership Project Agreement.

function of the time to develop the standard and firms can privately appropriate part of it through selling goods complying with the standard or (cross) licensing SEPs. The number of SEPs a firm expect to claim when participating in the development of a standard depends among other things, on their knowledge similarity with other participating firms. A *firm(f)* in this empirical model is any of the 35 organizations actively contributing to 3GPP.[37] The concept of *knowledge similarity* refers to the technological specialization or know-how firms have prior to joining any standardization group measured as the cosine similarity between their patent portfolio as explained in subsection 3.1.

The timing of events is as follows: first, firms decide whether to participate in each standardization group, depending on the profits they expect to get and on the match between their technological expertise and the technological expertise required to develop the standard (fixed cost of participation). At this stage firms form expectations on other firms participation and contribution decisions based on their knowledge of other firms technological knowledge, marginal costs, and other observed characteristics such as business model. At this stage firms also know the complexity of the standard to be developed by the group.

Second, firms decide how many contributions to submit in the standardization group, given the observed participation decisions of the other firms. The time it takes to develop a standard depends on the number of contributions submitted and the cross-effects between the contributions of firms with different knowledge. Conditional on observed participation decision, firms at this stage update their expectations on other firms contributions and therefore the value of the common innovation and their expected number of SEPs. Third, members of Third-Generation Partnership Project (3GPP) decide which technologies to include in the standard and then the time to develop shock as well as the SEPs shock are realized.[38] Then, firms owning IP rights over these technologies claim their SEPs.[39] Finally, when all the standards in a release are finished, firms implementing the standards use them to manufacture phones or deploy the network to provide telecommunications services.[40] SEP holders also license their patents to implementers at this stage.

While understanding the reasons behind firms' participation in standardization groups

[37] 3GPP has hundreds of members, but I consider only those that submitted at least five contributions during the period 1999–2012. See Section 3.1 for more details on this.

[38] See Section 2, for more details on 3GPP and standards' development.

[39] SEPs are actually declared by their owners. Once the technological solutions are chosen, firms holding patents protecting the IP rights of those selected technologies have to declare it to 3GPP.

[40] See Section 2 for more details.

is not the main goal of this paper, having a model for firms' decisions to participate is crucial to endogenize firms'knowledge similarity within group and to perform a realistic counterfactual analysis. Firms' within-group similarity is not random but can be explained by some exogenous factors such as the match between firms' technological specialization and the technical requirements of the standard the group is aiming to develop. Appendix D shows reduced form evidence on the main factors behind firms' participation decision.

Group Outcomes. Assume that firms are labeled $f = 1, ..., F$. Then, Equation 5 defines the time production function as

$$TTD_{s,r} = \beta_1 \sum^{f \in N} c_{f,s,r} + \frac{1}{2}\beta_2 \sum^{f \in N} c^2_{f,s,r} + \frac{\phi}{2} \sum_{f \neq j}^{f \in F} \sum_{j \neq f}^{j \in F} c_{f,s,r} c_{j,s,r} sim_{f,j} + \alpha^T_s + \alpha^T_r + \epsilon^T_{s,r}, \quad (5)$$

where $TTD_{s,r}$ is, as in Section 4.2, the number of days it takes the group to develop technical specification s in release r, normalized by its broadness.[41] where $c_{f,s,r}$ is the number of contributions submitted by firm f toward the development of technical specification s for release r, $sim_{f,j}$ is a pairwise measure of the knowledge similarity between firms f and j, α^T_s is a technical specification specific term, that accounts for the unobserved heterogeneity in standard complexity, and α^T_r is a release-specific term. All variables in Equation 5 are in levels to make the final model more tractable. The term $\epsilon^T_{s,r}$ is the time to develop shock, it is technical specification–release-specific and accounts for all residual variation in TTD. $\epsilon^T_{s,r}$ is unexpected for firms and has a normal distribution with zero mean. The parameter ϕ in Equation 5 is an average measure of firms' contributions cross-effects. I allow complementarities in the number of contributions to vary with firm knowledge similarity $sim_{f,j}$. Finally, $\bar{\theta^T}$ represents the set of parameters in Equation 5.

Revenue function. Firms' revenues depend on how much of the common value of the innovation each firm can appropriate, whether it be through the sale of goods that comply with the standard or the licensing of SEPs. The profits a firm can make by selling goods are modeled based only on their exogenous and time-varying business model. Then, the firm revenue function becomes

[41] I normalize time by dividing it by the broadness of the standard, defined as the number of related technological goals (see Section 3.2 for more details on this measure).Normalization is chosen over controlling for the number of technology goals in order to avoid endogeneity issues.

$$R_{f,s,r} = \underbrace{(MT - TTD_r)}_{\text{Time Penalty (-)}} \times (\underbrace{A^M_{BM} BM_f}_{\substack{\text{Downstream} \\ \text{profits of} \\ \text{using } s}} + \underbrace{A^P_{r,BM} * SEP_{f,s,r}}_{\substack{\text{Value of } s \text{ that can be} \\ \text{privately appropriated} \\ \text{by IP rights}}}) \tag{6}$$

where

$$TTD_r = \sum_{s \in r} TTD_{s,r},$$

The term MT represents the maximum time to develop the set of standards, after which they have no value. I impose independence between the times it takes to develop the different component's standards in a given release of the technology. That is, there are no externalities between standards in a release. The parameter A^M_f accounts for the market revenues related to the implementation of the standards, while $A^P_{r,BM}$ is the average value for firms with business model BM of a SEP in release r.

Ideally, I would include the value of those SEPs, but this information is unavailable. I then consider only the number of SEPs, and use the model and its equilibrium conditions to back out the value of $A^P_{r,BM}$ and get an estimate of the firms' licensing revenues.[42]

SEP function. Different firms may have different technological solutions to meet the standard's requirements, as explained in section 2. I build on the empirical evidence in Section 4.3 and I rely on Equation 4 to model the SEP function.

Marginal costs and firms' profits. In the model, firms have a quadratic marginal cost mc_f of providing contributions, whereas, conditional on participating, they face no fixed costs. Marginal costs are heterogeneous across firms but constant across technical specifications and releases. They are also common knowledge for all firms but unobserved by the researcher. I assume that:

$$c_f \sim lognormal(\mu^C_f, \sigma^2) \tag{7}$$

with an unknown set of parameters μ^C_f and σ^2.

Combining Equation 4, Equation 6 and Equation 7, I construct the following empirical firm profit function:

[42] There are several problems when dealing with the value of a SEP: (i) firms usually license their entire portfolio of patents; (ii) royalties are usually set in court, are proprietary data, and vary depending on who is the licensee (Abrams et al., 2019); and (iii) even data on royalties collected by firms would not capture the whole value of a SEP due to cross-licensing agreements between vertically integrated firms. See Section 2 for more details on this.

$$\pi_{f,s,r} = (MT - TTD_r(c_{f,s,r}, c_{-f,s,r}, sim_{f,-f,s,r}\epsilon^T_{s,r}, \bar{\theta^T})) \times (A^M_{BM} BM_f \\ + A^P_{r,BM} * (\psi gsimil_{f,-f,s,r} + \mu^S_f + \mu^S_r + \epsilon^S_{f,s,r})) - \frac{mc_f}{2} c^2_{f,s,r} \tag{8}$$

5.2 Optimal number of contributions and second-stage equilibrium

Given their participation decision, firms choose how many contributions $c_{f,s,r}$, to provide by maximizing expected profits, assuming that other firms are also maximizing their own profits. I can write the equation for the expected profits as a functions of the contributions submitted by all firms $c_{f,s,r}$, observed variables (BM, MT) and a set of parameters θ .Then the best-response function for firm f in technical specification s in release r is defined by the number of contributions made by the other firms, the observed variables and θ. As shown in Appendix F, by rearranging terms I can write the optimal number of contributions $c^*_{f,s,r}$ of firm f as a linear function of the optimal number of contributions of the other firms in the group $c^*_{-f,s,r}$, the observable variables previously defined, and the set of parameters of the model. The Nash equilibrium of this stage of the model is the vector of the number of contributions submitted by each firm.and corresponds to the fixed point on firms' contributions.

As can be seen in Appendix F the reaction function of each firm is linear on others firms' number of contributions. This allows me to solve the model just by inverting matrices as in Appendix H.

5.3 Participation decision

Revisiting the first stage of the model, each firm simultaneously chooses in which group to participate. I model a firm's participation decision based on expected revenues and the fixed cost of participating. Firms generate their expectations over standardization profits according to the model presented in the previous section.

An important component of the fixed cost is the technological knowledge that a firm must possess to participate in the development of a given standard. Firms need to invest resources, such as engineers' hours, in order to understand the group's goal and assess its potential for the firm. If the standardization group is working in a field that is completely unrelated to the firm's technological expertise, the fixed cost is higher. As shown in Appendix D the fit between the technological requirements of the standard under development and the firm's technological knowledge is an important and exogenous determinant of firm participation. I therefore incorporate this friction in my model as a fixed cost.

Moreover, I assume the following structure for the observable part of the firm's fixed costs:

$$FC_{f,s,r} = \underbrace{\gamma_0^{FC}}_{Constant} + \underbrace{fit_{f,s,r}}_{\text{Firm–Standard fit}} + \underbrace{\gamma_f}_{\text{Firm-specific FC}}, \tag{9}$$

where:

$$fit_{f,s,r} = M(Broadness_{s,r}, Portfolio_{f,r}; \gamma^{fit}),$$

where γ_0^{FC} represents a constant fixed cost common to all firms in the market, $fit_{f,s,r}$ is an approximation to the fit between the firm's technological expertise and the standard's technological requirements, and γ_f is a firm-specific constant term accounting for the unobserved heterogeneity in firm's potential capacity to contribute to standardization groups. An example of such unobserved heterogeneity is the number of potential standardization groups in which a firm can participate. I model the fit between the firm and the standard as a function M of the standard's broadness $Broadness_{s,r}$ and the firm's technological capacity, proxied by the size of its patent portfolio $Portfolio_{f,r}$ the year prior to deciding whether to participate or not.

Participation condition (revealed preference assumption): $p_{f,s,r}$ is the participation decision chosen by firm f for technical specification s in release r, which takes value 1 if the firm decides to participate, and 0 otherwise. For ease of notation I abstract away from the release sub-index r; then,

$$\mathbb{E}(\pi_{f,s}(p_{f,s}, p_{-f,s}) - F_{f,s}(p_{f,s}) + \epsilon_{f,s}^{p_f} \mid \mathcal{J}_f) \geq \mathbb{E}(\Pi_{f,s}((1-p_{f,s}), p_{-f,s}) - F_{f,s}(1-p_{f,s}) + \epsilon_{f,s}^{1-p_f} \mid \mathcal{J}_f), \tag{10}$$

where $\pi_{f,s}(p_{f,s})$ and $F_{f,s}(p_{f,s})$ are the second-stage profits and fixed costs of choosing $p_{f,s}$ when all the other firms chose $p_{-f,s}$, respectively. The variable $\epsilon_{f,s}^{p_f}$ represents the unobserved (by the researcher) part of fixed costs firm f faces when choosing $p_{f,s}$. This unobserved term accounts for the part of the firm–standard technological match that is not captured by the M function. I assume this information is known by the firm.

Without loss of generality, assume that firm f participates in the development of technical specification s in release r. Once again, I abstract away from the r sub-index to ease notation. Then, adding **??**, I can write Equation 10 as

$$
\begin{aligned}
&(MT - \underbrace{TTD(c^*_{f,s}, c^{*p_{f,s}=1}_{-f,s})}_{\text{TTD with participation}}) \times \underbrace{(A^M_{BM} + A^P_{r,BM} SEP_{f,s})}_{\text{Revenues from participation}} - mc_f c^{*2}_{f,s} - F_{f,s} + \epsilon^{part}_{f,s} \\
&\geq (MT - \underbrace{TTD(0, c^{*p_{f,s}=0}_{-f,s})}_{\text{TTD without participation}}) \times \underbrace{(A^M_{BM})}_{\text{Revenues from no participation}} + \epsilon^{npart}_{f,s},
\end{aligned} \tag{11}
$$

where $TTD(c^*_{f,s}, c^{*p_f=1}_{-f})$ is the time it takes to develop the standard if firm f participates in the development of technical specification s in release r, providing the optimal number of contributions $c^*_{f,s}$, and the other firms $-f$ contribute with their optimal number of contributions $c^{*p_f=1}_{-f,s}$. Note that a firm's outside option of participating is not zero. The standard will still be developed in a counterfactual time, $TTD(0, c^{*p_f=0}_{-f,s})$.

I simplify notation in Equation 11 and write the participation condition in standard s as:

$$
p_{f,s} = 1 \iff \Delta(\pi_{f,s}) - FC_{f,s} \leq \epsilon^{p_f=0}_f - \epsilon^{p_f=1}_f, \tag{12}
$$

where $\Delta(\pi_{f,s})$ represents the difference between the expected second-stage profits if firm f participates and if it does not. Recall that this is a complete information game,[43] and therefore, in equilibrium, expectations equal observed values.

Equilibrium. A Nash equilibrium in this stage of the model is a vector of firm participation decisions for each standardization group. The revealed preference assumption is a necessary condition for any possible Nash equilibrium. It does not rule out multiple equilibria and it does not assume anything about the selection mechanism used when there are multiple equilibria.

6 Estimation and Identification

The unknown model parameters $\bar{\theta}$ are: (i) the set of parameters in the time production function parameters $\bar{\theta^T}$ in Equation 5; (ii) the set of parameters in the SEP function $\bar{\theta^S}$ in Equation 4; (iii) the market revenue set of parameters A^M_{BM}, the SEP's price set of parameters $A^P_{r,BM}$; (iv) the set of parameters of the firms' marginal cost distribution

[43] Althought the game is a complete information one, all firms receive an unexpected shock in the TTD and SEP equations with zero mean.

μ_f^c and σ in Equation 6 and Equation 26; and the set of fixed costs parameters $\bar{\gamma}$ in Equation 9. Formally,

$$\bar{\theta} = \{\bar{\theta^T}, \bar{\theta^S}, A^M_{BM}, A^P_{r,BM}, \mu^c_f, \sigma, \bar{\gamma}\},$$

where

$$\bar{\theta^T} = \{\beta_0, \beta_1, \beta_2, \phi, \mu^T_f\}; \bar{\theta^S} = \{\psi, \mu^S_f, \mu^S_r\}; \bar{\gamma} = \{\gamma^R, \gamma^B, \gamma^P, \gamma_f\}$$

To estimate the parameters in my structural model, I rely on a three-stage procedure. I first estimate the parameters in the time production function $\bar{\theta^T}$ and the SEP equation $\bar{\theta^S}$, relying on the conditional exogeneity of the number of contributions and the knowledge similarity of the participating firms for their identification, respectively. I then use those estimates and the equilibrium equations of the model to get some moments, which I then use to identify those parameters. I rely on a minimum distance estimator to back out this last set of structural parameters. Finally, I use all the previously estimated parameters to compute $\Delta\Pi_{f,s}$ and impose a parametric distribution on $\epsilon^{p=1}$ and $\epsilon^{p=0}$ and estimate $\bar{\gamma}$ by maximum likelihood, using the fixed cost of participation as an exclusion restriction to identify the participation parameters from the ones in the profit function. The interested reader may refer to Econometric Appendix A for a more detailed discussion on the identification and estimation of the profit function parameters.

The participation model parameters

The participation model of this paper can be linked to the class of discrete complete information choice models applied to oligopolistic markets. Firms in the model know all about the other firms, and know the distribution of the shocks each of them face. The standard approach to the estimation of this type of entry models relies on assuming that a firm's profits are declining in rivals' decisions (Bresnahan and Reiss (1991*b*), Bresnahan and Reiss (1990)). This assumption does not hold in my model, since firms can benefit from the presence of other firms in the group due to the complementarities in their contributions. Another standard approach to solving these models is deriving choice probabilities from a theoretical framework and finding the parameter values that maximize the likelihood of entry choice in the data (Bresnahan and Reiss (1991*a*)). I rely on this last approach.[44]

[44] While the incomplete information assumption can also make sense in this set up, a model à la Aguirregabiria and Mira (2007) would not be possible to estimate due to the high number of players (35).

I rely on a Nash equilibrium concept, and use Nash equilibrium conditions to derive firms' (unobserved) choice set. As a standard way of solving for a Nash equilibrium, I start from the observed equilibrium in each group, and consider the vector of observed participation decisions when only one firm deviates at a time as a feasible unobserved group configuration.

I assume that the unobserved participation terms $\epsilon_{s,r}^{part}$ and $\epsilon_{s,r}^{npart}$ in Equation 12 are identically and independently distributed across firms and standards with a type I extreme value distribution. Then, the probability of firm f participating in standard s is

$$Prob(p_{s,r}=1)=\frac{exp(\Delta\Pi_{f,s}-FC_{f,s})}{1+exp(\Delta\Pi_{f,s}-FC_{f,s})}, \tag{13}$$

where $\Delta(\Pi_{f,s})$ represents the difference between the expected second-stage profits if firm f participates and if it does not, defined in Equation 6, and FC is the fixed cost defined in Equation 9.

After constructing the counterfactual group configuration for each standardization group and computing the corresponding $\Delta(\Pi)$, I proceed to estimate the participation parameters in Equation 12 by maximizing the likelihood function corresponding to the probabilities in Equation 13. For a more detailed discussion on the identification and estimation of the participation parameters, the interested reader may see Econometric Appendix B.

7 Estimation results and fit of the model

The model matches the moments of the data well: notably, it perfectly captures the average number of contributions per firm business model. A broader discussion on the fit of the model and a set of different measures for it can be find at Appendix G.

Table 3 shows estimates for the direct effect of the number of contributions and the cooperation and competition effects. All average point estimates of the coefficients of interest are significantly different from zero at a 5% confidence level.

The positive sign of the cooperation effect suggests that contributions provided by different firms and their knowledge similarity are indeed complements. The same number of contributions provided by firms that are 0.1 closer technologically reduces the expected time to finish the standard by 0.0068 days. The significant and negative coefficient of β_2 suggests that there are decreasing marginal returns from contributions provision. That

Table 3: Time production function and SEP estimates

	Individual effect of contributions ($-\beta_1$)	Contributions' squared term ($-\beta_2$)	Cooperation effect ($-\phi$)	Competition effect(ψ)
Estimate	0.4068	-0.0027	0.0068	-5.1673
SE	0.0510	0.0007	0.0027	0.6493
Standard charact.	Yes	Yes	Yes	Yes
Release FE	Yes	Yes	Yes	Yes
Standard FE	No	No	No	No
Firm FE	No	No	No	Yes
N	1,880	1,880	1,880	2,824
R^2	0.5650	0.5650	0.5650	0.08

Bootstrap standard errors (with reposition) at a standardization group level, 1000 samples.

is, on average, the first contribution reduces standardization time in 0.4014 days,[45] while the second one reduces it by only 0.3906 days. The reduction on standardization time for the average number of contributions in a group, that is 65 contributions, is of 0.06 days.

Column 4 of Table 3 shows that firms working in the same group with technologically similar firms claim to have a lower number of SEPs. The point estimate of the ψ parameter suggests that an increase of 1 p.p in the average similarity of the other firms in the group reduces the expected number of SEPs by 0.7% for each firm. Contrary to the cooperation effect, the competition effect generates incentives for firms to provide less contributions when teaming up with other firms that are specialized in similar technologies.

Table A.2 in Appendix A presents the structural parameter estimates of the remaining parameters of the profit function. I use 100 simulations to compute each of the model's moments.

Given the lack of scale in these estimates, I quantify the importance of licensing SEPs for a firm's expected profits by constructing an index that captures the relative importance of royalty revenues with respect to the overall expected revenues from standardization. To that end, I define

$$IL_{bm,r} = \frac{A^P_{r,BM} \times AvgSEP_{r,BM}}{A^P_{r,BM} \times AvgSEP_{r,BM} + A^M_{BM}},$$

[45]The marginal effect of contributions on time is 0.4068 - 0.0021 * Number of contributions.

where $IL_{bm,r}$ is the weight of expected licensing revenues with respect to the total expected revenues from standardization for firms with business model bm in release r. Figure 4 shows the IL index for vendors and intermediary firms, per release. Before 4G (Release 8), the licensing of SEPs had a higher weight in a vendor's profit function than in of a firm producing intermediate goods. This changes with 4G, when the licensing of SEPs becomes more important for firms in general and for firms producing intermediate goods in particular. Specially, for those firms, the licensing of SEPs from Release 10 onward represents a up to 30% of the total expected revenues from standardization.

These results implies that royalties' importance increased between 3G and 4G from 4.2% to 25% for the intermediaries and from 8.7% to 23% for vendors, consistent with findings in Galetovic, Haber and Zaretzki (2018). According to the authors estimations royalty revenues increased at least 20% between 3G and 4G.[46]

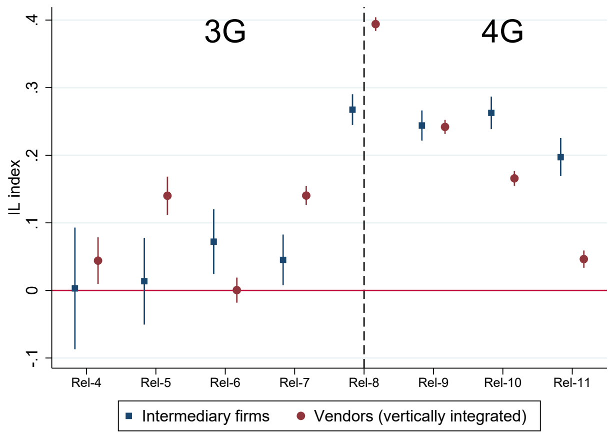
As another robustness check of the model, I compare my results with those from Qualcomm's earnings reports, one of the few firms in the sample reporting separately earnings from licensing and good selling. Qualcomm's reports show that from 2010-2016, licensing profits constituted between 63-73% of their total profits, aligning with my model's estimate of 60-66%.[47] [48]

[46]The 20% increase corresponds to comparing the \$67,760 millions in royalties collected between 2008 and 2011 (3G) with the \$37,143 collected in 4G royalties between 2012 and 2016. The \$37,143 are calculated on the conservative basis that 3G royalties in this period equal the 3G royalties of the 2008–2011 period.

[47]See https://investor.Qualcomm.com/financial-information/quarterly-results.

[48]4G was commercially launched in 2010.

Figure 4: IL index for vendors and intermediary firms



Note: Bands represent 95% confidence intervals. The variance of this index comes from the variance of averaging the number of SEPs per business model and release. Release 4, 5, 6, and 7 are part of the third- generation and Release 8 onward belong to the 4$^{\text{th}}$ one.

8 Free licensing: A counterfactual policy

In an attempt to curb the monopoly power that they create, 3GPP requires the holders of SEPs covered by the standard to grant licenses on fair, reasonable, and non-discriminatory (FRAND) terms.[49] Needless to say, such loose price commitments have led to intense litigation activity, as discussed in Lerner and Tirole (2015). Nevertheless, as 5G and beyond technologies continue to develop, including the Internet of Things (IoT) and connected cars, the licensing of standard patents becomes increasingly complex. This has led several major jurisdictions to consider regulatory actions, (EC, 2022), such as the US launching two public consultations in December 2021 and April 2022, the UK launching a public consultation in December 2021, Japan adopting guidelines in 2018, 2020 and 2022, and the European Commission releasing a Communication in 2017 titled "Setting out the EU approach to Standard Essential Patents" and a 2020 action plan on intellectual property.[50] Consequently, when considering the regulation of standard-related patents, it is crucial to assess their impact on firms' incentives to innovate.

While free licensing hasn't been discussed in 3GPP, it can be thought of as an extreme case of the potential regulation spectrum for SEP licensing.[51][52]Though an extreme case,

[49]See Section 2 for more details on this.
[50]See EC (2022) for more information.
[51]Under royalty-free clauses, firms must license their patents at no cost.
[52]Other SSOs, such as the 3WC, the organization in charge of the development of HTML protocols, view free licensing as a way to ensure wide implementation of their standards and full realization of the standard's global benefits.

it helps us to understand the main mechanisms through which the time it takes to develop a standard might be affected when changing licensing rules as well as their magnitudes in equilibrium.

The impact of enforcing a royalty-free licensing scheme is ambiguous. On the one hand, it would shut down the competition effect, by aligning firms' private and common incentives and encouraging similar firms to cooperate more to take full advantage of their complementarities, so as to develop the standards in less time. On the other hand, it would also shut down one of the potential revenue streams, by disincentivizing firms from participating and providing contributions. This second channel is particularly important for firms that do not profit from selling products. To quantify this trade-off, I compare the predictions of my economic model, using the estimated parameters against an economic model in which patents are licensed for free. In my counterfactual scenario, I allow contributions and participation decisions to vary with the new licensing policies.

For the participation model, enumerating each of the potentially many equilibria is computationally infeasible at present, and so I follow Lee and Pakes (2009) who suggest a learning process to reduce this burden.[53] In short, the program assumes an ordering of decisions based on participation probabilities over all standardization groups. The first firm decides whether to participate or not as a best response to all other firms' participation decisions in the baseline scenario. The second firm similarly best responds, but substitutes the participation decision of the first firm with the first firm own best response. The third firm similarly best responds, but it substitutes the participation decision of the first and second firms with their own best responses. The program cycles through the firms, continually updating the participation decisions until no firm wishes to deviate. The result is a simultaneous-move Nash equilibrium, conditional on a single draw of the sunk costs. I take 100 such draws and report the average outcomes across them. The weakness of this approach is that each "run" results in a unique equilibrium, which is only a small fraction of those possible. The results are robust to completely reversing the order and rerunning the program.

I find that the overall effect of restricting patent licensing would be a delay in the development of the standards. Despite the increase in the similarity of firms working

[53] Solving the game requires calculating the potential profits for each firm in each potential group configuration. For each group there are 2^{35} potential configurations. Calculating expected profits for each firms requires solving the model $2^{35} \times 35$ in each group, which is currently computationally unfeasible.

together, which fosters the cooperation effect, the restriction on patent licensing would have a big and negative impact on participation and contribution decisions, as can be seen in Figure A.5 in Appendix A. On average, under a royalty-free licensing policy there would be 7% less firms participating in each standardization group, and they would contribute 18% less.

The results are heterogeneous across firms' business models. While participation of telecom operators remains unchanged, pure upstream firms would barely participate in this counterfactual scenario, representing less than 1% of the total number of participants. intermediate firms would be the second most affected group, since the restriction of patent licensing would reduce their participation by 10%. Finally, vendors would participate 4% less than in a scenario in which they could license their patents.

The results are also heterogeneous across releases. In the case of the first release of 4G, which took 3 years to develop, forcing firms to license their patents for free would have delayed completion by an additional year.

8.1 The downstream effect of free licensing

Royalties are part of the cost of products sold in the downstream part of the market, such as mobile devices. A free licensing policy would then have effects on the final price of those goods by reducing their cost. To complement my analysis on the effects of a free licensing policy in this market, I calculate the effect on the downstream price of mobile devices for the American market.

Based on the standard price equation for oligopolistic markets, I get

$$\Delta p = \frac{\epsilon_f}{1+\epsilon_f}\Delta mc,$$

where Δp is the variation in the good's final price, ϵ_f is the firm's price elasticity, and Δmc is the variation in the good's marginal cost. I calculate the firm's price elasticity using a Cournot approach; that is, I use the industry elasticity and divide it by the Herfindahl–Hirschman Index (HHI) of the industry.

To calculate the impact of free licensing on the final price of mobile devices, I rely on the average cumulative royalty yield calculated by Galetovic, Haber and Zaretzki (2018).[54] I take the industry price elasticity from Fan and Yang (2020). I calculate the HHI based on the data in Galetovic, Haber and Zaretzki (2018). I consider four scenarios resulting

[54]The cumulative royalty yield calculated by Galetovic, Haber and Zaretzki (2018)

from combining 2 options for the average cumulative royalty yield and 2 for the industry price elasticity.

Table 4: Free licensing impact on downstream mobile device prices

Scenario	(I)	(II)	(III)	(VI)
Change in marginal cost[1]	3.30%	5.60%	3.30%	5.60%
Industry elasticity[2]	0.75	0.75	0.61	0.61
Firm elasticity	7.99	7.99	6.50	6.50
Pass-through[3]	0.89	0.89	0.87	0.87
Change in price	**2.93%**	**4.98%**	**2.86%**	**4.85%**

[1]Change in the marginal cost equals the reduction in cumulative royalties calculated by Galetovic, Haber and Zaretzki (2018). [2]From Fan and Yang (2020). [3]Calculated as $\frac{\epsilon_f}{1+\epsilon_f}$

Table 4 presents the results. Depending on the scenario, free licensing might reduce between 3%–5% the final price of a mobile device. Considering the average smartphone price in 2012 was 387 dollars,[55] this implies a reduction of 11–20 dollars per smartphone. If I consider also feature phones, whose average price in 2012 was 340 dollars, then the reduction would have been around 10–17 dollars per device.

Overall, the free licensing policy would have entailed a delay of an extra year in the completion of the first generation of the 4G standards and a reduction between of 10–20 dollars in the final price of the average mobile device. Comparing how much consumers value each of these reductions is beyond the scope of this paper. Nevertheless, in their paper on the US smartphone market, Fan and Yang (2020) find that for consumers: (i) a one-hour increase in battery talk time is equivalent to a price decrease of $8.40; and (ii) an increase in the screen size by 0.1 inches is equivalent to a price decrease of $15. Though no equivalency is calculated for the time consumers have to wait for a faster generation of mobile networks, we can see that they are willing to exchange relative non-core features for the price reduction that free licensing would result in.

[55]Consistent with Galetovic, Haber and Zaretzki (2018) I used from http://www.statista.com/statistics/309472/global-average-selling-price-smartphones/ accessed 22 october 2021. Statalist relies on data from Worlwide IDC, 2014

9 Conclusions

This paper proposes a novel framework for collaborative innovation between competitors, assessing the effect of private appropriation through the licensing of IP rights on firms incentives to innovate and the common outcome. The analysis combines reduced-form analysis with a structural model of participation and contribution decisions on the development of the 3G, 4G and 5G telecommunications standards.

Three key findings arise from the descriptive analysis. First, I demonstrate an inverse-U-shaped relationship between the number of contributions provided by a firm to the standardization group and the average knowledge similarity between the firm and the other contributing firms in that group. Second, I provide evidence suggesting that firms can expedite technology development by collaborating, and that this reduction in time is positively dependent on the technological distance between the firms. I refer to this as the *cooperation effect*. Third, I provide evidence indicating that firms compete within standardization groups to have their own technology included in the standards, which I call the *competition effect*.

Drawing on this empirical evidence, I develop and estimate a two-stage model to analyze the incentives that drive firms' participation and contribution to the joint development of telecommunications standards. I find that licensing revenues represent a substantial share of participating firms' revenues, particularly in the context of 4G. For intermediary firms, the licensing of SEPs from Release 10 onward can account for up to 30% of their total expected revenues from standardization. Given the high number of standard-compliant products that are expected to emerge with the introduction of 5G, it is likely that this share will continue to increase, making licensing an increasingly important incentive for firms to engage in the development of telecommunications standards.

I then use the model to assess the effects of a royalty-free policy on the development of telecommunications standards, with the aim of identifying the key mechanisms through which changes in licensing rules can affect the time required for standard development, as well as their magnitude in equilibrium. I find that such policy would delay the development of standards through two mechanisms: (i) a decrease of 9% in the number of participating firms; and (ii) a decrease of 18% in the number of contributions submitted per participating firm. In the case of the first release of 4G, this would have delayed its completion by 1 year beyond the almost 3 years it took to develop the standards. On the other hand, in the downstream part of the market, in the case of the US, the overall effect of a free licensing policy would have been a 3%–5% price reduction of the average mobile device. Though free licensing might be an extreme policy, this paper shows evidence of the quantitative importance of IP revenues for firms developing technology in the telecommunications market.

In summary, this paper sheds light on the intricate economic incentives that govern the joint development of telecommunications standards, a critical and rapidly evolving sector. The findings highlight the significant role that licensing revenues play in incentivizing firms to participate in standardization efforts, particularly in the case of 4G and beyond technologies. Any policy that seeks to cap these revenues must take into account the potential trade-offs and unintended consequences that could arise, such as a slowdown in technology development. It is essential that policymakers carefully consider these implications in order to ensure that any regulatory actions are effective in promoting innovation and competition, while avoiding potential negative consequences.

References

Abrams, David S, Ufuk Akcigit, Gokhan Oz, and Jeremy G Pearce. 2019. "The Patent Troll: Benign Middleman or Stick-Up Artist?" National Bureau of Economic Research.

Aguirregabiria, Victor, and Pedro Mira. 2007. "Sequential estimation of dynamic discrete games." *Econometrica*, 75(1): 1–53.

Angrist, Joshua D, and Jörn-Steffen Pischke. 2008. *Mostly harmless econometrics: An empiricist's companion.* Princeton university press.

Bala, Venkatesh, and Sanjeev Goyal. 2000. "A noncooperative model of network formation." *Econometrica*, 68(5): 1181–1229.

Ballester, Coralio, Antoni Calvó-Armengol, and Yves Zenou. 2006. "Who's who in networks. Wanted: The key player." *Econometrica*, 74(5): 1403–1417.

Baron, Justus, and Daniel F Spulber. 2018. "Technology standards and standard setting organizations: Introduction to the searle center database." *Journal of Economics & Management Strategy*, 27(3): 462–503.

Baron, Justus, and Kirti Gupta. 2018. "Unpacking 3GPP standards." *Journal of Economics & Management Strategy*, 27(3): 433–461.

Baron, Justus, and Tim Christoph Pohlmann. 2010. "Essential Patents and Coordination Mechanisms: The Effects of Patent Pools and Industry Consortia on the Interplay between Patents and Technological Standards." *Available at SSRN 1655660.*

Baron, Justus, and Tim Pohlmann. 2013. "Who Cooperates in Standards Consortia—Rivals or Complementors?" *Journal of Competition Law and Economics*, 9(4): 905–929.

Baron, Justus, and Tim Pohlmann. 2018. "Mapping standards to patents using declarations of standard-essential patents." *Journal of Economics & Management Strategy*, 27(3): 504–534.

Bar, Talia, and Aija Leiponen. 2014. "Committee composition and networking in standard setting: The case of wireless telecommunications." *Journal of Economics & Management Strategy*, 23(1): 1–23.

Bekkers, Rudi, Christian Catalini, Arianna Martinelli, Cesare Righi, and Timothy Simcoe. 2017. "Disclosure rules and declared essential patents." National Bureau of Economic Research.

Benlahlou, Adhen. 2019. "Team production game on bipartite networks." *Economics Letters*, 180: 94–98.

Bresnahan, Timothy F, and Peter C Reiss. 1990. "Entry in monopoly market." *The Review of Economic Studies*, 57(4): 531–553.

Bresnahan, Timothy F, and Peter C Reiss. 1991*a*. "Empirical models of discrete games." *Journal of Econometrics*, 48(1-2): 57–81.

Bresnahan, Timothy F, and Peter C Reiss. 1991*b*. "Entry and competition in concentrated markets." *Journal of political economy*, 99(5): 977–1009.

Brismark, Gustav. 2021. "On the Timing of ETSI Disclosures." *Available at SSRN 3988411.*

Delcamp, Henry, and Aija Leiponen. 2014. "Innovating standards through informal consortia: The case of wireless telecommunications." *International Journal of Industrial Organization*, 36: 36–47.

EC, Comission. 2022. "The European Commission's initiative on Standard Essential Patents." *JPO SEP event.*

Fan, Ying, and Chenyu Yang. 2020. "Competition, product proliferation, and welfare: A study of the US smartphone market." *American Economic Journal: Microeconomics*, 12(2): 99–134.

Galetovic, Alexander, Stephen Haber, and Lew Zaretzki. 2018. "An estimate of the average cumulative royalty yield in the world mobile phone industry: Theory, measurement and results." *Telecommunications Policy*, 42(3): 263–276.

Goyal, Sanjeev, and Sumit Joshi. 2003. "Networks of collaboration in oligopoly." *Games and Economic behavior*, 43(1): 57–85.

GSMA. 2022. "The Socio-Economic Benefits of Mid-Band 5G Services." *GSMA monthly report February.*

Jackson, Matthew O, and Asher Wolinsky. 1996. "A strategic model of social and economic networks." *Journal of economic theory*, 71(1): 44–74.

Jaffe, Adam B. 1986. "Technological opportunity and spillovers of R&D: evidence from firms' patents, profits and market value."

Jones, Stephen L, Aija Leiponen, and Gurneeta Vasudeva. 2021. "The evolution of cooperation in the face of conflict: Evidence from the innovation ecosystem for mobile telecom standards development." *Strategic Management Journal*, 42(4): 710–740.

Kang, Byeongwoo, and Rudi Bekkers. 2015. "Just-in-time patents and the development of standards." *Research Policy*, 44(10): 1948–1961.

Layne-Farrar, Anne. 2011. "Innovative or indefensible?: An empirical assessment of patenting within standard setting." *International Journal of IT Standards and Standardization Research (IJITSR)*, 9(2): 1–18.

Layne-Farrar, Anne, Gerard Llobet, and Jorge Padilla. 2014. "Payments and participation: The incentives to join cooperative standard setting efforts." *Journal of Economics & Management Strategy*, 23(1): 24–49.

Lee, Robin S, and Ariel Pakes. 2009. "Multiple equilibria and selection by learning in an applied setting." *Economics Letters*, 104(1): 13–16.

Leiponen, Aija Elina. 2008. "Competing through cooperation: The organization of standard setting in wireless telecommunications." *Management Science*, 54(11): 1904–1919.

Lerner, Josh, and Jean Tirole. 2006. "A model of forum shopping." *American Economic Review*, 96(4): 1091–1113.

Lerner, Josh, and Jean Tirole. 2015. "Standard-essential patents." *Journal of Political Economy*, 123(3): 547–586.

Myerson, Roger B. 1994. "Communication, correlated equilibria and incentive compatibility." *Handbook of game theory with economic applications*, 2: 827–847.

Roth, Alvin E. 1988. *The Shapley value: essays in honor of Lloyd S. Shapley.* Cambridge University Press.

Rysman, Marc, and Timothy Simcoe. 2008. "Patents and the performance of voluntary standard-setting organizations." *Management science*, 54(11): 1920–1934.

Shapiro, Carl. 2000. "Navigating the patent thicket: Cross licenses, patent pools, and standard setting." *Innovation policy and the economy*, 1: 119–150.

Simcoe, Timothy. 2012. "Standard setting committees: Consensus governance for shared technology platforms." *American Economic Review*, 102(1): 305–36.

Simcoe, Timothy, and Qing Zhang. 2021. "Does Patent Monetization Promote SSO Participation?" *Available at SSRN 3973585.*

Simcoe, Timothy S, Stuart JH Graham, and Maryann P Feldman. 2009. "Competing on standards? Entrepreneurship, intellectual property, and platform technologies." *Journal of Economics & Management Strategy*, 18(3): 775–816.

Spulber, Daniel F. 2013. "Innovation economics: The interplay among technology standards, competitive conduct, and economic performance." *Journal of Competition Law and Economics*, 9(4): 777–825.

Spulber, Daniel F. 2016. "Patent licensing and bargaining with innovative complements and substitutes." *Research in Economics*, 70(4): 693–713.

Spulber, Daniel F. 2019. "Standard setting organisations and standard essential patents: Voting and markets." *The Economic Journal*, 129(619): 1477–1509.

Econometric Appendix: Cooperation and Competition: The case of Innovation in the telecommunications sector

A Estimation and identification of the profit function parameters

Identification of β_1, β_2, ϕ, ψ , μ^S_f relies on the parametric assumption on the distributions of $\epsilon^T_{s,r}$ and $\epsilon^S_{f,s,r}$ and the classic moment conditions derived from the orthogonality assumption in Equation 5 and **??**:

1. $\mathbb{E}[\epsilon^T_{s,r} \mid c_{f,s,r}, \alpha^T_s, \alpha^T_r, \mathcal{J}_{f,s,r}] = 0 \rightarrow$ Contributions are exogenous conditional on participation and technical specifications and release fixed effects

2. $\mathbb{E}[\epsilon^S_{f,s,r} \mid sim_{f,s,r;-f,s,r}, \mu^S_f, \mu^S_r \mathcal{J}_{f,s,r}] = 0 \rightarrow$ Similarity is exogenous conditional on participation and firms and release fixed effects

The identification of the remaining parameter of the second stage of the model relies on the set of moments $m(\theta)$. Although the model is highly non-linear in θ, so that (almost) all parameters affect all outcomes, the identification of some parameters relies on some key moments in the data. Keeping this in mind, I use the following $m(\theta)$ moments:

1. The average number of contributions per firm business model, across standards and releases: 1 moment per business model.

2. The average number of contributions per release, across firms and standards: 1 moment per release.

3. The average number of contributions per firm, across standards and releases: 1 moment per firm.

The first set of moments in $m(\theta)$ exploits the variation in the number of contributions across firms' business model to identify A^M_{BM}. The identification assumption is that revenues of producing goods using the standards as inputs only vary with a firm's business model, and that the business model of a firm only affects its selling revenues. Then, the identification of A^M_{BM} relies on the idea that the difference between the number of contributions submitted by two firms with different business models, but otherwise having the same characteristics and expecting to have the same number of SEPs, must be driven by their expected selling revenues.

Identification of $A^P_{r,BM}$ comes from the variation of the number of contributions across releases. Assuming that the value of SEPs is the only component of the profit function that varies exclusively across releases, it follows that the variation across releases should reflect the changes in the value of SEPs.

Finally, I assume that a firm's marginal cost does not vary across technical specifications or releases. Therefore, other things being equal, two firms provide a different number of contributions because of the difference in their marginal costs. Then the identification of μ^c_f comes from the variation in the average number of contributions submitted by each firm across standards and releases.

Moreover, since the parameters in this model are identified up to a scale factor, I normalize them with respect to the parameter σ of the cost function distribution. Specifically, I use[56] $\sigma = 0.1$.

To get the point estimates of the parameters, I use a minimum-distance estimator that chooses the parameter vector θ that minimizes the criterion function:

$$(m(\theta) - m_d)'\Omega(m(\theta) - m_d),$$

where m_d are the corresponding data moments in the sample, and Ω is a symmetric, positive-definite matrix; in practice, I use the identity matrix. Since the moments of this model cannot be easily computed in closed form, I resort to simulation-assisted methods. More precisely, I take 10 random draws from a $lognormal(\mu^c_f, \sigma^2)$ and for a particular value of θ, I solve the model for each of these simulations.[57] I then average across simulations to obtain the moments of the model for this particular value of θ. I compute standard errors combining the standard delta method with the bootstrap method in order to account for the uncertainty in both stages.

[56] Other values of σ can be used for the normalization. For instance, the standard choice $\sigma = 1$ increases significantly the time it takes the algorithm to minimize the distance between the data and the model moments.

[57] I also computed the moments using 100 simulations. The results were very similar but the computational time increased significantly. While estimating the parameters using 10 draws takes between 1 and 2 hours, using 100 draws increases the computational time to more than 15 hours. Estimating standard errors by bootstrapping using 100 draws would take an incredibly long time.

B Identification and estimation of the participation model

I rely on a Nash equilibrium concept, and use Nash equilibrium conditions to derive firms' (unobserved) choice set. As a standard way of solving for a Nash equilibrium, I start from the observed equilibrium in each group, and consider the vector of observed participation decisions when only one firm deviates at a time as a feasible unobserved group configuration. Figure B.1 shows a simple example using a three-firm group. In the observed equilibrium, firm A and firm C participate, while firm B does not. Using a one-firm deviation approach, I consider the group in which only firm C or A participates in a potential group configuration, as well as a configuration in which all three firms participate. The number of potential unobserved group configurations under this approach is exactly the number of players, which in my game is 35. Recall that to compute each firm's expected profits, I need to compute the optimal number of contributions of all 34 of the remaining firms in each group. This entails solving the model 35 times per standardization group.

Figure B.1: Actual and counterfactual group configurations

Obs. group configuration	**Counterfactual alternatives**		
Firm A = 1	**Firm A = 0**	Firm A = 1	Firm A = 1
Firm B = 0	Firm B = 0	**Firm B = 1**	Firm B = 0
Firm C = 1	Firm C = 1	Firm 1 = 1	**Firm C = 0**

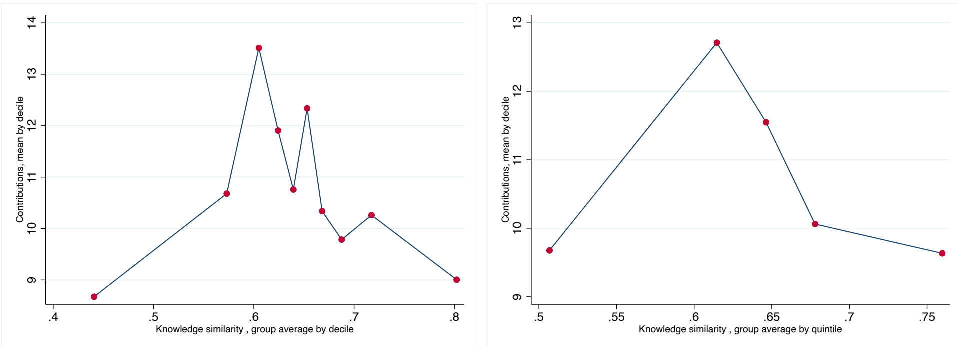
As is standard in deriving conditions for a Nash equilibrium, I don't consider second-round deviations. That is, in example 1, I don't consider the group that would arise if B were to decide to participate after A decides not to participate to be a potential counterfactual group configuration.

Tables and robustness appendix: Cooperation and Competition: The case of Innovation in the telecommunications sector

A Additional figures and tables

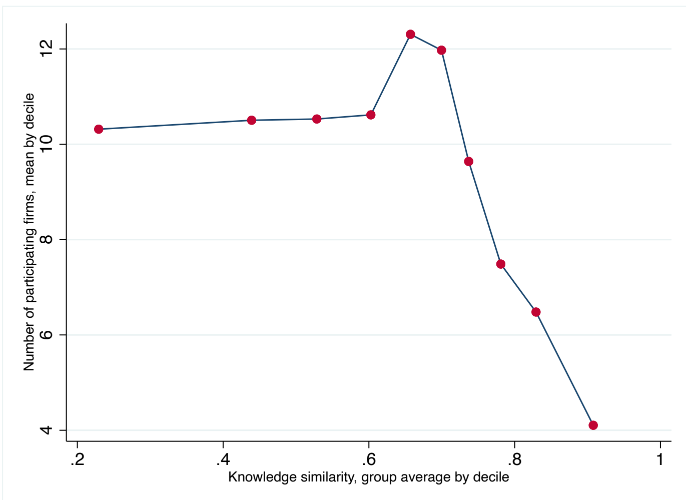
A.1 Contibutions and firms' knowledge similarity

Figure A.1: Contributions and firms' knowledge similarity



Notes: The figures show the average number of contributions submitted by firms with respect to the average similarity of the group of firms working in the standardization group where the contribution was made controlling by firm and technical specification fixed effects, discretized by deciles in the similarity distribution (Panel a) and by quintiles (Panel b).

Figure A.2: Number of participating firms and firms' knowledge similarity



Notes: The figure shows the average number of participating firms in a standardization group with respect to their average knowledge similarity, discretized by deciles in the similarity distribution.

A.2 Seps and firms' knowledge similarity

Figure A.3 and Figure A.4 show a negative and significant relationship between the averge number of SEPs firms declare to have in a standard and the knowledge similarity of the firms, with and without controls. The right panel in Figure A.3 and Figure A.4 show that this relationship still holds when using the share of SEPs, that is, the number of SEPs held by a firm in a given standard over the total number of SEPs for that standard. In all panel, means are adjusted by firm fixed-effects. Table A.1 shows the full set of estimates of Equation 4.

A.3 Estimation and counterfactual results

Table A.2 shows estimates of the downstream revenues and SEP parameters in Equation 8 of the structural model. Figure A.5 shows observed and counterfactual firms' participation and contributions as a function of the broadness of the standard.

Figure A.3: Number of SEPs (reft), share of SEPs (right) and over firms' knowledge similarity (95% confidence bands)

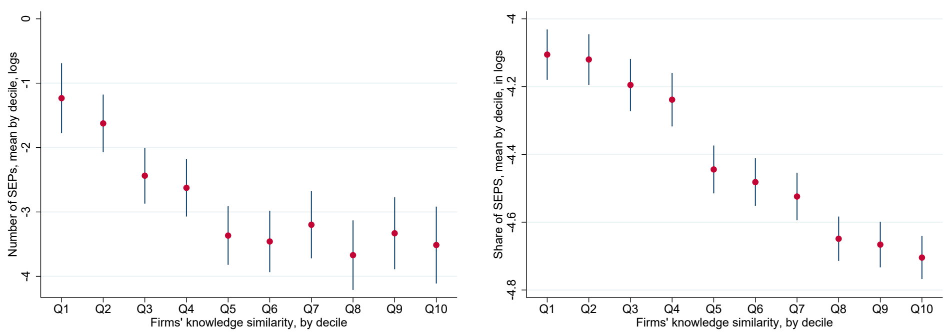


Figure A.4: Number of SEPs (left) and share of SEPs (right) and firms' knowledge similarity, controlling for firm fixed effects and number of firms in the group (95% confidence bands)

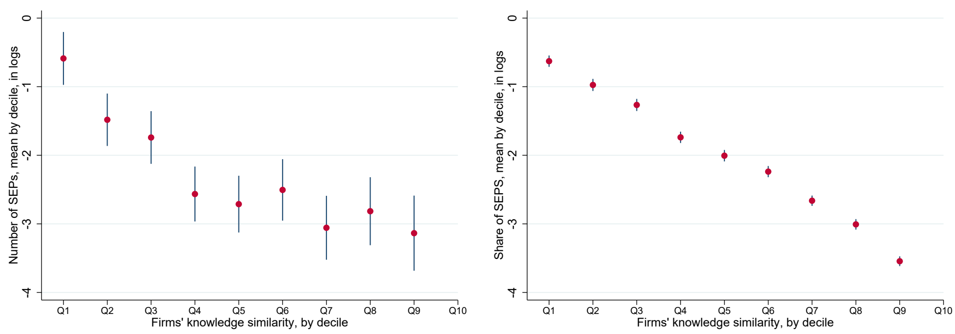
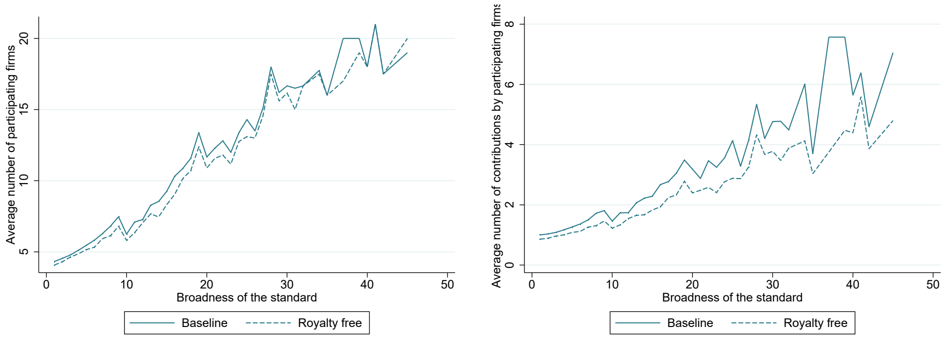


Figure A.5: Number of participating firms and contributions per standardization group



B Test and robustness analysis

B.1 Test on the inverse-U-shaped relationship between contributions and knowledge similarity

For a formal test on the inverse-U-shaped relationship between the number of contributions provide by a firm to the standardization group and the average knowledge similarity

Table A.1: SEP and firms' knowledge similarity, all coefficients

	(1) Baseline	(2) Controls	(3) Other firms controls	(4) Tobit	(5) Tobit
Firms' knowledge similarity	-1.723	-0.875	-1.286	-2.470	-3.204
	(0.418)	(0520)	(0528)	(0.693)	(0.704)
Number of firms	0.956	-0.0437	0.339	1.566	2.027
	(0.119)	(0.247)	(0.246)	(0.233)	(0.252)
Portfolio size		0.131	0.172	0.448	0.495
		(0.210)	(0.212)	(0.431)	(0.430)
Standard's broadness		0.377	0.321	-0.204	-0.248
		(0.125)	(0.123)	(0.125)	(0.126)
R&D expenditures		0.0924	0.129	0.0327	0.0672
		(0.057)	(0.057)	(0.106)	(0.106)
First-time dummy		-0.124	-0.196	0.302	0.223
		(0.223)	(0.220)	(0.289)	(0.288)
Other firms' portfolios			-0.513		-0.260
			(0.233)		(0.256)
Other firms' R&D			1.424		1.735
			(0.199)		(0.349)
N	2059	2059	2059	2059	2059
adj. R^2	0.137	0.286	0.300		
Firm FE	Yes	Yes	Yes	Yes	Yes
Release FE	Yes	Yes	Yes	Yes	Yes
Standard FE	Yes	Yes	Yes	No	No

p-values are in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

between the firm and the other contributing firms in that group shown in Figure 2, I estimate the following equations:

$$Contributions_{f,t,s} = \alpha_1 gsimil_{(f,-f),t,s} + \alpha_2 gsimil^2_{(f,-f),t,s} + \epsilon_{f,s,r} \quad (14)$$

$$Contributions_{f,t,s} = \alpha_1 gsimil_{(f,-f),t,s} + \alpha_2 gsimil^2_{(f,-f),t,s} + \alpha_3 gsimil^3_{(f,-f),t,s} + \epsilon_{f,s,r} \quad (15)$$

where $Contributions_{f,t,s}$ is the number of contributions provided by firm f and $gsimil_{(f,-f),t,s}$ is the average knowledge similarity between firm f and all other firms $-f$ participating in the development of the technical specification t in release r, $gsimil^2$ is the squared average similarity and $gsimil^3$ the cubic term of the aforementioned variable. All variables are in levels as in Figure 2.

Table B.1 shows the estimates of Equation 14 and Equation 15. Estimates of α_1 and α_2 in columns 1 and 2 show that, conditioning on being a second order polynomial, a concave function fits well the data. Column 3 and 4 show results for a third order

Table A.2: Downstream revenue and SEP value estimates

Panel A: Estimates of the market revenues parameters

	Pure Upstream A^M_{up}	Vendors A^M_v	Telecoms A^M_t	Intermediary A^M_I
Estimate	0	5.56	5.34	5.46
SE	-	(0.026)	(0.040)	(0.023)

Panel B: Estimates of the SEP value parameters

	Rel-3	Rel-4	Rel-5	Rel-6	Rel-7	Rel-8	Rel-9	Rel-10	Rel-11
Upst.	0.55	0.61	0.71	0.78	0.80	1.17	0.91	1.07	0.75
	(0.000)	(0.001)	(0.001)	(0.003)	(0.012)	(0.014)	(0.019)	(0.018)	(0.017)
Vend.	0.51	0.55	0.49	0.00	0.33	0.77	0.36	0.20	0.08
	(0.002)	(0.001)	(0.003)	(0.005)	(0.021)	(0.028)	(0.019)	(0.034)	(0.015)
Inter.	0.55	0.55	0.43	0.60	0.56	0.48	0.55	0.55	0.55
	(0.000)	(0.003)	(0.023)	(0.019)	(0.022)	(0.007)	(0.001)	(0.000)	(0.000)

Note: Bootstrapped SE in parentheses. Bootstrap (with reposition) at a standardization group level, 1000 samples.

polynomial approximation of the function. When no controls are added, a third order polynomial approximation can't be rejected by the data, but when firm and release fixed effects are included the third order term of the polynomial (α_3) is no longer significant. These results show evidence in favor of a concave second order polynomial approximation for the relationship between the number of contribution provided by a firm and its average knowledge similarity with the other firms in the group.

Table B.1: Contributions and knowledge similarity

	No controls	FE	No controls	FE
Knowledge similarity (α_1)	44.12	42.57	-28.82	5.59
	(3.30)	(4.21)	(8.62)	(17.05)
Squared knowledge similarity (α_2)	-38.51	-50.71	180.85	32.78
	(2.81)	(3.73)	(21.10)	(34.37)
Cubic knowledge similarity (α_3)			-108.94	-51.92
			(13.88)	(21.02)
Firm FE	No	Yes	No	Yes
Release FE	No	Yes	No	Yes
N	9265	9265	9265	9265
adj. R^2	0.0079	0.0424	0.0124	0.0430

Note: Robust standard errors in parenthesis. All variables are in levels.

B.2 Test on the increasing complementarities with knowledge similarity

For a formal test on the increasing complementarities, I estimate a model including a *quintile trend*, that is, a unique variable that takes the value of the number of contributions made by pair of firms in each quintile of the similarity distribution. This allows me to see if this trend has a positive coefficient, what will show a positive and increasing relationship between complementarities and similaritiy level. Formally, I estimate

$$ttd_{s,r} = -\beta_1 \sum^{f \in F} c_{f,s,r} - \frac{\beta_2}{2} \sum^{f \in F} c^2_{f,s,r} - \gamma trendquintile_{(f,j)} - \mu^S_s - \mu^R_r - \epsilon_{s,r} \tag{16}$$

where $trendquintile_{(f,j)}$ is the trend variable described above. All the other variables are defined as in Equation 5.

The positive and significant estimate of γ shown in column 1 of Table B.2 provides extra evidence in favor of the *complementarity effect*.

Table B.2: Time production function including similarity quintile trend

	Quintile trend
Contributions ($-\beta_1$)	0.20
	(0.050)
Squared number of contributions ($\frac{-\beta_2}{2}$)	-0.11
	(0.005)
Trend quintile (γ)	0.007
	(0.003)
Standard first time (dummy)	Yes
Standard FE	Yes
Release FE	Yes
N	1789
adj. R^2	0.541

Note: Robust standard errors in parenthesis. All variables are in logs.

B.3 Time to develop and standard's quality

Standards quality is a very relevant outcome when it comes to study standards development, but defining quality at a standard (technical specification-release) level is not straightforward, and is beyond the scope if this paper. Even assessing the quality of the whole set of standards for a given version of the technology is not trivial. Nevertheless, Spulber (2019) show that given the current rules of the SSO, in equilibrium, standards and market outcomes are efficient, and Rysman and Simcoe (2008) find that SSOs identify promising solutions when studying internet standards. These results suggest quality may be assured by SSOs rules on how to select the technology to be included in the standard.

As an attempt to provide evidence on the relationship between the time to develop a standard and its quality, I use the probability of a standard to be updated in the next release as a proxy of its quality, as well as the number of releases a standard is updated in the ongoing releases. Formally, I estimate

$$QualityOutput_{s,r} = \omega_0 + \omega_1 ttd_{t,r} + \omega_2 Firsttime_{s,r} + \mu_s^S + \mu_r^R + \epsilon_{s,r} \tag{17}$$

where $QualityOutput_{s,r}$ is either a dummy variable that takes value 1 if the technical specification s is updated in the following release to r and 0 otherwise either the number of releases the technical specification is updated considering the following 4 releases.[58]

[58]To avoid the censoring problem that arises from the data observability span, when using as proxy

As in Equation 5 ttd is the time it takes the group to develop technical specification s in release r, normalized by its broadness, in logs, $Firsttime_{s,r}$ is a dummy variable that takes value 1 if the technical specification is develop for the first time in release r, and μ_s^S and μ_r^R are a set of dummy variables that account for the technical specification and release unobserved heterogeneity respectively.

Table B.3: Time to develop and quality

	Updated next (1)	Number releases updated (2)	Updated next release (3)	Number releases updated (4)
Time to develop (ω_1)	-0.035	-0.071	-0.021	-0.035
(standardized and in logs)	(0.012)	(0.037)	(0.021)	(0.065)
Standard first time	No	No	Yes	Yes
Standard FE	No	No	Yes	Yes
Release FE	No	No	Yes	Yes
N	1557	1238	1557	1238
R^2	0.03	0.02	0.36	0.45

Note: Robust standard errors in parenthesis. All variables are in logs.

Estimated parameters of Equation 17 are presented in Table B.3. Column 1 and 2 estimates imply a negative and significant correlation between time to develop a standard, standardized by its level of broadness, and its quality[59] Once accounted for the unobserved heterogeneity between standards and releases, the point estimation of $omega_1$ remains negative but it is not statistically different from zero. This evidence suggest no trade-off between quality and the time it takes to develop a standard, at least when quality is proxy by its survival probability or the number of releases it will be updated.

B.4 Patents and number of contributions

The SEP function I use in the model (Equation 4) assumes that the number of contributions submitted by a firm in the development of a standard has no impact on the

of quality the probability of a technical specification being updated I do not consider the last observed release and for the number of releases I only consider the following 4 releases and restrict the analysis to the first 5 releases.

[59]Estimate of ω_1 using the probability of the standard to be updated in the next release is significant at a 5% level while the estimation using the number of times the standard is updated in the following 4 releases is significant at a 10% level.

probability of the firm ending up claiming a SEP in that standard, once we account for participation. At first, this assumption might look strong, but it doesn't play a role in the main mechanism of the model and it allows the second stage of the game to be written in matrix form and therefore largely reduces the computational burden of solving it.[60] Besides this advantage, in this section I present evidence on why I consider this to be the right way of modeling the probability of a firm to claim a SEP.

In support of anecdotal evidence I collected from engineers attending standardization meetings, Rysman and Simcoe (2008) show that the technology finally included in standards developed in SSOs are promising technologies and not the result of vested interests. It should be borne in mind that contributions in my setup refers to the effort exerted to "create the standard", that is, provide technical solutions, draft the document, attend meetings, and finally decide on the technology to be included in the standard.

From an empirical point of view, showing that the number of contributions has no impact on the number of Seps implies estimating an equation like 18. Nevertheless, inferring the effect of contributions on the number of Seps from an OLS estimation of that equation would not be valid given that the number of contributions would be endogenous. We only observe Seps if the firm participated in the development of the standard, and in the empirical analysis participation takes value 1 if the firm provided at least one technical contribution to the standard. Mechanically, the relationship between the number of contributions and participation decision is going to be significant and different from zero, i.e.,

$$SEP_{f,s,r} = \alpha^S + \beta Contributions_{f,s,r} + \psi gsimil_{f,s,r;-f,s,r} + \mu_f^S + \mu_s^S + \mu_r^S + \epsilon_{f,s,r}^S, \quad (18)$$

where $Contributions_{f,s,r}$ is the number of contributions made by firm f, to technical specification s in technological release r. The remaining variables are defined as in the main specification.

To overcome the endogeneity problem in Equation 18, I rely on instrumental variables. I use as instrument for the number of contributions the number of standard specifications the firm is contributing to develop in a given technological release. Although the number of specifications the firm is participating can be related to the effort of the firm since it captures the enthusiasm of the firm in pushing forward the standards, this variable should

[60] This time reduction is key given the estimation strategy based on simulations.

not be related to the number of Seps the firm ends up claiming in a particular standard, once I control for the firm's technological capacity (captured by the firm's fixed effects and its patent portfolio size).

Table B.4: Standard contributions and Seps

	(1) OLS	(2) First stage	(3) IV	(4) IV with control
Group similarity (log)	-0.834	-0.352	-3.019	-1.106
	(0.500)	(0.185)	(0.436)	(0.5074)
Number of contributions	0.340		-0.201	-0.384
	(0.068)		(0.167)	(0.386)
Number of standards		0.135		
the firm is contributing to		(0.019)		
Standard's broadness	0.262	0.305		0.477
	(0.119)	(0.045)		(0.159)
First-time dummy	-0.287	0.494		0.059
	(0.218)	(0.082)		(0.273)
Portfolio size		0.159		0.268
		(0.078)		(0.201)
N	2059	2059	2059	2059
adj. R^2	0.296	0.350	0.078	0.249

p-values are in parentheses. Standard errors are robust to heteroskedasticity.
All specifications include firm, specification and release fixed effects.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Column 1 of Table B.4 presents OLS estimates for Equation 18. I find a positive and significant effect of the number of contributions on the number of Seps a firm claims in a standard, as expected. Notice that including this control doesn't change the negative coefficient of similarity, i.e., the competition effect. Column 2 presents the first-stage estimates showing the relevance of the instrument. Finally, Columns 3 and 4 show the results once the number of contributions is instrumented with the number of standards the firm is contributing in that release. Once the endogeneity is addressed I find that there is no effect of the number of contributions to a standard on the number of SEPs a firm claims in that standard. An increase of 1% in the average knowledge similarity of firms in the group decreases the number of Seps obtained by firms in that group by between 3% and 1.1% depending on the specification. As in the main specification, this evidence supports the hypothesis of a competition effect.

B.5 IV estimation of the time to develop function

To address potential endogeneity issues regarding the number of contributions in Equation 1, I instrument it with the size of the firm's patent portfolio the year prior to joining the standardization group. Portfolio size prior to the standard's development is a valid instrument in this setup. Its exogeneity comes from (i) the difference in time with *ttd*, and (ii) the fact that the size of its portfolio is the result of the firm's IP policy, which is a more comprehensive decision than the firm's participation in the development of any specific standard. Its relevance comes from the fact that the size of such a portfolio can be easily related to the firm's size and hence its potential to contribute to standard's development.

While the number of contributions is the only variable I am treating as endogenous in this section of the paper, given the non linearity of Equation 1the variable ends up appearing three times in the equation. The first two times it refers to as the total number of contributions made by all firms to technical specification s in release r and its square. The third time it refers to the interaction of the contributions made by firms. To address this difference in the aggregation level of the variable, I propose to estimate two different first stages and calculate the corresponding Wald estimator:

$$C_{s,r} = \pi_0 + \pi_1 \sum^{f \in F} ln(Patents_{f,s,r}) + \pi_2 X_{s,r} + \pi_s^S + \pi_r^R + \nu_{1,s,r} \tag{19}$$

$$\sum^{f \in F} \sum^{j \in F} c_{f,s,r} c_{j,s,r} = \gamma_0 + \gamma_1 \sum^{f \in F} \sum^{j \in F} c_{f,s,r} c_{j,s,r} + \gamma_2 X_{s,r} + \gamma_s^S + \gamma_r^R + \nu_{2,s,r}, \tag{20}$$

where $C_{s,r} = \sum^{f \in F} ln(c_{f,s,r})$ for every firm f participating in the development of technical specification s in release r, $Patents_{f,s,r}$ is the number of patents in firm f patent portfolio the year prior to participating in the development of the standard , $X_{s,r}$ is a set of control variables as in Equation 1, and π_s^S and π_r^R accounts for technical specification and release unobserved heterogeneity, respectively.

Based on the first-stage estimates I compute the OLS predictions of $C_{s,r}$ $C_{s,r}^2$ and $\sum^{f \in F} \sum^{j \in F} c_{f,s,r} c_{j,s,r}$, and compute the IV/Wald estimates.[61] Table B.5 reports the results.

[61] Wald estimates $= \frac{reducedformestimates}{Firststageestimates}$. See Angrist and Pischke (2008) for more details.

Table B.5: Wald estimates of the effect of contributions on the time to develop a standard

Time to Develop (-)			Contribut.	Interaction Contribut.	IV/Wald estimates		
Firms' portfolio effect	Firms' portfolio sq. effect	Firms' portfolios' interaction			Contribut.	Contribut. sq	Interaction contribution
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
0.0112	-0.0001	0.0106	0.0347	2.928	**0.3240**	**-0.0828**	**0.0036**
(0.0047)	(0.00004)	(0.0040)	(0.001)	(0.087)	(0.1389)	(0.0348)	(0.0014)

Bootstrapped standard errors are in parentheses.
All specifications include the same control variables as in Equation 1.

Columns 1, 2 and 3 of Table B.5 present the reduced-form estimates, while columns 4 and 5 show the first-stage estimates. Finally columns 6, 7 and 8 present the IV/Wald estimates. An increase of 1% in the number of contributions made by firms to a standard (technical specification–release) decreased the time to develop the standard by 0.25%.

B.6 Alternative estimation of the complementarity parameter

Figure B.1: Estimates of ϕ_q using similarity deciles (95% confidence bands)

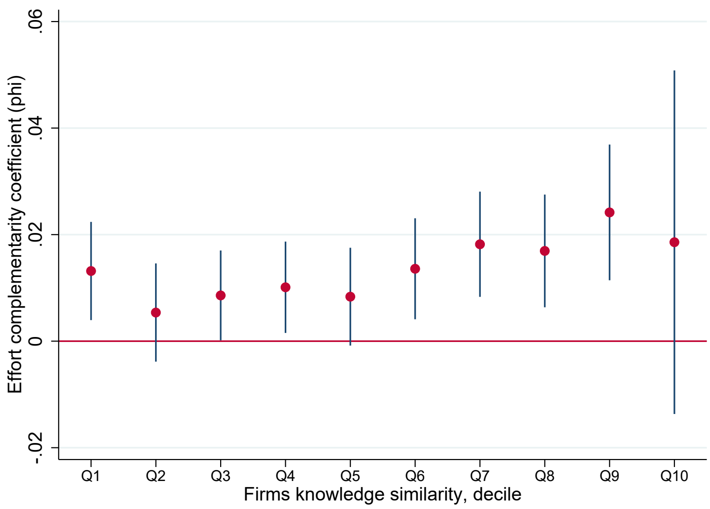
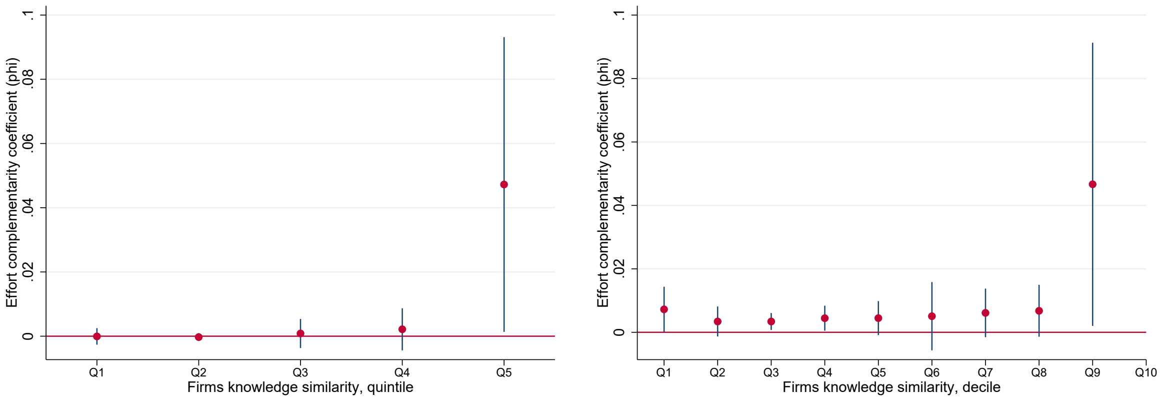


Figure B.2: Estimates of ϕ_q using all variables in levels (95% confidence bands)



C Dataset, estimation sample and empirical measures

C.1 Top contributors and firms' business models

During 1999–2012, a total of around 280 firms contributed to the development of telecommunications standards. But the majority of these firms contributed very little. 265 of these firms contributed, in total, with less than 30,000 written contributions, that is, less than 15% of total contributions. Therefore, and since the goal of this paper is to study strategic interaction between firms, I concentrate my analysis in the top 15 contributors per year, ending up with 35 firms in my sample.To select the top 15 contributions per year I pooled all contributions made each year an selected the 15 companies that contributed the most. page 62 shows the name of the top 35 contributing firms during the analyzed period.

To determine firms' business model I used information available in firms web pages and/or financial reports. During the sample period, 1999–2012 any of the 35 firms changed their business model. According to their official report, Nokia and Ericsson (and its joint venture with Sony, Sony Ericsson), who were vendors during that period, changed their business model in 2013 and 2011 respectively.[62]

C.2 Firms' knowledge similarity

I rely on patented technologies to measure firms'knowledge. Using USPTO data on granted patents, I construct a patent portfolio for each firm in the dataset by counting the number of valid patents in each technological class, as defined by the International Patent Classification (IPC). IPC is a hierarchical system for the classification of patents according to the different areas of technology to which they pertain. Most of the firms in the dataset specialize in Information and Communication Technologies (ICT) and have no patents in classes unrelated to ICT. To avoid "false similarities" driven by zeros in non-ICT categories, I consider only the 15 most relevant classes for this market. To determine relevance, I consider all technological classes of all patents declared to be essential

[62]See https://www.nokia.com/about-us/company/our-history/ and https://www.ericsson.com/en/about-us/history/changing-the-world/the-future-is-now/the-problematic-mobile-phone-sector for more details.

to any standard. I then select the 15 most frequent ones. These 15 classes cover a little over 85% of all essential patents. With the 15 classes for each firm in each year, I follow Jaffe (1986) and use Cosine Similarity (CS) to measure the similarity between any two firms, following . CS is also commonly used in the machine-learning literature as a metric for the similarity between two documents, and is defined as follows:

$$CS(A,B) = \frac{\vec{A}\vec{B}}{\|\vec{A}\|\|\vec{B}\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i}\sqrt{\sum_{i=1}^{n} B_i}}.$$

Since there can only be a non-negative number of patents in any class, CS will take values between 0 (no similarity, vectors are orthogonal) and 1 (completely equivalent, vectors have the exact same direction).

The advantage of CS over the Euclidean distance is that it depends only on the direction, not the length, of the vectors. Here, I consider the classes in which a firm has patents but not how many. Since CS is a pairwise measure, to account for the similarity of a firm in a given group, I average the CS between this firm and all the other firms in the group.

C.3 Merging USPTO and Searle Center dataset

Matching information from USPTO and the SCDB is not trivial. Firms can be identified in both datasets only by names, and this name can vary even within a dataset, depending for example, on firms' IP rights policies. That is, some firms register their inventions always under a subsidiary name of the firm specialized in IP rights, while others just register them under the name of the subsidiary that developed the invention. In the majority of cases we observe both strategies. For example, we can find "AT&T INTELLECTUAL PROPERTY I, L.P." but also "AT& TCORP."

I started by cleaning firm names and aggregating all entries under a firm name, independently of the subsidiary. Therefore, in each dataset I end up with only one observation per firm per year. To do so, I relied on the Levenshtein distance to identify entries that potentially refer to the same firm. The Levenshtein distance is a string metric for measuring the difference between two sequences. Informally, the Levenshtein distance between two words is the minimum number of single-character edits (insertions, deletions, or substitutions) required to change one word into the other. It is very often used in computer science to assess the similarity between string variables.

Prior to measuring the distance between two names, I cleaned firms names by capitalizing them, and extracting all common words such as "Corp." and "Inc.". Finally I used the *FuzzyWuzzy* Library of Python to measure the distance between the variables and try different approaches with exact matches and best matches.

I ended up with 290 matches from the original 575 firms that appeared in the SCDB. It should be borne in mind that several of the organizations that appear in the SCDB do not hold any patent at all. That is the case of governments and ministries, for example. For the top 35 firms I use in my analysis, I was able to match them all.

D Participation and standard–firm match

Participation is relatively low in the data, with the overall probability of joining a standardization group estimated at 16.64%. These decisions are not random, and while the

Table C.1: Firms business model

Firms	Business Model	Structure
Alcatel Lucent	Vendor	Vertically integrated
Anritsu	Telecommunications equipment	Intermediary
Catt - Chinese Academy Of	Research/Consultancy	Upstream
Cingular	Telecom operators	Downstream
Cmcc - China Mobile	Telecom operator	Downstream
Deutsche Telekom	Telecom operator	Downstream
Ericsson	Vendor/Equipment	VI/Intermediary
France Telecom	Telecom operator	Downstream
Gemalto	Telecommunications equipment	Intermediary
Huawei	Vendor	Vertically integrated
Infineon	Semiconductors	Intermediary
Intel	Semiconductors	Intermediary
Interdigital	Research/Consultancy	Upstream
Koninklijke Kpn N V	Telecom operator	Downstream
Lg	Vendor	Vertically integrated
Lucent	Telecom operator	Downstream
Melco Mobile	Telecom operator	Downstream
Mitsubishi	Telecommunications equipment	Intermediary
Motorola	Vendor	Vertically integrated
Nec	Computer hardware	Intermediary
Neustar Inc	Telecom operator	Downstream
Nokia	Vendor	Vertically integrated
Ntt Docomo	Telecom operator	Downstream
Panasonic	Vendor	Vertically integrated
Qualcomm	Semiconductors	Intermediary
Racal Instruments	Telecommunications equipment	Intermediary
Research In Motion	Vendor	Vertically integrated
Samsung	Vendor	Vertically integrated
Sasken	Semiconductors	Intermediary
Sharp	Vendor	Vertically integrated
Sony	Vendor	Vertically integrated
St Ericsson	Semiconductors	Intermediary
Telecom Italia	Telecom operator	Downstream
Vodafone	Telecom operator	Downstream
Zte	Vendor	Vertically integrated

Note: Based on firms' webpage and financial reports. The business model is considered up to 2012. Nokia and Ericsson change their business model in 2013 according to the information provided in their official reports, and therefore, are considered as vertically integrated firms in this study.

Table C.2: Descriptive statistics

	N	Mean	SD	Min	Max
Panel A: Standard's characteristics					
Number of participating firms	1,796	6.28	4.53	2	25
Number of contributions	1,796	68.8	163.5	2	2463
Number of contributions, in logs	1,796	3.04	1.46	0.69	7.81
Time to develop a standard, in days	1,796	723.68	641.99	1.58	4,030
Broadness, in units	1,796	7.48	10.26	1	173
Time to develop by unit of broadness, in logs	1,796	4.62	1.17	-1.25	8.26
Knowledge similarity of participating firms	1,796	0.67	0.19	0.01	1.00
Number of SEPs declared to a standard	946	9.49	19.78	1	175
Panel B: Firms' characteristics					
Number of standards participating	315	36.75	55.93	0	313
Number of patents in the patent portfolio	315	4,476	8,722	0	46,609
Number of declared SEPs	315	18.13	53.30	0	650
Number of declared SEPs, in logs	315	8.01	19.74	0	176.6
Size (sales) per year, in dollars	115	24,385	24,925	0	116,466
R&D expenditures per year, in dollars	115	1,803	1,867	0	7,150

Note: Table produced considering top 35 contributors and using SCDB data. The broadness of a standard measure the number of initial goals covered by each standard. For Panel B each statistic in computed at a firm(35)-release(9) level.

literature provides insides on participation at SSO or consortia level, it sheds little light on why firms choose to participate in the development of the standard for one of the technology's component standard and not others.[63] In an attempt to model participation in a realistic manner, I draw on qualitative survey information, complemented by informal talks with industry practitioners.

In 2003, ConsortiumInfo.org conducted a small survey in which they asked major players in the technology sector about the standardization process in different SSOs. Specifically, they asked, "What are the three most important things that you look for in any standard setting organization in deciding whether to join?'. Firms responded with reasons such as th standard's topic or goals, how relevant a standard was to their technical expertise; IP rights policies, cost effectiveness vis-à-vis alternatives, procedures and group composition, and other members' commitment to investing resources(i.e., paying for engineers'hours).

I group these answers in two categories: (i) the potential overall profits firms expect

[63]The reader can refer to Lerner and Tirole (2006), Baron and Pohlmann (2013), and Leiponen (2008) for more information on how firms decide to participate in different SSOs or more informal standardization groups such as consortia.

Table C.3: Descriptive statistics by release

Release	Number of standards in the sample	Average number of firms per standard	Average tech. goals per standard
Rel - 99	54	4.5	4.6
Rel - 4	70	4.9	5.1
Rel - 5	100	4.7	7.1
Rel - 6	194	5.4	6.3
Rel - 7	275	5.9	6.4
Rel - 8	407	7.1	5.5
Rel - 9	389	7.1	5.5
Rel - 10	361	6.9	7.1
Rel - 11	285	6.6	10.4

Note: Table produced considering top 35 contributors and using SCDB data.

to get from participation in a standardization group; and (ii) the match between the firm and the standard's goals. Firms are specialized in certain technologies and, therefore, are more willing to participate in groups developing standards involving such technologies. For example, if a group is developing a standard for a new kind of antenna for 5G, then firms working in the fields related to antennas are more likely to participate in that group. I refer to this second point as the *firm–standard match* hypothesis. While (i) is endogenous to all the firms' decisions and characteristics, (ii) is exogenously determined by the technological needs of the standard and the technological knowledge of the firm.

The empirical challenge of modeling the firm–standard match is the unobservability of the standards' technological needs. Nevertheless, I observe the broadness of a standard.[64] Then, if the firm–standard technological match hypothesis is true, I should observe that broader standards, which require a higher number of distinct technologies, are subject to higher participation. This is because if more technologies are required, it is more likely that one of them will be relevant to a given firm's knowledge and expertise. On the other hand side, if a firm works in several technological areas, it is more likely to be interested in participating in more standards. To capture this empirically, I use patent portfolio size to measure firms' technological capacity. If the firm–standard match hypothesis is true, I should observe that firms with bigger portfolios are more likely to participate in standardization groups.

As an initial exploration of this hypothesis, I estimate the following logit model for participation at the firm-standard level:

$$p_{f,s,r} = \mathbb{1}\{\beta_p X^p_{f,s,r} + \gamma^p Portfolio_{f,r} + \gamma^b Broadness_{s,r} + \nu^p_{f,s,r} > 0\}, \tag{21}$$

where $p_{f,s,r}$ is a dummy variable that equals one if firm f participates in technical specifi-

[64] Another approach would be to look at the technological classes of the standard's Seps. However, these are observed ex-post, and therefore, Seps' technological classes are likely to match the technological classes of patents held by participating firms.

cation s in release r, $X^p_{f,s,r}$ is a set of proxy variables for the revenues that f would obtain if it were to participate, $Portfolio_{f,r}$ is the number of patents in firm f's portfolio the year prior to release r, $Broadness_{s,r}$ is the broadness of technical specification s in release r as measured by the number of initial goals affecting the standard, and $\nu^p_{f,s,r}$ captures the unobserved (by the researcher) determinants of the firm's participation decision, including the quality of the fit between the standard's technological needs and the firm's technological capacity. As extra controls, I also include a dummy variable that takes value 1 if standard s is developed for the first time in release r, as well as release and standard fixed effects.[65]

The matrix $X^p_{f,s,r}$ includes proxies for firms' standardization revenues, including the amount of downstream sales of the firm and firm fixed effects. I rely on downstream sales as a proxy for the size of the firm. Including this covariate allows me to control for the heterogeneity in downstream profits across firms that vary between releases. Firm fixed-effects control for other unobserved firm characteristics, invariant across standards, affecting firms' likelihood of participating in a standardization group.

Table D.1: Logit estimates for participation decisions

	(1) Baseline	(2) Fixed Effects	(3) Controls
Portfolio size of the firm (log)	0.134 (0.004)	0.146 (0.027)	0.345 (0.058)
Broadness of the standard	0.038 (0.002)	0.018 (0.002)	.022 (0.004)
Firm FE	No	Yes	Yes
Standard FE	No	Yes	Yes
Release FE	No	Yes	Yes
Standard and firm characteristics (First time standard, sales)	No	No	Yes
N	59,395	59,395	26,835
Pseudo R^2	0.0415	0.3712	0.3975

Robust standard errors in parentheses.

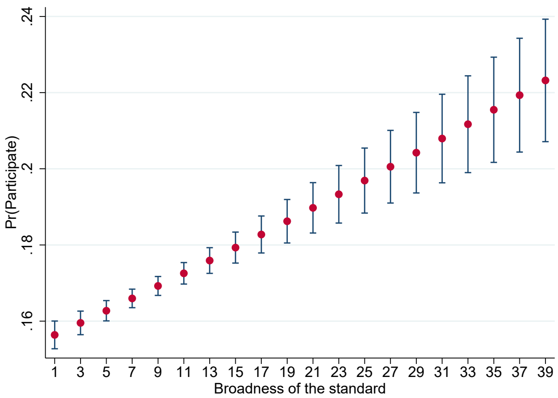
Columns 1, 2, and 3 of Table D.1 present estimates for Equation 21. I find a positive and significant γ_p across all specifications, meaning that firms with bigger portfolios are more likely to participate in a standardization group, other things being equal. I also find a positive and significant γ_b, suggesting that firms are more likely to participate in broader standards.

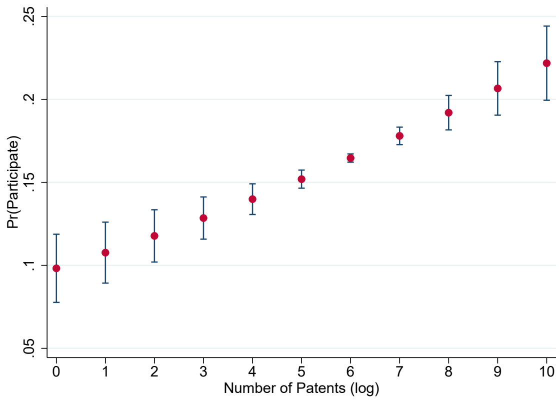
[65] Given the large number of standards (645) and the small number of observations per standard, estimations of standard fixed effects are biased due to the incidental parameters problem. However, since I am not interested in the estimates of those parameters, I do not adjust for them.

As is usual in logit models, due to the normalization of $\sigma_\epsilon^2 = \pi^2/3$, parameters are identified up to a scale factor. To quantify the effect of adding an extra patent or broadening a standard by 1 unit, I calculate the marginal effects of those variables on the participation probabilities. Figure D.1 shows the results of this estimation. The probability of a firm participating in a standardization group in charge of developing a standard with a broadness of 30 or more units is almost 30%, double the overall probability of participation of 16%. On the other hand, a firm with a portfolio of 8000 patents (e^9) is twice as likely to participate as a firm with a portfolio of 3 patents (e^1).

These results provide evidence in support of the firm–standard match hypothesis. The match between a standard and a firm matters for participation and the broadness of a standard, which is partially captured by the size of a firm's portfolio.

Figure D.1: Marginal effect of standard broadness and firm portfolio size on participation probabilities





Note: Confidence intervals are at a 95%. Marginal effects computed using the model include firm, release, and working group fixed effects.

E 3GPP and mobile telecommunications standards

The Third-Generation Partnership Project (hereafter, 3GPP) is the main SDO in charge of supplying mobile telecommunications standards to the industry. It is a private, worldwide organization comprised of almost 1000 organizations. These includes anything from phone manufacturers and telecommunications operators to national regulators. Participation in 3GPP is open to organizational partners for a fee.[66] It is important to note that being a member of 3GPP does not require any obligation in terms of contributing to the development of the standards. In fact, the majority of their members do not contribute to such development.

The documents delivered by 3GPP are not proper standards, in the strict sense, but Technical Recommendations (TR) or Technical Specifications (TS). Once these documents are drafted, they are passed on to ETSI for formal endorsement. TS and TR documents may introduce new standards or modify existing ones. Since I am interested in the

[66] Formally, 3GPP is comprised of 7 national and regional SDOs. These local SDOs, called organizational partners, are: ARIB (Japan), ATIS (USA), CCSA (China), ETSI (Europe), TSDSI (India), TTA (Korea), and TTC (Japan). A firm joins these SDOs by paying a fee, and any member of these organizations can participate in 3GPP.

development of standards and not on their endorsement, I will simply refer to 3GPP's TS and TR documents in a specific release as *standards*.

3GPP was established in December 1998 with the signing of "The Third- Generation Partnership Project Agreement," and since then they have been in charge of developing standards for the first, second, third, fourth, and fifth generation of mobile technology. 3GPP structure evolved during the years. Figure E.1 shows 3GPP structure nowadays. Currently, the work in 3GPP is organized in 3 technical specification groups representing the main technical areas: (i) Radio Access Network , (ii) Core Network and Terminals; and (iii) Service and System Access. Inside each technical specification group, there are working groups, which are further defined by their technological scope and organize meetings to develop standards. All working groups are coordinated by a single project coordination group.

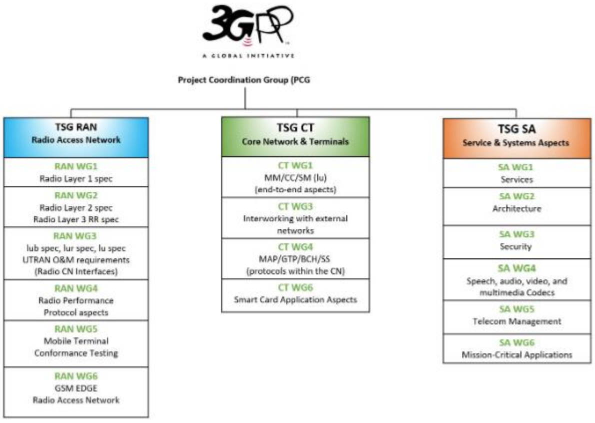
One of the most important rules set out by SDOs relates to the licensing of IP rights protecting the innovations included in a standard. 3GPP has two main rules regarding IP rights:[67] (i) members should declare the existence of patents protecting any essential technology included in the standard (SEPs); and (ii) holders of such patents must make licenses available to all interested third parties under fair, reasonable, and non-discriminatory (FRAND) terms. The use of these clauses allows SDOs to avoid hold-up problems. By forcing participating firms to license their SEP under FRAND terms, SDOs avoid any potential strategic use of SEPs to prevent competitors from launching rival products. This also encourages the early adoption of a standard by assuring implementers of a "reasonable" cost of using it. FRAND is meant to balance the tension between providing developers with incentives to invest in technology development and ensuring downstream competition.

Table E.1: Releases and technology generations

Release	Start Year	Generation	Technology
Rel-99	1996	3G	WCDMA
Rel-4	1998	3G	UMTS
Rel-5	2000	3G	IMS HSDPA
Rel-6	2000	3G	HSUPA WLAN
Rel-7	2003	3G	EDGE EVOLUTION
Rel-8	2006	4G	LTE
Rel-9	2008	4G	WIMAX LTE Dual Cell
Rel-10	2009	4G	LTE Advanced
Rel-11	2010	4G	LTE HetNet
Rel-12	2011	4G	ProSe
Rel-13	2012	4G	NB-IoT
Rel-14	2014	4G	LTE Advances Pro
Rel-15	2016	5G	5G system phase 1
Rel-16	2017	5G	5G system phase 1

[67] See https://www.3gpp.org/about-3gpp/3gpp-faqs for more details on the licensing policies of 3GPP.

Figure E.1: 3GPP's structure



Note: Figure from 3GPP's webpage

F Optimal number of contributions in the empirical model

Given their participation decision, firms choose how many contributions $c_{f,s,r}$ to provide by maximizing expected profits, assuming that other firms are also maximizing their own profits. I can write the following equation for the expected profits:

$$
\begin{aligned}
E(\pi_{f,s,r} \mid I_{f,s,r}) = (- \beta_1 \sum_{s \in R} \sum_{f \in S} c_{f,s,r} - \frac{\beta_2}{2} \sum_{s \in R} \sum_{f \in S} c^2_{f,s,r} - \frac{\phi}{2} \sum_{s \in R} \sum_{f \in S} \sum_{j \in S} c_{f,s,r} c_{j,s,r} sim_{i,j} - \mu^S_s + \mu^R_r) \\
\times (A^M_{BM} BM_f + A^P_{r,BM} * (\psi sim_{f,s,r;-f,s,r} + \mu^S_f + \mu^S_r + \epsilon^S_{f,s,r})) \\
- \frac{mc_f}{2} c^2_{f,s,r}.
\end{aligned}
\tag{22}
$$

Then the best-response function for firm f in technical specification s in release r is defined by

$$
\frac{\partial E(\pi_{f,s,r} \mid I_{f,s,r})}{\partial c_{f,s,r}} = (-\beta_1 - \beta_2 c_{f,s,r} - \frac{\phi}{2} \sum_{j \neq f j \in S} c_{f,s,r} c_{j,s,r} sim_{f,j}) * (A^M_{BM} BM_f + A^P_{r,BM} * SEP_{f,s,r}) - mc_f c_{f,s,r} = \tag{23}
$$

Rearranging, I can write the optimal number of contributions $c^*_{f,s,r}$ of firm f as a function of the optimal number of contributions of the other firms in the group $c^*_{j,s,r}$, the observable variables previously defined, and the set of parameters of the model. That is

$$
\begin{aligned}
c^*_{f,s,r} = & -\beta_1 \frac{A^M_{BM} BM_f + A^P_{r,BM} * (\psi sim_{f,s,r;-f,s,r} + \mu^S_f + \mu^S_r + \epsilon^S_{f,s,r})}{mc_f + \beta_2 (A^M_{BM} BM_f + A^P_{r,BM} * (\psi sim_{f,s,r;-f,s,r} + \mu^S_f + \mu^S_r + \epsilon^S_{f,s,r}))} \\
& - \frac{\phi}{2} \sum_{\substack{i \in S \\ i \neq f}} \frac{A^M_{BM} BM_f + A^P_{r,BM} * (\psi sim_{f,s,r;-f,s,r} + \mu^S_f + \mu^S_r + \epsilon^S_{f,s,r})}{mc_f + \beta_2 (A^M_{BM} BM_f + A^P_{r,BM} * (\psi sim_{f,s,r;-f,s,r} + \mu^S_f + \mu^S_r + \epsilon^S_{f,s,r})} c^*_{j,s,r} sim_{f,j}.
\end{aligned}
\tag{24}
$$

Then the matrix representation of the game becomes

$$
\underbrace{\begin{bmatrix} c_1 \\ c_2 \\ \vdots \\ c_{N_s} \end{bmatrix}}_{\mathbf{C}_{N_s \times 1}} = \underbrace{\begin{bmatrix} \beta_1 B_1 \\ \beta_1 B_2 \\ \vdots \\ \beta_1 B_N \end{bmatrix}}_{K_{N_s \times 1}} + \underbrace{\begin{bmatrix} \frac{\phi}{2} B_1 & \dots & \frac{\phi}{2} B_1 \\ \frac{\phi}{2} B_2 & \dots & \frac{\phi}{2} B_2 \\ \vdots & \ddots & \vdots \\ \frac{\phi}{2} B_N & \dots & \frac{\phi}{2} B_N \end{bmatrix}}_{\mathbf{W}_{N_s \times N_s}} \circ \underbrace{\begin{bmatrix} sim_{1,1} & \dots & sim_{1,N_s} \\ sim_{2,1} & \dots & sim_{2,N_s} \\ \vdots & \ddots & \vdots \\ sim_{N_s,N_s} & \dots & sim_{N_s,N_s} \end{bmatrix}}_{\mathbf{S}_{N_s \times N_s}} \times \underbrace{\begin{bmatrix} c_1 \\ c_2 \\ \vdots \\ c_{N_s} \end{bmatrix}}_{\mathbf{C}_{N_s \times 1}} \tag{25}
$$

where

$$
B_f = \frac{A^M_{BM} BM_f + A^P_{r,BM} * (\psi sim_{f,s,r;-f,s,r} + \mu^S_f + \mu^S_r + \epsilon^S_{f,s,r})}{mc_f - \beta_2 (A^M_{BM} BM_f + A^P_{r,BM} * (\psi sim_{f,s,r;-f,s,r} + \mu^S_f + \mu^S_r + \epsilon^S_{f,s,r})}.
$$

Then I can write the reaction functions as

$$
\mathbf{C^*}_{N_s \times 1} = \mathbf{K}_{N_s \times 1} + \mathbf{W}_{N_s \times N_s} \circ \mathbf{S}_{N_s \times N_s} * \mathbf{C^*}_{N_s \times 1} \tag{26}
$$

where

$$
\mathbf{W}_{N_s \times N_s} = \mathbf{V}_{N_s \times 1} \circ \mathbf{Ones}_{N_s \times N_s}
$$

G Fit of the model

The model matches the moments of the data well: notably, it perfectly captures the average number of contributions per firm business model.Table G.1 compares the empirical moments and the moments calculated from the model at the estimated parameters. Similarly, Figure G.1 shows how the model perfectly captures the average firm number of contributions for most of the firms in the sample.

Figure G.2 plots the observed average number of contributions per decile of firms' knowledge similarity in the data and the average number of contributions computed from the model at the estimated parameters. Considering that those moments are not targeted when estimating the parameters, the model predicts the non-monotonic relationship between the number of contributions and firms' knowledge similarity remarkably well.

H A framework for cooperation and competition between team members

H.1 The set-up

In this section, I present a theoretical framework that captures the most relevant trade-off firms face when deciding how much effort to exert in a standardization group. This

Figure G.1: Difference between average number of contributions per firm in the data and in the model

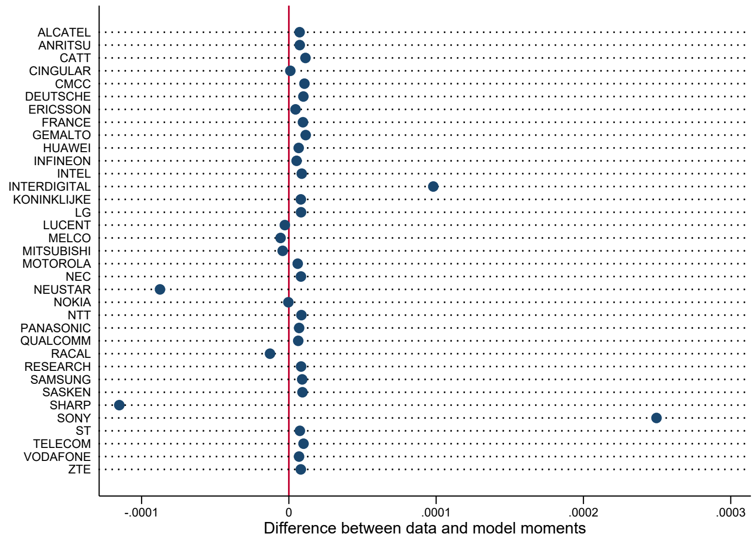
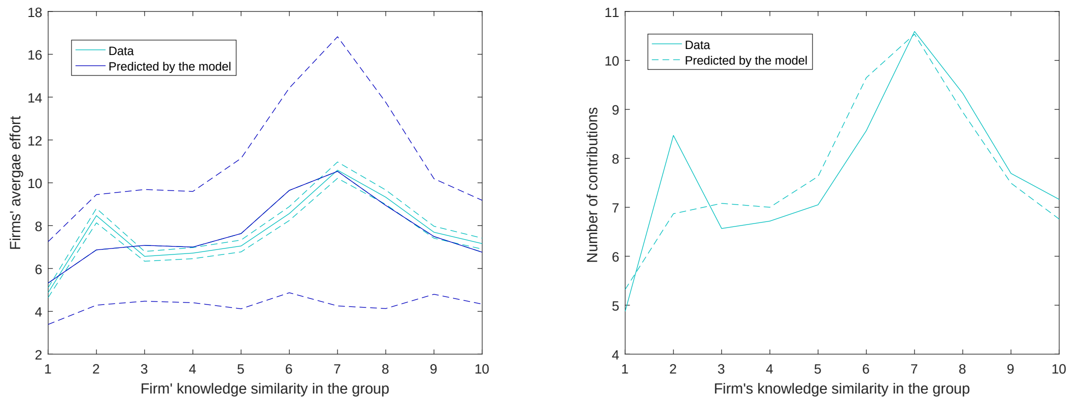


Figure G.2: Contributions per firms' knowledge similarity decile: moments not used for estimation



Note: Dashed lines in the left panel represent 95% confidence intervals. Simulated number of contributions in both panels are computed using observed participation.

framework predicts: (i) the level of effort firms will exert in a group given the exogenous similarity between their technological specialization and those of their partners (knowledge similarity); (ii) the value of the common output in equilibrium; and (iii) the share of this common output obtained by each participating firm.

The model focuses on the effort decisions taken by firms in a standardization group and how their knowledge similarity shapes those decisions. The timing of events is as follows. First, given its technological similarity with other firms, a firm decides how much effort to exert in the standardization group. The value of the common innovation depends on the total effort exerted and the cross-effects between the efforts of firms with different areas

Table G.1: Model fit: Moments used for estimation

	Data	Model
Upstream firms' average contributions	0.04512	0.04512
Vendors' average contributions	0.90027	0.90026
Operators average contributions	0.16442	0.16442
Intermediary firms average contributions	0.21695	0.21695
Firms' average contributions in Release 4	0.02075	0.01980
Firms' average contributions in Release 5	0.02641	0.02696
Firms' average contributions in Release 6	0.07082	0.07090
Firms' average contributions in Release 7	0.11904	0.11931
Firms' average contributions in Release 8	0.31930	0.31969
Firms' average contributions in Release 9	0.32449	0.32489
Firms' average contributions in Release 10	0.27032	0.27072
Firms' average contributions in Release 11	0.16146	0.16162
Firms' average contributions in Release R99	0.01417	0.01286

of expertise (*knowledge*). Second, members of 3GPP decide which technologies to include in the common innovation. Since firms submit contributions for technologies they are specialized in, the more similar firms are, the more their contributions compete. Finally, firms with IP rights over these selected technologies claim the essentiality of their patents.

H.2 Group Outcomes

I model the value of the common innovation developed by group g as a function of the effort exerted by each firm f and the complementarities between these efforts. Assume that firms are labeled $f = 1, ..., N$; then I define the value of the common innovation as:

$$V_g = \beta_1 \sum_{f=1}^{f=N} e_{f,g} + \frac{1}{2}\beta_2 \sum_{f=1}^{f=N} e_{f,g}^2 + \frac{\phi}{2} \sum_{f \neq j}^{N} \sum_{j \neq f}^{N} e_{f,g} e_{j,g} s_{f,j} \tag{27}$$

where $e_{f,g}$ is the effort exerted by firm f in group g toward the development of the common innovation, and $s_{f,j}$ is a measure of the knowledge similarity between firms f and j. The parameters β_1 and β_2 capture the returns of effort on the innovation's value. The parameter ϕ in Equation 27 represents the cross-effects of firms' effort. If $\phi > 0$, then the efforts are complements. If instead $\phi < 0$, then they are substitutes. I allow complementarities in effort to vary with firm's knowledge similarity $s_{f,j}$ in order to capture potential heterogeneities in the cross-effects. I focus on the case $\phi \geq 0$, and call the case $\phi > 0$ the *cooperation effect*

H.3 Revenue and IP function

There are two channels through which firms can benefit: (i) producing goods downstream using the technology developed upstream, and (ii) licensing the IP rights. To profit from the implementation of the standard, a firm must operate downstream or produce intermediate goods. Then, since many vertically integrated firms can produce downstream at the same time, there is no rivalry over the implementation of the standard. On the other hand, each SEP is a rival good because only one firm can own it.

To account for both channels in my model, I include: (i) a parameter A_f^M that accounts for firms' presence in the intermediate and downstream part of the market; (ii) an IP equation $IP_{f,g}$ that models firms' competition over including technologies with proprietary IP rights in the standardization group; and (iii) a parameter A_g^{IP} that accounts for the value of those IP rights.

$$R_{f,g} = \underbrace{V_g}_{\substack{\text{Value of the}\\ \text{common innovation}}} \times (\underbrace{A_f^M}_{\substack{\text{Non-rival part of the value}\\ \text{represented by downstream exposure}}} + \underbrace{A_g^{IP} * IP_{f,g}}_{\substack{\text{Value that can}\\ \text{be privately}\\ \text{appropriated}\\ \text{by IP rights}}}) \tag{28}$$

Most of the technologies included in the 3GPP standards are protected by IP rights. Some of these technologies were already developed, patented, and ultimately included in a standard, while others were developed specifically to meet the standard's goals. Moreover, different firms may have different technological solutions to meet the standard requirements. I assume that the more similar the firms' knowledge, the more they compete for their solution to be included in the standard, i.e.,

$$IP_{f,g} = \alpha_f + \psi similarity_{f_g,-f_g}, \tag{29}$$

where $similarity_{f_g,-f_g}$ is the knowledge similarity between f and all other firms $-f$ in group g, and ψ accounts for the effect that firms' similarity has on their capacity to privately appropriate a part of the common value. By $\psi < 0$ I mean that the more similar a firm is to the other firms in the group, the less it can privately appropriate the common value. I call this the *competition effect*.

H.4 Firms' profits

In my model, firms have a quadratic marginal cost c_f of exerting effort, whereas conditional on participating, they face no fixed cost. I then construct the following firm profit function:

$$\begin{aligned}\Pi_{f,g} = &\left(\beta_1 \sum_{f=1}^{f=N} e_{f,g} + \frac{1}{2}\beta_2 \sum_{f=1}^{f=N} e_{f,g}^2 + \frac{\phi}{2} \sum_{f\neq j}^{N} \sum_{j\neq f}^{N} e_{f,g} e_{j,g} s_{f,j}\right) \\ &\times \left(A_f^M + A_g^{IP} * (\alpha_f + \psi similarity_{f_g,-f_g})\right) \\ &- \frac{c_f}{2} e_{f,g}^2\end{aligned} \tag{30}$$

H.5 Optimal effort and an inverted U-shaped equilibrium

Given their participation, firms choose how much effort $e_{f,g}$ to exert by maximizing expected profits, while assuming that other firms are also maximizing their own profits.

This is therefore a game of perfect information, where all players have access to the same information.

The Nash equilibrium of this model is a vector of efforts exerted by each firm. In equilibrium each firm is exerting the effort that maximizes its profits given that all the other firms are also playing their best response. This corresponds to the fixed point on firms' efforts.

The best response function for firm f in group g is defined by:

$$\frac{\partial E(\Pi_{f,g} \mid I_{f,g})}{\partial e_{f,g}} = (\beta_1 + \beta_2 e_{f,g} + \frac{\phi}{2}\sum_{j\neq f} e_{j,g}s_{f,j}) * (A_f^M + A_g^{IP} * IP_{f,g}) - c_f e_{f,g} = 0, \quad (31)$$

Rearranging, I can write the optimal effort $e^*_{f,g}$ of firm f as a function of the optimal efforts of the other firms in the group $e^*_{j,g}$, their similarity, and the set of parameters of the model. That is

$$\begin{aligned} e^*_{f,g} = \beta_1 &\frac{A_f^M + A_g^{IP} * (\alpha_f + \psi gsimil_{f_g,-f_g})}{c_f + \beta_2(A_f^M + A_g^{IP} * (\alpha_f + \psi gsimil_{f_g,-f_g})} \\ &+ \frac{\phi}{2}\sum_{i\neq f}\frac{A_f^M + A_g^{IP} * (\alpha_f + \psi gsimil_{f_g,-f_g})}{c_f + \beta_2 A_f^M + A_g^{IP} * (\alpha_f + \psi gsimil_{f_g,-f_g})} e^*_{j,s,r} s_{f,j}. \end{aligned} \quad (32)$$

Then the matrix representation of the game becomes

$$\underbrace{\begin{bmatrix} e_1 \\ e_2 \\ \vdots \\ e_{N_s} \end{bmatrix}}_{\mathbf{E}_{N_s\times 1}} = \underbrace{\begin{bmatrix} \beta_1 C_1 \\ \beta_1 C_2 \\ \vdots \\ \beta_1 C_N \end{bmatrix}}_{K_{N_s\times 1}} + \underbrace{\begin{bmatrix} \frac{\phi}{2}C_1 & \dots & \frac{\phi}{2}C_1 \\ \frac{\phi}{2}C_2 & \dots & \frac{\phi}{2}C_2 \\ \vdots & \ddots & \vdots \\ \frac{\phi}{2}C_N & \dots & \frac{\phi}{2}C_N \end{bmatrix}}_{\mathbf{W}_{N_s\times N_s}} \circ \underbrace{\begin{bmatrix} s_{1,1} & \dots & s_{1,N_s} \\ s_{2,1} & \dots & s_{2,N_s} \\ \vdots & \ddots & \vdots \\ s_{N_s,N_s} & \dots & s_{N_s,N_s} \end{bmatrix}}_{\mathbf{S}_{N_s\times N_s}} \times \underbrace{\begin{bmatrix} e_1 \\ e_2 \\ \vdots \\ e_{N_s} \end{bmatrix}}_{\mathbf{E}_{N_s\times 1}}, \quad (33)$$

where

$$C_f = \frac{A_f^M + A_g^{IP} * (\alpha_f + \psi gsimil_{f_g,-f_g})}{c_f + \beta_2 A_f^M + A_g^{IP} * (\alpha_f + \psi gsimil_{f_g,-f_g})}$$

Then I can write the reaction function as

$$\mathbf{E^*}_{N_s\times 1} = \mathbf{K}_{N_s\times 1} + \mathbf{W}_{N_s\times N_s} \circ \mathbf{S}_{N_s\times N_s} * \mathbf{E^*}_{N_s\times 1} - \quad (34)$$

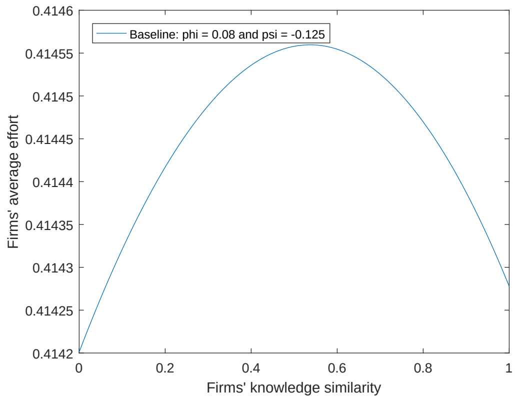
Then, the Nash equilibrium of the model becomes:

$$\mathbf{E^*}_{N_s\times 1} = (\mathbf{I}_{N_s} - \mathbf{WS}_{N_s\times N_s})^{-1} * \mathbf{K}_{N_s\times 1}. \quad (35)$$

As can be seen in Equation 32, the reaction function of each firm is linear on other firms' effort. This allows me to solve the model just by inverting the matrices.

Figure H.1 shows that for some given values of the parameters the model exhibits an inverted u-shaped equilibrium relationship between the similarity of the firms in the group and the exerted effort. In this scenario, we observe how for lower values of similarity the cooperation effect dominates the competition effect, whereas for higher values of similarity the competition effect dominates the cooperation effect.

Figure H.1: Inverted U-shaped equilibrium



Notes: Figure obtained using $\beta_1 = 0.3$, $\beta_2 = -0.01$, $A_f^M = 1$, $A_{f,g}^{IP} = 3$, $\alpha_f = 2$, and $c_f = 5$.

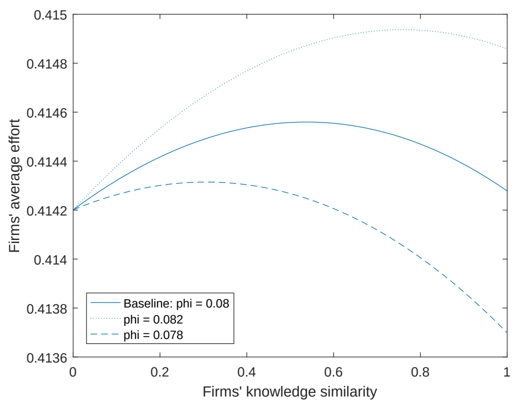
H.6 Comparative statics

In this subsection I show how the cooperation effect and the competition effect interact in equilibrium and how different values of the parameters shape this interaction and the equilibrium outcome. Without lost of generality, I focus on the symmetric equilibrium case for simplicity.

H.6.1 The ϕ parameter and the cooperation effect

The parameter ϕ accounts for the complementarities between firms' effort. A positive and high ϕ induces, other things being equal, a higher equilibrium effort. Figure H.2 shows how ϕ shapes the relationship between similarity and effort. For some high enough values of ϕ, the cooperation effect dominates the competition effect by creating incentives for firms to exert more effort when collaborating with more similar firms. The opposite occurs with low values of ϕ, for which the competition effect dominates the cooperation one and leads to a negative relationship between similarity and equilibrium effort.

Figure H.2: Equilibrium effort for different values of ϕ

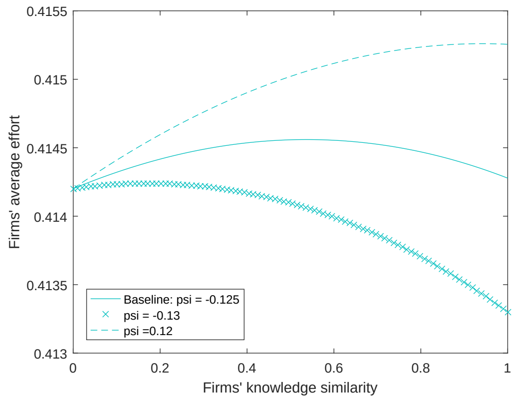


Notes: Figure obtained using $\beta_1 = 0.3$, $\beta_2 = -0.01$, $A_f^M = 1$, $A_{f,g}^{IP} = 3$, $\alpha_f = 2$, $c_f = 5$.

H.6.2 The ψ parameter and the competition effect

Figure H.3 shows how equilibrium effort varies with different values of the competition parameter, ψ. Other things being equal, higher values of ψ (in absolute terms) induce lower equilibrium effort due to a greater competition effect. The opposite happens for an equilibrium with lower ψ, in which the cooperation effect dominates , and therefore induces a higher level of effort and a positive relationship between the similarity of the firms in the group and their exerted effort.

Figure H.3: Equilibrium effort for different values of ψ



Notes: Figure obtained using $\beta_1 = 0.3$, $\beta_2 = -0.01$, $A_f^M = 1$, $A_{f,g}^{IP} = 3$, $\alpha_f = 2$, $c_f = 5$