Patents that Match your Standards: Firm-level Evidence on Competition and Innovation

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Abstract

Standardization is a prerequisite for an industry to adopt a technology among competing ones. When a technology becomes the new standard, the firms that are leaders in producing this technology have a competitive advantage. Matching the semantic content of patents to standards and exploiting the exogenous timing of standardization, we show that firms closer to the new technological frontier increase their market share and sales. In addition, if they operate in a very competitive market, these firms also increase their R&D expenses and investment to escape future competition.

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1 Introduction

Some technologies can be so groundbreaking and pivotal that they become the new *standard* for an entire industry. The ability of firms to adapt to the new standard, which depends on their past technological choices, has direct implications not only for firms' economic performance, but also for innovation and competition. In fact, the large-scale adoption of a technology could benefit firms closer to the new frontier, thus resulting in shifts in market power in their favor. This raises a trade-off between the necessity to reward successful innovators and to avoid the creation of monopolies preventing future technological progress. Despite the vast literature studying the link between innovation, competition and growth (e.g. Aghion et al., 2005), there is little empirical evidence on the effects of the industry-wide *selection* and *adoption* of a specific technology on firm dynamics and market competition. This paper aims to fill the gap.

Addressing this question empirically is challenging as it requires (i) knowledge of which technologies have been adopted by an entire industry and (ii) the innovative activity of individual firms. For the former, we rely on the fact that large-scale technology adoption demands industry participants to coordinate on a set of common rules, a process formally known as *standardization*. For this we use documents approved by industry experts from standard-setting organizations (SSOs) that describe the basic features of the selected technology (known as *standards*). Prominent examples are mobile telecommunication standards (such as the 5G standard family) or Internet protocols. For the latter, we use patent data which is the preferred means to measure innovative activity at the firm-level (see Hall et al., 2005). Combining these two different sources, we match the semantic content of patents to standard documents and introduce a novel measure of the proximity of a firm to the new technological frontier. This allows us to characterize in detail firms response to standardization and to provide new evidence on its macroeconomic implications for innovation and competition.

Our results show that, in response to the release of a new standard, firms owing patents closer to the newly defined frontier gain in terms of sales and market shares. In fact, if a firm has already the capacity to develop products based upon the new standard, it has an immediate comparative advantage that translates into market expansion. However, such an effect is only temporary, which suggests that standards overall do not create monopolies or lead to rent-seeking behavior. Actually, if firms operate in a competitive market, standards encourage subsequent investment in R&D and capital formation. These results are consistent with the interpretation of standardization as a (temporary) competition shock benefiting technological leaders.

Our analysis proceeds in two steps. First, we apply a semantic algorithm to measure the distance between a standard and a patent. In particular, we use the fact that each standard is associated with a set of relevant keywords that can be directly compared to the information in patent abstracts. From this procedure, we are able to link 21.5 million patents to over 0.6 million standards and measure the semantic similarity between each patent and standard. This new measure represents a substantial novelty as most of the literature focuses on either patent data to measure innovation at the firm-level (e.g., see Griliches, 1990 and Hall et al., 2005), or standards data to measure technological adoption at the industry-level (e.g., see Baron and Schmidt, 2014). We show that this measure of *actual adoption* is meaningful as it correlates with the economic value of patents (defined as in Kogan et al., 2017), their scientific value (measured by forward patent citations) and their private value (patent holders are more likely to pay renewal fees).

In the second part of our investigation, we use the data from Kogan et al. (2017)[1] to match firm-level quarterly data from Compustat, Crisp and Ibes to patent data and our new measure of technological proximity (now aggregated at firm-quarter level). Then, we study whether standardization can actually be considered as an exogenous shock to the firm by looking at stock market reactions. We show that financial markets respond only at the time the content of the standard is made public. In fact, in that very moment, firms closer to the new technological frontier experience higher abnormal returns while professional forecasters review upwards their expectations on firms' future earnings-per-share. Therefore, we conclude that the timing of release and content of the standard can be interpreted as exogenous.

Then, we investigate the implication of this shock for the real economy. For this purpose, we use a dispersed lead-lag model, which allows to capture the entire response dynamic to a standardization shock while mitigating for the potential bias due to subsequent and previous standards releases. Under this identification strategy, we first show that firms closer to the new frontier gain both in terms of sales and market shares for roughly five quarters after the publication of the standard. In particular, we estimate that –for frontier firms– this translates into an (average) increase of sales and market share respectively by 6.0%. and 5.6% by the end of the first year following the standard' release.

Thereafter, we consider the post-standardization responses of investment in R&D and new capital, which we expect to be heterogeneous across firms. In fact, as explained in Aghion et al. (2005), there exists a theoretical and empirical u-shaped relationship between innovation and competition. Coherent with this theory, we find that if a firm is operating in a competitive (non-competitive) market and is close to the technological frontier, it will invest more (less) in R&D and new capital after the release of the standard. Actually, firms operating in a highly competitive market have an incentive to keep on innovating and investing in order to maintain their leadership position in the future (the "escape competition" effect). Overall, for the sample of firms under consideration, the expansion of R&D and capital is the prevailing effect. We estimate

[1] We use an updated version of Kogan et al. (2017) taken from their Github repository.

that frontier firms (on average) increase their investment in innovation and capital respectively by 4.4% and 7.2% by the end of the first year following the standard' release.

In light of this evidence, this paper contributes to the policy debate on the link between competition and innovation. The literature has emphasized the fact that the incentive to innovate depends on the level of competition in a non-linear way. Standardization and its consequences represent an important and overlooked dimension to study this question. On the one hand, proponents of standardization argue that it is both an acknowledgment that a technology is leading compared to its potential competitors and also a way to speed up the diffusion of this technology and subsequent improvements. On the other hand, the release of a standard can lock a certain industry in the chosen technology. This might prevent the emergence of competing technologies by transferring substantial market power to firms that have a considerable stake in the standardized technology. Not surprisingly, the policy debate among regulators and standard-setting organizations has centered around this complex trade-off (Lerner and Tirole, 2015).

In this respect, we show that the above described effects are of only temporary nature. In fact, technology leaders are compensated for their past investment into innovation, but eventually lagging firms catch-up over time. Moreover, as long as the market is competitive, technological standardization does not lead to rent-seeking behavior as frontier-firm keeps on investing and innovating.

Related Literature. Our study relates to different strands of the literature. The first one is on technological standardization which has received much attention in the industrial organization (IO) literature, but has been largely ignored in macroeconomics despite the omnipresence of standards in every aspect of economic activity (see Kindleberger, 1983 for an historical overview).

The IO literature has identified a wide range of benefits of standardization. By allowing for interoperability, compatibility and network effects (Katz and Shapiro, 1985; Farrell and Saloner, 1985), lower transaction costs and the reduction of information asymmetries (Leland, 1979), standardization is especially important for the large-scale deployment of inventions and technologies. In order to reap the benefits of standardization, technological specifications and details must be agreed upon. Therefore, Standard Setting Organizations (SSOs) are fundamental in that process (Rysman and Simcoe, 2008).

Consequently, standardization is an essential prerequisite for the industry-wide adoption of new technologies, especially in the case of general purpose technologies (Basu and Fernald, 2008; Jovanovic and Rousseau, 2005). This has macroeconomic implications (see Baron and Schmidt (2014), who exploit the timing of standard releases to study the business cycle implications of technology adoption).

The benefits of standardization notwithstanding, several concerns have been highlighted by the literature. With the arrival of new technologies, the optimality of the incumbent standard is called into question. However, high switching costs may prevent the adoption of new technologies such that industries become "locked in" a certain standard (Farrell and Klemperer, 2007; Farrell and Saloner, 1986). The QWERTY keyboard is an often cited example of such a lock-in effect as consumer habits and compatibility prevent the adoption of more efficient keyboards such as DVORAK (David, 1985).

Another related concern is that standards, by favouring one technology over another, give too much market power to the owners of the technology in question, especially if its use is safeguarded by patent protection. It is for this reason that SSOs insist that holders of so-called standard-essential patents (SEPs) respect fair, reasonable and non-discriminatory (FRAND) licensing principles. This loose prescription has led to an intense debate among regulators, economists and lawyers, and to a theoretical literature on the optimal design of rules on standard development, SEP licensing or voting procedures (Lerner and Tirole, 2015; Schmalensee, 2009; Llanes and Poblete, 2014; Spulber, 2019). While empirical studies have used data for selected SSOs for which SEP declarations are available (Bekkers et al., 2017; Baron and Pohlmann, 2018), true standard essentiality is often questioned and problems of both over-declaration and under-declaration may arise (see the discussion in Brachtendorf et al., 2020).

The second strand of literature this paper speaks to is on the link between innovation and competition. In standard endogenous growth models (in particular Romer, 1990; Aghion and Howitt, 1992; Grossman and Helpman, 1991) an increase in the level of competition should reduce the incentive to innovate as it also reduces future rents. However, as surveyed in Aghion et al. (2005) and Aghion and Griffith (2005), this prediction is not very clear in the data. This motivates the authors to emphasize the non-linear relationship between competition and innovation: while competition can still dampen innovation, it also induces firms to intensify their innovation activities in order to escape competition. To the extent that patents give a temporary monopoly power to its assignee and that standards lock a whole industry in a given technology, then standardization can be interpreted as shock that reduces competition if the underlying technology is owned by a small number of firms. Our paper leverages on this idea to demonstrate that standards have macroeconomic implications for competition and innovation.

Moreover, this work relates also to the literature studying how financial markets react to innovation-related corporate events. For example, Eberhart et al. (2004), Chan et al. (1990) and Szewczyk et al. (1996) show that firms exhibit positive abnormal returns and higher share value when the management announces an unexpected R&D investment plan. Similar results are found in Kogan et al. (2017), Pakes (1985), Nicholas (2008) and Austin (1993), which show that markets positively reacts to news on patenting activity. All these papers demonstrate that the market efficiency hypothesis (among the many, see for example Daniel et al., 1998, Mitchell and Stafford, 2000) holds also when information on corporate innovation activity is disclosed: markets are able to correctly understand and discount what the future benefits of innovation will be. Our paper shows that this is the case also when information on a new standard is released.

Finally, our work contributes to the literature on text-mining applied to the semantic analysis of patents and standards. Text mining methods are increasingly used in economics and in particular in innovation economics, notably for the analysis of patent data (see Abbas et al., 2014 for an overview). For example, the semantics of patent documents can be used to measure patent similarity (Arts et al., 2018; Kuhn et al., 2020). Based on the amount of textual dissimilarity with previous patents and high similarity with subsequent ones, Kelly et al. (2021) construct importance weights to identify breakthrough innovations. Argente et al. (2020) use textual analysis to match products to patents, Bergeaud et al. (2017) extract relevant features from the text of patents' abstract to classify the corpus of patents filed at the US patent office since 1975, Webb et al. (2018) look at the occurrence of a number of pre-selected words to study the dynamics of some recent technologies[2]. Dechezleprêtre et al. (2021) use the prevalence of selected keywords in patent documents to measure automation adoption by firms. Bloom et al. (2021) use textual analysis to identify disruptive technologies and study their geographical diffusion and labour market impact. Our paper uses semantic analysis to define the proximity of patents to new standards. By doing so, it introduces a new measure of firm- and patent-level distance to the new technological frontier, as defined by the standard itself.

Mirroring our methodological approach of mapping standards to patents using textual analysis, Brachtendorf et al. (2020) use SEP declarations for one specific SSO, namely, the European Telecommunications Standards Institute (ETSI) to evaluate the true standard essentiality of patents. Contrary to their paper, we concentrate on the universe of standards released by a large variety of SSOs and are interested in how the standardization of patented technologies affects real outcomes on the firm-level and what this implies at the macroeconomic level. As such, we are not focusing on questions about the standard essentiality of patents, but are studying firm dynamics and the interplay between innovation and the competitive shifts that standardization generates.

The paper is organized as follows: Section 2 briefly describes the matching procedure and the construction of the data, Section 3 looks at how standardization relates to indicators of patent quality. Section 4 presents our firm-level results and discuss the link with the theoretical literature on innovation and competition. Section 5 concludes.

[2] See also Verluise and Bergeaud (2021) for a more global approach leveraging the text of patent publications to identify specific technologies.

2 Data construction and matching

2.1 Data sources

Patent data. A patent is an exclusive right granted to an inventor or an assignee for an invention in exchange for the disclosure of technical information. It prevents or stops others from commercially exploiting the patented invention. For the matching procedure, we use all priority applications that are available in the `IFI CLAIMS` database from 1980 to 2020, without restrictions on the technological field.[3]

The `IFI CLAIMS` database contains most of the information we need about patents. In particular, we extract the abstract, the technological field (through the International Patent Classification code, or IPC), the filing date of the patent application. We restrict our sample to patents filed between years 1980 and 2010. This corresponds to over 21.5 million observations on the patent-level.

Standard data. A standard, similar to a patent, is a document that describes certain features of a product, a production process or a protocol. Contrary to patents which are filed by individual inventors or firms, standards are developed by standard-setting organizations (SSOs) which unite industry experts from both the private and public sector in working groups and technical committees. Well known examples are international SSOs such as ISO (International Organization for Standardization), national standard bodies such as DIN (Deutsches Institut für Normung) or industry associations such as IEEE (Institute of Electrical and Electronics Engineers). Most standards are considered public goods and many SSOs are non-profit organizations. Requiring approval by all stakeholders involved in the development of standards, they are often called *consensus standards*.

To collect information on standards, we use the Searle Centre Database on Technology Standards and Standard Setting Organizations (see Baron and Spulber, 2018 for more details). This data is largely based on `Perinorm`, a bibliographical database of product standards whose purpose is to provide subscribers (usually professionals) with basic information on the standard and the possibility to purchase the access to individual standard documents. Our database covers all types of standards that have been released in a large number of industrialized countries. The `Perinorm` database also contains keywords describing each standard. These keywords were provided by

[3]Patents are grouped into families which include different publications that are more or less related to the same invention. More precisely, during a 12-month period following the filing of an application, the applicant has a *right of priority* meaning that during this period, she can file a similar patent in a different patent office and *claim the priority* of the first application. If the priority claim is valid, the date of filing of the first application is considered to be the effective legal date for all subsequent applications. All the patents sharing a similar *priority application* defined a family. The priority application is the first patent in a family (see Martinez, 2010 for more details).

Perinorm experts when including standards into their database to facilitate the search for specific standards by its users. These keywords are one of the main ingredients for our matching procedure.

We clean the standards data as follows. First, we regroup standard documents that are equivalent. Indeed, a single standard can be released several times, for example once by a French SSO and once by a German SSO. To avoid keeping duplicates, we regroup those standards and create a database in which we store the standards group identifiers, the standards contained in the group, their ICS (International Classification of Standards) and the earliest date of publication. We remove standards that have an ICS of 01, 03, 13, 97, 99, as they do not refer to technology standards. Finally, we store the keywords associated to the standards of the group. More details are provided in Appendix A.

2.2 Semantics-based matching of patents to standards

Matching procedure. We start by processing the keywords that have been provided by Perinorm experts for each standard. We first clean these keywords using common techniques used in text-mining (such as removing upper-case letters, special symbols, punctuation or stop words such as *the*, *at*, *from*, etc.). We then form k-grams, i.e. sequence of k words that we consider as a unique entity (i.e. the 2-gram *air condition* is not the same as considering *air* and *condition* separately). We stem these k-grams which consists in only keeping the "root" of the keyword (i.e. *fertilizing* and *fertilizer* become both *fertiliz*). As a result, we obtain a database where each standard is associated with a list of k-grams.

Then, we proceed similarly and extract keywords from the patent abstracts, form and stem k-grams, and keep those that are in the list of standards keywords. Thus, we obtain a database where each patent and standard is listed with their associated k-grams. We calculate the so-called *inverse document frequencies* for each k-gram in our respective database of extracted standard and patent k-grams to assign them an importance weight.[4] We only keep k-grams that do not appear in more than 1 out of 1000 (5000) standard (patent) documents. Then, we register all patent-standard combinations which share the same k-gram on the k-gram-level. A score is then calculated by summing the importance weights across all patent-standard combinations and normalizing the score by the number of k-grams that were extracted from the patent abstract. This score forms the basis of our analysis and measures the semantic distance between each patent and standard. This matching procedure results in more than 2 billion patent-standard combinations and their associated score of which we extract the

[4]The inverse document frequency is based on a measure of how often a word shows up in a database of documents. See appendix B for details.

first 100 million best matches (based on the score). Appendix B describes the matching procedure in detail.

Selection. Based on the extraction of the first 100 million matches , we report in table 1 descriptive statistics of our score. The first row reports the distribution of the score based on the first 100 million matches extracted from the matching procedure. We also compute the number of standards that a patent is matched to: the median patent is closely linked to 8 standards, but the distribution is highly skewed, with the majority of patents only being matched to one or a few standards and 1% to more than 400 standards.

For the econometric analysis on the patent- and firm-level (respectively sections 3 and 4), we consider both patents that are matched and those that are not matched to a standard. The descriptive statistics for this sample can be found in the second panel of table 1. In table 1, we also report the time lag between the release of the patent and the release of the matched standard for this sample. On average, the release of a matched standard occurs 2.6 years before the filing date of the patent, thus indicating that standards more often lead than lag an associated patent. Standardization may actually lead to more patenting if the standardized technology leads to follow-up innovation. Actually, such standard-induced innovation is a specific aim of the standardization process: by defining common rules for the design and use of an *underlying* technology, firms are incentivized to invest into the technology and develop marketable applications and products. Patenting activity might also increase following standardization if firms patent for strategic purposes (Hall and Ziedonis, 2001; Choi and Gerlach, 2017, see also Kang and Bekkers, 2015 for a discussion of "just-in-time" patenting).

However, for our analysis, we are interested in the firm-level effects of the standardization of a firm's patent portfolio and therefore exclude patent-standard matches occurring after the release of the standard. Restricting the sample to only those matches where the release of the standard occurs the same year or subsequent to the filing of the patent application reduces the number of matched standards. The median time lag for this restricted sample is 8.0 years while the average is slightly higher, at 10.1 years.

In the final line of table 1, we report the aggregated score, summing all scores across all matched standards on the patent-level. Mirroring the distribution of zero matches, we note once again a highly skewed distribution.

In section 3, we evaluate the meaningfulness of our score on the patent-level by investigating its relation with measures of economic and scientific patent value. As we will show and discuss in more detail later, we find that there is a clear, positive association of our aggregated score with other measures of economic importance. Another way to evaluate the quality of our matching procedure is to verify how individual patent-standard matches relate broad categories of the IPC (patents) and ICS (standards) classifications. Essentially, we are linking the two classification systems on the basis of the

Table 1: DESCRIPTIVE STATISTICS OF THE MATCHING PROCEDURE

	Mean	SD	Min	Max	p1	p5	p25	p50	p75	p95	p99	N
(A) Keyword matching sample												
Score	715.7	1,766.6	138.8	658,691.2	141.3	151.8	211.8	315.2	638.7	2,345.7	6,289.0	100,000,000
Standards	41.9	87.5	1.0	1,233.0	1.0	1.0	2.0	8.0	35.0	217.0	471.0	2,389,251
(B) All patents (matched and unmatched)												
Score	599.6	1,634.6	0.0	658,691.2	0.0	0.0	166.4	262.4	543.5	2,026.9	5,622.0	113,427,683
Time lag	-2.6	15.6	-50.0	38.0	-40.0	-31.0	-13.0	-1.0	8.0	21.0	30.0	95,201,007
Standards	4.6	31.9	0.0	1,233.0	0.0	0.0	0.0	0.0	0.0	10.0	136.0	20,506,259
(C) Restricted sample: excl. matches with patent filing year > standard release year												
Score	505.6	1,549.8	0.0	658,691.2	0.0	0.0	0.0	227.1	480.4	1,799.8	5,139.7	64,574,039
Time lag	10.1	7.7	0.0	38.0	0.0	0.0	4.0	8.0	15.0	26.0	32.0	46,347,363
Standards	2.6	163.7	0.0	681,495.0	0.0	0.0	0.0	0.0	0.0	4.0	72.0	17,596,230
(D) Aggregated sample												
$\sum$ score	1,592.2	30,814.2	0.0	2.8e+07	0.0	0.0	0.0	0.0	0.0	1,495.9	31,087.2	20,506,259

Notes: The table reports descriptive statistics for the score, the number of matched standards per patent and the time lag (in years) between the release of the standard and the filing year of the patent. The keyword matching sample comprises the extraction of the first 100 million scores of our matching procedure. The sample of utility patents discards design patents and also includes unmatched patents which receive a score of zero. The restricted sample only comprises utility patents, matched and unmatched, for which the patent filing year does not exceed the standard release year. The aggregated sample sums all scores on the patent-level for the restricted sample.

individual matches obtained in our matching procedure. The results of that exercise can be found in appendix B where table B.1 lists the closest IPC class for every ICS field. Across the board, the matching seems reasonable and confirms our approach.

2.3 Firm-level Data

Aggregation of scores at the firm-level. Given the mapping between each patent of the firm and the corresponding standard, we aggregate patent-to-standard scores at the firm-quarter level by weighting the sum of patents' scores with the relative importance of each 3-digit IPC classes in the firm initial (pre-sample) stock of patents. Formally, define J as the set of all IPC classes such that $j \in J$ is a specific IPC class, and call $\text{Score}_{i,p,j,t}$ the score obtained by firm i when matching patent p –belonging to the IPC class j– to a standard published at time t. Then, the weighted aggregation of scores over IPC classes can be written as the following measure of proximity which we refer to as "Shock" throughout:

$$\text{Shock}_{i,t} = \sum_{j \in J} \omega_{j,t_0} \sum_{p \in j} \text{Score}_{i,p,j,t},$$

where ω_{j,t_0} is the share of patents in the IPC class j measured in t_0, i.e. before 1980. We do this weighting for two reasons: first, the weighting reduces the role of those patents in IPCs that are not at the core of the firm's research activity and technological field; second, computing the weights in a pre-sample periods reduces the problem of firm self-selection into a specific IPC, which they anticipate would become important for a potential standard at some point in time.

In conclusion, the variable $\text{Shock}_{i,t}$ is a firm-quarter level information shock expressing the (IPC-weighted) proximity of the stock of patents of a firm to the standard released in quarter t. This shock can be either equal to zero, if the patents of a firm do not map into a new standard, or positive. In this case, the higher is the shock the closer is the stock of patents of the firm to the newly released standard.[5]

Balance-sheet data. We use firms' balance-sheet data from Standard&Poor's Compustat to build all (real) dependent and control variables used in the empirical analysis of Section 4. The dependent variables under consideration are four: sales, capital investment, R&D investment and market-share. Sales are the revenues of the firm as reported at the end of the quarter in the income statement. Capital investment is the gross (flow) expenditure for new capital at the net of depreciation. Since it is usually under-reported, R&D expenditure is measured as a 4-quarter moving average. For comparability across firms, we normalize these three variables by the (mean) level of fixed assets (property, plant, equipment).[6] The last variable of interest is the market share of the firm, defined as the ratio of firm-level sales on the total volume of sales in a NAICS 3-digit industry (NAICS3).

Along with these variables, we consider also the following characteristics: the age of the firm (expressed in quarters), the q-value of investments (build as book value of liabilities plus the market value of common equity divided by the book value of assets), leverage (as debt over the book value of assets), market capitalization (expressed in Billion of U.S dollars), a dummy taking value one if the firm is operating in a high-tech industry (i.e. drugs, office equipment and computers, electronic components, communication equipment, scientific instruments, medical instruments, and software) as defined in Chan et al. (1990). Finally, we follow De Loecker et al. (2020) to construct NAICS3 industry mean markups. This information allows to understand which industry is (on average) less or more competitive and –therefore– which firms operate in a less or more competitive market. We define a firm as belonging to a non-competitive market if the markup of its industry is above the 75$^{\text{th}}$ percentile of the distribution. Hence, we construct a dummy variable accordingly.

Financial market data. As explained in Mitchell and Stafford (2000), abnormal returns are useful to study short-term market reactions to corporate events. Following this line, we want to evaluate how markets interpret the standardization shock. Since

[5] Our baseline measure of "Shock" has a support that ranges from 0 to over 6. It is equal to 0 for more than half of the sample. See Table 2 for more details.

[6] As we show in this paper and also in Bergeaud et al. (2021), the value of assets, equity and investments are sensitive to the standardization shock. For this reason, we prefer to normalize sales, capital investment and R&D with the mean-level of fixed assets rather then with the contemporaneous level or some lag. By doing so, the change in the numerator of the index is not influenced by the change in the denominator.

our analysis focuses on the real effects of the shock on competition and sales within NAICS3 industry, we calculate abnormal returns at that level of disaggregation. Here, we describe the procedure of extrapolation. First, we match Compustat with data from the Center for Research in Security Prices (CRSP). Then, for each NAICS-3 industry, we build the returns of a portfolio composed of all firms listed in that industry. Formally, given the number of firms I_t belonging to the NAICS-3 industry s at time t, the return on the industry s portfolio can be written as $r^s_t = \sum_{i=1}^{I_t} \omega^s_{i,t} r_{i,t}$. Notice that $\omega^s_{i,t}$ is the weight of each firm i in the industry-specific portfolio s, and it is equal to the relative market capitalization of firm i in industry s at that moment in time. Hence, we estimate a statistical model which differ from the baseline Capital Asset Pricing Model (see Jensen et al., 1972) only for the definition of the market portfolio, here defined at industry level. Formally –given information on the 3-month t-bill rate (r^f_t) and the return on each industry portfolio (r^s_t)– for every firm i belonging to industry s and 10-year rolling window with ending period τ, our asset pricing model is:

$$r_{i,t} - r^f_t = \alpha_{i,\tau} + \beta_{i,\tau}(r^s_t - r^f_t) + \varepsilon_{i,t}, \quad \forall t \in (\tau - 10yrs, \tau]$$

where $r_{i,t} - r^f_t$ is the excess return of firm i, $r^s_t - r^f_t$ is the excess return of industry s portfolio, $\varepsilon_{i,t}$ is the error term. Then, we use the OLS estimates $\widehat{\alpha}_{i,\tau}$ and $\widehat{\beta}_{i,\tau}$ to predict the firm's (excess) return one quarter after the end of each 10-year estimating window, i.e. in period $\tau + 1$. Finally, we define the abnormal return ($ar^s_{i,t}$) of a firm i from industry s as the difference between the observed (excess) return and the predicted one:

$$ar^s_{i,\tau+1} = (r_{i,\tau+1} - r^f_{\tau+1}) - \left(\widehat{\alpha}_{i,\tau} + \widehat{\beta}_{i,\tau}(r^s_{\tau+1} - r^f_{\tau+1})\right).$$

We repeat this procedure for every firm i in the sample and for all available 10-year rolling windows with ending period equal to $\tau, \tau + 1, \tau + 2, ..., \tau + T$.

In order to look at markets' reaction beyond abnormal returns, we match Compustat to data from the Institutional Brokers' Estimate System (IBES). From this dataset, we collect professional analysts expectations over the future Earning-Per-Share (EPS) ratio of the firm. In particular, we look at how forecasters expect the EPS to be at the end of the following fiscal year. In fact, by considering a fixed forecasting horizon, we can study how expectations change over time as the end of the fiscal year approaches. Therefore, for each firm and quarter, we take the mean of the 1-year EPS forecast across all professional forecasters, and obtain a measure of market expectations over the future economic performance of the firm.

Sample selection. Once created firm-level variables, we follow Brown et al. (2009) and exclude all regulated utility and financial firms as well as firms with missing assets. Then, we match the remaining sample of Compustat firms with patent data and our standardization shocks. Then, in order to implement our identification strategy

Table 2: Descriptive Statistics

	Mean	SD	p1	p5	p25	p50	p75	p95	p99	N
(A) Standardization Shock										
Shock	0.34	2.02	0.00	0.00	0.00	0.00	0.10	1.27	6.24	24,162
$\mathbb{I}[\text{Shock} > 0]$	0.48	0.49	0.00	0.00	0.00	0.00	1.00	1.00	1.00	24,162
(B) Firm Characteristics										
Sales	0.62	0.72	0.01	0.08	0.25	0.47	0.78	1.60	2.99	24,162
R&D	0.04	0.26	0.00	0.00	0.00	0.01	0.02	0.14	0.56	24,162
CapX	0.02	0.03	0.00	0.00	0.01	0.02	0.03	0.07	0.14	24,162
Market Share (NAICS3)	0.05	0.10	0.00	0.00	0.00	0.01	0.05	0.21	0.49	24,162
Age (quarters)	98.99	49.92	21.00	21.00	53.00	110.00	137.00	171.00	181.00	24,162
Q	1.93	2.15	0.74	0.90	1.17	1.49	2.12	4.43	8.69	24,162
Leverage	0.19	0.15	0.00	0.00	0.06	0.17	0.27	0.45	0.65	24,162
Market Cap. (Billion$)	9.17	28.99	0.00	0.02	0.19	1.27	5.61	42.22	139.89	24,162
$\mathbb{I}$(*Tech-firm*)	0.30	0.45	0.00	0.00	0.00	0.00	1.00	1.00	1.00	24,162
Industry Markup (NAICS3)	1.50	0.30	1.05	1.13	1.25	1.40	1.75	1.92	2.43	24,162
$\mathbb{I}$(*Non-Competitive Industry*)	0.25	0.43	0.00	0.00	0.00	0.00	1.00	1.00	1.00	24,162
(C) Financial Mkts										
ar^{NAICS3}	0.00	0.40	-0.58	-0.32	-0.09	0.00	0.08	0.27	0.56	18.531
1yr EPS Forecast ($)	1.43	0.96	0.06	0.19	0.67	1.25	1.99	3.40	3.99	15,766

Notes: The variable Shock measures the proximity of the stock of patent of the firm to the standard. $\mathbb{I}[\text{Shock} > 0]$ is a dummy that takes value one for positive values of the variable Shock. Sales is the firm-level of sales normalized by the mean-level of fixed assets (property, plant, equipment). The *Market Share* is constructed at the NAICS 3-digit level. R&D and CapX are respectively the level of R&D expenditure and capital investment normalized by the mean-level of fixed assets. Age is the number of quarters the firm is active. Q is the q-value of investments, and is built as the value of liabilities plus the market value of common equity divided by the book value of assets. Leverage is debt over the book value of assets. *Market Capitalization* is expressed in Billion of U.S dollars. The dummy variable $\mathbb{I}(\text{Tech} - \text{firm})$ takes value one if the firm operate in one of the following industries: drugs, office equipment and computers, electronic components, communication equipment, scientific instruments, medical instruments and software. The NAICS 3-digit industry markup is constructed following De Loecker et al. (2020). $\mathbb{I}$(*Non-Competitive Industry*) is a dummy that takes value one if a firm is operating in a NAICS 3-digit industry with markup above the 75^{th} percentile. ar^{NAICS3} is a measure of stock market abnormal return built from a standard CAPM model with a NAICS 3-digit index as market portfolio. The *1yr EPS Forecast* is the mean forecast across all professional forecasters of the earning-per-share expected by the end of the following fiscal year, and it is expressed in dollars.

(see Section 4), we keep only firms that are publicly listed, for which all constructed variables are jointly available (except abnormal returns and EPS forecasts), and that have registered at least one patent in their life. By doing so, we end up with a sample of 24,162 firm-quarter observations spanning from 1984 to 2010.

Table 2 reports descriptive statistics for this sample. As from panel (A), the standardization shock has mean equal to 0.34 and standard deviation equal to 2.02. In our sample, 48% of firms have a positive shock. As from panel (B), the mean level of sales is 62% of the value of fixed assets. Mean (flow) investments in research and development (R&D) and capital (CapX) are respectively equal to 4% and 2% of the value of fixed assets. Within NAICS3 industry, the average firm has a market share equal to 5%. The average age of the firm is roughly 25 years, with a q-value equal to 1.93, 19% of its balance-sheet is composed by debt, it has a market capitalization of 9.17 Billion dollars and 28% probability to be in a high-tech industry. The average firm operates in a NAICS3 industry with markup of 1.5. 25% of firms are from industries with markups above or equal to 1.75, and we define these industries as non-competitive. When matching this data with information on abnormal returns and EPS forecast, the sample reduces. As from panel (C), our sample contains 18,531 observations on abnormal returns and 15,766 observations on EPS forecasts. The average abnormal return is zero while the average 1-year EPS forecast is 1.43 dollars per share.

3 Innovation and standardization: patent-level results

In this section, we verify the validity and quality of our matching procedure by looking at the characteristics of patents that are associated with a high score, i.e. patents semantically close to a specific standard. In particular, we compare the computed score with measures of patent quality or value.

3.1 Economic value of a patent à la Kogan et al. (2017)

Kogan et al. (2017, hereafter KPSS (2017)) compute the financial value of a patent based on the stock market reaction to the news of a patent application being granted. This is a forward-looking measure of economic agents' evaluation of the granted patent. While we expect our score to correlate with the KPSS (2017) measure, there are conceptual differences. While both measures are indicative of the economic value of a the patent, our score captures the underlying technology's potential for market-wide adoption. It is therefore particularly meaningful to study questions of market share and competition. The economic value à la KPSS (2017) measures markets' perception of the future value of the technology at the time of the patent grant, but potentially abstracts from any future developments that are not known at the time of the grant (standardization being one of them).

To relate our score with the economic value of a patent as calculated by KPSS (2017), we sum the score across all associated standards on the patent-level, essentially weighing each patent-standard association by their individual score (unmatched patents have a zero score). We then merge these data with the KPSS (2017) dataset. We run the following patent-level regression:

$$\log\left(\text{value}_i\right) = c + \alpha \log\left(1 + \text{score}_i\right) + \beta \log\left(1 + \text{cit}_i\right) + \gamma Z_i + \varepsilon_i \tag{1}$$

where value_i is the economic value of patent i (in millions USD) from KPSS (2017) and score_i is the sum of scores across all associated standards of patent i. We include the number of forward citations cit_i as a control variable as well as various fixed effects such as the year and quarter of the grant date as well as the 3-digit IPC class and combinations of these fixed effects.

Table 3 summarizes the results. Across the different specifications, our aggregated score is positively associated with a higher financial value of the patent and is statistically significant. In order to translate these results into quantitative numbers, we run regression specification 1 with a dummy indicating whether a patent is matched to at least one standard or not, adding controls and fixed effects as in table 3. The coefficient for the dummy for a non-zero score ranges between 0.0190 and 0.0363 for the different specifications, implying that a close link with at least one standard is associated with a

Table 3: Regression results for KPSS (2017) patent value

	(1)	(2)	(3)	(4)	(5)	(6)
Score	0.0088***	0.0062***	0.0064***	0.0051***	0.0062***	0.0050***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Citations		0.1579***		0.1538***		0.1442***
		[0.006]		[0.004]		[0.004]
Observations	1,165,487	1,165,487	1,165,462	1,165,462	1,163,913	1,163,913
R^2	0.05	0.06	0.10	0.11	0.13	0.14
Adjusted R^2	0.05	0.06	0.10	0.11	0.12	0.13
Time	Yes	Yes	Yes	Yes	No	No
IPC	No	No	Yes	Yes	No	No
Time × IPC	No	No	No	No	Yes	Yes

Notes: Regression of the nominal USD value of patent i from KPSS (2017) on the sum of scores across all associated standards of patent i, the number of forward citations and the sum of IDFs of the abstract of patent i. All variables enter the regression in logs where the value of 1 was added to the sum of scores and the number of citations to take into account zero values. Year designates the inclusion of grant year fixed effects, IPC designates 3-digit IPC fixed effects and Year × IPC their interaction. Standard errors are clustered at the grant year-level. [XXX JULIA: Give time period in sample XXX] "*", "**" and "***" designate significance at the 1%, 5% and 10% level.

1.9–3.6% higher patent valuation. The median (mean) patent being valued at 2.9 (16.3) mio USD, this amounts to raising its value by 55,000–105,000 (310,000–592,000) USD.

Results do not change when deflating the dependent value with the US Consumer Price Index or using unweighted counts, i.e. by simply counting the number of associated standards per patent.

3.2 Scientific value of a patent: forward citations

A popular measure of the scientific value of a patent are forward citations (Hall et al., 2005), i.e. citations of the patent in question by subsequent patents. A highly cited patent is used by a larger number of future inventions and therefore signals high technological content and to a certain extent also high economic value.

We extract forward citations from `Google Patents` and concentrate on the number of forward citations received within five years after publication and use a Poisson regression model approach to take into account the discrete nature of the dependent variable and use the year of the filing date rather than the grant date for the fixed effects. In all other respects, the regression setup follows equation (1).

The results in Table 4 mirror the ones from Table 3. There is a clear positive relation between our aggregated score and the number of citations a patent receives. Once again, results are robust to using unweighted counts of the number of standards associated to a patent.

Table 4: Regression results for forward citations

	(1)	(2)	(3)
Score	0.0053***	0.0056***	0.0054***
	[0.001]	[0.001]	[0.001]
Observations	19,374,605	19,374,540	19,374,229
Time	Yes	Yes	No
IPC	No	Yes	No
Time × IPC	No	No	Yes

Notes: PPML regression of the number of forward citations of patent i on the sum of scores across all associated standards of patent i and the sum of IDFs of the abstract of patent i. All independent variables enter the regression in logs where the value of 1 was added to the sum of scores and the number of citations to take into account zero values. Year designates the inclusion of grant year fixed effects, IPC designates 3-digit IPC fixed effects and Year × IPC their interaction. Standard errors are clustered at the filing year-level. "*", "**" and "***" designate significance at the 1%, 5% and 10% level.

3.3 Private value of patent protection: renewals

As a last exercise, we look at the economic value of a patent not in terms of its external valuation by financial markets or other patenting firms, but how patent owners themselves value their patents. Patent holders have to pay maintenance or renewal fees to keep a patent in force.[7] Pakes and Schankerman (1984) and Pakes (1986) have argued that these expenses for the renewal of patents is an indicator of the private return of holding a patent. The duration of effective patent protection is therefore an indicator of the economic value of a patent, either for the purpose of extracting royalties or to hinder competitors from using the technology. The OECD Patent Quality Indicators Database (Squicciarini et al., 2013) includes the number of years a patent is maintained. We therefore run a similar Poisson regression of the number of years a patent is in force on our aggregated score, similar to the above regressions. We include an additional fixed effect, namely a dummy on whether the respective patent is filed at the EPO or USPTO.

Table 5 summarizes the results. Patents with a high aggregated score tend to be renewed more often; in quantitative terms, however, the regression coefficient is relatively small. Results do not change when using unweighted counts of the number of standards associated to a patent.

[7] After 20 years, patent protection cannot be renewed.

Table 5: Regression results for renewals

	(1)	(2)	(3)	(4)	(5)	(6)
Score	0.0009***	0.0007***	0.0004***	0.0004***	0.0003***	0.0002**
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Citations		0.0393***		0.0307***		0.0294***
		[0.006]		[0.004]		[0.004]
Observations	2,551,281	2,551,281	2,551,280	2,551,280	2,551,255	2,551,255
Time	Yes	Yes	Yes	Yes	No	No
IPC	No	No	Yes	Yes	No	No
Time × IPC	No	No	No	No	Yes	Yes
EPO/USPTO	Yes	Yes	Yes	Yes	Yes	Yes

Notes: PPML regression of the number of years that patent i is in force on the sum of scores across all associated standards of patent i, the number of forward citations and the sum of IDFs of the abstract of patent i. All independent variables enter the regression in logs where the value of 1 was added to the sum of scores to take into account zero values. Year designates the inclusion of grant year fixed effects, IPC designates 3-digit IPC fixed effects and Year × IPC their interaction. EPO/USPTO designates the inclusion of fixed effects for whether the patent is an EPO or USPTO patent. Standard errors are clustered at the filing year-level. "*", "**" and "***" designate significance at the 1%, 5% and 10% level.

4 Standardization as a competition shock: firm-level results

In this section, we move from patent- to firm-level data and show that the release of a standard generates the same firm-level response of a temporary negative competition shock. In particular, we provide evidence that the variable $\mathtt{Shock}_{i,t}$ –the firm-level aggregation of patent-to-standard scores– measures well the proximity of a firm to the newly set technological frontier and consequently, it captures the technological advantage of that firm with respect to others. Our empirical strategy relies on the exogeneity of the timing and magnitude of this variable, which we explore by considering the market reaction and, namely, its absence of anticipation. Then, we use $\mathtt{Shock}_{i,t}$ to assess the causal impact of standardization on various firm-level outcomes.

4.1 Empirical model

Our goal is to analyse the response of firms to standardization shocks. To do so and to better tailor our empirical strategy, it is important first to understand how the standardization procedure works in practice, the timing of events and which information are at our disposal.

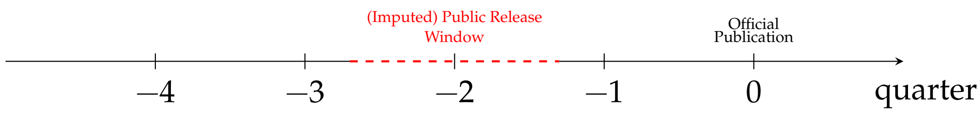
We can briefly summarize the administrative path of a standard as follows.[8] Once the standard is proposed and drafted, it goes under the scrutiny of a committee. This first phase concludes with a vote. If the committee's vote is positive, then the draft of the standard is publicly released and circulated to other sub-committees, external commit-

[8]As a reference, see the International Standard Organization website.

tees of experts, other national or international standards' organizations for comments. Thus, it is in this very moment that information on the content of the standard becomes of public knowledge. In the following phase –which lasts 3 months– suggestions and comments are collected. If no substantial critique is raised, the final version of the draft will be immediately approved and published within the next 6 weeks. On the contrary, if some revision is needed or some further analysis is required, then the process is extended in order to give the proposing organ some extra-time (2 to 3 months) to comply with the specific requests. Then, the committee has 2 months to judge the revision to the document. If the new draft of the standard is satisfying, then it is approved and published within the following 6 weeks.

Given our data-mining methodology, we are considering only published standards, i.e. standards that successfully passed the entire process. For these standards, we have only information on the exact publication date, but none on the date at which the first version was made publicly available after the initial (positive) vote. However, we have knowledge of the approval procedure such that we can back up for each standard the time-window in which the first draft became of public knowledge, i.e. roughly between (minimum) 4 and (maximum) 8 months before the final publication date. Figure 1 sketches the timeline (in quarters) of the administrative procedure of standards' approval along with the official publication date in black and the imputed time-window of public release of the first version of the standard in red. As shown, if the publication occur in time 0, the first (imputed) public release of the standard occurs in a time-window around quarter -2.

Figure 1: THE TIMING OF STANDARDS APPROVAL



Notes: This Figure sketches the administrative procedure of standards' approval. The official date of publication of the standard on the organization gazette is known and occur at quarter 0. Given information on the administrative procedure of approval and publication of a standard, we back up the (imputed) time-window in which the judging committee voted in favor of the standard and made the standard's draft available to public information. This happens roughly around −2, i.e. 2 quarters before the official publication date.

Given this procedural information, we can now introduce our empirical model to assess the impact of a standardization shock on firm dynamics. Yet, it is important to stress that different standards can be released in subsequent periods such that firms can receive multiple shocks throughout time. Therefore, in order to better isolate the effect of a specific shock, we resort to a distributed lead-lag model (see e.g. Aghion et al. (2018) for a similar application). The main interest of this approach with respect to a static analysis is that it allows to capture the full dynamic of the response. In particular, in our setting, we know that a static model would be biased since the firm's response could be affected also by subsequent and previous shocks. Our generic model is described in equation (2):

$$Y_{i,t} = \alpha_i + \phi_s + \delta_t + \phi_s \times \delta_t + \sum_{n=-12}^{N=16} \beta_n \mathtt{Shock}_{i,t+n} + X'_{i,t-1}\eta + \varepsilon_{i,t}, \tag{2}$$

where $Y_{i,t}$ is the firm-level dependent variable under consideration. α_i is a firm fixed effect, ϕ_s a NAICS 3-digit industry fixed effect and δ_t is a time fixed effect. The interaction $\phi_s \times \delta_t$ controls for any time effect that might differ across industries (e.g. because of sector specific demand variation, seasonality, changes in legislation at the industry level, momentum, etc.). $\mathtt{Shock}_{i,t}$ expresses the proximity of the stock of patents of firm i at time $t-4$ to the standard publicly released at t. We include 12 lags and 16 leads of the information shock (recall that the time unit here is a quarter). Finally, $X_{i,t-1}$ is a vector of control variables (which we discuss later) and $\varepsilon_{i,t}$ is the error term, which we assume to be normally distributed (conditional on all our covariates) and to be independent across different i.

In this model, β_n measures the effect of a shock happening at $t+n$ on the value of Y measured at t, controlling for the effect of all previous and future shocks. Our identification strategy relies on the assumption that the variable $\mathtt{Shock}$ is not correlated with previous realization of Y. We will check that the response of the firm to future shocks remains insignificant and will present our results by plotting the values of $\hat{\beta}_n$ for all n, along with its 95% confidence interval.

4.1.1 Exogeneity of the standardization shock

The potential to innovate is heterogeneous across firms (see Baumol, 2002 and Griliches, 2007) and this certainly matters for standardization. In fact, we can imagine that firms innovating more could be more likely to see their patents becoming the grounding of future standards. In this sense, we can think to standardization as a long-run endogenous process. However, in the short-run, the timing and outcome of the standardization can be considered exogenous to the firm. In fact, firms do not know when the standard will be released, its content and to which extent their stock of patent match the frontier defined by the standard itself. This fact is key for our identification. We dedicate this section to demonstrate that the standardization shock (i.e. the magnitude and timing of the variable $\mathtt{Shock}_{i,t}$) is indeed unexpected and exogenous.

To show this, we look at how financial markets and operators react when the content of a standard becomes public. In fact, if markets are efficient (e.g., see Eberhart et al., 2004, Daniel et al., 1998, Mitchell and Stafford, 2000) and the release of the first version of the standard –along with its content– is unexpected, we should observe movement in stock market returns and changes in market expectations around that date. In order to test this, we consider our baseline lead-lag model of equation (2) using two alternative dependent variables aiming at capturing markets reaction:

1. the abnormal return over a NAICS3-industry portfolio, i.e. $ar_{i,t}^{NAICS3}$;

2. the change in the 1-year EPS forecast from professional agencies, i.e. $\Delta\mathbb{E}[EPS_{i,t+4}] = \mathbb{E}[EPS_{i,t+4}|\mathbb{I}_t] - \mathbb{E}[EPS_{i,t+4}|\mathbb{I}_{t-1}]$, where $\mathbb{I}_t$ is the information-set available to professional forecasters in that period.[9]

The vector of controls $X_{i,t-1}$ includes age, q-value of investment, leverage and market capitalization of firm i along with a dummy variable taking value one if the firm is operating in a high-tech industry. We consider these variables to take into account respectively for how long a firm has been listed, its growth opportunities, its capital structure, market value and whether it is already working in an innovative sector. As explained in Chan et al. (1990) and Szewczyk et al. (1996), these characteristics are important for the magnitude of the stock-market reaction following abnormal R&D activity or other innovation-related events.

Figure 2a plots all estimated β_n (along with 95% confidence intervals) for the dependent variable $ar_{i,t}^{NAICS3}$. Standard errors are double-clustered at NAICS3 level and date since the release of a new standard has implication at industry level, with contemporaneous effects on all firms operating in the same industry and period. The red area indicates the imputed time-window of public release of the standard's content, based on knowledge of the procedure of approval. The red-dashed line indicates the official publication of the standard, as reported in the gazette of the standards' organization.

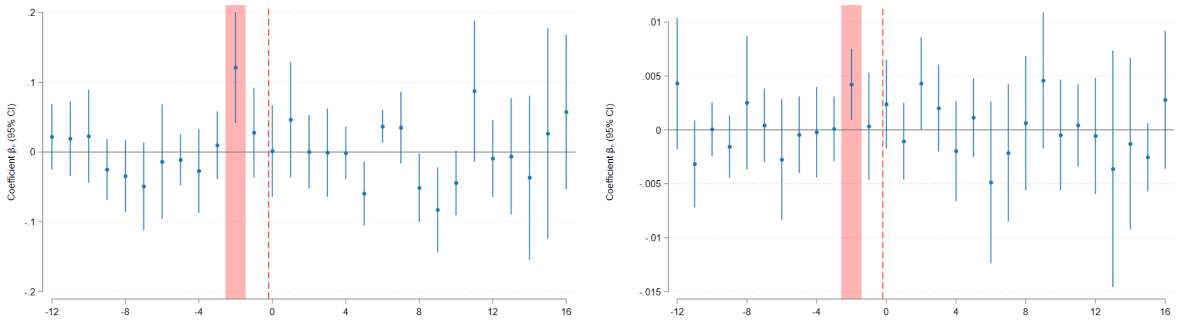
Until the (imputed) public release of the standard, the estimated coefficients are not significantly different from zero, i.e. there is common pre-trend across firms. At $t = -2$, the estimated β is positive and significantly different from zero, which indicates that firms whose patents are closer to the standard over-perform on the stock market and exhibit unprecedented returns. This proves that markets efficiently internalize the proximity of the firm to the technological content of the standard only at the moment of the information release. In Figure 2b, we use the change in the 1-year EPS forecast as dependent variable. Also in this case, we do not observe any pre-trend, but we find that professional forecasters indeed updated their expectations over the future EPS precisely at the public release of the standard. In words, once the information is public, firms whose stock of patent is closer to the standard are now expected to have a higher EPS in one year.

In Appendix C.1 we show that these results hold also when abnormal returns are extracted with other methodologies (e.g. using the SP500 as measure of market portfolio or through the French-Fama 3-factor model). On the other hand, we do not find that

[9]Since the release of a new standard can affect returns and expectations of all firms in the same industry and period, we normalize both dependent variables respectively by the volatility of the NAICS3-industry portfolio and EPS forecast in that period.

Figure 2: STANDARDIZATION SHOCK AND FINANCIAL MARKETS' REACTION

(a) ar^{NAICS3} (b) $\Delta\mathbb{E}(EPS)$



Notes: Figure 2a plots the estimated coefficients of equation (2) when the dependent variable is the firm-leve abnormal return computed through the CAPM model with market portfolio defined at the NAICS3 industry level. Figure 2b plots the estimated coefficients when the dependent variable is the change in the 1-year EPS forecast. See Section 2.3 for more information on variables construction. In both Figures, the 95% confidence intervals for each point-estimate is reported. Standard errors are double-clustered at (NAICS3) industry level and date. The red area indicates the imputed time-window of public release of the standard's content, based on knowledge of the procedure of approval. The red-dashed line indicates the official publication of the standard, as reported in the gazette of the standards' organization.

professional forecasters review their EPS expectations over a longer horizon.[10]

In light of this evidence, we conclude that the timing and content of the information shock is exogenous to investors and operators, who internalize it and react to it only at the moment of the information disclosure.

4.1.2 Implications for Sales and Market Shares

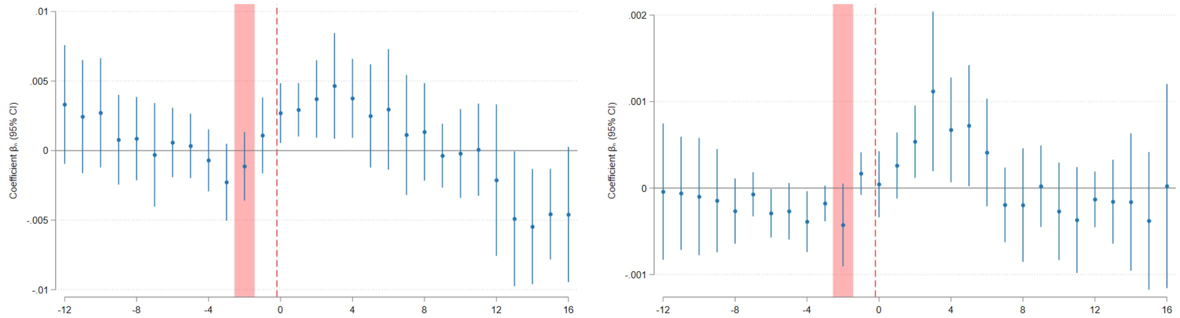
Why do markets appreciate more those firms that are closer to the new technological frontier? What does the standardization shock stand for? Typically, in the context of a corporate event, market reacts accordingly by discounting today the future cash-flows following the event itself. In this section we investigate whether this is the true also in the context of a standardization shock. In particular, we study what are the real effects of the shock on sales and market shares.

To do so, we reconsider our baseline lead-lag model of equation (2), but with the normalized value of sales as dependent variable. As from Figure 3a, after the official date of publication of the standard, firms with a stock of patents closer to the new technological frontier starts to sell more. This increase of sales is positive and significantly different from zero (at the 95% level of significance) for five consecutive quarters. In other words, the firm that is closer to the new technological frontier generates higher cash-flows through higher sales. Now, it is important to understand if the increase in sales is due to an overall expansion of the market following the standardization shock

[10] This is consistent with the dynamic of sales and its persistency observed after the publication of the standard. See Section 4.1.2

Figure 3: STANDARDIZATION SHOCK, SALES AND MARKET SHARE

(a) Sales (b) Market Share



Notes: Figure 3a and 3b plot the estimated coefficients of equation (2) (see Section 4.1) when the dependent variable is respectively the level of sales (normalized by the mean-level of fixed assets) and the firm-level market-share defined at NAICS3 industry level. See Section 2.3 for more information on variables construction. In both Figures, the 95% confidence intervals for each point-estimate is reported. Standard errors are double-clustered at (NAICS3) industry level and date. The red area indicates the imputed time-window of public release of the standard's content, based on knowledge of the procedure of approval. The red-dashed line indicates the official publication of the standard, as reported in the gazette of the standards' organization.

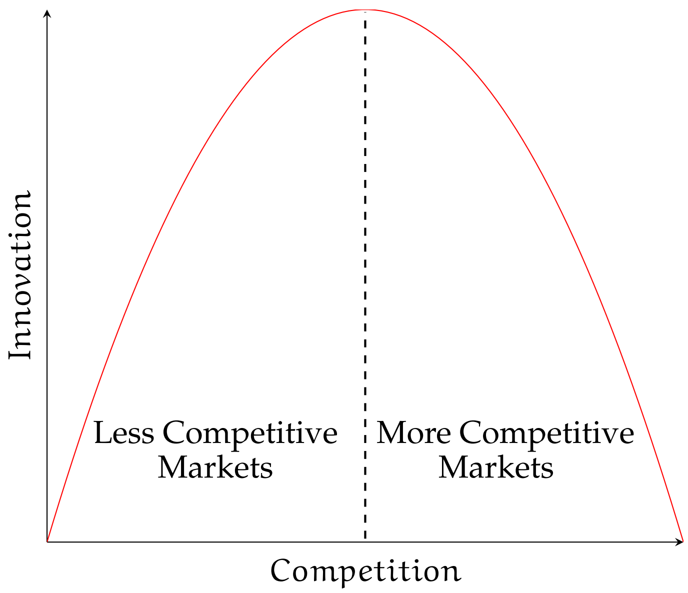
(*demand effect*) or whether the shock leads also to gains in terms of market shares (*competition effect*). To check this, we reconsider the same model but with the firm-level market share –defined at NAICS3 level– as dependent variable. As shown in Figure 3b, firms that are closer to the frontier experience also a significant –but temporary– expansion of their market share. In other words, the shock can affect competition and market concentration for roughly one year and a half.

Can we better quantify the effect of standardization? Given the way we build the shock, it is hard to interpret the estimated coefficients of Figure 3a and 3b. For this reason, we re-estimate equation (2) but including in the sample only firms with a zero-shock or a shock above the 75$^{\text{th}}$ percentile of the distribution of positive shocks. Moreover, instead of the continuous variable $\mathtt{Shock}_{i,t}$, we use the dummy $\mathbb{I}[\mathtt{Shock}_{i,t} > 0]$ as explanatory variable in the regression. Thus, we can measure the (average) effect of standardization on sales (now in logs) and market share for frontier firms vis-á-vis to firms not affected by standardization at all. By summing up the estimated β_n for the first four quarters after the shock, we find that frontier firms increase sales and market share respectively by 6.0% and 5.6% by the end of the first year after the publication of the standard.

In Appendix C.2-C.6, we show that these results hold also when clustering errors at the firm-level, when including non-listed firms in the sample, when excluding the top 20% of most innovative firms in each industry, when considering the standardization shock at the intensive margin (which demonstrates that proximity to the new standard really matters), when using another semantic measure for the computation of the shock.

To conclude, these evidence suggests that the publication of a standard attributes a comparative advantage to those firms with a stock of patents closer to the new technological frontier. This advantage translates into higher sales and higher market shares.

Figure 4: Aghion et al. (2005): Innovation vs. Competition



Notes: This graphs summarizes the empirical and theoretical results of Aghion et al. (2005). In particular, see page 706 of the paper.

For this reason, we claim that a standardization shock operates on the market as a (negative) temporary competition shock.

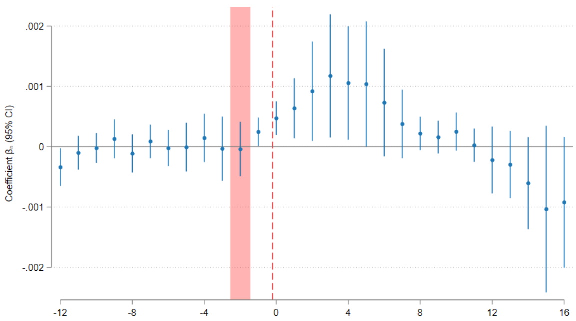
4.1.3 Implications for R&D and CapX Expenditure

If the shock leads to higher sales and market shares, it may affect also firm-level incentives to invest and innovate in the future. In fact, as we know from the growth literature, firms not always exploit the economic premium of innovation to foster further investments and growth. This mostly depends on the level of competition each firm is facing on the market. In fact, as explained in Aghion et al. (2005), there exists a theoretical and empirical inverted u-shaped relationship between innovation and competition. For convenience, we plot this relationship in Figure 4. If a firm is operating in a non-competitive market (the left-hand side of the curve), any increase (decrease) in competition incentivizes the firm to increase (decrease) investments in innovation as this will move the firm away from a near-monopolistic situation. Conversely, if a firm is operating in a competitive market (the right-hand side of the curve), any increase (decrease) in competition incentivizes the firm to decrease (increase) investments in innovation. We leverage on this result to corroborate the fact that a standardization shock is indeed a negative competition shock. In other words, we should observe heterogeneous investment responses to standardization depending on the degree of competition that each firm is facing.

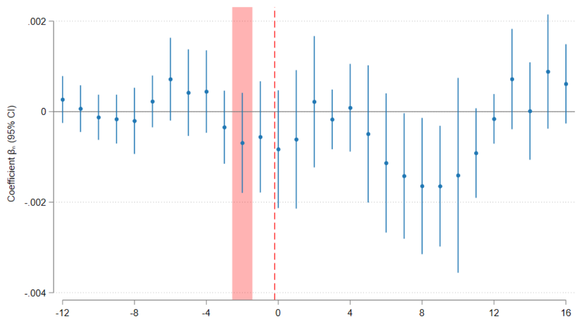
To investigate this, first we need to define competitive and non-competitive markets.

Figure 5: STANDARDIZATION SHOCK, R&D AND CAPX

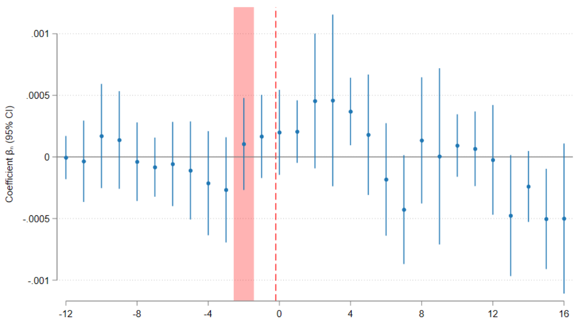
(a) R&D (Competitive Ind)



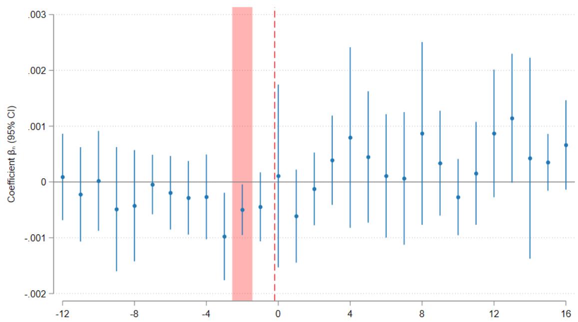
(b) R&D (Non-Competitive Ind)



(c) CapX (Competitive Ind)



(d) CapX (Non-competitive Ind)



Notes: Figure 5a and 5b plot the estimated coefficients when the dependent variable is the 4-quarter moving average of R&D expenditure (normalized by the mean-level of fixed assets) and the sample is composed respectively by firms operating in a competitive and non-competitive industry. Figure 5c and 5d plot the estimated coefficients when the dependent variable is capital expenditure (normalized by the mean-level of fixed assets) and the sample is composed respectively by firms operating in a competitive and non-competitive industry. See Section 2.3 for more information on variables construction. In all Figures, the 95% confidence intervals for each point-estimate is reported. Standard errors are double-clustered at (NAICS3) industry level and date. The red area indicates the imputed time-window of public release of the standard's content, based on knowledge of the procedure of approval. The red-dashed line indicates the official publication of the standard, as reported in the gazette of the standards' organization.

For this we follow the work of De Loecker et al. (2020), which studies markups across industries (see data description in Section 2.3). Then, we split industries in those that historically have a markup above the 75$^{\text{th}}$ percentile (non-competitive industries) and those below (competitive industry). We then use our lead-lag model to study the impact of the standardization shock on R&D and CapX investments in competitive and non-competitive industries. If the standardization shock is really a negative competition shock, we should find asymmetric results across the two groups of industries. As shown in Figure 5a, firms operating in a competitive industry and closer to the technological frontier invest more in R&D when the standardization shock realizes. This effect starts already in the same quarter of the official publication of the standard and lasts one year and a half. Conversely, when considering non-competitive industries, as in Figure 5b, we find that firms do significantly cut R&D expenditure starting from six quarters after the publication of the standard. Now, we repeat the same analysis with CapX as dependent variable. As shown in Figure 5c, firms operating in a competitive industry and closer to the new technological frontier significantly increase capital investment four quarters after the official publication of the standard. Conversely, when considering non-competitive industries, as in Figure 5d, we find that the standardization shock leads to a decline in capital investment already around the imputed date of release of the first version of the standard. As shown in Appendix C.2-C.6, these results hold to the same robustness checks previously listed.

All in all, these asymmetric responses corroborate the idea that our standardization shock is a temporary (negative) competition shock that gives a comparative advantage to frontier firms. Since their stock of patents better comply with the standard, they are able to expand their market share and –if the market was very competitive before the shock– they invest more in R&D and CapX in order to reinforce and protect their position.

Yet, it is important to mention that –when considering all firms in the sample– the increase in CapX and R&D is the dominating effect. In order to quantify the effect of standardization on these variables, we repeat the same analysis explained at the end of Section 4.1.2, which compares frontier firms to firms not directly affected by the standardization shock. In this case, we find that frontier firms increase R&D and CapX respectively by 4.4% and 7.2% by the end of the first year following the publication of the standard.

5 Conclusion

This paper studies how standardization –i.e. the selection and adoption of a new technology at the industry level– affects firm's dynamics, competition and innovation. The contribution of the paper is twofold.

First, we use semantic algorithms to match the content of patents to the content of standards. This methodology allows to measure the proximity of each patent to the new technological frontier imposed by the standard, and –therefore– the effective adoption of specific patents at industry scale. We show that the information retrieved from the semantic matching is meaningful as patents closer to the content of a standard are more cited after the standard release, are associated with greater economic value and get renewed more often.

Second, we cross this novel measure with firm-level data to study (i) to which extent the timing of release and content of a new standard are exogenous to the firm, and (ii) how firm dynamics change depending on the proximity of the firm's stock of patents to the new standard.

We address these questions through a dispersed lead-lag model, which captures the entire response following the release of a new standard. Under this strategy, we show that financial markets do not anticipate the timing and content of a standard. In fact, markets react only at the very moment at which information on the new standard become public. This evidence of exogeneity is key to identification strategy.

What does the shock represent? We show that firms closer to the new standard temporary gain in terms of sales and market shares once the standard is published. This suggests that standardization can be considered as a competition shock since it gives a temporary comparative advantage to those firms that have the technology and knowledge to immediately adjust to the standard specifications. As a consequence, we also observe heterogeneous reaction across firms. In markets with high level of competition, firms closer to the new technological frontier invest more and do more R&D after the release of the standard, in line with Aghion et al. (2005).

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ONLINE APPENDIX

A Data

A.1 Standards data

Variables used. We rely on the following information from a Perinorm dataset, which is part of the Searle Centre Database on Technology Standards and Standard Setting Organizations (see Baron and Spulber, 2018). In particular, we use the following information:

- *Identifier*: Each standard document is registered with a unique identifier from Perinorm.
- *Publication date*: The date of the release (publication) of the standard by the respective SSO.
- *Equivalences*: A standard can be released by several SSOs. Indeed, the internationalization of the standard-setting process where the bulk of standards originates in supranational SSOs such as European SSOs (ETSI, CEN, CENELEC) or international SSOs (ISO, ITU, IEC) results in the co-existence of equivalent standards in Perinorm. A standard developed by an international SSO is often accredited by national SSOs to include it in the national standard catalogue. Similarly, accreditations by several SSOs in the same country can be observed, often due to the standard being developed jointly by two or more SSOs. Two standards can be considered equivalent if their content are the same, but they often differ with respect to the release date and the language used in the standard document.
- *Version history*: Standards are constantly updated and several versions can succeed or supersede a previous version. In the latter case, a subsequent standard explicitly replaces a former version whereas the former case implies just a simple update. SSO-specific norms determine the details. Given some of the technical complexities, it is also possible that several standards share a common previous version because standard projects are split into different directions.
- *ICS classification*: The International Classification of Standards is a classification system maintained by the International Organization for Standardization, aimed at covering all possible technical or economic sectors that standards are govering. The ICS classes are composed of three levels, the first one (two digits) designating a general field such as 49 – Aircraft and space vehicle engineering, followed by a second level (three digits) such as 49.030 – Fasteners for aerospace construction, and sometimes a third level (two digits) such as 49.030.10 – Screw threads.
- *Keywords*: Perinorm is a bibliographical database, which allows subscribers to search for a standard and to purchase the standard document. To facilitate the search, keywords have been assigned to each standard document. These comprise both 1-grams such as "automation" or 3-grams such as "internal combustion engine".

Cleaning. We clean the standards data, in particular with respect to the publication dates, the equivalences, the version history, ICS classification as well as the keywords.

For some publication dates, the month or the day of the date are missing in which case we assume December for the month and 28 for the day, thus implicitly favoring standards for which the date information is complete.

For some of the equivalences, there is additional information on whether a standard is identical/equivalent or not equivalent. As we want to regroup only those standards that are identical, we correct the list of equivalences and exclude non-equivalent standards. Du to misreporting or chronological reporting, a single standard observation does not necessarily reveal all equivalences. In the case of chronological reporting, only equivalences known at the time of the release are listed and subsequent equivalences are only reported for newly released standards. The identification of equivalent standards is implemented with the algorithm described below.

We take the list of standard identifiers that constitute the version history of each standard document and identify prior versions by comparing the publication dates of these identifiers with the standard document in question. If there is at least one standard with prior publication date in the version history, the standard is not considered a first version.

ICS classifications can be erroneous and are cleaned to only include official codes, respecting the format designed by the ICS.

Keywords are cleaned and processed as described in appendix B below.

Identifying equivalences. We use graph theory to identify all standards that belong to one group by assigning them the same group identifier. In particular, we use the following breadth-first search algorithm (which we specifically adapt to the structure of the dataset) to connect all standards by exploring their equivalences:

1. Initialize the group identifier, equal to a standard's row number in the dataset, for each standard.
2. Starting with $n = 1$, store the group identifier of standard n in the database (i.e. A).
3. Add the group identifiers of the equivalent standards, i.e. B, to the vector of stored group identifiers.
4. Note the smallest element of the vector of stored group identifiers.
5. Modify the group identifiers of standard n and its equivalent standards by assigning them the value identified in step 4 (i.e. A and B will have the same group identifier).
6. Delete the stored group identifiers.
7. Go on to the next standard $n + 1$ and repeat from step 2 onwards.

In order to minimize the computing power needed to run the algorithm, we use a simple hash function to build a dictionary of all standards whose IDs, which are strings, are mapped one-to-one to numeric values.

Relevant subset and grouping of keywords. For each group of standards (defined as regrouping all equivalent standard documents), we exclude within-country duplicate standard releases, only keeping the earliest standard release. We then restrict the sample to first versions only. All ICS and keywords are aggregated on the level of the group identifier. Only unique keywords are kept to avoid double counting due to the fact that a group includes a large number of individual, equivalent standard documents.

B Matching

B.1 Matching procedure

B.1.1 Brief outline of the matching procedure

Our goal is to find the patents that are the "closest" to a given standard. Our approach relies on the set of keywords associated with a standard, which we take to be a sufficient information set to describe the standard, and on the abstract of patents. More specifically, for each standard, we scan our patent database and give a score for each patent that reflects how relevant these standard's keywords are to describe the patent's abstract. One of the main challenge with this type of large scale data mining approach is to design a method that is suitable for big data (there are around 0.8m standards and 1.9m patents in our dataset). We briefly present our approach below.

The standard database includes, among others, a standard identifier, the title, a release date and a number of keywords that were manually provided by `Perinorm` staff when incorporating a standard into the database. For example, the Austrian standard AT98957039 with the title "OENORM Aerospace series - Nickel base alloy NI-B15701 (NiPd34Au30) - Filler metal for brazing - Wire" is included in the database with the following keyword information:

standard id	date	ICS	keywords
AT98957039	01/07/1997	49.025.15	Aerospace transport⋆Air transport⋆Brazing alloys⋆Nickel base alloys⋆Space transport⋆Wires

We process these keywords as follows.

1. **Stemming and cleaning keywords**: this first step consists in "normalizing" the set of keywords contained in each standard by removing upper-case letter, punctuation and "stop-words" (*the*, *at*, *from* etc...). We then keep only the stem of each word.[11]

2. **Constructing k-grams**: the second step consists in associating successive stems into one unique semantic unit. These "multi-stems", or *k-grams* are constructed

[11] Families of words are generally derived from a unique root called stem (for example *compute*, *computer*, *computation* all share the same stem *comput*).

as groups of size k, with $k \leqslant 3$. The rationale from considering group of words can be illustrated with the example of a standard containing "air conditionning" as one of its keywords. If we do not consider k-grams in addition to single stems, then we would be screening the patent database for the stems *air* and *condition*, which are clearly irrelevant in that case. Thus, at the end of this procedure, we can associate for each standard j a set $\mathcal{A}(j)$ of 1-grams, 2-grams and 3-grams taken from its keywords.[12]

3. **Computing Inverse Document Frequency**: we then associate for each k-grams $l \in \bigcup_{j \in \mathcal{J}} \mathcal{A}(j)$ a quantity that seeks to measure how frequent this k-gram is. This is known as the inverse document frequency and is defined as follow:

$$\mathrm{IDF}(l) \equiv \log \left(\frac{1 + |\mathcal{J}|}{1 + \sum_{j \in \mathcal{J}} \mathbb{1}\left(l \in \mathcal{A}(j)\right)} \right)$$

   Where $\mathbb{1}(X)$ is equal to 1 if X is true and $|\mathcal{J}|$ is the cardinal of $\mathcal{J}$ (the number of standards). In other words, $\mathrm{IDF}(l)$ is calculated from the inverse of the share of standards that contains k-gram l.

4. **Removing uninformative k-grams**: from the set of k-grams l and their associated IDF, we further restrict the sample by removing k-grams whose IDF is below a given threshold T. The choice of such a threshold will be discussed below and results from a trade-off between efficiency and exhaustiveness (see Chavalarias and Cointet, 2013 and Bergeaud et al., 2017 for a discussion).

Whereas we have keywords already provided in the standards database, this is not the case for the patents where we rely on their abstracts to extract keywords as described further below. The EPO patent EP0717749A4 with the title "Self-addressable self-assembling microelectronic systems and devices for molecular biological analysis and diagnostics" is included in the database with the following information:

```
patent id     date         IPC         abstract
49188362      25/01/2000   G01/C40     A self-addressable,
                                       self-assembling
                                       microelectronic device is
                                       designed and fabricated to
                                       actively carry out and
                                       control multi-step and
                                       multiplex molecular
                                       biological reactions ...
```

We use these abstracts to form k-grams contained in the abstract of patents by considering all possible combinations of words in these continuous up to k-grams of 3 words.

[12] One might wonder why we do not consider groups of words as they appear in the standard's keywords list. The reason is that we still believe that matching part of a k-grams still bring some information. Consider the (real) case of a keyword "ISO screw thread", then a patent containing the 2-gram "screw thread" is still highly relevant.

We proceed to the same cleaning and stemming procedure as for standards' keywords. Patent abstracts contain on average [XXX JULIA XXX] XX words, and YY k-grams once cleaned (here again, $k \leqslant 3$). Note that contrary to other studies that have used semantic analysis on patents' abstract (see e.g. Bergeaud et al., 2017 or more generally regarding patents Adams, 2010), we are not doing anything to select words based on their grammatical functions in the abstract. This is because the number of standards' keywords is limited and there is no need to reduce the size of the patents' abstracts to improve the performance of the algorithm.

B.1.2 Measuring distance

Once the procedure detailed above is done, we are left with a set of patent $i \in \mathcal{P}$ and a set of standards $j \in \mathcal{J}$. For each patent i, we denotes the set of extracted k-grams by $\mathcal{B}(i)$ while for each standards j, we denotes the set of k-grams by $\mathcal{J}(j)$. We then compute a score $S(i,j)$ for each pair of patent and standard based on the semantic proximity between $\mathcal{B}(i)$ and $\mathcal{A}(j)$. In constructing this score, we keep several criteria in mind:

- We want to give more weight to keywords that have a high IDF since they are more likely to be useful in describing the specificity of a given standard.
- We want to favor a patent whose abstract matches different keywords rather than a patent that match the same keyword several time.[13]. We therefore only consider keywords once even if they show up several times in a patent abstract.
- We want to value the length of the matched k-grams (i.e. a matching 3-gram will have more relevance than a matching 1-gram).

We thus considered five scores that more or less reflect those criteria. Starting from the simplest possible one:

$$S_1(i,j) = \sum_{l \in \mathcal{A}(j)} \sum_{k \in \mathcal{B}(i)} \mathbb{1}(l = k) \mathrm{IDF}(l) \tag{B.1}$$

$$S_2(i,j) = \sum_{l \in \mathcal{A}(j)} \frac{n(k,i)}{|\mathcal{B}(i)|} \mathrm{IDF}(l) \tag{B.2}$$

$$S_3(i,j) = \sum_{l \in \mathcal{A}(j)} \frac{n(k,i)}{|\mathcal{B}(i)|} \mathrm{IDF}(l)\,(|\mathcal{A}(j) \cap \mathcal{B}(i)|) \tag{B.3}$$

$$S_4(i,j) = \sum_{l \in \mathcal{A}(j)} \left(\frac{n(k,i)}{|\mathcal{B}(i)|}\right)^{s(l)} \mathrm{IDF}(l)\,(|\mathcal{A}(j) \cap \mathcal{B}(i)|) \tag{B.4}$$

$$S_5(i,j) = \sum_{l \in \mathcal{A}(j)} \sqrt{\left(\frac{n(k,i)}{|\mathcal{B}(i)|}\right)^{s(l)}} \mathrm{IDF}(l)\,(|\mathcal{A}(j) \cap \mathcal{B}(i)|) \tag{B.5}$$

[13] Indeed, a patent abstract $\mathcal{B}(i)$ can contain the same k-gram several time.

where we have denoted

$$n(l,i) \equiv \sum_{k \in \mathcal{B}(i)} \mathbb{1}(l = k)$$

the number of times k-gram l appears in $\mathcal{B}(i)$. The first score S_1 in (B.1) simply counts the number of times a k-gram in $\mathcal{A}(j)$ appears in patent i's abstract, weighted by the inverse document frequency of this k-gram. The second score S_2 in (B.2) standardizes this score by the length of patent i's abstract $|\mathcal{B}(i)|$, and score S_3 in (B.3) adds a multiplicative term for the number of common k-grams between $\mathcal{A}(j)$ and $\mathcal{B}(i)$. Score S_4 in (B.4) adds a power terms $s(l)$, which returns the length of the k-gram l ($s(l) = 1, 2$ or 3) to the number of concurrences between $\mathcal{A}(j)$ and $\mathcal{B}(i)$ so as to give more weights to longer k-grams. Finally, score S_5 in (B.5) adds a concave function to reduce the impact of the term frequency in the patent to increase the impact of the number of distinct common keywords. From now, we will only consider score S_5 as a way to measure proximity between patents and standards but see Appendix C.6 for results using alternative shocks.

B.1.3 Implementation in practice

The size of the databases poses technical difficulties. Because there are more than 21 million priority patents and over 640,000 unique standard documents, we are faced with over 1.4×10^{13} possible matches. We proceed as follows. We first extract all the cleaned and stemmed k-grams from the standards keywords and store these as a dictionary with which all patent abstracts are compared in the next step. When extracting k-grams from the patent abstract, we do not store any k-grams that do not appear in our dictionary of admissible keywords obtained from the standards keywords. We do so for two reasons. First, as the goal of the keyword extraction from patent abstracts is to match those to standard keywords, we do not need to store redundant keywords as they do not match with anything that is in our standards database. Second, the keyword extraction proceeds in forming k-grams from a continuous text that has been stemmed, thus building a large number of k-grams void of sense. For example, from the sentence “The authentication procedure allows for personal data protection.” which becomes “authenticat proced allow personal data protect” after stemming, the following 3-grams are extracted from the text: “authenticat proced allow”, "proced allow personal", "allow personal data", "personal data protect" as well as the corresponding 2-grams. Only the 3-gram "personal data protect" as well as the 2-grams “authenticat proced”, “personal data” and “data protect” are probably meaningful, which is why the use of a pre-defined dictionary as a benchmark is warranted.

After extracting all keywords for each standard, we regroup all associated standard identifiers. We store for each unique keyword in the standards database its associated IDF and a list of all standard ids that correspond to this keyword. We do so similarly for the patent database and store additionally for each associated patent id the number of occurrences of the keyword in the patent abstract as well as the total number of keywords per patent id. Equipped with these two lists, we can match patents to standards by simply building the Carthesian product of the associated standard identifiers and the associated patent identifiers of each keyword. We then add up all patent-standard combinations across all common keywords to compute the scores as described above.

B.2 Matching of ICS and IPC classes

One way to evaluate the quality of our matching procedure is to verify how individual patent-standard matches relate broad categories of the IPC (patents) and ICS (standards) classifications. Essentially, we are linking the two classification systems on the basis of the individual matches obtained in our matching procedure. For the IPC classification, we consider the second hierarchical level, which is the IPC class, and for which 122 classes exist (for example C06 – Explosives; matches.). For the ICS classification, we consider the two-digit level which comprises 40 different ICS fields (for example 49 – Aircraft and space vehicle engineering). Summing the score over all patent-standard combinations that belong to the same IPC-ICS combinations; we obtain a concordance between the two classification systems. Table B.1 lists the closest IPC class for every ICS field.

Table B.1: ICS-IPC concordance

ICS	ICS description	IPC	IPC description
1	Generalities. Terminology. Standardization. Documentation	E04	Building
3	Services. Company Organization, Management And Quality. Administration. Transport. Sociology	G06	Computing; calculating; counting
7	Mathematics. Natural Sciences	C12	Biochemistry; beer; spirits; wine; vinegar; microbiology; enzymology; mutation or genetic engineering
11	Health Care Technology	A61	Medical or veterinary science; hygiene
13	Environment. Health Protection. Safety	C02	Treatment of water, waste water, sewage, or sludge
17	Metrology And Measurement. Physical Phenomena	G01	Measuring; testing
19	Testing	G01	Measuring; testing
21	Mechanical Systems And Components For General Use	F16	Engineering elements or units; general measures for producing and maintaining effective functioning of machines or installations; thermal insulation in general
23	Fluid Systems And Components For General Use	F16	Engineering elements or units; general measures for producing and maintaining effective functioning of machines or installations; thermal insulation in general
25	Manufacturing Engineering	B23	Machine tools; metal-working not otherwise provided for
27	Energy And Heat Transfer Engineering	G21	Nuclear physics; nuclear engineering
29	Electrical Engineering	H01	Basic electric elements
31	Electronics	H01	Basic electric elements
33	Telecommunications. Audio And Video Engineering	H04	Electric communication technique
35	Information Technology. Office Machines	H04	Electric communication technique
37	Image Technology	G03	Photography; cinematography; analogous techniques using waves other than optical waves; electrography; holography

Continuation of Table B.1

ICS	ICS description	IPC	IPC description
39	Precision Mechanics. Jewellery	A44	Haberdashery; jewellery
43	Road Vehicles Engineering	B60	Vehicles in general
45	Railway Engineering	B64	Aircraft; aviation; cosmonautics
47	Shipbuilding And Marine Structures	B63	Ships or other waterborne vessels; related equipment
49	Aircraft And Space Vehicle Engineering	B64	Aircraft; aviation; cosmonautics
53	Materials Handling Equipment	B66	Hoisting; lifting; hauling
55	Packaging And Distribution Of Goods	B65	Conveying; packing; storing; handling thin or filamentary material
59	Textile And Leather Technology	D01	Natural or artificial threads or fibres; spinning
61	Clothing Industry	A44	Haberdashery; jewellery
65	Agriculture	A01	Agriculture; forestry; animal husbandry; hunting; trapping; fishing
67	Food Technology	A23	Foods or foodstuffs; their treatment, not covered by other classes
71	Chemical Technology	F42	Ammunition; blasting
73	Mining And Minerals	E21	Earth or rock drilling; mining
75	Petroleum And Related Technologies	C07	Organic chemistry
77	Metallurgy	C23	Coating metallic material; coating material with metallic material; chemical surface treatment; diffusion treatment of metallic material; coating by vacuum evaporation, by sputtering, by ion implantation or by chemical vapour deposition, in general; inhib
79	Wood Technology	B27	Working or preserving wood or similar material; nailing or stapling machines in general
81	Glass And Ceramics Industries	C03	Glass; mineral or slag wool
83	Rubber And Plastic Industries	C08	Organic macromolecular compounds; their preparation or chemical working-up; compositions based thereon
85	Paper Technology	D21	Paper-making; production of cellulose
87	Paint And Colour Industries	B05	Spraying or atomising in general; applying liquids or other fluent materials to surfaces, in general
91	Construction Materials And Building	E04	Building
93	Civil Engineering	E02	Hydraulic engineering; foundations; soil-shifting
95	Military Engineering	F41	Weapons
97	Domestic And Commercial Equipment. Entertainment. Sports	A63	Sports; games; amusements

C Robustness Checks

C.1 Other measures for abnormal returns and EPS forecasts

In this section we provide further evidence of the exogeneity of the standardization shock by using other measures for cumulative abnormal returns.

To construct abnormal returns, now we consider two alternative statistical models. First, we consider the baseline CAPM model, with the SP500 as market portfolio. Second, we use the the French-Fama 3-factor model[14], which augments the baseline CAPM model by considering also the excess returns of small-cap companies over large-cap companies, and the excess returns of value stocks (high book-to-price ratio) over growth stocks (low book-to-price ratio).

We follow the methodology explained in Section 2.3, and estimate these two models over 10-year rolling windows. Hence, we define the abnormal return as the difference between the observed excess return of the company in this period and the one predicted from the model whose estimating windows ends in the previous period. Hence, we end up with two different measures: (i) $ar_{i,t}^{CAPM}$, i.e. the abnormal return measured through the CAPM model, and (ii) $ar_{i,t}^{French-Fama}$, i.e. the abnormal return measured through the French-Fama 3-factor model.

When using these measure as dependent variable in the empirical model of equation (2), we confirm the results of Section 4.1.1. As shown in Figure C.1a and C.1b, firms whose stock of patents is closer to the new standard experience a significant increase of cumulative returns at the (imputed) time of public release of the content of the standard.

Finally, we look at the EPS forecast over a 2-year horizon. Hence, we define $\Delta\mathbb{E}[EPS_{i,t+8}] = \mathbb{E}[EPS_{i,t+8}|\mathbb{I}_t] - \mathbb{E}[EPS_{i,t+8}|\mathbb{I}_{t-1}]$ as the change in the 2-year EPS forecast from professional agencies. As shown in Figure C.1c, in this case we do not find any effect. In words, professional forecasters do not significantly change their expectations when considering how the EPS will be two fiscal years from now. This view is consistent with the dynamic of sales observed after the publication of the standard: as explained in Section 4.1.2, sales increase only for fiver consecutive quarters.

C.2 Main results under other clustering procedure

Since standards have an impact at industry level, in Section 4.1.1-4.1.3 we chose to double-cluster errors at the (NAICS3) industry and date level in order to account for correlation of the error term for firms belonging to the same industry and "shoked" by the standard release in the same period. Here instead, we assume the shock to have a purely firm-level impact. Therefore, we cluster errors at the firm-level thus taking into account how residuals auto-correlate within each firm and over time. As shown in figure C.2, results do not change.

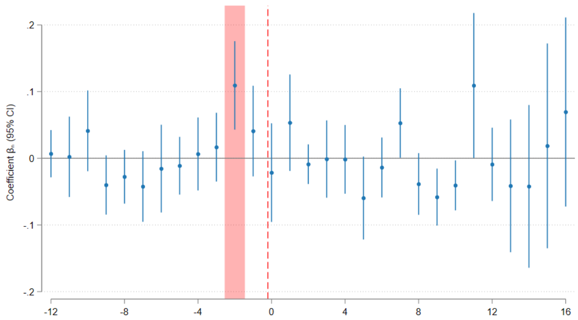
C.3 Main results including sample of non-listed firms

In Section 4.1.1-4.1.3 we consider only a sample of firms for which stock market data is available, i.e. publicly listed firms. Here, we add to the sample also firms that are not listed on the equity market. Then, we reconsider model 2 but without market capitalization and q-value of investment as control variables (they depend on stock

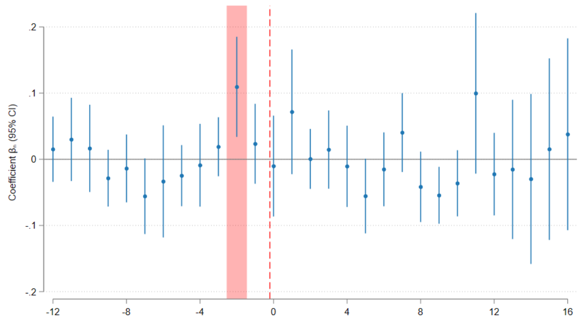
[14] Data on SMB_t and HML_t is available on the data library of Kenneth French's website.

Figure C.1: STANDARDIZATION SHOCK AND FINANCIAL MARKETS' REACTION

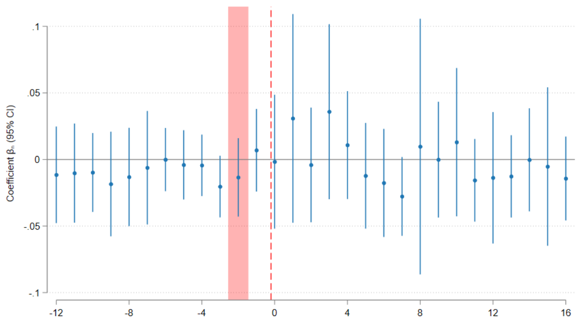
(a) ar^{CAPM}



(b) $ar^{French-Fama}$



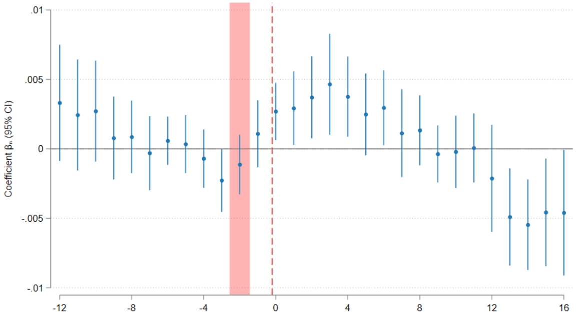
(c) $\Delta\mathbb{E}(EPS)$



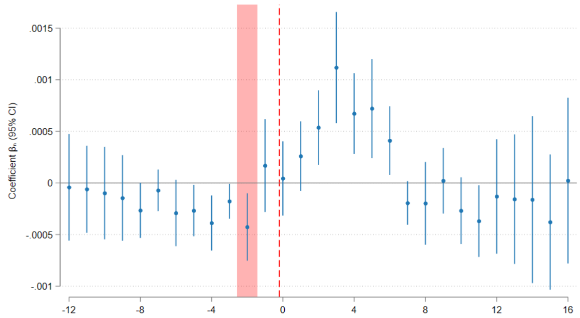
Notes: Figure C.1a and C.1b plots the estimated coefficients of equation (2) when the dependent variable is the firm-leve abnormal return computed through the CAPM model and French-Fama 3-factor model. Figure 2b plots the estimated coefficients when the dependent variable is the change in the 1-year EPS forecast. See Section 2.3 for more information on variables construction. In both figures, the 95% confidence intervals for each point-estimate is reported. Standard errors are double-clustered at (NAICS3) industry level and date. The red area indicates the imputed time-window of public release of the standard's content, based on knowledge of the procedure of approval. The red-dashed line indicates the official publication of the standard, as reported in the gazette of the standards' organization.

Figure C.2: MAIN RESULTS UNDER DIFFERENT CLUSTERING

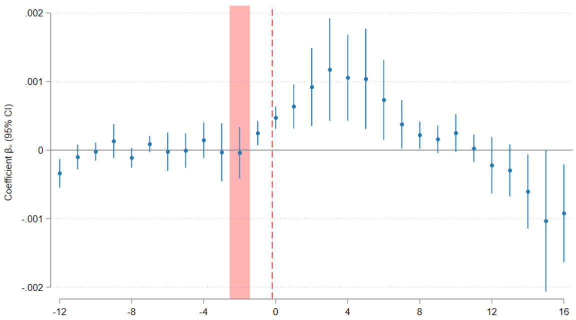
(a) Sales



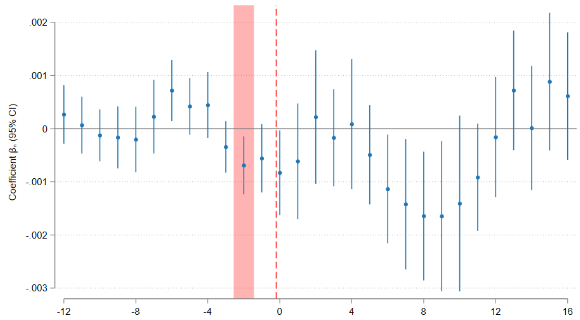
(b) Market Share



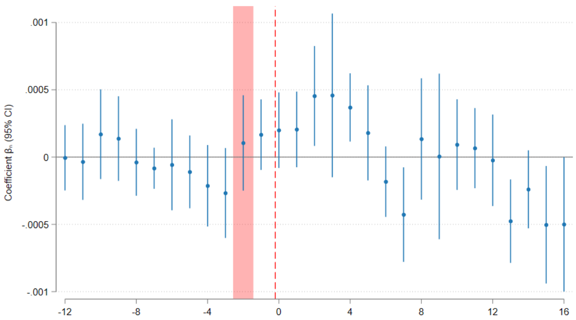
(c) R&D (Competitive Ind)



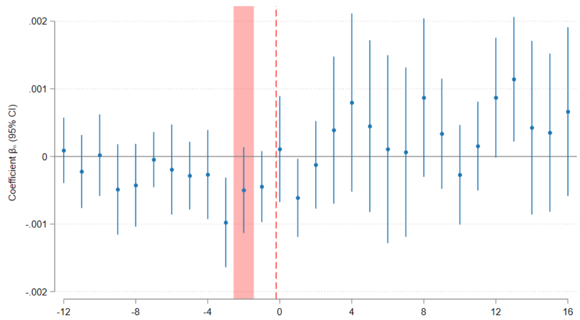
(d) R&D (Non-Competitive Ind)



(e) CapX (Competitive Ind)



(f) CapX (Non-competitive Ind)



Notes: Figure C.2a and C.2b plot the estimated coefficients of equation (2) (see Section 4.1) when the dependent variable is respectively the level of sales (normalized by the mean-level of fixed assets) and the firm-level market-share defined at NAICS3 industry level. Figure C.2c and C.2d plot the estimated coefficients when the dependent variable is the 4-quarter moving average of R&D expenditure (normalized by the mean-level of fixed assets) and the sample is composed respectively by firms operating in a competitive and non-competitive industry. Figure C.2e and C.2f plot the estimated coefficients when the dependent variable is capital expenditure (normalized by the mean-level of fixed assets) and the sample is composed respectively by firms operating in a competitive and non-competitive industry. See Section 2.3 for more information on variables construction. In all figures, the 95% confidence intervals for each point-estimate is reported. Standard errors are clustered at the firm level. The red area indicates the imputed time-window of public release of the standard's content, based on knowledge of the procedure of approval. The red-dashed line indicates the official publication of the standard, as reported in the gazette of the standards' organization.

market prices, which are available of course only for listed firms). Finally, re-estimate our results. Figure C.3 shows results. Also under this augmented sample and different set of controls, the essence of the results do not change.

C.4 Main results excluding most innovative firms

It can be that it is always the same few firms that experience a positive shock ($\text{Shock}_{i,t} > 0$) in a specific industry. In this section, we check that our results are not driven only by these group of firms. To do so, first we study how much the shocks of a single firm explain the sum of shocks received by the entire NAICS3 industry. Formally, for a firm i belonging to NAICS3 industry s, we define:

$$[\textit{Shock Concentration}]_{i,s} = \frac{\sum_t \text{Shock}_{i,t}}{\sum_{i \in S} \sum_t \text{Shock}_{i,t}}$$

as a concentration measure capturing by how much a single firm explains the total amount of shocks received by it industry across time. This variable has mean 0.9% (median equal to 0%) and standard deviation equal to 6%, which means that the average firm explain alone only 0.9% of the shocks realized in its corresponding industry. Then, within each NAICS3 industry we drop the top 20^{th} percentile of firms that explain the most the shocks received at sectorial level. Finally, we re-estimate the results of Section 4.1.1-4.1.3.

Figure C.4 shows results. Also under this sample selection, the essence of the results do not change: results are not driven by firms that consistently score more in their industry.

C.5 Intensive vs. extensive margin of the shock

As from Table 2, we know that 50% of firms receive a positive shock, i.e. they have patents whose content can be matched to a new released standard. Here, we exploit this fact to understand (i) if the intensive margin of the shock really matters or (ii) whether our results are explained by the extensive margin of the shock only.

To answer the first question, we re-estimate the results of Section 4.1.1-4.1.3 when using only the sample of firms receiving a positive shock. As shown in Figure C.5, the intensive margin matters for our results to hold, with one exception: the effect of the shock on CapX for firms operating in a competitive industry (Figure C.5e) is significant only at 90% significance level. Overall, this evidence corroborates the idea that the size of the shock –i.e. the intensity of the shock– really matters.

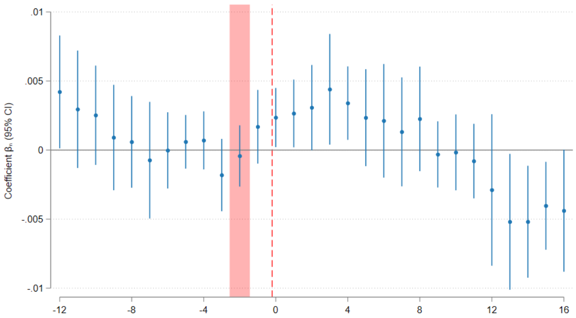
To answer the second question, we consider the entire sample of firms and we modify our empirical model of equation (2) as follows:

$$Y_{i,t} = \alpha_i + \phi_s + \delta_t + \phi_s \times \delta_t + \sum_{n=-8}^{N=20} \beta_n \mathbb{I}[\text{Shock}_{i,t+n} > 0] + X'_{i,t-1}\eta + \varepsilon_{i,t}$$

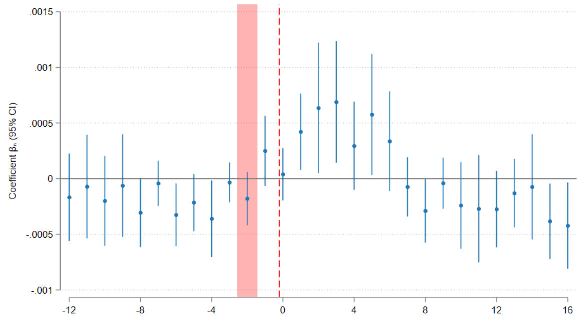
where $\mathbb{I}[\text{Shock}_{i,t} > 0]$ is a dummy variable taking value equal to one if firm i receive a positive shock at time t. We re-estimate the results of Section 4.1.1-4.1.3 under this

Figure C.3: Main Results with Non-listed Firms Included

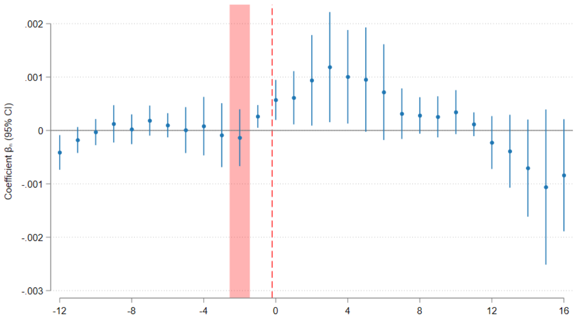
(a) Sales



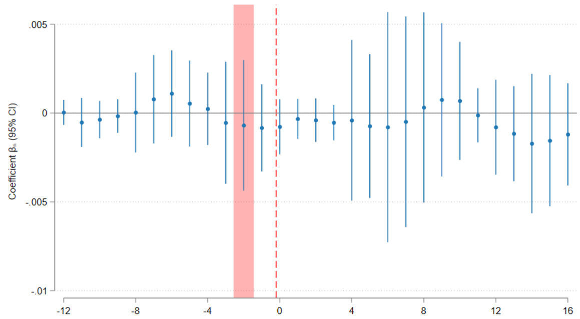
(b) Market Share



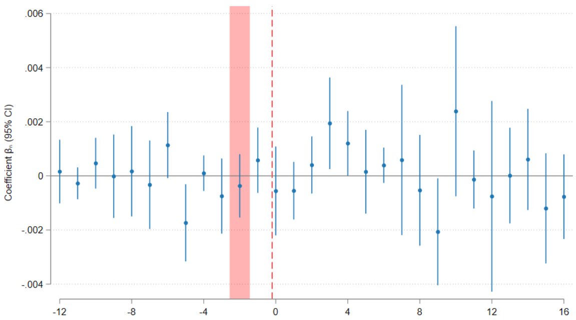
(c) R&D (Competitive Ind)



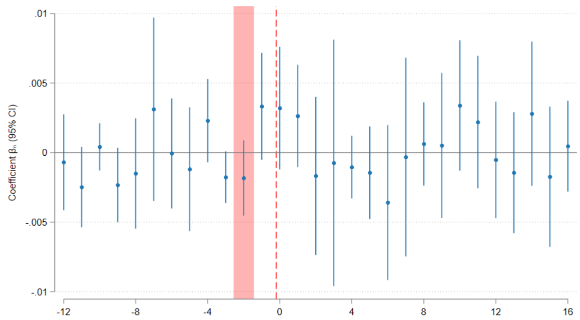
(d) R&D (Non-Competitive Ind)



(e) CapX (Competitive Ind)

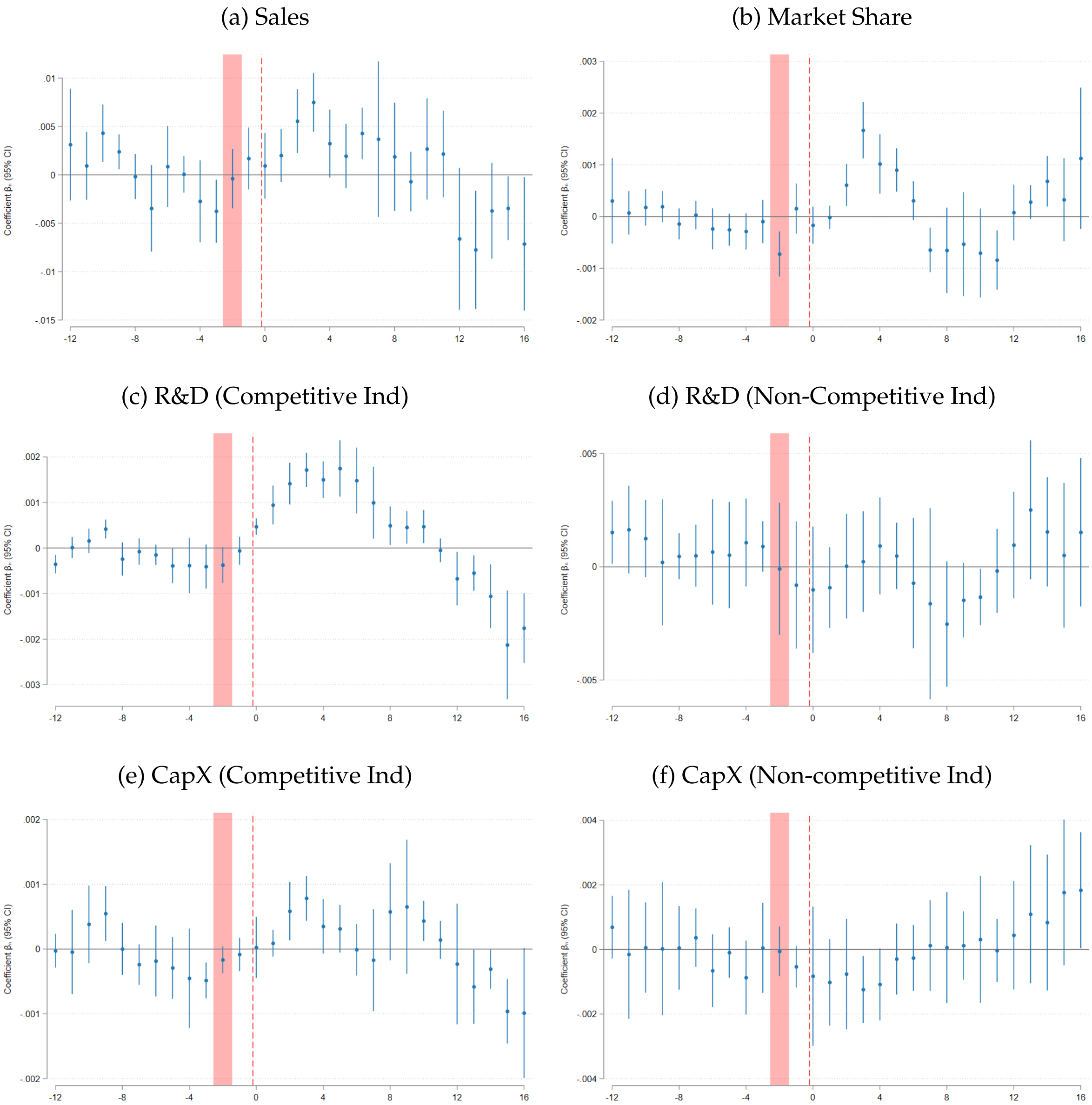


(f) CapX (Non-competitive Ind)



Notes: Figure C.3a and C.3b plot the estimated coefficients of equation (2) (see Section 4.1) when the dependent variable is respectively the level of sales (normalized by the mean-level of fixed assets) and the firm-level market-share defined at NAICS3 industry level. Figure C.3c and C.3d plot the estimated coefficients when the dependent variable is the 4-quarter moving average of R&D expenditure (normalized by the mean-level of fixed assets) and the sample is composed respectively by firms operating in a competitive and non-competitive industry. Figure C.3e and C.3f plot the estimated coefficients when the dependent variable is capital expenditure (normalized by the mean-level of fixed assets) and the sample is composed respectively by firms operating in a competitive and non-competitive industry. See Section 2.3 for more information on variables construction. In all figures, the 95% confidence intervals for each point-estimate is reported. Standard errors are double-clustered at (NAICS3) industry level and date. The red area indicates the imputed time-window of public release of the standard's content, based on knowledge of the procedure of approval. The red-dashed line indicates the official publication of the standard, as reported in the gazette of the standards' organization.

Figure C.4: Main Results with Most Innovative Firms Excluded



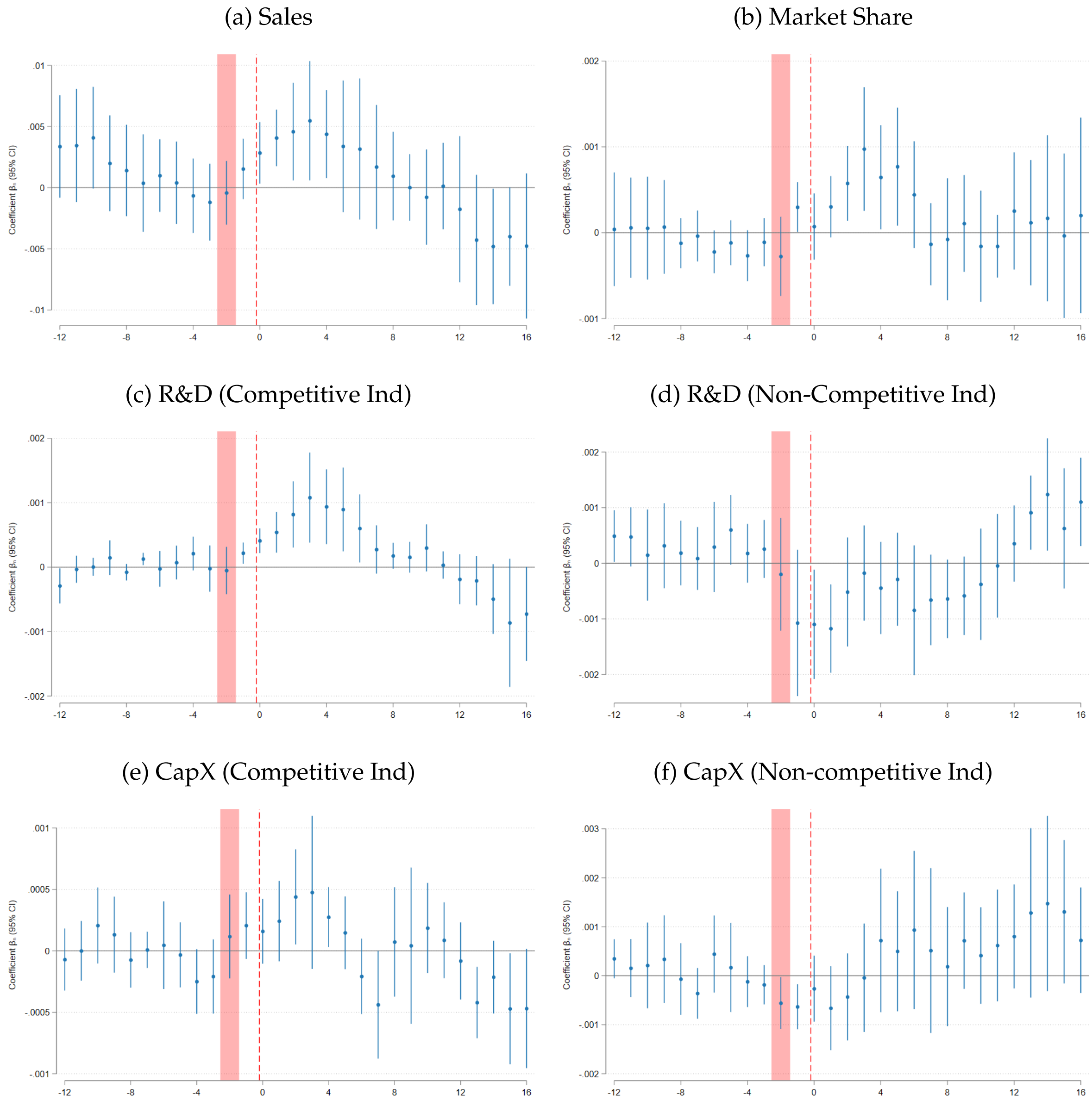
Notes: Figure C.4a and C.4b plot the estimated coefficients of equation (2) (see Section 4.1) when the dependent variable is respectively the level of sales (normalized by the mean-level of fixed assets) and the firm-level market-share defined at NAICS3 industry level. Figure C.4c and C.4d plot the estimated coefficients when the dependent variable is the 4-quarter moving average of R&D expenditure (normalized by the mean-level of fixed assets) and the sample is composed respectively by firms operating in a competitive and non-competitive industry. Figure C.4e and C.4f plot the estimated coefficients when the dependent variable is capital expenditure (normalized by the mean-level of fixed assets) and the sample is composed respectively by firms operating in a competitive and non-competitive industry. See Section 2.3 for more information on variables construction. In all figures, the 95% confidence intervals for each point-estimate is reported. Standard errors are double-clustered at (NAICS3) industry level and date. The red area indicates the imputed time-window of public release of the standard's content, based on knowledge of the procedure of approval. The red-dashed line indicates the official publication of the standard, as reported in the gazette of the standards' organization.

specification. As shown in Figure C.6, the extensive margin clearly matters only for market shares: firms receiving a 0-shock immediately loose shares of sales to firms receiving a positive shock.

C.6 Main results under a different definition of the shock

Finally, we want to check whether our results differ much if we use another methodology to compute scores in the process of matching patents to standards. Here, we re-estimate the results of Section 4.1.1-4.1.3 when using score B.3 (see Appendix B.1.2) to build the firm-level standardization shock. As Figure C.7, results do not substantially change.

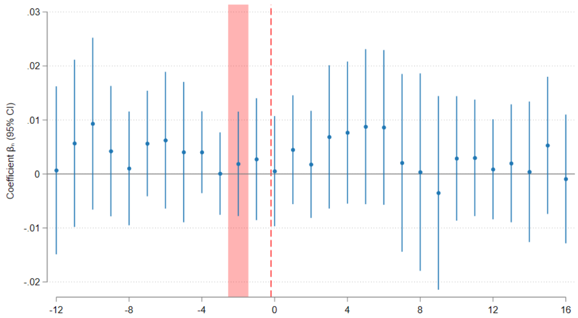
Figure C.5: Main Results: the Intensive Margin of the Shock



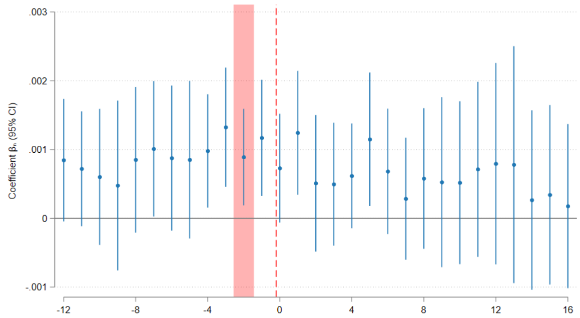
Notes: Figure C.5a and C.5b plot the estimated coefficients of equation (2) (see Section 4.1) when the dependent variable is respectively the level of sales (normalized by the mean-level of fixed assets) and the firm-level market-share defined at NAICS3 industry level. Figure C.5c and C.5d plot the estimated coefficients when the dependent variable is the 4-quarter moving average of R&D expenditure (normalized by the mean-level of fixed assets) and the sample is composed respectively by firms operating in a competitive and non-competitive industry. Figure C.5e and C.5f plot the estimated coefficients when the dependent variable is capital expenditure (normalized by the mean-level of fixed assets) and the sample is composed respectively by firms operating in a competitive and non-competitive industry. See Section 2.3 for more information on variables construction. In all figures, the 95% confidence intervals for each point-estimate is reported. Standard errors are double-clustered at (NAICS3) industry level and date. The red area indicates the imputed time-window of public release of the standard's content, based on knowledge of the procedure of approval. The red-dashed line indicates the official publication of the standard, as reported in the gazette of the standards' organization.

Figure C.6: MAIN RESULTS: THE EXTENSIVE MARGIN OF THE SHOCK

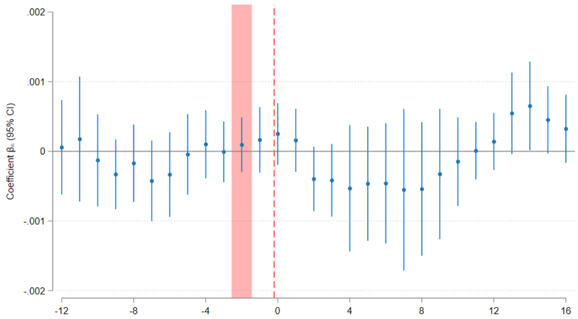
(a) Sales



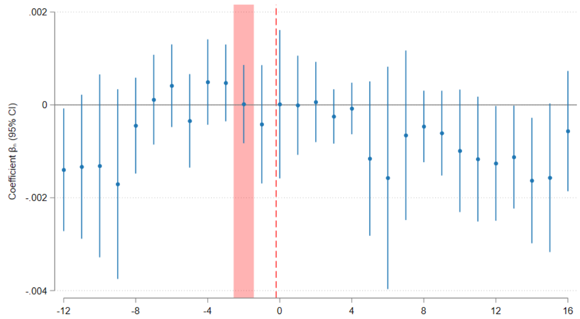
(b) Market Share



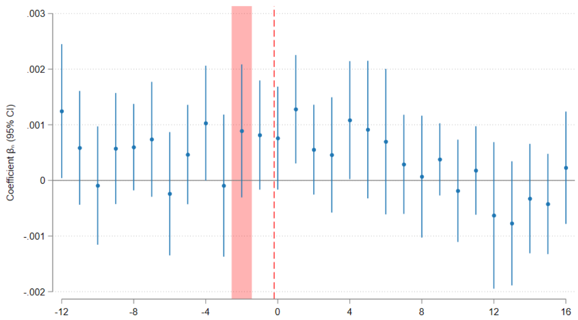
(c) R&D (Competitive Ind)



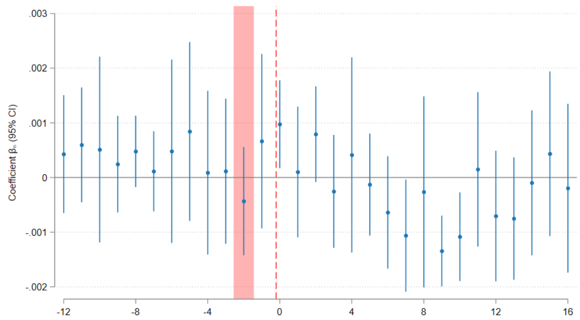
(d) R&D (Non-Competitive Ind)



(e) CapX (Competitive Ind)

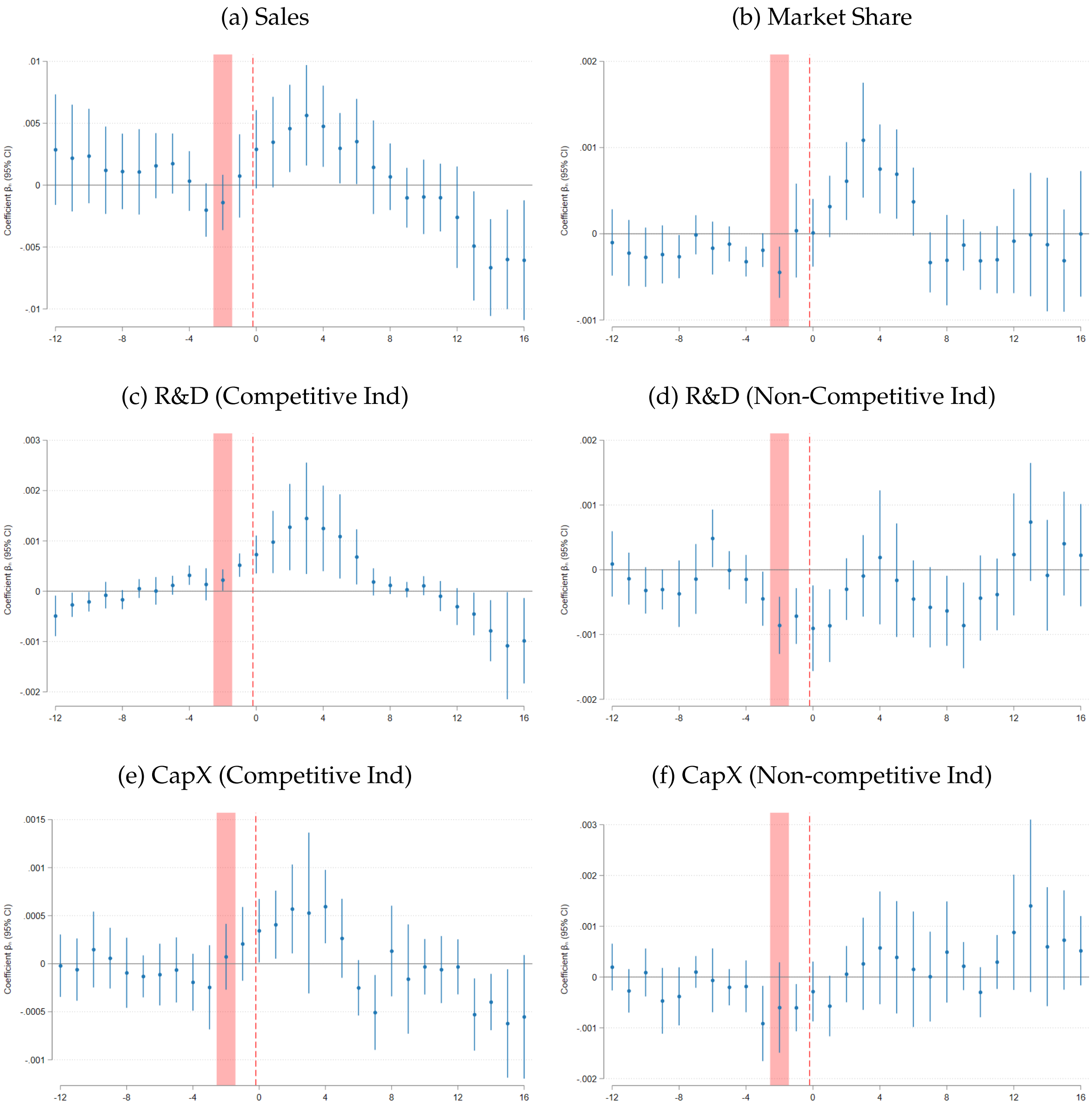


(f) CapX (Non-competitive Ind)



Notes: Figure C.6a and C.6b plot the estimated coefficients of equation (2) (see Section 4.1) when the dependent variable is respectively the level of sales (normalized by the mean-level of fixed assets) and the firm-level market-share defined at NAICS3 industry level. Figure C.6c and C.6d plot the estimated coefficients when the dependent variable is the 4-quarter moving average of R&D expenditure (normalized by the mean-level of fixed assets) and the sample is composed respectively by firms operating in a competitive and non-competitive industry. Figure C.6e and C.6f plot the estimated coefficients when the dependent variable is capital expenditure (normalized by the mean-level of fixed assets) and the sample is composed respectively by firms operating in a competitive and non-competitive industry. See Section 2.3 for more information on variables construction. In all figures, the 95% confidence intervals for each point-estimate is reported. Standard errors are double-clustered at (NAICS3) industry level and date. The red area indicates the imputed time-window of public release of the standard's content, based on knowledge of the procedure of approval. The red-dashed line indicates the official publication of the standard, as reported in the gazette of the standards' organization.

Figure C.7: MAIN RESULTS UNDER OTHER DEFINITION OF THE SHOCK



Notes: Figure C.7a and C.7b plot the estimated coefficients of equation (2) (see Section 4.1) when the dependent variable is respectively the level of sales (normalized by the mean-level of fixed assets) and the firm-level market-share defined at NAICS3 industry level. Figure C.7c and C.7d plot the estimated coefficients when the dependent variable is the 4-quarter moving average of R&D expenditure (normalized by the mean-level of fixed assets) and the sample is composed respectively by firms operating in a competitive and non-competitive industry. Figure C.7e and C.7f plot the estimated coefficients when the dependent variable is capital expenditure (normalized by the mean-level of fixed assets) and the sample is composed respectively by firms operating in a competitive and non-competitive industry. See Section 2.3 for more information on variables construction. In all figures, the 95% confidence intervals for each point-estimate is reported. Standard errors are double-clustered at (NAICS3) industry level and date. The red area indicates the imputed time-window of public release of the standard's content, based on knowledge of the procedure of approval. The red-dashed line indicates the official publication of the standard, as reported in the gazette of the standards' organization.