Intellectual Property Protection Lost and Competition: An Examination Using Machine Learning

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Abstract

We examine the impact of lost intellectual property protection on innovation, competition, mergers and acquisitions and employment agreements. We consider firms whose ability to protect intellectual property (IP) using patents is potentially invalidated following the Alice Corp. vs. CLS Bank International Supreme Court decision. This decision has impacted patents in multiple areas including business methods, software, and bioinformatics. We use state-of-the-art machine learning techniques to identify firms' existing patent portfolios' potential exposure to the Alice decision. While all affected firms decrease patenting post-Alice, we find an unequal impact of decreased patent protection. High market share affected firms benefit as their sales and market valuations increase, and their exposure to lawsuits through patent trolls decreases. They also acquire fewer firms post-Alice. Low market share affected firms lose as they face increased competition, product-market encroachment, and lower profits and valuations. They increase R&D and have their employees sign more nondisclosure and noncompete agreements.

Keywords: Patents, intellectual property protection, innovation, competition, litigation, Alice. **[JEL Codes: O31, O34, D43, F13]**

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What though the field be lost? All is not lost

Paradise Lost, John Milton, 1674.

1 Introduction

Intellectual property protection is at the core of innovation and competition policy. Economic and legal scholars have debated extensively whether intellectual property (IP) protection increases the incentives of firms to innovate and conduct R&D. The general consensus by many economists has been that patents stifle innovation as Boldrin and Levine (2013) describe in their survey article. Galasso and Schankerman (2015) reinforce this view by documenting a positive impact on small firm innovation following patent invalidation of patents by large patentees. Examining 60 countries over 150 years, Lerner (2002) also finds limited benefits of increasing patent protection. He finds decreased domestic patenting following increased IP protection but increases in foreign patenting, suggesting foreign competitors enter with the increased protection. Yet not all studies agree that IP protection is harmful to innovation. Budish et al. (2015) models how the length of patent protection should optimally increase for long-term costly innovation when commercialization occurs later, otherwise companies may not have enough incentives to innovate.

Thus, a natural question is how strong to make IP protection? The theories behind optimal IP protection begin with Nordhaus (1969). In Nordhaus (1969) the debate is about the trade-off between giving patents to encourage innovation and the cost of reducing subsequent competition resulting from giving the patentee a local monopoly over the life of the patent. There are also issues with the scope of the patent. If patent protection is too broad, new entrants and new innovation may be discouraged as the protected scope of existing innovation might imply high entry barriers. Monopoly profits that arise from IP protection would also be high, harming consumers. If too weak, then firms would be discouraged from engaging in costly innovation as the fruits of that innovation would be potentially available to all to copy without incurring the costs of discovery.

Our study examines the consequences of weakened IP protection across multiple categories in a setting that shocked both existing patents and also incentives for *future* innovation and patenting in the U.S. in multiple patent categories. We examine firms whose patents are exogenously invalidated by the Alice Corp v. CLS Bank International, 573 U.S. 208 (2014) Supreme Court decision (Alice, henceforth). This decision revoked patent eligibility in multiple patent areas. We examine the impact of lost intellectual property protection on a wide array of future firm decisions including firm innovation, competitive entry, acquisitions, lawsuits, patent trolls, and secrecy via non-disclosure agreements.

The Alice decision revoked patent protection on business methods patents whose fundamental idea is considered abstract with a transformation that is not novel. As part of this decision, the Supreme Court also ruled that the media and systems claims are similar to the business methods claims, and they are also patent ineligible. Thus, the Alice decision impacted multiple industries with patenting including data processing methods, software, and measuring or testing in microbiology and enzymology. The outcome of this decision was in doubt given prior court decisions and thus we show that it had an impact after the ruling. In the next section, we provide details on the extensive disagreements on this case until the Supreme Court ruling.[1].

We show that Alice has had a large impact on patent rejections, and it led to further decreases in patenting in exposed areas in the years since 2014. We document a large impact both in the incidence of patenting and in the rejection rate on patent applications in areas ranging from data processing methods, games, and business methods to microbiology testing. Even post-Alice, there is considerable uncertainty about whether a particular patent sufficiently transforms an abstract idea enough to make it patent-eligible. Rejections based

[1] Indeed when the case was being considered at the Supreme Court, there were extensive Amicus briefs filed on both sides. Amicus briefs filed with the Supreme Court in support of CLS Bank included briefs filed by Google, Amazon, Dell, LinkedIn, Verizon, Microsoft, Checkpoint Software, the Software Freedom Law Center and Opensource Initiative, and prominent lawyers and economists. There were over 20 Amicus briefs in support of Alice Corp., including Advanced Biological Laboratories, IBM, Trading Technologies International, Inc., and prominent lawyers and economists. See http://www.alicecorp.com/fs_patents.html

on Alice represented approximately 10% of the patent rejections overall in 2015 and 2016. For example, in the commerce and data processing methods industry, 36.2% of patents filed in 2013 were rejected citing Alice. Analyzing future patents, we calculate a conservative estimate suggesting Alice also resulted in 2,362 fewer patents per year since 2014.

While the decision had an extremely large ex post impact on patenting, there was and still exists uncertainty about whether an existing or proposed patent transforms an idea sufficiently to be granted patent protection. Given the uncertain impact on each patent, we apply novel machine learning techniques on regulatory and patent textual corpora to assess how much a given firm's patent portfolio is exposed to Alice. Many legal scholars have written about the Alice decision and the difficulties of measuring and deciding whether there is sufficient transformation of an abstract idea to warrant a patent.[2]

We examine all patents in Alice impacted areas that were granted by 2014 (the date of the Alice decision). Some of these patents are likely to be invalidated if challenged in a court in the post-Alice period. This is a challenging task as there are more than 3.8 million patents granted between 1994 and 2014. We thus concentrate on the patents which have the same primary Cooperative Patent Classification (CPC) as the ones that are rejected by the United States Patent and Trademark Office (USPTO) per Supreme Court's Alice criteria. Given the uncertainty about whether a given patent will be rejected, we use machine learning to gauge each patent's textual semantic similarity to patents previously rejected under Alice.

We use a deep learning-based language model called BERT to predict the likelihood that each of the pre-Alice granted patents in the sample may be invalidated by the Alice decision. The BERT model was released by Google in 2019 and achieves state-of-the-art performance on various Natural Language Processing (NLP) tasks (Devlin et al. (2019)). The model is also used in Google search queries, and Google argues that BERT helps Google Search better understand one in ten searches in the U.S. in English.[3] The breakthrough innovation

[2]See Kesan and Wang (2020) and Lim (2020) for an extensive discussion of these debates and issues. These difficulties and the impact of Alice gave rise to U.S. Senate subcommittee hearings promoted in 2019 on potential revisions to strengthen intellectual property law in the "Stronger Patents Act."

[3]https://blog.google/products/search/search-language-understanding-bert/

of Google's BERT technique is that it processes words in relation to all the other words in a sentence, rather than one-by-one in order or in a fixed-sized sliding window approach. Therefore, the BERT model can examine the full context of a word by looking at the words that come before and after it.

We find a large impact of Alice on future patenting and innovation. We verify that ex post patenting by firms whose patent stock is exposed to Alice significantly decreases for all impacted firms. We then split the firms by high and low market share. We split by market share as we hypothesize that smaller, low market share firms may be hurt more by the repeal of patent protection in this area as they have less resources (managerial, financial and organizational) to defend their product spaces while firms with high market shares are the leading firms with more resources, who can defend their product areas. The differential impact on innovation for leading vs. laggard firms has been modeled by Aghion et al. (2005). In their paper, they postulate an inverted u shape between competition and innovation. To the left of the inverted U, firms will increase innovation with increases in competition. We discuss these predictions provided by Aghion et al. (2005) and compare them to a Schumpeterian model of innovation and competition.

When we examine R&D, we find no change for large firms but find a significant increase in R&D for small firms. These results are consistent with small firms' attempting to replenish their innovative portfolio to "escape the competition" and to rebuild product differentiation. Examining ex-post changes in sales growth and profitability along with firm value, we find an unequal impact. Large firms gain and small firms lose. Exposed large firms increase sales and their market valuation, as measured by Tobin's q. Small firms whose patent portfolio is exposed to Alice experience a decrease in operating margins and their market valuations.

Our paper examines the impact of the decreased intellectual property protection in whole areas on small and big firms. It is not surprising that small firms lose from the possibility of invalidating their intellectual property. Farre-Mensa et al. (2020) shows that small firms gain from patent protection beyond the value of the idea using the an instrument of random assignment of patent examiners from Sampat and Williams (2019). They show that small firms gain access to increased funding post-patent. Previous research by Galasso and Schankerman (2015) also showed that when larger firms' patents were invalidated, small firms increased innovation. In our setting, we are examining who gains and loses after a change in intellectual property protection that impacts whole areas of technology for both high and low market share firms, which differs from the prior focus on individual firms losing patent protection.

We show that these differential losses for small firms are related to changes in competition that occur from decreased intellectual property protection. These small firms face increased competition on a number of different measures. Both high and low market share firms face increased venture capital financed entry into their product space, but the increased entry is more severe for small firms. Small firms face increased product similarity with their existing competitors, and they complain more about increased competition. Small firms also resort to non-compete clauses for their employees and they mention non-disclosure agreements more in their 10-K filings. Thus, small firms resort to increased secrecy to defend new IP in the face of the lost patent IP protection. This finding shows that disclosure is important which was noted as potentially important by Sampat and Williams (2019) in the case of technologies that shift from patentable to unpatentable.

We examine patent infringement and intellectual property risk directly. We find that high market share firms experience fewer claims that they infringe on other firms. The decrease in patent infringing claims is mostly from the reduction of patent-troll lawsuits. This is intuitive as firms would be less likely to sue a deep-pocket firm when the validity of the patents is questionable. However, we find no differences for alleged claims for small firms. Confirming this view, only small firms mention that they face increased IP risk post-Alice in their 10Ks. Our results are consistent with losses in IP protection enabling large firms to increase product market power at the cost of established smaller firms in their markets.

Examining acquisitions post-Alice, we find that high market share firms sharply decrease their acquisition activity. This is consistent with the theoretical arguments and empirical evidence in Phillips and Zhdanov (2013). They model how high market share firms may buy small firms after they have successfully patented an innovation. High market share firms buy smaller firms to access their technology to then apply it to their larger customer base. Without a patent, there is less reason for a large firm to buy a smaller firm. If a high market share firm can forecast that a small firm's patent may be invalidated post-Alice, there is less incentive to buy small firms for their technology as they can implement it for free without infringing the smaller firm's patents.

We confirm that high market share firms gain and small firms lose in their product market position by examining pairwise similarities of firms to other firms post-Alice. Changes in pairwise similarities are a measure of the changes in competitive encroachment by one firm on another. We find that big firms experience a decrease in product similarity when their patent portfolio is exposed to Alice, while small firms experience an increase in product similarity between them and rival firms after being exposed to Alice. These results are consistent with small firms experiencing increased product encroachment and competition, while high market share firms experience reduced direct competition post-Alice.

Our paper contributes to the debate on intellectual property protection and competition. Our evidence and results are different from Galasso and Schankerman (2015) and Farre-Mensa et al. (2020) who examine exogenous invalidations or granting of particular patents and not invalidations of entire patent areas. Galasso and Schankerman (2015) show that small firms innovate more when large firms' patents are rejected in a market. Farre-Mensa et al. (2020) shows the benefit of getting a patent for small firms on subsequent funding and commercialization for the firm itself but does not examine the impact on other firms.

We document the impact of lost IP protection for all firms in an entire area and examine future firm performance, litigation, competition, secrecy, and acquisitions. Empirically we show how and why small firms lose more from lost intellectual property protection. Small firms lose as they face increased competition. They increase R&D and increase secrecy as they use more nondisclosure agreements and non-compete agreements with their employees. In contrast, high market share firms benefit from area-wide invalidations as their sales and market values increase while their acquisitions decrease. They also litigate less and face less litigation targeting large firms following losses in IP protection. These results are consistent with high market share firms having more resources - technological, financial and managerial - to protect their product market position. The results are also consistent with the Schumpeterian effect dominating, with increased innovation after the shock being preformed by laggard low market share firms with low profits as Acemoglu et al. (2010) note. We thus conclude that patent protection is particularly important for small firms that face competing larger firms.

Our paper also contributes methodologically by applying big data machine learning techniques to a difficult and ambiguous legal environment where the impact of Supreme Court decisions on individual firms is not known until after a patent is litigated. Using a novel measure of potential exposure generated through machine learning, we show the impact of potential exposure to multiple firm decisions and outcomes including innovation, firm performance, competition, and acquisitions.

Our paper points to the benefits of increased competition and fewer lawsuits from reduced patent protection but costs for existing small firms who most directly face the impact of increased competition from both large firms and new entrants. Our results thus show the costs and benefits of decreased IP protection.

2 Innovation and Alice *v.* CLS Bank International

There is a substantial debate on how strong to make IP protection. The general academic consensus is that patents stifle innovation. Boldrin and Levine (2013) state that there is no empirical evidence that patents serve to increase innovation and productivity. They advocate for a policy of abolishing patents entirely and using other legislative instruments to increase innovation. Galasso and Schankerman (2015) document a positive impact on small firm innovation of patent invalidation of large patentees as it triggers follow on innovation by smaller firms. However, these were exogenous invalidations of particular existing patents and these tests are not about forward-looking changes to entire patent areas as is the case for Alice. Lerner's comprehensive study of over 60 countries used patent law changes and showed some benefits of strengthening patent protection for countries with initially weaker patent protection. Over time, however, domestic innovation declines with increases in IP protection while foreign patenting goes up. Frequently, however, these expansions of IP protection have been enacted simultaneously with relaxations of trade protections.[4] There is also evidence (see Budish et al. (2015) for example using cancer clinical trials) that there needs to be incentives to engage in innovation if the ideas take a long time to develop and can be copied freely when innovation is costly.

We examine firm outcomes and competition after the landmark Supreme Court case, Alice Corp *v.* CLS Bank International, 573 U.S. 208 (2014). This decision impacted large industry areas - and key for us, not just a subset of an area. These areas previously had substantial patenting activity in them. Kesan and Wang (2020) review the impact of this case and document large decreases in 11 patent categories including bioinformatics, business methods, business methods of finance, business methods of e-commerce, software (in general), databases and file management, cryptography and security, telemetry and code generation, digital cameras, computer networks, and digital and optical communications. They showed significant rejections of patents under Alice based on whether the proposed invention sufficiently transforms an abstract idea or natural law. Section 101 of the Patent Statute specifies four categories of the invention that are patent eligible: process, machine, manufacture, and composition of matter. However, there are, three court made exclusions to these categories that carve out from patent-eligibility: laws of nature, natural phenomena, and abstract ideas.

[4] Lerner uses an indicator for whether the change took place in the aftermath of the Paris Convention of 1883 or the TRIPs agreement of 1993 to control for endogeneity.

2.1 Legal Background of the Alice Case

In 2014, the Supreme Court of the United States decided a landmark case, Alice Corp *v.* CLS Bank International, 573 U.S. 208 (2014). It had a major effect on patent eligibility across multiple patent categories. In this case, the issue was whether certain patent claims for a computer-implemented scheme encompass abstract ideas, making the claims ineligible for patent protection. The Supreme Court decided that known ideas are abstract, and discussing the computer implementation of a known idea in a claim does not make it a patentable subject matter.

The result of the case was quite uncertain, and it caused a debate among the judges. After a district court held the patents invalid, the case reached to the Court of Appeals for the Federal Circuit (CAFC). In this court, a randomly assigned three-judge panel could not unanimously decide on the case, and the panel reversed the district court decision with a majority opinion.[5] However, given the case's complexity and its importance for the whole industry, the CAFC vacated the panel's opinion and decided to the hear the case in a full session of all ten judges that then heard the case.[6][7]

The uncertainty in the en banc session was not any less than the one in the three-judge panel. Five of the ten judges upheld the district court's decision that Alice's systems claims were not patent-eligible, and five judges disagreed. Seven of the ten judges upheld the district court's decision that Alice's method claims were not patent-eligible. However, these seven judges reached their opinions for different reasons. Overall, the judges could not agree on a single standard to determine whether a computer-implemented invention is a patent-ineligible abstract idea.

After the deep division in the CAFC, the Supreme Court of the US granted certiorari and affirmed the en banc decision of the Federal Circuit Court of Appeals.[8] The Court held

[5] CLS Bank Int'l v. Alice Corp. Pty. Ltd., 685 F.3d 1341, 1356 (Fed. Cir. 2012)
[6] CLS Bank Int'l v. Alice Corp. Pty. Ltd., 484 Fed. Appx. 559 (Fed. Cir. 2012)
[7] CLS Bank Int'l v. Alice Corp. Pty. Ltd., 717 F.3d 1269, 1273 (2013).
[8] Alice Corp. Pty. Ltd. v. CLS Bank Int'l, 134 S. Ct. 2347, 2354 (2014).

a two-step framework for determining the patent eligibility of applications that would be applied to claims of abstract ideas. The Court decided that the claims in Alice patents cover an abstract idea and the proposed method claims fail to transform the abstract idea into a patent-eligible invention. The Court also ruled that the media and systems claims are similar to the methods claim and that they are also patent ineligible.

The Alice decision had a large impact in the stock market. We computed the excess returns at the time of the Alice decision to the impacted firms. We subtract the equally weighted CRSP market return to get each firm's excess return on days surrounding Alice. We found a significant negative coefficient for the -1 to +1 days surrounding the Alice decision. Excess returns at the judgment for impacted firms were significantly negative at the 1% level. We do have substantial variation, as at the average of our treatment variable, the excess returns were close to zero at -.1%. For the top five percent of our treatment variable, this excess return is larger at -.8%. To interpret this spread, we note as we show later, that our median treatment variable is itself close to zero as we include untreated competitors of Alice impacted firms in our control set, and we have many firms with a minor impact from Alice as only a few of their patents were impacted.

2.2 Consequences of Lost IP protection

The Alice case had a large impact on ex post patenting. The process to eventually reject a patent first starts with a petition by a litigant or an office action that is filed by a USPTO examiner. In Table 1, we present statistics for the top 12 industries with patent applications that were rejected by USPTO patent examiners citing Alice as the reason for reject for patents applied for prior to the Alice decision. Over 33,700 distinct patent applications made prior to Alice have been rejected in the 3 years post-Alice by examiners citing the Alice precedent. These rejected patents cover over 5,831 distinct CPC Subgroups (out of 126,540 total), 919 Groups, 283 Classes, and 8 CPC Sections.

Insert Table 1 here

This table reports annual statistics from USPTO patent application rejections based on the Supreme Court's Alice decision for the top 12 industries based on Alice rejections. We present the number of patent applications from 2008 to 2017, with the percentage of rejections in parentheses for these industries. We use rejection data provided by Lu et al. (2017) that extends until 2016; therefore the ratio of rejection is assigned NA for 2017. *Change* reports the percentage change from the number of patent applications in 2013 to the average number of patent applications for the 2015-2017 period. Corresponding CPCs for each industry are provided in Table 2.

Insert Table 2 here

Table 2 provides a description of the main CPC groups that are impacted by the Alice decision. In Panel B, we provide the industry that contains these Alice impacted CPC groups.

Kesan and Wang also document that about 17.9% of office action final decisions were rejected based on section 101 before Alice was decided. This rate increased to 72.4% of the rejections of applications filed before Alice but decided afterwards and 72.8% of applications filed after Alice. Other categories including computer networks, GUI, document processing, and cryptography and security also had significant increases in section 101 rejections after Alice. The number of patent applications per month dropped significantly post-Alice from 12-31% in different categories. For example, patent applications in the business method area dropped 29.5%. Kesan and Wang (2020) show using a difference-in-difference regression that section 101 Alice rejections increased significantly in 11 different patent categories.

While Alice had a large impact on patenting, the Supreme Court left substantial ambiguity about whether an individual patent transformed abstract ideas sufficiently to make them patent-eligible. As legal scholars have noted, the court did not define "abstract" and the court did not define how to decide whether the abstract idea has been transformed sufficiently into an inventive concept by including additional limitations to the patent claim, thereby rendering the claim eligible for patent protection. Given the uncertainty about whether a patent will be rejected because of Alice, we use machine learning to gauge a patent applications similarity to patents previously rejected under Alice. We use a deep learning based language model called BERT to predict the likelihood that each of the pre-Alice granted patents in the sample may be invalidated by the Alice decision.

We study ex post firm decisions based on our predicted likelihood of whether a firm's existing patents are exposed to Alice.

We examine competition and the impact on patenting post-Alice and we split firms by high and low market share. We use market share as we hypothesize that smaller, low market share firms may be hurt more by the repeal of patent protection in this area as they have less resources (managerial, financial and organizational) to defend their product spaces while firms with high market shares will be the leading firms with more resources who can defend their product area. The differential impact on innovation by leading vs. laggard firms has been modeled by Aghion et al. (2005). In their paper, they postulate an inverted u shape between competition and innovation. To the left of the inverted U, firms will increase innovation with increases in competition. To the right of the inverted U, firms will behave like the Schumpeter (1942) model where innovation is preformed by laggard firms with low initial profits.

Aghion et al. (2005) also develop predictions on the impact of competition based on whether firms are "level" with equal access to leading innovation vs. industries where there are differences between leader and laggard firms. In our setting, given the large increase in competition post-Alice, we expect firms left behind will innovate more in order to escape competition from other small firms. Larger firms are predicted to behave more like the Schumpeterian model and will innovate less as most innovation will be preformed by laggard firms with low initial profits.

We thus examine firm R&D and performance outcomes including changes in sales, operating income, and market valuations and the impact on competition overall between firms. While we could conjecture that the impact of the loss of IP protection may be negative for affected firms, such an unconditional prediction is not clear given predicted differences in impact for firms with different market shares and innovative resources. We thus focus on testing predictions for firms with high and low market shares. Firms with high ex ante market shares may benefit from losses in IP protection in their sector, for example, as they may be able to adopt new ideas without paying the firms who originally created the ideas. Therefore, these high market share firms might see decreases in the competitive threats they face. We, relatedly, test whether acquisitions by high market share firms decrease after Alice, as these larger firms might be able to copy ideas without buying the firms who created them. Finally, we predict that firms might seek alternative ways to increase secrecy and protect IP after patent protection is lost. We predict that afflicted firms will thus use more non-disclosure agreements and non-compete clauses to replace some of this lost IP protection.

3 Data and Methods

In this paper, we assess the impact of a decrease in patent protection on small and large firms. As an exogenous variation in patent rights, we exploit the Supreme Court's Alice Corp *v.* CLS Bank International, 573 U.S. 208 (2014) decision, which has drastically reduced the probability of being granted a patent in the software industry.

In our experiment, we create a measure of treatment from the Alice decision based on the value of each firm's pre-Alice granted patents that are expected to be invalidated, if challenged in the court, after the Supreme Court decision. To find the patents that are more likely to be invalidated, we use a technique that exploits Deep Learning based language model Bidirectional Encoder Representations from Transformers (BERT). The BERT was released by Google in 2019 and achieves state-of-the-art performance on various Natural Language Processing (NLP) tasks (Devlin et al. (2019)).

3.1 Experimental Challenges

For the experiment, we need to identify patents that were granted in the pre-Alice period but that would be invalidated if they are tested in a court in the post-Alice period. This identification is challenging as there are more than 3.8 million patents granted between 06/19/1994 and 06/19/2014. Therefore, to make the experiment more tractable, we concentrate on the patents which have the same primary CPC as the ones that are rejected by the USPTO per Supreme Court's Alice criteria. This filtering leaves us 642,697 patents that we need to have a prediction for the likelihood of invalidation. Since manual examination of such big data may not be feasible, we need an automation model that has reliable predictions in this context.

However, standard text-based similarity techniques such as term frequency–inverse document frequency (TF-IDF) have two major shortcomings. First, as the technology vocabulary frequently changes or there exist differences between the vocabulary usage of patent applicants, TF-IDF may have limited power to capture similarity between two patents. Secondly, between two patents that share a similar vocabulary, the Supreme Court's Alice decision may affect one patent but not the other. Therefore, an automatized system should be able to catch both syntactic and semantic information. We choose the BERT model which overcomes these limitations. We also compare the BERT model's out-of-sample prediction performance to TF-IDF and other computational linguistics methods such as Word2Vec. In addition, we examine economic outcomes, and we also compare the impact of firm exposure using BERT to TF-IDF, and to simple binary CPC category identification models. Overall, since BERT has better out-of-sample predictions, we expect that BERT will give us more precise identification of the impact of Alice on economic outcomes.

3.2 The BERT Model

We use a Deep Learning based language model BERT to predict the likelihood that each of the pre-Alice granted patents in the sample may be invalidated per the Alice decision. The

BERT was released by Google in 2019 and achieves state-of-the-art performance on various Natural Language Processing (NLP) tasks (Devlin et al. (2019)). The model is also used in Google search queries, and Google argues that BERT helps Google Search better understand one in ten searches in the U.S. in English.[9]

The breakthrough innovation of Google's BERT technique is that it processes words in relation to all the other words in a sentence, rather than one-by-one in order or in a fixed-sized sliding window approach. Therefore, the BERT model can examine the full context of a word by looking at the words that come before and after it. This mechanism provides the capability to understand the intent behind a sentence. To illustrate, we examine two sentences that have a similar meaning: i) Symptoms of influenza include fever and nasal congestion; ii) A stuffy nose and elevated temperature are signs you may have the flu. While TF-IDF model that filters the stop words (such as "and") has a similarity score of 0, the BERT model finds 0.86 similarity for these two sentences.

A large number of empirical analysis also documents that BERT is superior to the traditional NLP models such as Bag-of-Words (BOW), Term Frequency-Inverse Document Frequency (TF-IDF), Word Embedding models such as Word2Vec, FastText, GloVe, and other approaches that combine Word Embedding Models with Neural Networks for Text Classification tasks (Adhikari et al. (2020); Maltoudoglou et al. (2022); Esmaeilzadeh and Taghva (2021); Minaee et al. (2021); Roman et al. (2021)).

Since deep-learning models require high computational power, the standard BERT model is pre-trained using Wikipedia and BooksCorpus texts. The pre-trained model is then fine-tuned for a specific NLP task using an additional deep learning layer with labeled data. In our task, the vocabulary of patents may include more technical terminologies than Wikipedia and BooksCorpus may offer. Beltagy et al. (2019) and Lin et al. (2020) find that in text classification problems that involve scientific literature, SciBERT performs better compared to the original BERT. Therefore, instead of using the standard BERT, we exploit SciBERT

[9]https://blog.google/products/search/search-language-understanding-bert/

(Beltagy et al. (2019)), which is pre-trained on a large multi-domain corpus of scientific publications including the ones in computer science.[10]

One shortcoming of BERT is that it is capable of processing only 512 "tokens", which roughly corresponds to 400 words on an average text. Since patent texts are usually longer than 400 words, we use the description of patent applications to train the model.[11] However, even the patent descriptions are nearly always longer than 400 words as only 35 patents have descriptions less than 400 words (the 1st percentile is 1,743 words long). We thus use the TextRank automatic summarization tool, which internally uses Google's popular PageRank algorithm, to reduce the text size to 400 words (Mihalcea and Tarau (2004), Upasani et al. (2020)).

3.3 Rejected Patent Applications

We first gather the list of patents that are rejected under 35 U.S.C. §101 from the USPTO website.[12] Then, we filter for applications that are classified as Alice-rejection based on the method of Lu et al. (2017). This step leaves us with 56,709 rejected patent applications. However, some of them are reapplications with a minor change (i.e., a change of only one or two sentences). Therefore, we compute pairwise similarities between the applications using the TF-IDF method and label the ones with 0.99 similarity score as duplicates. For the duplicate observations, we only keep the application with the latest date. After removing the duplicates, there remain 33,734 unique rejected patent applications that have a document number and Cooperative Patent Classification (CPC) information. We download patent application texts from Google Patents using a web crawler.

For the sample of 33,734 rejected patent applications, we aggregate primary CPC information and create a frequency table. We find that Alice-rejected patents belong to 5,831 unique CPCs. We consider all patents which have the same primary CPC with one of these

[10] We also conduct experiments with Robustly Optimized BERT Pretraining Approach (RoBERTa). However, the results of SciBERT is superior to RoBERTa for our dataset.

[11] Technically, two tokens are flag tokens. Therefore, the number of available tokens is 510.

[12] https://developer.uspto.gov/product/patent-application-office-actions-data-stata-dta-and-ms-excel-csv

5,831 CPCs as "to be examined for invalidation", and there are 642,697 patents that fit this criteria.

3.3.1 Training The BERT Model

In our deep learning experiment, there are two phases. First, we train the system with texts of Alice-rejected patent applications (positives) and texts of applications that were eventually granted (negatives). After the training, we evaluate the success of BERT's prediction using a test sample.

In the set of 33,734 Alice-rejected patent applications, we randomly choose 10,000 for testing and use the remaining 23,734 as positives to train the system. Next, we create a sample of negatives from patents that are granted after 06/19/2014 (i.e., the Supreme Court's Alice decision). For the negatives, we conduct four experiments (A to D) in which the only difference is the way we create the training samples, based on the granularity of a patent's CPC that has five items: i) section; ii) class; iii) subclass; iv) group; and v) main group or subgroup. To illustrate, in CPC "B60K35/00"; B, 60, K, 35, 00 correspond to the Section, Class, Subclass, Group, and Main Group, respectively.

In experiment A, for each of the 23,734 positives, we find a matching negative patent that is in the same CPC Group that was granted after 6/19/2014. In samples B, C, and D, we keep adding 23,734 more matching patents to the negatives pool based on CPC Subclass, Class, and Section, respectively. Therefore, from A to D, each sample has 23,734 more negatives but the newly added ones are less granular than the previous ones.

3.3.2 Testing BERT and Other Models

In this section, we evaluate how the prediction results from BERT Model compare to prediction results using TF-IDF and Word2Vec. For prediction models for TF-IDF and Word2Vec, we combine the model with logistic regression, decision tree, and random forest.

For the testing, we have 10,000 positives that are randomly selected from the rejected applications pool and 20,000 negatives that are randomly selected from the granted patents pool based on the CPC frequency distribution of the whole sample (i.e., 642,678 patents).

To evaluate the results, we use the standard performance metrics: precision, recall, F1 score, and accuracy. These metrics can be calculated from a confusion matrix. The matrix has the following elements: True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN). True (False) Positives are the predictions that are positive and correct (incorrect). True (False) Negatives are the prediction that are negative and true (false). Using these elements, we calculate the metrics as follows:

$$Precision = \frac{TP}{TP + FP} \quad (1)$$

$$Recall = \frac{TP}{TP + FN} \quad (2)$$

$$F_1\ Score = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \quad (3)$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (4)$$

Table 3 reports the evaluation of prediction results for the machine learning models. The results show that, for the same training set, SciBERT model is superior to all feature extraction techniques in all different machine learning algorithms. In terms of F1 score, SciBERT Finetune with the training sample A has the highest score (0.647). In terms of Accuracy, Scibert with training sample D has the highest score (0.781).

Insert Table 3 here

3.3.3 BERT Model Predictions for Existing Granted Patents

Our set of "to be examined for invalidation" consists of patents that were granted between 06/19/1994 and 06/19/2014 and share the same primary CPC with at least one of the applications that were rejected by the USPTO based on the Alice decision. In total, there are 642,678 patents that fit the examination criteria. These patents represented 16.6% of the total granted patents over this period.

The results in Table 4 show that 62,687 out of 642,678 patents (or 9.75% of the sample) have BERT score higher or equal to 0.5, the default threshold of high likelihood of invalidation if these patents are challenged in a court.

Insert Table 4 here

Panel B of Table 4 provides the list of CPCs that have the highest number of patent applications that were rejected by the USPTO and the list of CPCs that belong to patents that have a BERT score of 0.5 or higher. There has been a big overlap in these two lists. Eight out of top ten CPCs in the Alice-rejected patents are also in the list of top CPCs of patents that belong to BERT predictions.

Insert Table 5 here

In Table 5 we provide further detail by industry and year on the number of granted patents in impacted Alice industries. We present these by industry for the top 10 industries along with the percentage of patents our BERT model projects would be invalid with BERT scores $> .5$. The table shows that of the granted patents in these industries, multiple industries have over 25% of granted patents with BERT scores $> .5$, indicating that these patents would likely be invalid under current guidelines. Corresponding CPCs for each industry are provided in Table 2. These percentages are very similar to patents applied for in industries presented in 1 that were actually rejected in post-Alice years.

To give researchers an idea of the key words in the BERT model in our CPC groups, we produce a table with the top 15 informative words for the top CPC groups impacted by Alice.

Insert Table 6 here

Table 6 lists the words that are used most frequently in patents with high BERT scores (≥ 0.5) compared to ones with low BERT scores (<0.5). These words help "open the black box" and give researchers an idea of which words are important to the model. We first label patents with a BERT score ≥ 0.5 as positives and the remaining ones as negatives. We remove non-alphabetic characters from patent texts, apply the lemmatizing method to each word,[13] and calculate the number of positive and negative patents that each word appears in. The lemmatizing method uses WordNet's built-in morphy function, and it returns the input word unchanged if it cannot be found in WordNet, which is a lexical database of semantic relations between words in more than 200 languages.[14] We filter out words that do not appear in at least 1% of the positive patents. For each word w, we first assign it to a CPC Group with the highest ratio of the number of positive patents that contain the word to the total number of positive patents in that CPC. Then, we sort the words according to their appearance ratio, defined as $\frac{Count_w^+}{1+Count_w^-}$, where $Count_w^+$ and $Count_w^-$ are positive and negative number of patents a word w appears in, respectively. We list the top 15 words sorted according to their appearance ratio.

3.3.4 BERT Scores Pre- and Post-Alice

There is a strong reason to believe that Alice will not only impact current patents but also the future patents applied for in the technological areas impacted by Alice. While it is hard to estimate such a counterfactual, we provide some statistics to gauge the potential impact of Alice. Thus, we try to estimate how the Alice decision impacted the number of patents applied for pre- and post-Alice using differences in the patents applied for in each technological area as a fraction of total patents applied for in each area. We further consider in this analysis that firms would particularly avoid trying to patent innovations that are most likely to be rejected by the USPTO due to Alice considerations. We examine both pre-Alice (2011-2013) and post-Alice in 2017.

[13] See https://www.nltk.org/modules/nltk/stem/wordnet.html for the lemmatizing method.
[14] https://wordnet.princeton.edu/

Insert Table 7 here

Table 7 shows the distributional density of the BERT Score before the Alice shock (2011 to 2013) and after the shock (2017) for the Top 20 technological areas impacted by Alice. To compute the density in a given year, we first identify, the set of patents granted in that year in the Top 20 technological areas. The number of patents in each year ranges from 21,404 in 2011 to 31,249 in 2013 to 32,662 in 2017 (of those patents granted in 2017, 17,299 were applied for after the Alice decision). For the year 2017, as our goal is to examine the patent distribution post-Alice, we restrict attention to the 17,299 patents applied for in the post-Alice period. We sort all patents each year into 10 bins based on each patent's BERT Score. Bins are defined as the ten equal segments in the interval (0,1), which is the range of the BERT Score. For each bin, the density is the number of patents in the given bin in the given year divided by the total number of patents in the given year.

Finally, to illustrate the impact of Alice on these areas, we compute the ratio in the final column as the density in 2017 (column 5) divided by the average pre-Alice density averaged over the years 2011 to 2013 (column 4). A ratio below unity indicates that the rate of patenting in the given bin declined post-Alice.

Column (6) of Table 7 shows that, for all Alice areas except those with the lowest decile of BERT scores, patenting has declined sharply. In decile 10, the decile with the highest BERT scores, patenting is only 55% of pre-Alice patenting. Overall, these numbers can be applied to the number of patents in 2013 to estimate the total number of patents that "likely would have been applied for in 2017 if the Alice judgment had not occurred. In particular, for each bin having materially positive BERT Scores (all bins but the first one in Table 7), we multiply one minus the ratio in Column (6) by the number of patents in the given bin in 2013. We then add these "likely lost patents" over the nine bins, and the result is 2362 patents. This calculation thus estimates that Alice resulted in 2362 fewer patents per year by 2017 in these 20 technological areas. Because Alice is still in effect, this annual total is likely to recur every year, indicating an economically large impact.

The impact of Alice is also illustrated graphically in Figure 1, which shows the percentage of post-Alice patents (those applied for after the Alice decision) granted in 2017 in each bin relative to the numbers in 2011-2013 (the figure shows Column (6) of Table 7 graphically). The sharp drop-off on the RHS of the figure illustrates that firms greatly reduced patenting in technologies that had the most exposure to Alice.

Insert Figure 1 here

3.4 Patent Sample and Treatment Measure

We create the treatment measure for each firm i that we use in the regression as follows:

$$Treatment_i = \frac{Total\ Number\ of\ Patents_i}{Sales_i} X \frac{\sum_{j=1}^{N} PatentValue_{i,j} x AliceScore_{i,j}}{\sum_{j=1}^{N} PatentValue_{i,j}} \tag{5}$$

In this equation, $Total\ Number\ of\ Patents_i$ refers to firm i's total number of patents granted between 06/19/1994 and 06/19/2014. $Sales_i$ is firm i's total sales in 2013. $PatentValue_{i,j}$ refers to the dollar value of patent j for firm i obtained from the KPSS database Kogan et al. (2017). The treatment variable is computed for each firm in 2014 using all granted patents prior to the Alice decision, and the patent values in equation (5) are depreciated using an annual 20% rate relative to the base year 2014, and figures are further adjusted for inflation.[15] $AliceScore_{ij}$ refers to the BERT's predicted probability that a patent j is invalidated conditioning on that it is challenged in a court.

The treatment variable has two features. The first component captures how much a firm is dependent on patents. We scale the number of patents by sales following Fang et al. (2018), who use this variable as a measure of firm innovativeness.[16] This variable is important as some firms rely more on trade secrets than patents. The second component gauges what percent of the dollar value of a firm's patent portfolio was affected by the Alice decision.

[15]We use a 20% depreciation rate following Hall and Li (2020)'s finding that depreciation rates are likely higher than the 15% typically used in the literature, especially in high technology sectors. We also note that our results are fully robust to using a 15% rate.

[16]In Appendix Table 17, we use enterprise value instead of sales and our results are robust.

As an alternative to KPSS-based valuation, we create a citation-based metric to estimate $PatentValue_{i,j}$ in Equation (5). In this method, for each patent p in the sample, we gather the number of granted patents that cite p and have an application date that is within five years of p's grant date. Similar to the approach that we performed in the KPSS-based methodology, we depreciate citation-based value using an annual 20% rate relative to the base year 2014.

3.5 Sample and Key Variables

We include public firms with at least one patent from a CPC category that has a rejected patent. We used the matched public firms using the matches of patents to public firms provided by Kogan et al. (2016). We extend the matches of patent firms to 2017 using all patents applied for up to 2017 matching them using a fuzzy text matching algorithm. Our patent text data comes directly from the USPTO website. We also include the competitors of each firm in our sample using the TNIC-3 competitor network of Hoberg and Phillips (2016). Our sample thus includes 1,586 unique firms: 1,159 patenting firms and also 427 competitor firms.

Table 8 displays summary statistics for the sample of firms used in our analysis.

Insert Table 8 here

Our sample contains 9,106 firm-year observations based on our sample screens noted above, and these firm-year observations span the period from 2011 to 2017 (excluding 2014, the treatment year). We briefly describe all of the variables we use in our analysis here (full details of these variables and a variable list is in Appendix A). Table 8 presents summary statistics for firms both in the pre-Alice period of 2011-2013 and also for in the post-Alice period of 2015-2017.

Our goal is to examine firms with granted patents that were exposed to Alice as identified by our BERT model. We examine their innovation decisions, their lawsuits and other legal consequences. We then examine the impact of Alice on their ex post profitability and the competition they face in their product markets. Lastly, we examine how they change their acquisitions in response to their Alice exposure.

Panel A of Table 8 presents accounting characteristics including the size of firms measured by assets and sales, sales growth, age, and profitability (Operating income / Sales) of firms. We also present firm Tobin's q (market value of equity + book value of debt / book value of assets). The table shows that overall operating earnings and sales growth decline, while overall Tobin's q increases. Later, we explore these findings including firm fixed effects, and see if they differ for large vs. small firms.

Panel B presents the key innovation and legal variables for firms in our sample. The variable *Treatment Effect* measures the extent a firm's patent portfolio is impacted by the court decision as measured using the BERT model in equation (5). It captures how much a firm is dependent on sales and also the percentage of patents value that is impacted by the Alice court decision. R&D/Sales is Compustat R&D divided by total sales of the firm and is set to zero if R&D is missing for our base tests. Log(# of Patents) is the log of one plus the number of patent applications. Acquisitions/Sales is the number of acquisitions and the amount of acquisitions are acquisitions from the Securities Data Corp (SDC) database matched to the Compustat database.

The legal variables we examine are *Is Alleged*, *Is Accuser*, *IPrisk* and *PatInfringe*. We compute the first two using information in Public Access to Court Electronic Records (PACER) database, which provides public access to all cases litigated in the U.S. District Courts, and the second two using textual queries of each firm's 10-K statement filed with the SEC. *Is Alleged* is an indicator variable that equals one if a firm was alleged in a patent lawsuit at least once in that year, and zero otherwise. *Is Accuser* is an indicator variable that equals one if a firm is accused by any party in a patent lawsuit at least once in that year, and zero otherwise. *IPrisk* is the total number of paragraphs mentioning "intellectual property" in the risk factor section of the firm's 10-K, scaled by the total number of paragraphs in the 10-K. *PatInfringe* is the total number of 10-K paragraphs containing both a patent word and a word that contains the word root "infringe", also scaled by the total number of paragraphs in the firm's 10-K. The table shows that patents decline and lawsuits and patent infringement all decline post-Alice while IP risk increases.

Lastly, Panel C of Table 8 presents the competition variables we examine. *VCF/Sales*, is the a measure of VC entry in a given firm's product market and is the cosine similarity of the text in the focal firm's 10-K business description and the total text describing all VC-funded startups in the same year as measured using the verbal product descriptions of startups provided by Venture Expert (see Hoberg et al. (2014)). *TSIMM* is the firm's TNIC-3 text-based total similarity to other public firm competitors from Hoberg and Phillips (2016). The next three variables are constructed using the metaHeuristica software package to run high speed queries on 10-Ks filed with the Securities and Exchange Commission. *Complaints* is the number of paragraphs in the firm's 10-K that complain about competition divided by the total number of paragraphs in the firm's 10-K. *Noncompete* is the number of paragraphs in a firm's 10K mentioning "non-compete" agreements, scaled by the total paragraphs in the 10-K. *Nondisclose* is the number of paragraphs mentioning "non-disclose" or NDA agreements in a firm's 10K, scaled by the total paragraphs in the 10-K. The table shows that competition overall increases post-Alice while nondisclosure agreements increase. We now turn to regressions that include firm fixed effects and explore the differences for high and low market share firms using market shares based on TNIC-2 industry definitions from Hoberg and Phillips (2016).

Our treatment scores are not binary as they represent the multiplication of percentage of a firm's patent portfolio value that is exposed to Alice and the number of patents scaled by sales. Each patent's Alice exposure score is the probability from our BERT model that the patent will be ruled ineligible if it is challenged in court.In around half of the sample, treatment score is close to 0. The median and average scores of treatment in our sample are 0.001 and 0.062, and the 75^{th} percentile and 90^{th} percentiles are 0.034 and 0.224, respectively.

Panel D shows the distribution and financial characteristics for the sample of firms divided based on treatment scores. We show the full distribution of firm-level treatment scores in Figure 2. Panel A shows the histogram and Panel B shows the cumulative distribution function of our firm-level treatment scores.

Insert Figure 2 here

Panel A of Figure 2 shows that about 26% have zero treatment scores, it also shows that 30% of our firms have scores that are close to zero. Thus, we have about 56% of our firms with treatment score equal to zero or slightly greater than zero (from 0.0 to .005). About 5% of firms have very high exposure to Alice with treatment scores above .5. Using a continuous treatment score allows us to show how the ex post outcomes vary with the intensity of treatment.

4 The Impact and Outcomes of Alice

We now analyze the impact of Alice on innovation, firm performance and value, competition, lawsuits and legal risk, and acquisitions. Throughout this section, we present results separately for small and large market share firms, as we have found uniformly that there are key differences for firms based on high versus low firm market share.

The justification for examining whether there are heterogeneous effects based on market shares follows from Aghion et al. (2005) and is based on the fact that larger firms are more able to defend their product markets as they have access to more resources - both managerial and financial. We base our market share variable on each firm's market share in its industry in 2013 (market shares are based on TNIC-2 industry definitions from Hoberg and Phillips 2016), and $High$ indicates that the firm is equal to or above the sample median market share in that industry based using on firm sales in 2013. *Low* equals one if the firm is below the sample median market share based on firm industry sales in 2013.

For all regression tables that follow, *Post* is a indicator variable that equals one if the year is after the Alice decision (2015 to 2017) and zero if before (2011 to 2013). We omit 2014 itself from our analysis as it is partially treated. *Treatment* throughout is a firm-level measure that combines information about the extent to which patents are important for the firm and the extent the firm's patent portfolio was affected by the Alice court decision. Throughout, we use the firm treatment value using each patent's Bert score weighted by the patent's importance to the firm. We present results using two different weights: (1.) using each patent's KPSS weighted value and also (2.) using each patent's citations weighted value. The mathematical notation for the estimation of this measure is provided in equation (5), with citations replacing patent value for the citation based measure. Inspection of the subsequent tables reveals that there is little difference in the results across these two different weighting methods for a patent's importance to the firm. All regressions include firm and year fixed effects. Standard errors are clustered at the firm level.

4.1 Alice and Innovation

We first examine the impact of Alice on firm innovation and we examine the number of patents scaled by sales, the log of 1 plus the number of patents, and R&D/Sales.

Insert Table 9 here

The results for patents in columns (1)-(4) of Table 9 show that both high and low market share firms reduce patenting in the years after Alice. These results are highly significant at the 1% level, and these findings confirm the large importance of the Alice decision to reduce the incentives to patent through its weakening of IP protection. The effect is also larger for large firms in columns (3) and (4) consistent with large firms getting more patents in general. The economic effect of the decision is large. Using the coefficients in column (3), We calculate that high (low) market share firms patenting decreases by 3.2% (9.3%) at the mean with a one standard deviation in the treatment variable. We show these results graphically in Figure 3 including yearly indicator variables to test for pre-trends. The graphical evidence shows no evidence of pre-trends and shows that patents discretely shifted downwards in the years following Alice.

Insert Figure 3 here

The results for R&D in columns (5)-(6) show that low market share firms increase R&D after Alice, while there is no change for high market share firms. Using the coefficient from column (6), we calculate that small firms R&D increase by 16% with a one standard deviation in treatment relative to the mean pre-Alice.

The R&D results are consistent with small firms trying to increase R&D to make up for lost intellectual property, an interpretation more broadly supported in our later tables. In contrast, high market share firms do not increase R&D, indicating they were impacted by the shock in a fundamentally different way in which more R&D was not seen as a necessary response. This muted response by larger firms echoes results throughout our paper suggesting that larger firms (presumably due to their deep pockets and wider-array of knowledge capital) came out of the Alice shock as winners, whereas smaller firms experienced significant losses.

We also note that all of our regressions include controls for firm fixed effects, thus we do not report the lower interactions including the individual variables (Low, High, and Treat) as these are absorbed by firm fixed effects given that they are defined in the treatment year and then held fixed.

We examine changes in competition in the next section, and relevant to the current discussion, we find that competition increases the most for small firms in their local product markets. The results on innovation combined with these increases in competition are consistent with innovation increasing by small firms to "escape-the-competition". While high market share firms do not increase R&D as much, they also do not decrease R&D. The results are consistent with the Schumpeterian effect where more of the innovation is preformed by smaller firms.

4.2 Alice and Competition

Unlike some existing studies, which focus on the impact of individual patent invalidations, our study examines the impact of a technology-area-wide loss in IP protection. Such a market wide shock impacts both existing patents and also the incentives to patent more in the future. These shifts in patenting incentives furthermore affect incentives also of potential competitors, and thus it is important to examine the impact of Alice on competition coming from either new VC funded entrants as well as from existing public firms.

We thus examine several different measures of changes in firm-level competition. We begin by examining entry by venture capital financed firms in each firm's product market, and we also examine changes in competition from existing public firms using product similarity from Hoberg and Phillips (2016). We also examine the most broad measure of competition as the intensity at which firms complain about competition in their 10-Ks. Finally, especially given the strong results we find in firm-year panel data analysis, we then examine measures of product market encroachment at the level of firm-pairs over time, to specifically examine if big firms or small firms move "closer" together in the product space post-Alice using firm-pair-level product similarity scores.

Columns (1) and (2) of Table 10 examine venture capital entry into a firm's local product market. The dependent variable, *VCF/Sales*, is the cosine similarity of the text in the focal firm's 10-K business description and the total text describing all VC-funded startups in the same year (as measured using the verbal product descriptions of startups provided by Venture Expert (see Hoberg, Phillips and Prabhala 2014). Columns (3) and (4) examine the firm's TNIC text-based total similarity (*TSIMM*) to public firm competitors. We examine broad competition *Complaints* in columns (5) and (6). *Complaints* is the number of paragraphs in the firm's 10-K that complain about competition divided by the total number of paragraphs in the firm's 10-K.

Insert Table 10 here

Economically, using the results in Table 11 we calculate that entry by venture capital financed firms into the market of firms with low market shares increases by 47.4% with a one standard deviation increase in treatment relative to the average entry rate pre-Alice - significantly higher than the entry into the markets of high market share firms. Looking at direct measures of competition, both product similarity and complaints increase for low market share firms with no significant increases for high market share firms. Complaints by firms with low market shares increase by .44 and product similarity increase by 26.6% with a one standard deviation increase in treatment relative to the average entry rate pre-Alice. We also present these results graphically for firms with low market shares where we allow each pre- and post-year to have its own indicator variable. These results are presented in Figure 4.

Insert Figure 4 here

The results in Table 10 show, across all aspects of competition, that small firms face increased competition from myriad of sources post-Alice. In contrast, firms with high market shares face increased entry but do not experience changes in product similarity and complaints in any of the specifications and are generally unaffected. These results are consistent with our earlier results on profitability decreases for small firms and decreased market values for small firms. The results reinforce our conclusion that small firms whose patent portfolios are exposed to Alice experience losses, while large firms experience less increased entry but no increases in competition and actually experience some gains in the form of increased sales and market valuations.

We now examine local pairwise product market encroachment post-Alice in Table 11. *Delta TNIC Score* is computed as the change in the TNIC similarity of the pair of firms from year t-1 to year t. Our panel database for this test is thus a very large firm-pair-year panel. A higher value of the *Delta TNIC Score* indicates that the firms in the pair encroached upon one another in the current year. TNIC similarities are textual measures of product similarity from Hoberg and Phillips (2016), and such encroachment indicates that the pair of firms lost pairwise product differentiation and became more intense competitors. *Large* and *Small* are defined as in previous tables, and for parsimony given our current test is based on firm pairs, we denote the two firms associated with each pairwise observation as 1 and 2. In the RHS variables in Table 11, we use the tags "1" and "2" in each variable's name to indicate whether the given variable is a trait of the first or second firm in the pair. For example, the variable Treat1 indicates the treatment intensity of firm 1, and Treat2 indicates the treatment intensity of firm 2 in the pair.

Insert Table 11 here

the results in column (1) of Table 11 show that firms experiencing a larger treatment effect from Alice experience increased encroachment at the pair level. This is consistent with weaker IP protection resulting in rivals adopting patented technologies of rivals resulting in the product offerings of the pair become more similar. These results are highly significant despite the inclusion of rigid firm-pair fixed effects and clustering of standard errors by firm-pair.

Column (2) of Table 11 illustrates our main result that outcomes are different for low and high market share firms. In particular, we interact our baseline results from Column (1) with indicators for whether firm 1 or firm 2 have high or low market shares. The table shows that small firms are particularly sensitive to encroachment when they lose their IP protection. This is consistent with the view that these firms hold narrower advantages in the product market due to their patents, and losses in protection of these narrow advantages can be catastrophic as rival firms would have free access to these technologies post-Alice. In contrast, larger firms appear to be more agile and experience increases in product differentiation relative to their rivals when their overall markets are treated by Alice. This is consistent with these firms having very broad patent portfolios that span technology areas, making them harder to enter their product markets when part of their portfolio is treated by Alice.

The final column (3) in Table 11 interacts these results further to examine the four-way interactions of the sizes of both firm1 and firm 2 in the pair, to assess which size and treatment configurations matter most. The results indicate that positive encroachment only occurs when there is a small firm in the pair that is specifically treatd by Alice. Indeed, Small1xBig2xTreat1xPost has a positive coefficient as does Small1xSmall2xTreat1xPost. However, once the treated firm is a large firm, the coefficient flips to negative, indicating that larger firms tend to experience radically different outcomes than do the small firms. These results further show that shifts in the product market structure are important to understanding why large firms appear to be winners following the Alice shock, and small firms appear to be losers. Indeed many scholars argue that patent protection, in itself, could either be harmful or helpful to incentivize innovation and growth. Our results illustrate that the impact of removing intellectual property protection is actually not uniform across firms, as the large firms appear to realize some benefits whereas small firms experience the losses.

4.3 Alice and Firm Performance

We now examine the profitability of firms post-Alice. Table 12 displays panel data regressions that examine whether the sales, profitability and market value of high vs. low market share firms were differently affected by the Alice decision. In columns (1)-(2), the dependent variable is *Sales Growth*, calculated as the natural logarithm of total sales in the current year t divided by total sales in the previous year $t-1$. In columns (3) and (4), the dependent variable is *Operating Income/Sales*. In columns (5)-(6), the dependent variable is *Tobin's* q, calculated as the market to book ratio (market value of equity plus book debt and preferred stock, all divided by book value of assets).

Insert Table 12 Here

Table 12 shows that firms with high market shares whose patent portfolios are exposed to Alice experience growth and increase in market value (measured using Tobin's q) post-Alice. Their sales go up by 1.12 percentage points (23% of their 2013 average growth rate) and their Tobin's q goes up by 13.3 percent with a one standard deviation of treatment. Their profitability is also unchanged despite their increased scale. Thus, high market share firms appear to benefit when they are operating in technology markets that experience market-wide losses in patent protection. As our later results will suggest, these gains at least partially come at the expense of low market share firms, as large firms would face weakening competition when smaller firms have to scale back.

Consistent with this view, Table 12 shows that small firms (firms with low market shares) indeed experience losses after Alice. Small firms whose patent portfolio is exposed to Alice suffer decreased operating margins and also losses in their market valuations. These results persist when additionally controlling for firm age and also for firm size. Small firms' operating margins go down by 12.7 percentage points (71% of their pre-Alice operating margin) and their Tobin's q declines by .13 which is 6 percent of their pre-Alice Tobin's q with a one standard deviation increase in treatment.

4.4 Legal Impact: Contractual Provisions and Lawsuits

The matter of intellectual property protection is inherently a matter of legal protection and a means of reducing the risk that rival firms will extract a focal firm's technological advantage. Thus we examine, across multiple legal metrics, how the legal situation changes for firms with high and low market shares post Alice.

We start with two important aspects of firm legal outcomes: the intensity at which they disclose risk of loss of IP (an important test of validity), and the extent to which firms use alternative "second best" contracts including non-compete and non-disclosure agreements to improve IP protection after IP protection through patents is lost following the Alice decision.

Table 13 displays panel data regressions examining the impact of Alice on intellectual property risk and the use of non-compete and non-disclosure agreements. In columns (1)-(2), *IP Risk*, is the total number of paragraphs mentioning "intellectual property" in the risk factor section in the 10-K documents, scaled by the total number paragraphs in the 10-Ks. *Noncompete* is the total number of 10K paragraphs mentioning "non-compete" agreements, all scaled by the total paragraphs in the 10-K. *Nondisclosure* is the total number of 10-K paragraphs mentioning "non-disclose" or NDA agreements, all scaled by the total paragraphs in the 10-K.

Insert Table 13 here

The results presented in Table 13 show that small firms with low market shares disclose significantly more information about increased intellectual property risk in the risk section of their 10-K. This provides important validation of the primary impact of the Alice case itself, and that the negative consequences were particularly felt by smaller firms. The table also shows that small firms also use more non-compete and non-disclosure agreements post-Alice. Across all of these outcomes, we find no significant changes for large firms. Overall, the results show that small firms face greater IP risk and consistent with them using alternative contracts to protect their IP after the passage of Alice by the Supreme Court.

In Table 14, we next examine whether patent lawsuits involving small and large firms were differentially affected by the Alice decision. We use Stanford Non-Practicing Entity (NPE) Litigation Database to find NPE and operating company (OC) initiated lawsuits. In columns (1)-(2), the dependent variable, *is Alleged*, is a dummy variable equal to one if a firm was alleged to have infringed on a patent in a lawsuit at least once in that year, and zero otherwise. In columns (3) to (4), *Alleged by NPE* is a dummy variable equal to one if a firm was alleged to have infringed by a non-practicing entity (NPE) in a patent lawsuit at least once in that year, and zero otherwise. In columns (5) to (6), *Alleged by OC* is a dummy variable equal to one if a firm was alleged by a operating company to have infringed on a patent at least once in that year, and zero otherwise. In columns (7)-(8), *PatInfringe* refers to the total number of paragraphs containing a patent word and infringe* in the firm's 10-K, scaled by the total number of paragraphs in the 10-Ks. The 10-K based measure establishes robustness, as some cases of patent infringement might be settled out of court, and thus might not appear in court records, but nevertheless might be discussed in a firm's 10-K. In columns (9)-(10), *Is Accuser* is a binary variable equal to one if a firm accused any other party of infringement in a patent lawsuit at least once in that year, and zero otherwise.

Insert Table 14 here

In contrast to earlier findings that illustrated strong results for firms with low market shares, Table 14 shows that small firms' lawsuit exposure does not change post-Alice. This result is surprising as our earlier results showed that small firms faced greater IP risk and used more non-disclosure and non-compete agreements post-Alice. Table 14 shows that actual lawsuits including small firms did not change. To understand this result, we note that the result is different for firms with high market shares, whose lawsuit exposure significantly *decreases* after Alice is decided. Large firm are less likely to be alleged to infringe on other firms and their exposure to lawsuits decreases for lawsuits by non-performing entities, or patent trolls, post-Alice. These results are intuitively interpreted through two impacts of Alice. First, Alice reduced IP protection, resulting in lawsuits became less viable as a means to extract wealth from another party (one needs strong IP to successfully make a claim of infringement). Second, the gains associated with having fewer lawsuits, especially from patent trolls, accrued mostly to larger firms whose legal teams were able to internalize these gains. Smaller firms, whose ability to defend IP may be more limited, were less able to achieve this outcome. Overall our evidence again shows that large firms appear to benefit, and small firms experience losses, following the Alice ruling.

4.5 Alice and Acquisitions

We now examine the impact of Alice on firm acquisitions by small and large firms. There is strong a priori reason to believe that acquisitions will decline after Alice following the theory of Phillips and Zhdanov (2013). Phillips and Zhdanov (2013) show that large firms have strong incentives to buy small firms after small firms develop a new patentable innovation. Without patent protection, there will be little incentive for large firms to continue paying to buy these small firms for their patents, as they can just spend limited resources and copy the unprotected innovation. If they do purchase a small firm, the purchase price will be lower as the bargaining power of the small firms will have decreased post-Alice. We thus examine the impact of Alice on the dollar value spent on acquisitions scaled by sales and also the log of one plus the dollar value of acquisitions.

Insert Table 15 here

The results are displayed in Table 15. Across all specifications presented in Table 15, we indeed find that the amount spent by high market share firms on acquisitions post-Alice decreases significantly. For large firms, acquisitions/sales (log of amount spent on acquisitions) decreases by 16.5% (14.3%) with a one standard deviation increase in the treatment variable. In contrast, there is no impact on small firms acquisitions of other firms. The results are consistent with the predictions of Phillips and Zhdanov (2013) that decreased patent protection leads to decreased bargaining power for small firms that are targets, and thus high market share firms acquire less and pay less for any firms they do acquire. These results once again point to gains by high market share firms post-Alice (who save by spending less on acquisitions), and additional losses for smaller firms who have fewer options for monetizing their IP through exits via M&A.

4.6 Robustness Tests

Table 3 showed that the Bert model outperforms other linguistic models in predicting out-of-sample predictions of a patent's likelihood of being rejected. In this section, we also assess the economic advantages of using the BERT model. We preform several different types of robustness tests that use different methods to calculate the firm's patent exposure to Alice. These tests show the value of using the BERT model to calculate patent exposures, and resulting firm exposures, to Alice.

We use both the TF-IDF method and also a simple binary (or dummy variable) CPC category method to identify a patent's exposure to Alice. For the TF-IDF method, in the calculation of the treatment variable depicted in equation (5), we use a TF-IDF score instead of a BERT score. The binary or dummy method sets exposure equal to one if the patent's primary CPC code belongs to one of the top-20 CPCs that have the most frequent Alice rejections. We aggregate over all of the firm's patents as before to get a total firm exposure.

We present in the online appendix different tables using the TF-IDF method and the binary CPC category method to explore the impact of different methods on identifying firm exposure to Alice. Appendix Tables 18 and 19 display tests for the patenting and innovation results that are analogous to Table 9, but use the TF-IDF method and binary CPC category method, respectively. Appendix 20 and 21 display the results for competition analogous to Table 10. Tables 22 and 23 display the results for profitability, analogous to Table 12.

Overall, in all the robustness tables the signs are similar to the results presented using the BERT model. Yet the results also show the gains to using the more accurate BERT model, as we lose some significance for patenting for small firms using TF-IDF and for R&D using the binary dummy variable. We also lose significance for several of the competition variables for small firms using either of these two less sophisticated methods relative to the results using the BERT model. Given the higher out-of-sample prediction accuracy shown in Table 3 for the BERT model versus other methods, we conclude that the gains associated with using the deep learning neural network BERT model are both statistically and economically important.

5 Conclusions

We examine the impact of lost intellectual property protection on firm innovation, performance, competition, and mergers and acquisitions. We examine firms whose patents are potentially invalidated by the Alice Corp v. CLS Bank International, 573 U.S. 208 (2014) Supreme Court decision. This decision revoked patent protection on patents whose fundamental idea is considered abstract with a transformation that is not novel. It impacted multiple areas including business methods, software, and bioinformatics. The outcome of this decision was very much in doubt and was not anticipated.

While the decision had an extremely large ex post impact on patenting, there was (and is) uncertainty about whether an existing or proposed patent transforms an idea sufficiently to be granted patent protection. Given the uncertainty about whether the Alice decision impacts individual patents, we apply an array of novel machine learning techniques on regulatory and patent textual corpora to assess how much a given firm's patent portfolio is exposed to Alice.

We document that ex post patenting by firms whose patent stock portfolio is identified as being exposed to Alice significantly decreases for both high and low market share firms. We find a significant increase in R&D for small firms. These results are consistent with small firms' attempting to replenish their innovative portfolio as predicted by Aghion et al. (2005). Examining ex-post changes in sales growth and profitability along with firm value, we find an asymmetric impact of Alice on firms whose patent portfolio is exposed to Alice. High market share firms gain and small market share firms lose. Exposed high market share firms gain in sales and also in their market valuations as measured by Tobin's q. Small firms whose patent portfolio is exposed to Alice experience a decrease in operating margins and their market valuations also decline.

We show that these differential losses by firms with low market shares can be explained by changes in competition and limited legal options to replace losses in IP protection. We show that small firms face increased competition using a number of different measures, while the competition surrounding high market share firms is not significantly impacted. In the post-Alice period, small affected firms face increased venture capital financed entry into their product space, lost product differentiation relative to their existing competitors, and they complain more about increased competition. Consistent with trying to protect IP that was previously protected through patents, small firms resort more to non-compete and non-disclosure agreements with their employees post-Alice. In contrast, high market share firms once again appear to relatively gain as they face fewer lawsuits from non-producing entities ("patent trolls") and decreased direct competition from smaller firms. Overall our results illustrate an uneven impact of lost IP protection across firms with high and low market shares.

Our paper finds benefits of increased competition and fewer lawsuits from reduced patent protection but costs for existing small firms who most directly face the impact of increased competition from both large firms and new entrants. Our results thus show the costs and benefits of decreased IP protection.

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Figure 1: Ratio of Post-Alice Density to Pre-Alice Density

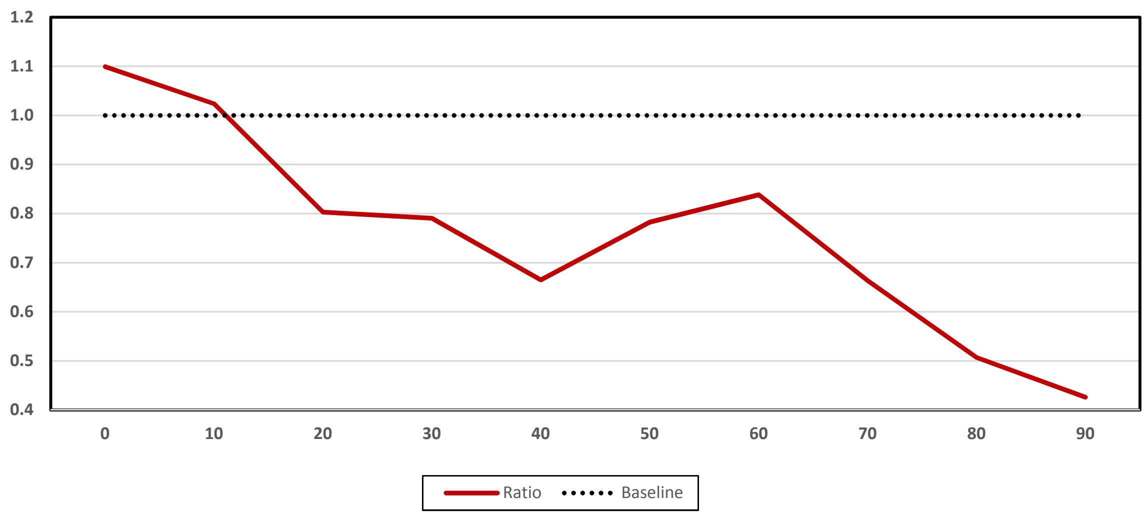
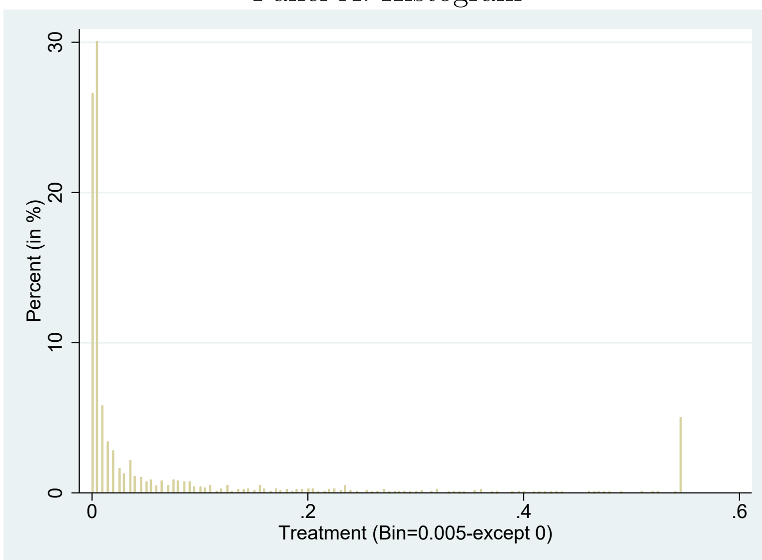


Figure 2: Histogram and CDF For Treatment

This figure shows the histogram and CDF for the treatment variable. In Panel A, the bin width is 0.005 and y-axis is the percentage of treatment falls into the bin. In Panel B, the y-axis displays the cumulative probability.

Panel A: Histogram



Panel B: CDF

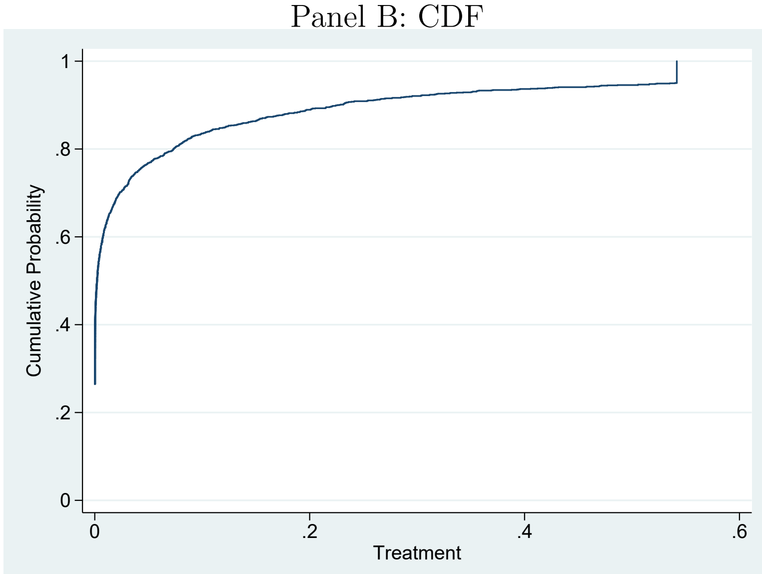
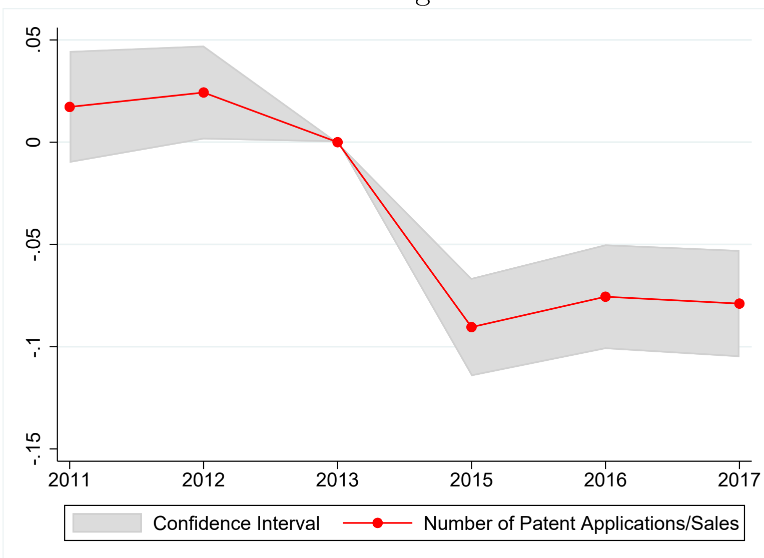


Figure 3: Patent Applications For Large and Small Firms

This figure reports the point estimates per year for $Large \times Treatment$ in Panel A and $Small \times Treatment$ in Panel B from Table 9, column (2) where the dependent variable is Patent Applications/Sales. The regression specifications are the same as those reported in columns [2] of Table 9, except that $Large \times Treatment$ and $Large \times Treatment$ are allowed to vary by year, and 2013 is chosen as the reference year. The gray line indicates the 90% confidence interval.

Panel A: Large Firms



Panel B: Small Firms

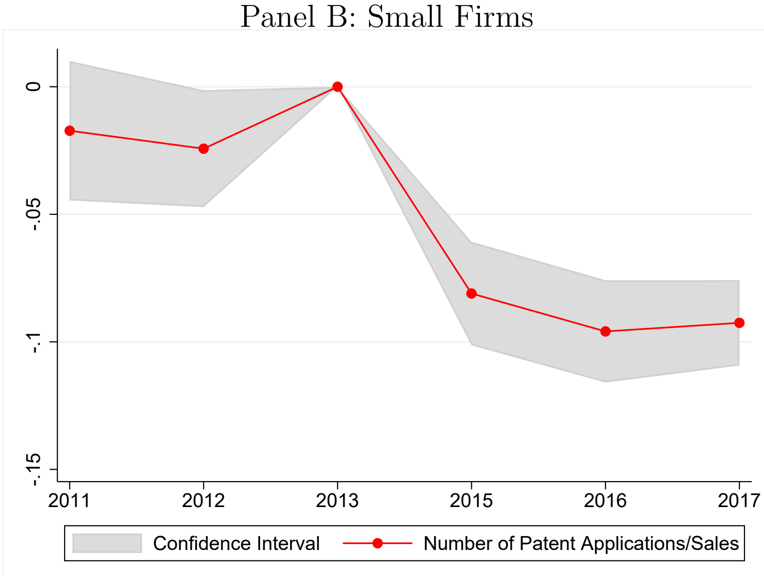
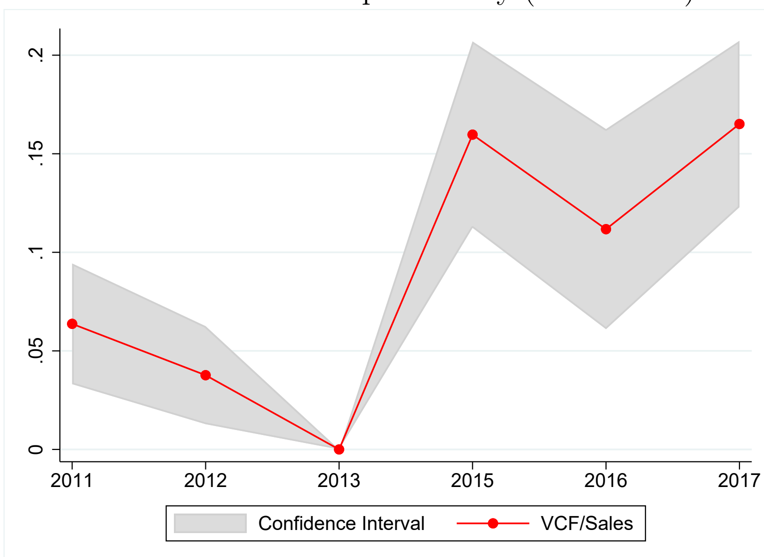


Figure 4: Competition For Small Firms

This figure reports the point estimates per year for $Small \times Treatment$ from Table 10 columns (2) and (4) where the dependent variable is VCF/Sales (Panel A) and Total Similarity (TSIMM) (Panel B). The regression specifications are the same as those reported in columns (2) and (4) of Table 10, except that $Small \times Treatment$ is allowed to vary by year, and 2013 is chosen as the reference year. The gray line indicates the 90% confidence interval.

Panel A: Venture Capital Entry (VCF Score)



Panel B: Total Similarity

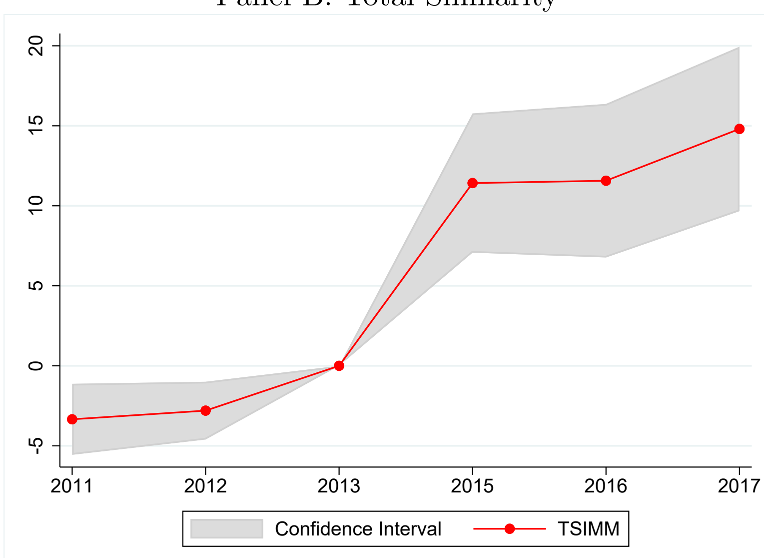


Table 1: Annual Patent Applications and Post-Alice Rejections By Industry

This table reports annual statistics from USPTO patent applications and the corresponding percentage that were rejected in parentheses based on the Supreme Court's Alice decision for the top 12 industries with patent rejections. The rejection data provided by Lu et al. (2017) extends until 2016; therefore ratio of rejection is assigned NA for 2017. *Change* reports the percentage change from the number of patent applications in 2013 to the average number of patent applications for the 2015-2017 period. Corresponding CPCs for each industry are provided in Table 2.

Patent Applications and USPTO Alice Rejections - Top 12 industries

	Number of Patent Applications & Rejection Percentage								
Industry	2008-2009	2010-2011	2012	2013	2014	2015	2016	2017	Change (2013 to 2014-2017)
Commerce (Data Processing Methods)	6582 (11.7%)	7675 (17.9%)	5033 (29.8%)	5563 (36.2%)	5223 (23.2%)	4246 (6.6%)	3405 (1.5%)	3240 (NA)	-34.7%
Administration (Data Processing Methods)	6681 (6.7%)	6250 (11.1%)	3658 (20.8%)	2958 (31.3%)	2970 (16.7%)	2500 (3.6%)	2527 (0.6%)	2568 (NA)	-14.4%
Finance (Data Processing Methods)	2297 (9.4%)	2662 (13.2%)	1545 (22.5%)	1752 (42.1%)	1512 (37.8%)	1035 (8.7%)	775 (1.9%)	711 (NA)	-52.0%
Payment Systems (Data Processing Methods)	1603 (9.9%)	2043 (12.9%)	1673 (26.6%)	1946 (36.7%)	2182 (24.4%)	2157 (5.8%)	2029 (1.9%)	1895 (NA)	4.2%
Coin-freed Facilities or Services (Coin-freed or Like Apparatus)	2385 (3.9%)	1665 (6.8%)	1221 (17.0%)	1407 (34.3%)	1134 (31.2%)	980 (14.9%)	939 (6.7%)	937 (NA)	-32.3%
Information Retrieval (Digital Data Processing)	7981 (0.5%)	8451 (1.2%)	5850 (2.4%)	6566 (4.1%)	6650 (5.1%)	6339 (2.0%)	6196 (1.0%)	5816 (NA)	-6.8%
Video Games (Games)	1414 (4.5%)	1504 (7.0%)	919 (12.5%)	1045 (27.4%)	1010 (19.6%)	781 (7.8%)	847 (3.4%)	929 (NA)	-18.4%
Specialized For Sectors (Data Processing Methods)	515 (4.9%)	918 (10.9%)	753 (15.5%)	845 (32.1%)	881 (19.3%)	669 (4.5%)	848 (0.6%)	806 (NA)	-8.4%
Computer Security (Digital Data Processing)	3886 (1.6%)	3926 (1.5%)	2617 (2.6%)	2684 (5.0%)	2641 (5.2%)	2604 (4.0%)	2675 (0.7%)	2872 (NA)	1.2%
Network Security (Transmission of Digital Information)	3522 (0.8%)	3208 (0.8%)	2206 (1.9%)	2864 (4.3%)	3433 (5.5%)	4042 (3.4%)	4124 (0.8%)	3817 (NA)	39.5%
Network Specific Applications (Transmission of Digital Information)	3389 (0.8%)	3441 (1.5%)	2282 (3.2%)	2891 (6.0%)	3174 (4.7%)	3172 (2.2%)	3098 (0.6%)	2414 (NA)	0.1%
Measuring or Testing Processes (Microbiology & Enzymology)	3759 (1.3%)	4311 (2.5%)	2237 (4.3%)	2356 (4.9%)	2336 (3.2%)	2105 (2.6%)	2099 (0.6%)	2082 (NA)	-11.1%

Table 2: CPC Descriptions by CPC group and Industry

This table provides descriptions for largest CPC patent subgroups for which we run the BERT patent rejection models. We also give the larger industry correspondence for the main CPC groups impacted by the Alice decision.

Panel A: CPC Main/Sub Group Descriptions

CPC Main/Sub Group	Description
G06Q10/06	Administration; Management-Resources, workflows, human or project management, e.g. organising, planning, scheduling or allocating time, human or machine resources; Enterprise planning; Organisational models
G06Q10/10	Administration; Management-Office automation, e.g. computer aided management of electronic mail or groupware ; Time management, e.g. calendars, reminders, meetings or time accounting
G06Q30/02	Commerce, e.g. shopping or e-commerce-Marketing, e.g. market research and analysis, surveying, promotions, advertising, buyer profiling, customer management or rewards; Price estimation or determination
G06Q30/06	Commerce, shopping or e-commerce-Buying, selling or leasing transactions
G06Q30/0631	Commerce, shopping or e-commerce-Buying, selling or leasing transactions-Electronic shopping-Item recommendations
G06Q30/08	Commerce, shopping or e-commerce-Buying, selling or leasing transactions Auctions; matching or brokerage
G06Q40/00	Finance; Insurance; Tax strategies; Processing of corporate or income taxes
G06Q40/02	Finance; Insurance; Tax strategies; Processing of corporate or income taxes-Banking, e.g. interest calculation, credit approval, mortgages, home banking or on-line banking
G06Q40/04	Finance; Insurance; Tax strategies; Processing of corporate or income taxes-Exchange, e.g. stocks, commodities, derivatives or currency
G06Q40/06	Finance; Insurance; Tax strategies; Processing of corporate or income taxes-Investment, e.g. financial instruments, portfolio management or fund management
G06Q40/08	Finance; Insurance; Tax strategies; Processing of corporate or income taxes-Insurance, e.g. risk analysis or pensions
G07F17/32	Coin-freed apparatus for hiring articles; Coin-freed facilities or games, toys, sports or amusements, casino games, online gambling

Panel B: Industries and Corresponding CPC Groups

Industry	CPC Group
Chemical & Physical Properties (Analyzing Materials)	G01N33
Coin-freed or Like Apparatus (Coin-freed Facilities or Services)	G07F17
Data Processing Methods (Administration)	G06Q10
Data Processing Methods (Commerce)	G06Q30
Data Processing Methods (Finance)	G06Q40
Data Processing Methods (Payment Systems)	G06Q20
Data Processing Methods (Specialized For Sectors)	G06Q50
Diagnosis, Surgery, Identification (Measuring for Diagnostic Purpose)	A61B5
Digital Data Processing (Arrangements for Program Control)	G06F9
Digital Data Processing (Computer Aided Design)	G06F30
Digital Data Processing (Computer Security)	G06F21
Digital Data Processing (I/O Arrangements for Data Transfer)	G06F3
Digital Data Processing (Information Retrieval)	G06F16
Digital Data Processing (Natural Language Processing)	G06F40
Games (Video Games)	A63F13
Graphical Data Reading (Recognizing Patterns)	G06K9
Microbiology & Enzymology (Measuring or Testing Processes)	C12Q1
Photogrammetry or Videogrammetry (Navigation)	G01C21
Pictorial Communication (Selective Content Distribution)	H04N21
Transmission of Digital Information (Network Security)	H04L63
Transmission of Digital Information (Network Specific Applications)	H04L67
Transmission of Digital Information (User-to-user Messaging)	H04L51

Source: https://patentsview.org/download/data-download-tables

Table 3: Comparison of Predictions For BERT vs. Other Models

This table compares predictions of BERT, TF-IDF (Robertson (2004)) and Word2Vec models (Mikolov et al. (2013)) based on Accuracy and F_1 Score. Accuracy is a ratio of correctly predicted observation to the total observations. F_1 Score is the harmonic mean of recall and precision, which are defined in Equation (1) and (2). For all models, we conduct four experiments in which the only difference is the way we create the training samples. In experiment A, for each of the 23,734 positives, we find a matching negative patent that is in the same CPC Group. In sample B, C, and D, we keep adding 23,734 more matching patents to the negatives pool based on CPC Subclass, Class, and Section respectively. Therefore, from A to D, each sample has 23,734 more negatives but the newly added ones are less granular than the previous ones.

	A		B		C		D	
Model Name	F_1 Score	Accuracy	F_1 Score	Accuracy	F_1 Score	Accuracy	F_1 Score	Accuracy
SciBERT Finetune	0.647	0.731	0.638	0.754	0.637	0.773	0.641	0.781
BERT Finetune	0.631	0.744	0.611	0.753	0.620	0.770	0.626	0.777
TF-IDF + Logistic Regression	0.571	0.676	0.604	0.643	0.626	0.688	0.589	0.765
TF-IDF + Decision Tree	0.524	0.631	0.549	0.544	0.554	0.578	0.526	0.733
TF-IDF + Random Forest	0.517	0.682	0.391	0.718	0.311	0.713	0.239	0.703
Word2Vec + Logistic Regression	0.585	0.707	0.414	0.728	0.375	0.730	0.357	0.729
Word2Vec + Decision Tree	0.477	0.581	0.436	0.619	0.446	0.665	0.440	0.678
Word2Vec + Random Forest	0.504	0.668	0.398	0.705	0.353	0.715	0.344	0.718

Table 4: Summary of BERT Prediction Statistics

This table reports statistics from BERT model predictions for the set of patents that are examined for invalidation. A patent is included in the examination set if it is granted between 06/19/1994 and 06/19/2014 and share the same primary CPC with at least one of the applications that were rejected by the USPTO based on the Alice decision. Panel A reports the frequency statistics from different thresholds for the 642,678 patents that fit to the examination criteria. In the default model, the threshold of 0.5 is used. The Panel B documents the most frequent primary CPCs for patent applications rejected by the USPTO, and for patents that have higher than 0.5 as the BERT score. In our sample, 62,687 patents that have higher than BERT Score of 0.5 have 64,394 primary CPCs. Panel C provides short descriptions for the most frequent CPCs.

Panel A: BERT Predictions For Different Thresholds

Threshold	Percentage of Patents ≥ Threshold (%)	Number of Patents ≥ Threshold	Number of Unique CPCs
0.5	9.75	62,687	4688
0.6	9.04	58,126	4615
0.7	8.31	53,406	4533
0.8	7.44	47,799	4417
0.9	6.20	39,868	4232

Panel B: Summary of CPCs For Alice Rejections and BERT Predictions by CPC group

Alice Rejections (For Patent Applications)			**BERT Predictions (For Granted Patents)**		
Most Frequent CPCs	Count	Percentage(%)	Most Frequent CPCs	Count	Percentage(%)
G06Q30/02	1185	3.49	G06Q30/02	1767	2.74
G06Q40/04	675	1.99	G06Q10/10	1117	1.73
G06Q10/06	486	1.43	G06Q10/06	1046	1.62
G06Q40/08	397	1.17	G06Q30/06	1003	1.56
G06Q40/06	383	1.13	G06Q40/02	939	1.46
G06Q10/10	370	1.09	G06Q40/04	870	1.35
G06Q30/06	343	1.01	G06Q40/06	577	0.90
G06Q40/02	293	0.86	G07F17/32	529	0.82
G06Q30/0631	248	0.73	G06Q40/00	500	0.78
G06Q30/08	247	0.73	G06Q40/08	482	0.76

Table 5: Patent Grants and Predicted BERT Rejection Statistics By Industry

This table displays the total number of patents granted in each industry that have a high percentage of patents predicted to be rejected by our BERT model. The numbers in parentheses show the percentage of patents iun that industry and period with a BERT score of 0.5 or higher. Corresponding CPCs for each industry are provided in Table 2.

Patent Grants and Predicted BERT Rejections

	Number of Patent Grants & Ratio of BERT Cases ($\geq$ 0.5)			
Industry	1994-1999	1999-2004	2004-2009	2009-2014
Commerce (Data Processing Methods)	355 (46.5%)	1460 (34.5%)	3536 (28.2%)	10389 (31.4%)
Administration (Data Processing Methods)	665 (37.3%)	2001 (28.1%)	4447 (21.5%)	11467 (21.0%)
Finance (Data Processing Methods)	204 (52.0%)	473 (45.0%)	1253 (38.4%)	6387 (43.0%)
Payment Systems (Data Processing Methods)	263 (38.0%)	565 (28.8%)	1175 (22.7%)	3411 (25.9%)
Coin-freed Facilities or Services (Coin-freed or Like Apparatus)	445 (34.8%)	1126 (25.2%)	1483 (23.3%)	4486 (21.7%)
Information Retrieval (Digital Data Processing)	1238 (23.6%)	3823 (10.1%)	5894 (5.6%)	15811 (5.7%)
Video Games (Games)	336 (32.1%)	912 (18.3%)	708 (13.4%)	2598 (13.5%)
Specialized For Sectors (Data Processing Methods)	21 (38.1%)	72 (15.3%)	220 (15.5%)	936 (23.8%)
Computer Security (Digital Data Processing)	509 (25.3%)	1176 (16.5%)	2965 (8.2%)	8659 (8.4%)
Network Security (Transmission of Digital Information)	242 (28.1%)	1109 (15.1%)	3742 (8.8%)	9003 (8.6%)
Network Specific Applications (Transmission of Digital Information)	98 (31.6%)	950 (12.0%)	2943 (7.0%)	7565 (7.5%)
Measuring or Testing Processes (Microbiology & Enzymology)	1369 (9.6%)	2107 (8.8%)	1887 (8.2%)	3749 (10.9%)

Table 6: Most Frequently Used Words in BERT Predictions

This table list words that are used mostly frequently in patents with high BERT scores ($\geq$ 0.5) compared to ones with low BERT scores (<0.5). We first label patents with a BERT score $\geq$ 0.5 as positives and the remaining ones as negatives. We remove non-alphabetic characters from patent texts, apply lemmatizing method to each word, and calculate the number of positive and negative patents that each word appears in. We filter out words that do not appear in at least 1% of the positive patents. For each word w, we first assign it to a CPC Group with the highest ratio of the number positive patents that contain the word to the total number of positive patents in that CPC. Then, we sort the words according to their appearance ratio, defined as $\frac{Count_w^+}{1 + Count_w^-}$, where $Count_w^+$ and $Count_w^-$ are positive and negative number of patents a word w appears in, respectively. We list the top 15 words sorted according to their appearance ratio.

Industry	Top Fifteen Words
Commerce (Digital Data Processing)	rebate, bidder, bidding, buyer, seller, discounted, discount, auction, incentive, referral, purchaser, selling, solicitation, sponsor, shopper
Administration (Digital Data Processing)	consultant, procurement, consultation, accountability, contractor, deadline, strategic, planner, objectively, satisfaction, logistics, revise, employee, vacation, staff
Finance (Digital Data Processing)	lender, beneficiary, underwriting, liquidity, treasury, financing, debt, equity, investor, hedge, earnings, investing, owed, reimbursement, earning
Payment Systems (Digital Data Processing)	refund, settlement, debited, credited, ach, debiting, fund, crediting, clearinghouse, deducted, payer, enroll, mastercard, payee, mailed
Coin-freed Facilities or Services (Coin-freed or Like Apparatus)	redeeming, redemption, redeem, redeemed, rewarded, payouts, earn, earned, payoff, dealer, awarding, redeemable, payout, eligibility, gambling
Information Retrieval (Digital Data Processing)	equ, spelling, categorize, ranked, linguistic, alphabetical, categorization, searchable, categorizing, relational, sorted, sql, mathematics, vocabulary, sentence
Video Games (Games)	contest, opponent, town, psychological, invitation, upcoming, verbally, him, motivation, personality, team, judgement, football, motivated, fitness
Specialized For Sectors (Digital Data Processing)	interview, prospective, forecasting, county, political, forecast, affiliation, pursue, education, legally, invited, district, attend, attorney, historic
Computer Security (Digital Data Processing)	licensing, certification, auditing, owner, license, violation, licensed, someone, exponent, creative, guess, cryptography, granting, unlimited, consulted
Network Security (Transmission of Digital Information)	certificate, confidentiality, login, refuse, logon, confidential, abuse, username, password, signing, signed, privacy, logged, authority, cookie
Network Specific Applications (Transmission of Digital Information)	consult, subscription, netscape, highway, portal, subscribing, provider, behavioral, outdated, locale, geographically, uploads, dated, cooky, uploaded
Measuring or Testing Processes (Microbiology & Enzymology)	questionnaire, enrolled, lifestyle, multivariate, emotional, disability, smoking,consent, birth, whom, gender, healthcare, college, percentile, electrocardiogram

Table 7: Comparison of Patent Alice BERT Scores in the Pre- and Post-Period

This table shows the distributional density of the BERT Score before the Alice shock (2011 to 2013) and after the shock (2017) for the Top 20 technological areas impacted by Alice. To compute the density in a given year, we first identify, the set of patents granted in that year in the Top 20 technological areas. The number of patents in each year ranges from 21,404 in 2011 to 31249 in 2013 to 32,662 in 2017 (of those patents granted in 2017, 17,299 were applied for after the Alice decision). For the year 2017, as our goal is to examine the patent distribution post-Alice, we restrict attention to the 17,299 patents applied for in the post-Alice period. We sort all patents in each year into 10 bins based on each patent's BERT Score. Bins are defined as the ten equal segments in the interval (0,1), which is the range of the BERT Score. For each bin, the density is the number of patents in the given bin in the given year divided by the total number of patents in the given year. Finally, to illustrate the impact of Alice on these density distributions, we compute the Ratio in the final column as the density in 2017 divided by the average pre-Alice density from years 2011 to 2013. A ratio below unity indicates that the rate of patenting in the given bin declined post-Alice.

BERT Score	2011	2012	2013	2011- 2013	2017	Ratio
(BS)	(1)	(2)	(3)	(4)	(5)	(6)
$0.0 \leq$ BS < 0.1	0.7783	0.7834	0.7868	0.7828	0.8606	1.0994
$0.1 \leq$ BS < 0.2	0.0320	0.0323	0.0331	0.0325	0.0332	1.0240
$0. \leq$ BS < 0.3	0.0182	0.0191	0.0187	0.0186	0.0150	0.8032
$0.3 \leq$ BS < 0.4	0.0133	0.0125	0.0137	0.0132	0.0104	0.7904
$0.4 \leq$ BS < 0.5	0.0114	0.0130	0.0108	0.0117	0.0078	0.6648
$0.5 \leq$ BS < 0.6	0.0104	0.0098	0.0097	0.0100	0.0078	0.7827
$0.6 \leq$ BS < 0.7	0.0114	0.0110	0.0105	0.0110	0.0092	0.8383
$0.7 \leq$ BS < 0.8	0.0138	0.0120	0.0132	0.0130	0.0086	0.6632
$0.8 \leq$ BS < 0.9	0.0211	0.0223	0.0186	0.0207	0.0105	0.5067
$0.9 \leq$ BS ≤ 1.0	0.0903	0.0845	0.0850	0.0866	0.0369	0.4259

Table 8: Firm Summary Statistics

This table provides summary statistics for our sample of public firms based on annual firm observations from 2011 to 2017 (excluding 2014, the treatment year). All variables are described in detail in the variable list in Appendix A and in Section 3 of the paper. In Panel D, firm characteristics are based on the values in 2013. Low Treatment and High Treatment firms are the ones which have treatment scores that are below and above the median, respectively. *, **, and *** denote significant difference of the mean post-Alice vs. pre-Alice at the 10%, 5% and 1% level.

			Pre-Alice			**Post-Alice**			
Variable	N	# of Firms	Median	Mean	Std. Error	Median	Mean	Std. Error	Diff (Post-Pre)
Panel A: Firm Characteristics									
Assets (in mil.)	8490	1490	732.821	5453.897	259.052	1038.763	6876.330	322.487	***
Sales (in mil.)	8490	1490	663.771	3212.802	136.333	851.168	3458.126	141.745	
OI/Sales	8454	1484	0.121	0.032	0.010	0.123	-0.039	0.016	***
Tobin's Q	8424	1490	1.361	1.782	0.031	1.493	1.844	0.029	
Sales Growth	8464	1490	0.069	0.082	0.003	0.029	0.034	0.004	***
Age	8490	1490	21.000	25.914	0.445	24.250	29.566	0.440	***
Panel B: Innovation, Acquisition & Lawsuit Characteristics									
R&D/Sales	8490	1490	0.029	0.110	0.004	0.031	0.126	0.005	**
Log(# of Patents)	8490	1490	0.828	1.279	0.034	0.462	1.104	0.034	***
Patents/Sales	8490	1490	0.003	0.018	0.001	0.001	0.011	0.000	***
Acquisitions/Sales	8490	1490	0.000	0.044	0.002	0.000	0.053	0.003	***
Log(Amt. of Acq.)	8490	1490	0.000	1.072	0.038	0.000	1.138	0.041	
Is Alleged	8490	1490	0.000	0.242	0.009	0.000	0.215	0.009	**
Is Accuser	8490	1490	0.000	0.106	0.006	0.000	0.085	0.006	**
IPrisk (10-K)	8441	1490	3.994	4.746	0.109	4.717	5.534	0.120	***
Patinfringe (10-K)	8441	1490	1.374	2.325	0.067	1.356	2.220	0.062	
Panel C: Competition Measures (Text-based measures from 10-Ks)									
VCF/Sales	8434	1490	0.000	0.017	0.001	0.000	0.030	0.002	***
TSIMM	8426	1490	1.713	4.851	0.203	1.635	6.451	0.310	***
Complaints	8441	1490	15.069	15.788	0.172	15.095	15.936	0.172	
Noncompete	8441	1490	0	0.567	0.028	0	0.502	0.026	*
Nondisclose	8441	1490	0	0.417	0.021	0	0.498	0.027	**

Panel D: Pre-Alice Firm Characteristics by Treatment

	Low Treatment (745 firms)			**High Treatment (745 firms)**			
Variable	Median	Mean	Std. Error	Median	Mean	Std. Error	Difference (High-Low)
Treatment (KPSS)	0.000	0.000	0.000	0.025	0.093	0.005	***
Treatment (Cites)	0.000	0.000	0.000	0.025	0.095	0.005	***
Assets (in mil.)	916.987	5390.866	354.455	713.379	6034.472	401.038	
Sales (in mil.)	907.728	3232.594	179.794	533.239	3296.747	204.564	

Table 9:
Patents and R&D

The table displays panel data regressions in which innovation and research related variables are dependent variables. In columns (1)-(2), the dependent variable is the number of patent applications in that year divided by sales; and in columns (3) and (4), it is one plus log of the number of patent applications in the respective year. In columns (5)-(6), the dependent variable is R&D expenses scaled by sales. *Treatment* is a firm-level measure that combines whether patents are important for the firm and the extent the firm's patent portfolio was affected by the court decision. The mathematical notation for the estimation of this measure is provided in equation (5). In the odd and even numbered columns, KPSS and the number of citations that a patent received are used for *Patent Value* in calculation of the treatment, respectively. *Low* is a binary variable equals one if a firm's TNIC market share is lower than the median industry-year market share in 2013 and zero otherwise. *High* is 1-*Low*. *Post* is a dummy variable equals one if the year is after the Alice decision and zero otherwise. All variables are described in detail in the variable list in Appendix A. All regressions include firm and year fixed effects. Standard errors are clustered at the firm level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

Dependent Variable:	$\frac{\#\ of Patents}{Sales}$		Log(# of Patents)		$\frac{R\&D}{Sales}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Low X Post X Treatment	-0.033***	-0.034***	-0.491**	-0.572***	0.232***	0.227***
	(-4.95)	(-5.39)	(-2.39)	(-2.82)	(5.77)	(5.90)
High X Post X Treatment	-0.034***	-0.034***	-0.796**	-0.871**	0.027	0.037*
	(-3.22)	(-3.63)	(-2.07)	(-2.43)	(0.97)	(1.74)
1/Sales	0.219***	0.230***	-0.611	-0.467	1.202***	1.144***
	(6.49)	(6.85)	(-1.04)	(-0.78)	(4.98)	(4.73)
Log(Age)	-0.019***	-0.020***	-0.125	-0.133	0.056***	0.063***
	(-6.89)	(-7.11)	(-1.07)	(-1.10)	(3.98)	(4.33)
Observations	8490	8315	8490	8315	8490	8315
Firm Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Treatment Calculation	KPSS	Citation	KPSS	Citation	KPSS	Citation
Adj. R^2	0.177	0.183	0.101	0.104	0.127	0.124

Table 10:
Competition and Patent Protection

The table displays panel data regressions in which competition variables are the dependent variables. In columns (1)-(2), the dependent variable, *VCF/Sales*, is the a measure of VC entry in a given firm's product market and is the cosine similarity of the text in the focal firm's 10-K business description and the total text describing all VC-funded startups in the same year (as measured using the verbal product descriptions of startups provided by Venture Expert (see Hoberg, Phillips, and Prabhala, 2014). *TSIMM* is the firm's TNIC text-based total similarity of the firm to public firm competitors. Complaints is the number of paragraphs in the firm's 10-K that complain about competition divided by the total number of paragraphs in the firm's 10-K. *Treatment* is a firm-level measure that combines whether patents are important for the firm and the extent the firm's patent portfolio was affected by the court decision. The mathematical notation for the estimation of this measure is provided in equation (5). In the odd and even numbered columns, KPSS and the number of citations that a patent received are used for *Patent Value* in calculation of the treatment, respectively. *Low* is a binary variable equals one if a firm's TNIC market share is lower than the median industry-year market share in 2013 and zero otherwise. *High* is 1-*Low*. *Post* is a dummy variable equals one if the year is after the Alice decision and zero otherwise. All variables are described in detail in the variable list in Appendix A. All regressions include firm and year fixed effects. Standard errors are clustered at the firm level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

Dependent Variable:	$\frac{VCF}{Sales}$		TSIMM		Complaints	
	(1)	(2)	(3)	(4)	(5)	(6)
Low *X* Post *X* Treatment	0.118***	0.102***	14.311***	13.699***	3.473***	3.969***
	(5.84)	(5.07)	(5.25)	(4.96)	(2.99)	(3.40)
High *X* Post *X* Treatment	0.042**	0.040**	1.037	0.959	0.411	-0.480
	(2.19)	(2.31)	(0.46)	(0.46)	(0.20)	(-0.25)
1/Sales	2.247***	2.230***	-21.236*	-23.787*	-8.742	-9.259
	(22.06)	(21.01)	(-1.71)	(-1.87)	(-1.57)	(-1.64)
Log(Age)	0.026***	0.027***	4.694***	5.085***	0.474	0.507
	(4.06)	(4.13)	(4.89)	(5.09)	(0.82)	(0.86)
Observations	8434	8259	8426	8251	8441	8266
Firm Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Treatment Calculation	KPSS	Citation	KPSS	Citation	KPSS	Citation
Adj. R^2	0.468	0.460	0.123	0.121	0.012	0.014

Table 11:
Firm Level Competition and Encroachment

The table displays firm-pair-year panel data regressions in which pairwise product market encroachment (Delta TNIC Score) is the dependent variable. Delta TNIC Score is computed the change in pairwise TNIC similarity (see Hoberg and Phillips 2016) from year t-1 to year t. A high value indicates increased similarity and product market encroachment. To compute the RHS variables, we first sort firms into above and below median market share based on firm sales in our focal year 2014. We denote the two firms associated with each pairwise observation as 1 and 2. The variable Treat1 (Treat2) is the Alice Score for firm 1 (2). Analogously, Big1 is an indicator if firm 1's market share is above the median in the given year, and Small1 indicates firm 1 has below median market share. Market share indicators are similarly defined for firm 2. Please note that all level effects and lower-order interactions are subsumed by the fixed effects and thus are not reported. All regressions include firm-pair and year fixed effects and standard errors are clustered at the firm-pair level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

Dependent Variable:		Delta TNIC Score	
	(1)	(2)	(3)
Treat1 *X* Post	0.115***		
	(12.13)		
Treat2 *X* Post	0.115***		
	(12.13)		
Big1 *X* Treat1 *X* Post		-0.181***	
		(-9.75)	
Small1 *X* Treat1 *X* Post		0.211***	
		(20.02)	
Big2 *X* Treat2 *X* Post		-0.181***	
		(-9.75)	
Small2 *X* Treat2 *X* Post		0.211***	
		(20.02)	
Big1 *X* Big2 *X* Treat1 *X* Post			-0.160***
			(-6.47)
Big1 *X* Small2 *X* Treat1 *X* Post			-0.215***
			(-7.88)
Small1 *X* Big2 *X* Treat1 *X* Post			0.237***
			(17.06)
Small1 *X* Small2 *X* Treat1 *X* Post			0.191***
			(12.28)
Big1 *X* Big2 *X* Treat2 *X* Post			-0.160***
			(-6.47)
Small1 *X* Big2 *X* Treat2 *X* Post			-0.215***
			(-7.88)
Big1 *X* Small2 *X* Treat2 *X* Post			0.237***
			(17.06)
Small1 *X* Small2 *X* Treat2 *X* Post			0.191***
			(12.28)
Observations	10,558,658	10,558,658	10,558,658
Pair Fixed Effects	YES	YES	YES
Year Fixed Effects	YES	YES	YES
R^2	0.116	0.117	0.117

Table 12:
Profitability

The table displays panel data regressions that examine whether the profitability of high and low market share firms were differently affected by the Alice decision. In columns (1)-(2), the dependent variable is sale growth, calculated as the natural logarithm of total sales in the current year t divided by total sales in the previous year t-1.; and in columns (3) and (4), it is Operating Income scaled by sales. In columns (5)-(6), the dependent variable is Tobin's Q, calculated as the market to book ratio (market value of equity plus book debt and preferred stock, all divided by book assets). *Treatment* is a firm-level measure that combines whether patents are important for the firm and the extent the firm's patent portfolio was affected by the court decision. The mathematical notation for the estimation of this measure is provided in equation (5). In the odd and even numbered columns, KPSS and the number of citations that a patent received are used for *Patent Value* in calculation of the treatment, respectively. *Low* is a binary variable equals one if a firm's TNIC market share is lower than the median industry-year market share in 2013 and zero otherwise. *High* is 1-*Low*. *Post* is a dummy variable equals one if the year is after the Alice decision and zero otherwise. All variables are described in detail in the variable list in Appendix A. All regressions include firm and year fixed effects. Standard errors are clustered at the firm level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

Dependent Variable:	Sales Growth		$\frac{OperatingIncome}{Sales}$		Tobin's Q	
	(1)	(2)	(3)	(4)	(5)	(6)
Low X Post X Treatment	0.094	0.088	-1.005***	-1.036***	-1.058**	-0.875*
	(1.27)	(1.17)	(-6.38)	(-6.60)	(-2.20)	(-1.76)
High X Post X Treatment	0.167**	0.115*	0.029	-0.013	1.898***	1.772**
	(2.45)	(1.71)	(0.34)	(-0.15)	(2.86)	(2.54)
1/Sales	3.817***	3.823***	-6.934***	-6.681***	13.183***	12.751***
	(10.54)	(10.40)	(-6.87)	(-6.56)	(4.65)	(4.44)
Log(Age)	-0.053*	-0.048	-0.278***	-0.289***	-1.076***	-1.071***
	(-1.82)	(-1.62)	(-5.08)	(-5.18)	(-4.32)	(-4.22)
Observations	8490	8315	8454	8279	8340	8168
Firm Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Treatment Calculation	KPSS	Citation	KPSS	Citation	KPSS	Citation
Adj. R^2	0.104	0.104	0.172	0.171	0.103	0.099

Table 13:
Firm IP Risk and Legal Protections

The table displays panel data regressions examining the impact of Alice on intellectual property and noncompete and disclosure clauses. In columns (1)-(2), *IP Risk*, is the total number of paragraphs mentioning "intellectual property" in the risk factor section in the 10-K documents, scaled by the total number paragraphs in the 10-Ks. *Noncompete* is the total number of 10K paragraphs mentioning "non-compete" agreements, all scaled by the total paragraphs in the 10-K. *Nondisclosure* is the total number of 10-K paragraphs mentioning "non-disclose" or NDA agreements, all scaled by the total paragraphs in the 10-K. *Treatment* is a firm-level measure that combines whether patents are important for the firm and the extent the firm's patent portfolio was affected by the court decision. The mathematical notation for the estimation of this measure is provided in equation (5). In the odd and even numbered columns, KPSS and the number of citations that a patent received are used for *Patent Value* in calculation of the treatment, respectively. *Low* is a binary variable equals one if a firm's TNIC market share is lower than the median industry-year market share in 2013 and zero otherwise. *High* is 1-*Low*. *Post* is a dummy variable equals one if the year is after the Alice decision and zero otherwise. All variables are described in detail in the variable list in Appendix A. All regressions include firm and year fixed effects. Standard errors are clustered at the firm level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

Dependent Variable:	IP Risk		Noncompete		Nondisclosure	
	(1)	(2)	(3)	(4)	(5)	(6)
Low *X* Post *X* Treatment	1.961***	2.187***	0.664***	0.558***	0.492***	0.432**
	(2.95)	(3.08)	(3.10)	(2.59)	(2.80)	(2.43)
High *X* Post *X* Treatment	0.075	-0.254	-0.137	-0.145	-0.257	-0.232
	(0.07)	(-0.25)	(-0.50)	(-0.53)	(-0.94)	(-0.99)
1/Sales	-3.536	-3.606	-2.197***	-2.202***	-0.992	-1.264
	(-1.11)	(-1.12)	(-2.85)	(-2.79)	(-1.06)	(-1.35)
Log(Age)	0.287	0.402	0.002	-0.009	0.203**	0.226**
	(0.86)	(1.17)	(0.02)	(-0.07)	(2.37)	(2.51)
Observations	8441	8266	8441	8266	8441	8266
Firm Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Treatment Calculation	KPSS	Citation	KPSS	Citation	KPSS	Citation
Adj. R^2	0.107	0.109	0.007	0.006	0.039	0.040

Table 14:
Lawsuits and Legal Protection

The table displays panel data regressions examining whether lawsuit metrics of high and low market share firms were differently affected by the Alice decision. In columns (1)-(2), the dependent variable, *is Alleged*, is a dummy variable equals one if a firm was alleged in a patent lawsuit at least once in that year, and zero otherwise. In columns (3) to (4), *Alleged by NPE* is a dummy variable equals one if a firm was alleged by a non-practicing entity in a patent lawsuit at least once in that year, and zero otherwise. In columns (5) to (6), *Alleged by OC* is a dummy variable equals one if a firm was alleged by a operating company in a patent lawsuit at least once in that year, and zero otherwise. In columns (7)-(8), *Patinfringe* refers to the total number of paragraphs containing a patent word and infringe* in 10-K documents, scaled by the total number of paragraphs in the 10-Ks. In columns (9)-(10), *Is Accuser* is a binary variable equals one if a firm accused any party in a patent lawsuit at least once in that year, and zero otherwise. *Treatment* is a firm-level measure that combines whether patents are important for the firm and the extent the firm's patent portfolio was affected by the court decision. The mathematical notation for the estimation of this measure is provided in equation (5). In the odd and even numbered columns, KPSS and the number of citations that a patent received are used for *Patent Value* in calculation of the treatment, respectively. *Low* is a binary variable equals one if a firm's TNIC market share is lower than the median industry-year market share in 2013 and zero otherwise. *High* is 1-*Low*. *Post* is a dummy variable equals one if the year is after the Alice decision and zero otherwise. All variables are described in detail in the variable list in Appendix A. All regressions include firm and year fixed effects. Standard errors are clustered at the firm level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

Dependent Variable:	Is Alleged		Alleged by NPE		Alleged by OC		Patinfringe		Is Accuser	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Low *X* Post *X* Treatment	0.045	0.060	-0.007	0.037	0.055	0.065	-0.250	-0.414	0.025	0.062
	(0.54)	(0.72)	(-0.11)	(0.54)	(0.82)	(0.95)	(-0.62)	(-1.03)	(0.30)	(0.79)
High *X* Post *X* Treatment	-0.344**	-0.267*	-0.271*	-0.175	-0.083	-0.100	-1.446**	-1.146*	-0.080	-0.097
	(-2.01)	(-1.69)	(-1.79)	(-1.23)	(-0.51)	(-0.69)	(-2.10)	(-1.69)	(-0.55)	(-0.72)
1/Sales	0.594*	0.575	0.645**	0.616*	0.947***	0.923***	-0.701	-0.496	0.819**	0.781**
	(1.72)	(1.64)	(2.02)	(1.91)	(2.92)	(2.81)	(-0.39)	(-0.27)	(2.08)	(1.96)
Log(Age)	-0.211***	-0.209***	-0.253***	-0.254***	-0.260***	-0.258***	-0.468**	-0.409*	-0.262***	-0.258***
	(-3.89)	(-3.78)	(-5.05)	(-4.95)	(-5.49)	(-5.33)	(-2.00)	(-1.72)	(-5.56)	(-5.33)
Observations	8490	8315	8490	8315	8490	8315	8441	8266	8490	8315
Firm Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Treatment Calculation	KPSS	Citation	KPSS	Citation	KPSS	Citation	KPSS	Citation	KPSS	Citation
Adj. R^2	0.020	0.020	0.020	0.019	0.020	0.019	0.009	0.008	0.014	0.014

Table 15:
Acquisitions and Legal Protection

The table displays panel data regressions in which acquisition variables are the dependent variables. In columns (1)-(2) and (3)-(4), the dependent variables are dollar value spent on acquisition scaled by sales and log of one plus total value spent on acquisitions in that year. *Treatment* is a firm-level measure that combines whether patents are important for the firm and the extent the firm's patent portfolio was affected by the court decision. The mathematical notation for the estimation of this measure is provided in equation (5). In the odd and even numbered columns, KPSS and the number of citations that a patent received are used for *Patent Value* in calculation of the treatment, respectively. *Low* is a binary variable equals one if a firm's TNIC market share is lower than the median industry-year market share in 2013 and zero otherwise. *High* is 1-*Low*. *Post* is a dummy variable equals one if the year is after the Alice decision and zero otherwise. All regressions include firm and year fixed effects. Standard errors are clustered at the firm level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

Dependent Variable:	$\frac{Acquisitions}{Sales}$		Log(Acquisitions)	
	(1)	(2)	(3)	(4)
Low X Post X Treatment	0.024	-0.001	-0.006	-0.161
	(0.88)	(-0.06)	(-0.02)	(-0.68)
High X Post X Treatment	-0.115**	-0.119**	-2.676***	-2.454***
	(-2.31)	(-2.45)	(-3.17)	(-2.92)
1/Sales	0.100	0.134	-0.464	-0.221
	(0.67)	(0.89)	(-0.52)	(-0.24)
Log(Age)	0.009	0.007	0.196	0.194
	(0.42)	(0.32)	(0.65)	(0.63)
Observations	8490	8315	8490	8315
Firm Fixed Effects	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES
Treatment Calculation	KPSS	Citation	KPSS	Citation
Adj. R^2	0.003	0.003	0.003	0.003

Appendix A. Variable definitions

Table 16: Variable definitions

Table 16

Variable	Definition
Panel A: Financial Characteristics	
Assets	Compustat item AT.
Sales	Compustat item SALE
OI/Sales	Compustat OIBDP divided by total sales.
Tobin's Q	
Sales Growth	Natural logarithm of total sales in the current year t divided by total sales in the previous year t-1.
Log(Age)	Natural logarithm of one plus the current year of observation minus the first year the firm appears in the Compustat database.
Panel B: Innovation, Acquisition & Lawsuit Characteristics	
Treatment Effect	Treatment is multiplication of two items: i) Number of valid patents the firms has in the third quarter of 2014 divided by sales. This item assesses how much a patent is important for a firm. ii) For each patent of a firm, an Alice score is multiplied by the dollar value of the patent. Then, the sum for all patents is divided by the total dollar value of firm's patent portfolio. This item measures the extent the patent portfolio of a firm is impacted by the court decision. The mathematical notation is provided in equation (5).
R&D/Sales	Compustat XRD divided by total sales. This variable is set to zero if XRD is missing
Log(# of Patents)	Log of one plus number of patent applications.
Patents/Sales	The number of patent applications scaled by firm sales.
Acquisitions/Sales	The total amount of acquisitions divided by firm sales.
Log(Acq. Amt.)	Log of one plus total amount of acquisitions.
Is Alleged	It is a dummy variable equals one if a firm was alleged in a patent lawsuit at least once in that year, and zero otherwise.
Is Accuser	It is a dummy variable equals one if a firm accused any party in a patent lawsuit at least once in that year, and zero otherwise.
IPrisk	The total number of paragraphs mentioning "intellectual property" in the risk factor section in the 10-K documents, scaled by the total number paragraphs in the 10-Ks.
Patinfringe	The total number of paragraphs containing a patent word and infringe* in 10-K documents, scaled by the total number of paragraphs in the 10-Ks.
Panel C: Competition Measures	
VCF/Sales	
TSIMM	
Complaints	
Noncompete	#10K paragraphs mentioning "non-compete" agreeements, all scaled by the total paragraphs in the 10-K.
Nondisclose	#10K paragraphs mentioning "non-disclose" or NDA agreeements, all scaled by the total paragraphs in the 10-K.

Online Appendix B: Not for publication

Table 17:
Patents and R&D (Treatment Scaled By Enterprise Value Instead of Sales)

The table displays the robustness tests for the results in Table 9. In this table, in the calculation of the treatment variable explained in equation (5), we use enterprise value instead of sales. Enterprise value is calculated as equity plus debt minus cash. In columns (1)-(2), the dependent variable is the number of patent applications in that year divided by sales; and in columns (3) and (4), it is one plus log of the number of patent applications in the respective year. In columns (5)-(6), the dependent variable is R&D expenses scaled by sales. *Treatment* is a firm-level measure that combines whether patents are important for the firm and the extent the firm's patent portfolio was affected by the court decision. The mathematical notation for the estimation of this measure is provided in equation (5). In the odd and even numbered columns, KPSS and the number of citations that a patent received are used for *Patent Value* in calculation of the treatment, respectively. *Low* is a binary variable equals one if a firm's TNIC market share is lower than the median industry-year market share in 2014, and zero otherwise. *High* is 1-*Low*. *Post* is a dummy variable equals one if the year is after the Alice decision and zero otherwise. All variables are described in detail in the variable list in Appendix A. All regressions include firm and year fixed effects. Standard errors are clustered at the firm level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

Dependent Variable:	$\frac{\#\ of Patents}{Sales}$		Log(# of Patents)		$\frac{R\&D}{Sales}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Low X Post X Treatment	-0.043***	-0.038***	-1.349**	-1.365***	0.176*	0.146*
	(-2.66)	(-2.79)	(-2.30)	(-2.85)	(1.77)	(1.70)
High X Post X Treatment	-0.063***	-0.045***	-2.303**	-1.875**	0.016	0.007
	(-3.42)	(-3.31)	(-2.46)	(-2.43)	(0.33)	(0.20)
1/Sales	0.211***	0.220***	-0.607	-0.481	1.254***	1.206***
	(6.03)	(6.25)	(-1.00)	(-0.77)	(5.16)	(4.90)
Log(Age)	-0.020***	-0.021***	-0.119	-0.131	0.062***	0.068***
	(-7.21)	(-7.28)	(-1.03)	(-1.09)	(4.26)	(4.54)
Observations	8421	8246	8421	8246	8421	8246
Firm Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Treatment Calculation	KPSS	Citation	KPSS	Citation	KPSS	Citation
Adj. R^2	0.167	0.170	0.102	0.104	0.095	0.093

Table 18:
Patents and R&D (Alice Scores Calculated by TF-IDF Instead of BERT)

The table displays the robustness tests for the results in Table 9. In this table, in the calculation of the treatment variable depicted in equation (5), we use TF-IDF instead of BERT technique. In columns (1)-(2), the dependent variable is the number of patent applications in that year divided by sales; and in columns (3) and (4), it is one plus log of the number of patent applications in the respective year. In columns (5)-(6), the dependent variable is R&D expenses scaled by sales. In the odd and even numbered columns, KPSS and the number of citations that a patent received are used for *Patent Value* in calculation of the treatment, respectively. *Low* is a binary variable equals one if a firm's TNIC market share is lower than the median industry-year market share in 2013 and zero otherwise. *High* is 1-*Low*. *Post* is a dummy variable equals one if the year is after the Alice decision and zero otherwise. All variables are described in detail in the variable list in Appendix A. All regressions include firm and year fixed effects. Standard errors are clustered at the firm level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

Dependent Variable:	$\frac{\#\ of Patents}{Sales}$		Log(# of Patents)		$\frac{R\&D}{Sales}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Low X Post X Treatment	-0.030***	-0.027***	-0.463	-0.321	0.244***	0.218***
	(-2.98)	(-2.93)	(-1.31)	(-1.00)	(3.78)	(3.56)
High X Post X Treatment	-0.045***	-0.040***	-1.062*	-1.145**	0.044	0.044
	(-2.95)	(-2.68)	(-1.83)	(-1.98)	(1.08)	(1.32)
1/Sales	0.212***	0.218***	-0.701	-0.681	1.250***	1.212***
	(6.08)	(6.30)	(-1.15)	(-1.10)	(5.15)	(4.96)
Log(Age)	-0.020***	-0.020***	-0.126	-0.133	0.059***	0.065***
	(-6.95)	(-7.16)	(-1.08)	(-1.11)	(4.12)	(4.40)
Observations	8490	8315	8490	8315	8490	8315
Firm Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Treatment Calculation	KPSS	Citation	KPSS	Citation	KPSS	Citation
Adj. R^2	0.169	0.172	0.100	0.101	0.106	0.104

Table 19:
Patents and R&D (CPC Dummy Variable Instead of Alice Score)

The table displays the robustness tests for the results in Table 9. In this table, in the calculation of the treatment variable depicted in equation (5), we use CPC dummy instead of Alice Score. CPC dummy equals one if a patent's primary CPC belongs to one of the top-20 CPCs that have the most frequent Alice rejections and zero otherwise. In columns (1)-(2), the dependent variable is the number of patent applications in that year divided by sales; and in columns (3) and (4), it is one plus log of the number of patent applications in the respective year. In columns (5)-(6), the dependent variable is R&D expenses scaled by sales. *Treatment* is a firm-level measure that combines whether patents are important for the firm and the extent the firm's patent portfolio was affected by the court decision. The mathematical notation for the estimation of this measure is provided in equation (5). In the odd and even numbered columns, KPSS and the number of citations that a patent received are used for *Patent Value* in calculation of the treatment, respectively. *Low* is a binary variable equals one if a firm's TNIC market share is lower than the median industry-year market share in 2013 and zero otherwise. *High* is 1-*Low*. *Post* is a dummy variable equals one if the year is after the Alice decision and zero otherwise. All variables are described in detail in the variable list in Appendix A. All regressions include firm and year fixed effects. Standard errors are clustered at the firm level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

Dependent Variable:	$\frac{\#\ of Patents}{Sales}$		Log(# of Patents)		$\frac{R\&D}{Sales}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Low X Post X Treatment	-0.019***	-0.014***	-0.323**	-0.267*	0.064**	0.044
	(-4.02)	(-3.57)	(-2.01)	(-1.89)	(2.09)	(1.60)
High X Post X Treatment	-0.019***	-0.020***	-0.598**	-0.699***	0.007	0.011
	(-3.30)	(-3.53)	(-2.50)	(-2.97)	(0.46)	(0.91)
1/Sales	0.214***	0.219***	-0.678	-0.662	1.264***	1.231***
	(6.09)	(6.21)	(-1.13)	(-1.08)	(5.21)	(4.99)
Log(Age)	-0.020***	-0.021***	-0.124	-0.136	0.061***	0.068***
	(-6.99)	(-7.26)	(-1.07)	(-1.14)	(4.21)	(4.55)
Observations	8490	8315	8490	8315	8490	8315
Firm Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Treatment Calculation	KPSS	Citation	KPSS	Citation	KPSS	Citation
Adj. R^2	0.172	0.175	0.101	0.104	0.098	0.095

Table 20:
Competition and Patent Protection (Alice Scores Calculated by TF-IDF Instead of BERT)

The table displays the robustness tests for the results in Table 10. In this table, in the calculation of the treatment variable depicted in equation (5), we use TF-IDF instead of BERT technique. In columns (1)-(2), the dependent variable, *VCF/Sales*, is the a measure of VC entry in a given firm's product market and is the cosine similarity of the text in the focal firm's 10-K business description and the total text describing all VC-funded startups in the same year (as measured using the verbal product descriptions of startups provided by Venture Expert (see Hoberg, Phillips and Prabhala 2014). *TSIMM* is the firm's TNIC text-based total similarity of the firm to public firm competitors. Complaints is the number of paragraphs in the firm's 10-K that complain about competition divided by the total number of paragraphs in the firm's 10-K. *Treatment* is a firm-level measure that combines whether patents are important for the firm and the extent the firm's patent portfolio was affected by the court decision. The mathematical notation for the estimation of this measure is provided in equation (5). In the odd and even numbered columns, KPSS and the number of citations that a patent received are used for *Patent Value* in calculation of the treatment, respectively. *Low* is a binary variable equals one if a firm's TNIC market share is lower than the median industry-year market share in 2013 and zero otherwise. *High* is 1-*Low*. *Post* is a dummy variable equals one if the year is after the Alice decision and zero otherwise. All variables are described in detail in the variable list in Appendix A. All regressions include firm and year fixed effects. Standard errors are clustered at the firm level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

Dependent Variable:	$\frac{VCF}{Sales}$		TSIMM		Complaints	
	(1)	(2)	(3)	(4)	(5)	(6)
Low X Post X Treatment	0.102***	0.094***	14.440***	16.330***	6.712***	6.400***
	(2.94)	(2.94)	(3.17)	(3.73)	(3.24)	(3.28)
High X Post X Treatment	0.037	0.009	2.469	-0.324	1.733	0.334
	(1.32)	(0.66)	(0.70)	(-0.11)	(0.60)	(0.13)
1/Sales	2.274***	2.261***	-18.246	-20.184	-8.635	-8.562
	(21.71)	(21.08)	(-1.42)	(-1.57)	(-1.56)	(-1.52)
Log(Age)	0.028***	0.029***	4.902***	5.224***	0.469	0.525
	(4.24)	(4.26)	(5.03)	(5.21)	(0.82)	(0.90)
Observations	8434	8259	8426	8251	8441	8266
Firm Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Treatment Calculation	KPSS	Citation	KPSS	Citation	KPSS	Citation
Adj. R^2	0.450	0.447	0.099	0.106	0.013	0.014

Table 21:
Competition and Patent Protection (CPC Dummy Variable Instead of Alice Score)

The table displays the robustness tests for the results in Table 10. In this table, in the calculation of the treatment variable depicted in equation (5), we use CPC dummy instead of Alice Score. CPC dummy equals one if a patent's primary CPC belongs to one of the top-20 CPCs that have the most frequent Alice rejections and zero otherwise. In columns (1)-(2), the dependent variable, *VCF/Sales*, is the a measure of VC entry in a given firm's product market and is the cosine similarity of the text in the focal firm's 10-K business description and the total text describing all VC-funded startups in the same year (as measured using the verbal product descriptions of startups provided by Venture Expert (see Hoberg, Phillips and Prabhala 2014). *TSIMM* is the firm's TNIC text-based total similarity of the firm to public firm competitors. Complaints is the number of paragraphs in the firm's 10-K that complain about competition divided by the total number of paragraphs in the firm's 10-K. *Treatment* is a firm-level measure that combines whether patents are important for the firm and the extent the firm's patent portfolio was affected by the court decision. The mathematical notation for the estimation of this measure is provided in equation (5). In the odd and even numbered columns, KPSS and the number of citations that a patent received are used for *Patent Value* in calculation of the treatment, respectively. *Low* is a binary variable equals one if a firm's TNIC market share is lower than the median industry-year market share in 2013 and zero otherwise. *High* is 1-*Low*. *Post* is a dummy variable equals one if the year is after the Alice decision and zero otherwise. All variables are described in detail in the variable list in Appendix A. All regressions include firm and year fixed effects. Standard errors are clustered at the firm level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

Dependent Variable:	$\frac{VCF}{Sales}$		TSIMM		Complaints	
	(1)	(2)	(3)	(4)	(5)	(6)
Low *X* Post *X* Treatment	0.061***	0.061***	3.879**	2.467	1.152	1.127
	(4.24)	(4.74)	(2.00)	(1.45)	(1.23)	(1.34)
High *X* Post *X* Treatment	0.002	0.001	-0.909	-0.390	1.415	0.636
	(0.32)	(0.25)	(-0.90)	(-0.35)	(1.06)	(0.53)
1/Sales	2.264***	2.251***	-17.509	-18.595	-7.862	-7.888
	(21.70)	(21.22)	(-1.33)	(-1.39)	(-1.41)	(-1.38)
Log(Age)	0.028***	0.029***	5.016***	5.407***	0.532	0.584
	(4.14)	(4.18)	(5.05)	(5.29)	(0.92)	(0.99)
Observations	8434	8259	8426	8251	8441	8266
Firm Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Treatment Calculation	KPSS	Citation	KPSS	Citation	KPSS	Citation
Adj. R^2	0.455	0.456	0.091	0.090	0.010	0.010

Table 22:
Profitability (Alice Scores Calculated by TF-IDF Instead of BERT)

The table displays the robustness tests for the results in Table 12. In columns (1)-(2), the dependent variable is sale growth, calculated as the natural logarithm of total sales in the current year t divided by total sales in the previous year t-1.; and in columns (3) and (4), it is Operating Income scaled by sales. In columns (5)-(6), the dependent variable is Tobin's Q, calculated as the market to book ratio (market value of equity plus book debt and preferred stock, all divided by book assets). *Treatment* is a firm-level measure that combines whether patents are important for the firm and the extent the firm's patent portfolio was affected by the court decision. The mathematical notation for the estimation of this measure is provided in equation (5). In the odd and even numbered columns, KPSS and the number of citations that a patent received are used for *Patent Value* in calculation of the treatment, respectively. *Low* is a binary variable equals one if a firm's TNIC market share is lower than the median industry-year market share in 2013 and zero otherwise. *High* is 1-*Low*. *Post* is a dummy variable equals one if the year is after the Alice decision and zero otherwise. All variables are described in detail in the variable list in Appendix A. All regressions include firm and year fixed effects. Standard errors are clustered at the firm level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

Dependent Variable:	Sales Growth		$\frac{OperatingIncome}{Sales}$		Market-to-Book	
	(1)	(2)	(3)	(4)	(5)	(6)
Low X Post X Treatment	0.137	0.213*	-1.096***	-0.976***	-0.359	-0.193
	(1.17)	(1.88)	(-4.22)	(-4.09)	(-0.45)	(-0.26)
High X Post X Treatment	0.355***	0.240**	0.200*	0.147	3.029***	2.559**
	(3.54)	(2.40)	(1.68)	(1.48)	(2.61)	(2.50)
1/Sales	3.824***	3.831***	-7.139***	-6.997***	12.774***	12.394***
	(10.61)	(10.48)	(-6.98)	(-6.74)	(4.54)	(4.35)
Log(Age)	-0.055*	-0.052*	-0.295***	-0.306***	-1.129***	-1.121***
	(-1.90)	(-1.74)	(-5.29)	(-5.31)	(-4.52)	(-4.40)
Observations	8490	8315	8454	8279	8340	8168
Firm Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Treatment Calculation	KPSS	Citation	KPSS	Citation	KPSS	Citation
Adj. R^2	0.105	0.105	0.151	0.147	0.101	0.097

Table 23:
Profitability (CPC Dummy Variable Instead of Alice Score)

The table displays the robustness tests for the results in Table 12. In this table, in the calculation of the treatment variable depicted in equation (5), we use CPC dummy instead of Alice Score. CPC dummy equals one if a patent's primary CPC belongs to one of the top-20 CPCs that have the most frequent Alice rejections and zero otherwise. In columns (1)-(2), the dependent variable is sale growth, calculated as the natural logarithm of total sales in the current year t divided by total sales in the previous year t-1.; and in columns (3) and (4), it is Operating Income scaled by sales. In columns (5)-(6), the dependent variable is Tobin's Q, calculated as the market to book ratio (market value of equity plus book debt and preferred stock, all divided by book assets). *Treatment* is a firm-level measure that combines whether patents are important for the firm and the extent the firm's patent portfolio was affected by the court decision. The mathematical notation for the estimation of this measure is provided in equation (5). In the odd and even numbered columns, KPSS and the number of citations that a patent received are used for *Patent Value* in calculation of the treatment, respectively. *Low* is a binary variable equals one if a firm's TNIC market share is lower than the median industry-year market share in 2013 and zero otherwise. *High* is 1-*Low*. *Post* is a dummy variable equals one if the year is after the Alice decision and zero otherwise. All variables are described in detail in the variable list in Appendix A. All regressions include firm and year fixed effects. Standard errors are clustered at the firm level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

Dependent Variable:	Sales Growth		$\frac{OperatingIncome}{Sales}$		Market-to-Book	
	(1)	(2)	(3)	(4)	(5)	(6)
Low X Post X Treatment	0.077	0.067	-0.336***	-0.218**	-0.115	-0.059
	(1.51)	(1.49)	(-2.81)	(-2.05)	(-0.32)	(-0.19)
High X Post X Treatment	0.101***	0.083**	-0.006	0.008	0.942**	0.729**
	(2.71)	(2.39)	(-0.20)	(0.25)	(2.14)	(2.05)
1/Sales	3.822***	3.838***	-7.172***	-7.067***	12.861***	12.424***
	(10.63)	(10.52)	(-7.03)	(-6.79)	(4.55)	(4.34)
Log(Age)	-0.053*	-0.048	-0.297***	-0.312***	-1.111***	-1.099***
	(-1.83)	(-1.62)	(-5.28)	(-5.39)	(-4.39)	(-4.25)
Observations	8490	8315	8454	8279	8340	8168
Firm Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Treatment Calculation	KPSS	Citation	KPSS	Citation	KPSS	Citation
Adj. R^2	0.104	0.104	0.144	0.137	0.099	0.096