Intellectual Property Protection Lost: The Impact on Competition and Acquisitions

Utku U. Acikalin, Tolga Caskurlu, Gerard Hoberg and Gordon M. Phillips*

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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 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' patent portfolios' potential exposure to the Alice decision. While all affected firms decrease patenting post-Alice, we find unequal impact across a myriad of outcomes. Large affected firms benefit as their sales and market valuations increase, and their exposure to lawsuits through patent trolls decrease. They also acquire fewer firms post-Alice. Small affected firms lose as they face increased competition, product market encroachment, and lower profits and valuations. They also increase R&D and have their employees sign more nondisclosure and noncompete agreements. Our results show that there are both costs and benefits of IP protection.

Keywords: Patents, Intellectual property protection, Innovation, competition, litigation.

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*TOBB University, University of Amsterdam, University of Southern California Marshall School of Business, and Tuck School of Business at Dartmouth College and National Bureau of Economic Research, respectively. Acikalin can be reached at u.acikalin@etu.edu.tr, Caskurlu can be reached at t.caskurlu@uva.nl, Hoberg can be reached at hoberg@marshall.usc.edu, and Phillips can be reached at gordon.m.phillips@tuck.dartmouth.edu. We thank Raj Aggarwal and Josh Lerner for helpful comments and discussions and Christopher Ball at metaHeuristica for excellent analytical tools for analyzing 10-K filings. All errors are the authors' alone.

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 of 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 potentially 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 very much in doubt and was not anticipated and thus we show that it had a sharp impact after the ruling. In the next section, we provide details on the extensive disagreements on this case until the Supreme Court ruling.

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, 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 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 individual 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.[1]

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.[2] 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

[1]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 in 2019 on potential revisions to intellectual property law.

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

that come before and after it.

We find a large impact of Alice on future patenting and innovation and find that Alice impacts both large and small firms. We verify that ex post patenting by firms whose patent stock is exposed to Alice significantly decreases for both large and small firms. 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 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 gain in sales and in 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 large and small 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, while the competition surrounding larger firms is not significantly impacted. In the post-Alice period, small affected firms also face increased venture capital financed entry into their product space, 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 larger 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 are 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 large firms sharply decrease their acquisition activity. This is consistent with the theoretical arguments and empirical evidence in Phillips and Zhdanov (2013). They model how large firms may buy small firms after they have successfully patented an innovation. Large 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 large 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 large 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 big 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 than 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 a 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 noncompete agreements with their employees. In contrast, large 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 them following losses in IP protection. We conclude that patent protection is particularly important for small firms facing larger firms.

Our paper also contributes methodologically in 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 benefit for small firms of removing the ambiguity of Alice or even repealing Alice as a recent bipartisan bill attempted.

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 use 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.[3] There is also evidence (see Budish et al. (2015) for example using cancer clinical trials) that there need 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.

[3] 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.

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 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.

2.1 Legal Background of the Alice Case

In 2014, the Supreme Court of the Unites States decided on a landmark case, Alice Corp *v.* CLS Bank International, 573 U.S. 208 (2014). It had a major effect on the 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.[4] 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 an en banc session where all ten judges heard the case.[5][6]

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

[4] CLS Bank Int'l v. Alice Corp. Pty. Ltd., 685 F.3d 1341, 1356 (Fed. Cir. 2012)
[5] CLS Bank Int'l v. Alice Corp. Pty. Ltd., 484 Fed. Appx. 559 (Fed. Cir. 2012)
[6] CLS Bank Int'l v. Alice Corp. Pty. Ltd., 717 F.3d 1269, 1273 (2013).

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.[7] The Court held 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 judgement 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

[7] Alice Corp. Pty. Ltd. v. CLS Bank Int'l, 134 S. Ct. 2347, 2354 (2014).

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 or 126,540 total), 919 Groups, and 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 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 and document processing 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 patent in the sample may be invalidated by the Alice decision.

We study ex post firm decisions based on our predicted likelihood of whether a firms existing patents are exposed to Alice. We examine firm R&D and lawsuits, firm outcomes including changes in sales, operating income, and market valuations and the impact on competition overall between firms. While we could conjecture the impact of the loss of IP protection may be negative for affected firms, it is not clear the differential impact on firms of different sizes and financial resources. Existing firms may benefit as they may be able to adopt new ideas without paying the firms who had previously had those patents. We test whether acquisitions by large firms decrease after Alice as large firms may be able to copy ideas without buying the firms who have come up with them. R&D may go up or down depending on whether firms need to invest in new ideas to differentiate themselves. We also predict increased secrecy to keep new ideas private and an increase in methods firms use to increase secrecy such as non-disclosure agreements and non-compete clauses.

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 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 is a challenging task as there are more than 3.8 millions of 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 with 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 a big data may not be feasible, we need an automation model that have 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 BERT model which overcome these limitations.

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 patent 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.[8]

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 filter 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 Classifi-

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

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

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.[9] For descriptions longer than 400 words, we use TextRank automatic summarization tool to reduce the text size to 400 words (Mihalcea and Tarau (2004)).

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.[10] 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

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

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

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

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 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:

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

$$F_1\ Score = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \tag{3}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

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" consist 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 to 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) has a 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 guideliens. 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.

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.

Insert Table 6 here

Table 6 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 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 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 6 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 6), 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 6 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 2014. $PatentValue_{i,j}$ 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.[11] $AliceScore_{ij}$ refers to the probability that a patent j is invalidated conditioning on that it is challenged in a court. This measure is estimated by the BERT model.

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.[12] 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.

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

Insert Table 7 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

[11] 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.

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

details of these variables and a variable list is in Appendix A). Table 7 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 to response to their Alice exposure.

Panel A of Table 7 presents accounting characteristics including the size of firms measured by assets and sales, sales growth, the age and the profitability (Operating income / Assets) of firms. We also present firm's Tobins's q (market value of equity + book value of debt / book value of assets). The table shows that overall operting 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/Assets is Compustat R&D divided by total assets 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/Assets 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 a 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 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 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 7 presents the competition variables we examine. *VCF/Assets*, 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* are 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 large and small firms.

Our treatment scores are not binary as they represent the multiplication of percentage of a firm's patent portfolio value that 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 score 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 our results, we present results separately for small and large firms as we have found throughout that there are key differences for firms based on size. We base our size variable on each firm's size in 2014, and *Large* indicates that the firm is equal to or above the sample median based using on firm assets in 2014. *Small* equals one if the firm is below the sample median based on firm assets in 2014.

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. The mathematical notation for the estimation of this measure is provided in equation (5). 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 assets, the log of 1 plus the number of patents, and R&D/Assets.

Insert Table 8 here

The results for patents in columns (1)-(4) of Table 8 show that both large and small 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, especially 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 (2), We calculate that large (small) firm patenting decreases by 27% (15%) at the mean with a one standard deviation in the treatment variable.

The results for R&D in columns (5)-(6) show that small firms increase R&D after Alice, while there is no change for large firms. Using the coefficient from column (6), we calculate that small firms R&D increase by 9.5% with a one standard deviation in treatment relative to the mean pre-Alice. We also present these results graphically where we allow each pre- and post-year to have its own indicator variable. These results are presented in Figure 3.

Insert Figure 3 here

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. We also present these results graphically for small firms 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

In contrast, large 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 (Small, Large, and Treat) as these are absorbed by firm fixed effects given that they are defined in the treatment year and then held fixed.

4.2 Alice and Firm Performance

We now examine the profitability of firms post-Alice. Table 9 displays panel data regressions that examine whether the sales, profitability and market value of small and large 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/Assets*. 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). We find the economic impact on *Tobin's q* is a decrease by 5.1% (3.1%) relative to the mean pre-Alice for large (small) firms with a one standard deviation increase in treatment.

Insert Table 9 Here

Table 9 shows that large firms whose patent portfolios are exposed to Alice experience growth and increases in market value (measured using Tobin's q) post-Alice. Their sales go up by 1.95 percentage points and their Tobin's q goes up by 5 percent with a one standard deviation of treatment. Their profitability is also unchanged despite their increased scale. Thus, large 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 smaller firms, as large firms would face weakening competition when smaller firms have to scale back.

Consistent with this view, Table 9 shows that small firms 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 1.8 percentage points and their Tobin's q declines by 3.1 percent with a one standard deviation increase in treatment.

4.3 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 resutls 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/Assets*, 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

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, large firms do not experience changes in competition in any of the specifictions 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 no increases in competition and actually experience some gains in the form of increased sales and market valuations.

Economically, we calculate that small firms entry by venture capital financed firms increases by 40.1% with a one standard deviation increase in treatment relative to the average entry rate pre-Alice. Likewise, small firms product similarity with rivals increases by 32% with a one standard deviation increase in treatment relative to the average entry rate pre-Alice. We also present these results graphically for small firms where we allow each pre- and post-year to have its own indicator variable. These results are presented in Figure 5.

Insert Figure 5 here

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 large and small firms. In particular, we interact our baseline results from Column (1) with indicators for whether firm 1 or firm 2 are large or small. 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.

4.4 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 small and large treated firms 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 12 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 12 here

The results presented in Table 12 show that small firms 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 13, 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 13 here

In contrast to earlier findings that illustrated strong results for small firms, Table 13 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 13 shows that actual lawsuits including small firms did not change. To understand this result, we note that the result is different for larger firms, whose lawsuit exposure significantly *decreases* after Alice is decided. Large firm exposure to lawsuits especially 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 assets and also the log of one plus the dollar value of acquisitions.

Insert Table 14 here

The results are displayed in Table 14. Across all specifications presented in Table 14, we indeed find that the amount spent by large firms on acquisitions post-Alice decreases significantly. For large firms, acquisitions/Assets (log of amount spent on acquisitions) decrease by 10.5% (11.9%) 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 large firms acquire less and pay less for any firms they do acquire. These results once again point to gains by larger 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.

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 large and small 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. 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. Large firms gain and small firms lose. Exposed large 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 small firms 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 larger 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, large firms once again appear to relatively gain as they face fewer lawsuits from non-producing entities ("patent trolls") and do not increase their use of noncompete and nondisclosure clauses. Overall our results illustrate an uneven impact of lost IP protection across large and small firms.

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

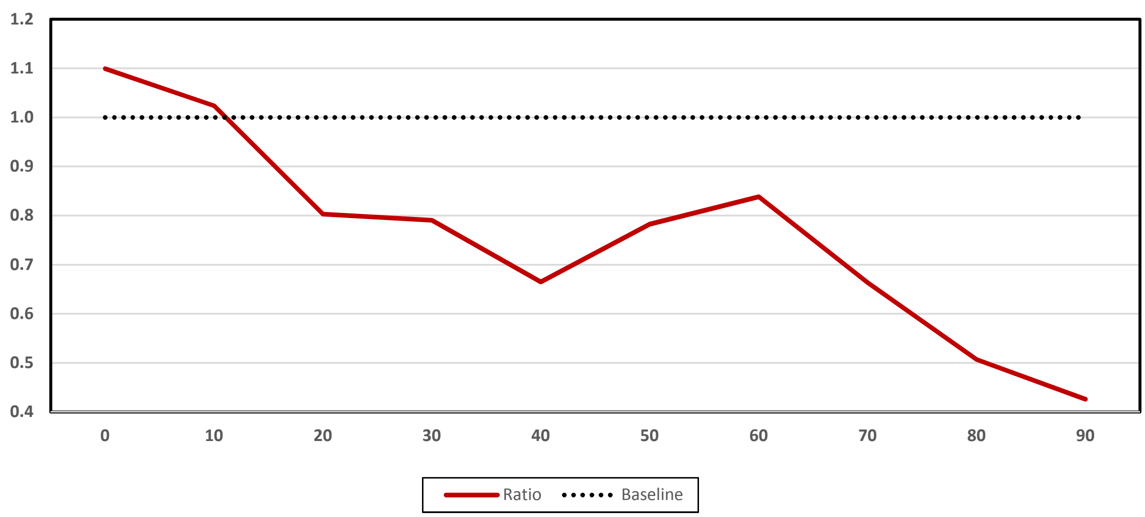
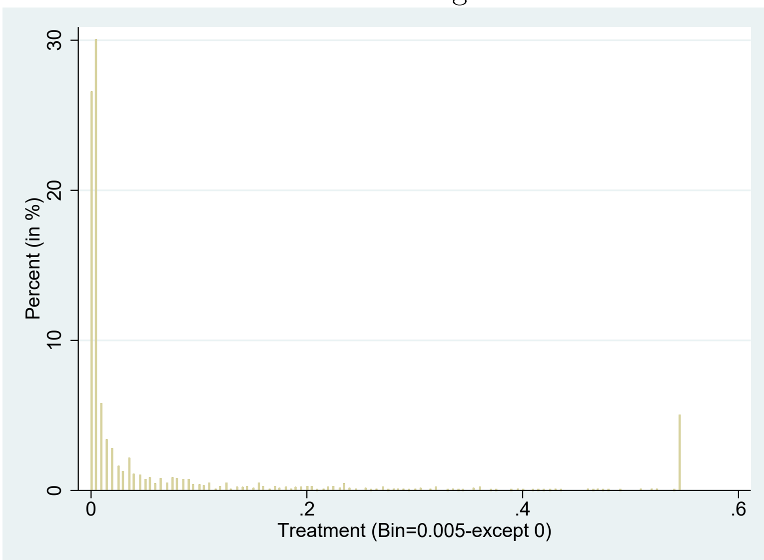


Figure 2: Histogram and CDF For Treatment

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

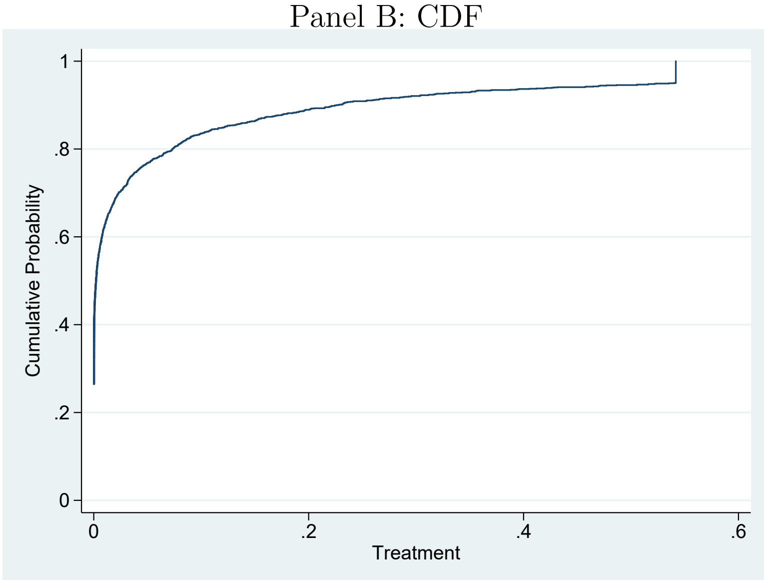
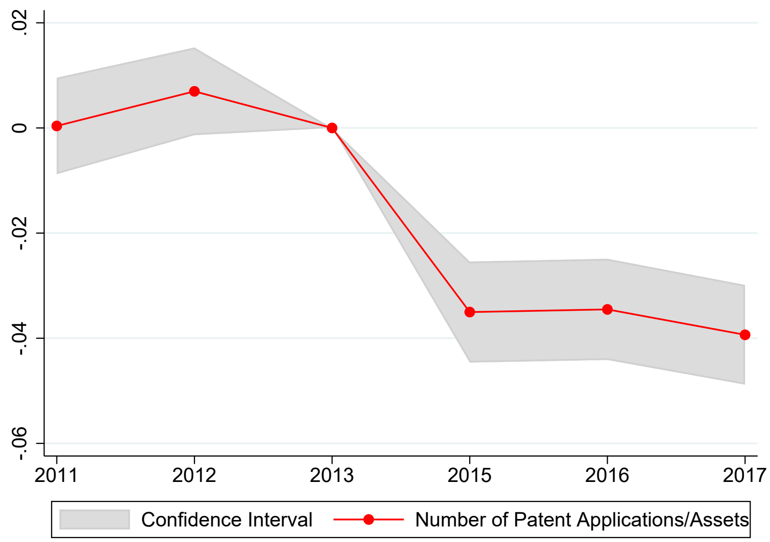


Figure 3: Patent Applications For Large and Small Firms

This figure reports the point estimates per year for $Large \times Treatment$ in Panel A and $Small \times Treatment$ in Panel B from Table 8, column (2) where the dependent variable is Patent Applications/Assets. The regression specifications are the same as those reported in columns [2] of Table 8, 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

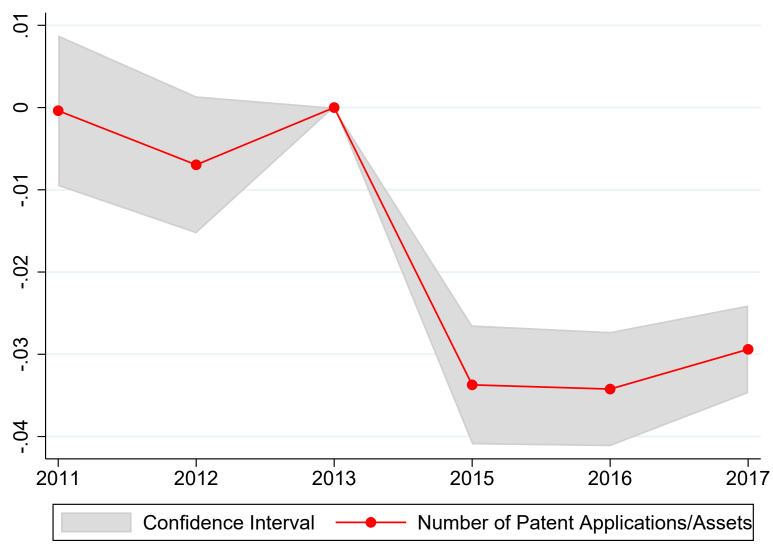


Figure 4: R&D For Small Firms

This figure reports the point estimates per year for $Small \times Treatment$ where the dependent variable is R&D/Assets. The regression specifications are the same as those reported in column (6) of Table 8, except that $Small \times Treatment$ is allowed to vary by year. The gray line indicates the 90% confidence interval.

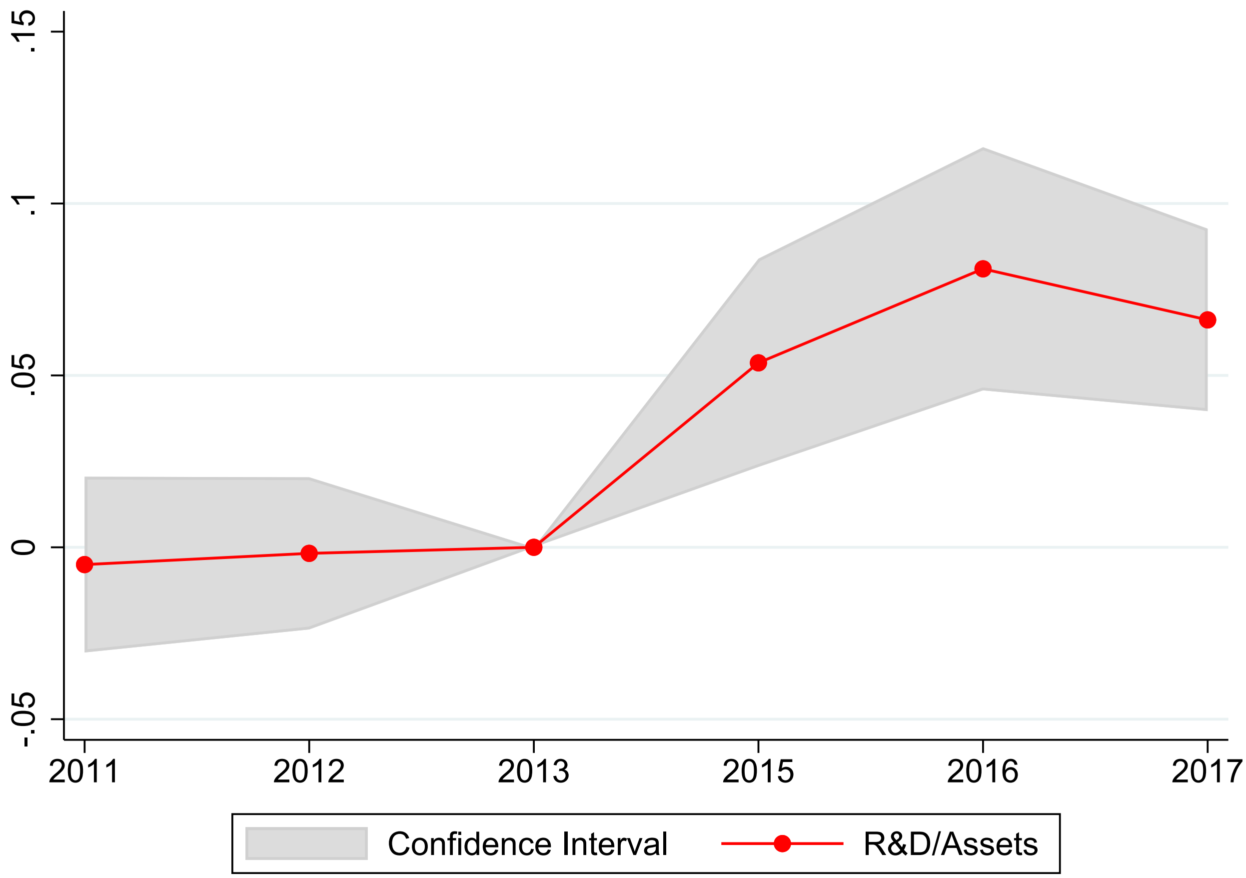
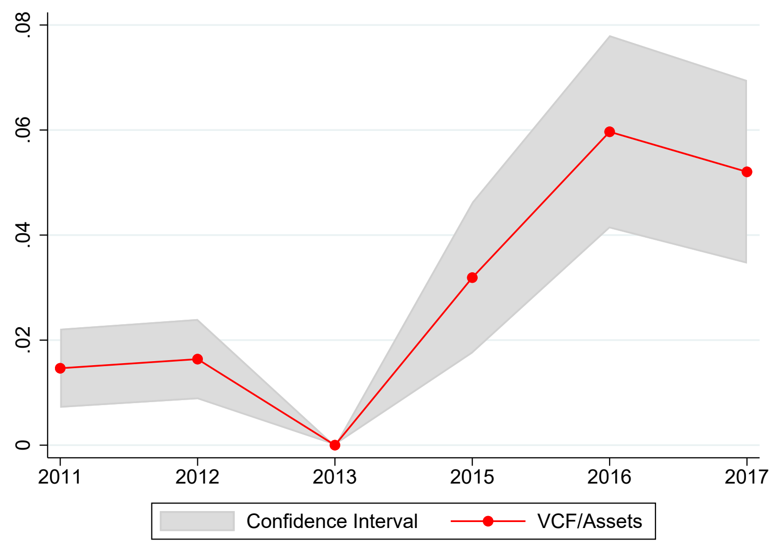


Figure 5: Competition For Small Firms

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/Assets (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

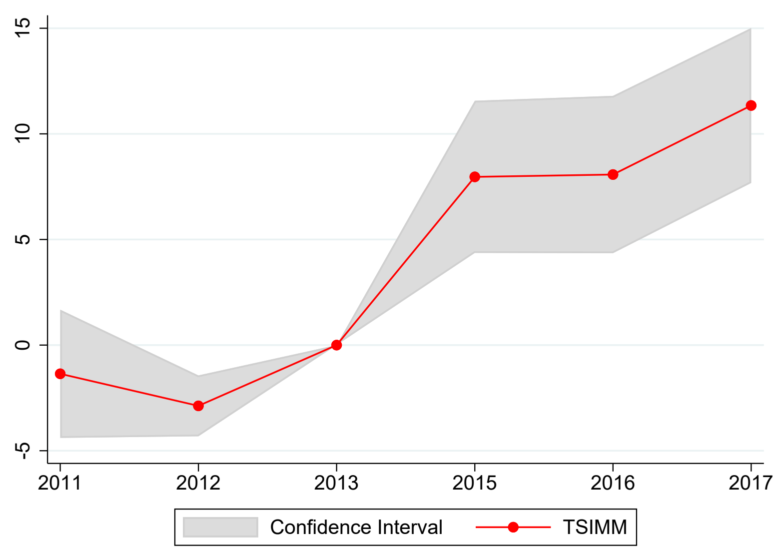


Table 1: Annual Patent Applications and Post-Alice Rejections By Industry

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

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: 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 (BS)	2011 (1)	2012 (2)	2013 (3)	2011- 2013 (4)	2017 (5)	Ratio (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 7: 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.)	9106	1586	828.798	6221.780	268.191	1159.069	7733.053	327.971	***
Sales (in mil.)	9106	1586	752.266	3623.693	141.448	930.379	3871.354	146.174	
OI/Assets	9070	1580	0.105	0.066	0.004	0.098	0.046	0.004	***
Tobin's Q	9041	1586	1.331	1.762	0.030	1.469	1.825	0.029	
Sales Growth	9045	1586	0.066	0.079	0.003	0.027	0.031	0.004	***
Age	9106	1586	20.000	25.772	0.421	24.000	29.402	0.413	***
Panel B: Innovation, Acquisition & Lawsuit Characteristics									
R&D/Assets	9106	1586	0.028	0.065	0.002	0.026	0.068	0.002	
Log(# of Patents)	9106	1586	0.924	1.344	0.034	0.536	1.155	0.033	***
Patents/Assets	9106	1586	0.002	0.010	0.000	0.001	0.006	0.000	***
Acquisitions/Assets	9106	1586	0.000	0.019	0.001	0.000	0.023	0.001	***
Log(Amt. of Acq.)	9106	1586	0.000	1.044	0.037	0.000	1.123	0.040	
Is Alleged	9106	1586	0.000	0.232	0.009	0.000	0.220	0.008	
Is Accuser	9106	1586	0.000	0.098	0.006	0.000	0.089	0.006	
IPrisk (10-K)	8343	1463	3.976	4.734	0.111	4.651	5.544	0.124	***
Patinfringe (10-K)	8343	1463	1.374	2.321	0.068	1.347	2.239	0.064	
Panel C: Competition Measures (Text-based measures from 10-Ks)									
VCF/Assets	8338	1463	0.000	0.008	0.001	0.000	0.015	0.001	***
TSIMM	8330	1463	1.708	4.797	0.202	1.634	6.465	0.316	***
Complaints	8343	1463	15.032	15.768	0.174	15.094	15.915	0.175	
Noncompete	8343	1463	0.000	0.561	0.029	0.000	0.493	0.026	**
Nondisclose	8343	1463	0.000	0.495	0.027	0.000	0.838	0.056	***

Panel D: Pre-Alice Firm Characteristics by Treatment

	Low Treatment (793 firms)			**High Treatment (793 firms)**			
Variable	Median	Mean	Std. Error	Median	Mean	Std. Error	Difference (High-Low)
Treatment	0.000	0.000	0.000	0.040	0.125	0.006	***
Assets	1167.202	6626.253	387.176	718.896	6404.616	398.713	
Sales	1073.508	3844.482	195.008	544.122	3510.135	204.960	

Table 8:
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 assets; 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 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). *Small* is a binary variable equals one if a firm's total assets is smaller than the median of assets in the sample in 2014 and zero otherwise. *Large* is 1-*Small*. *Post* is a dummy variable equals one if the year is after the Alice decision and zero otherwise. The even numbered columns include control variables 1/Assets and Log(Age). 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:	$\frac{\#\ of Patents}{Assets}$		Log(# of Patents)		$\frac{R\&D}{Assets}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Small X Post X Treatment	-0.014***	-0.013***	-0.377***	-0.368***	0.057***	0.056***
	(-6.20)	(-6.05)	(-2.63)	(-2.66)	(4.11)	(4.31)
Large X Post X Treatment	-0.023***	-0.022***	-1.041***	-1.035***	0.001	0.001
	(-4.59)	(-4.63)	(-2.97)	(-2.95)	(0.04)	(0.07)
1/Assets		0.121***		-10.360***		2.069***
		(3.34)		(-5.64)		(7.25)
Log(Age)		-0.009***		-0.145		0.008
		(-6.47)		(-1.26)		(1.24)
Observations	9106	9106	9106	9106	9106	9106
Firm Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Adj. R^2	0.169	0.180	0.108	0.112	0.028	0.100

Table 9:
Profitability

The table displays panel data regressions that examine whether the profitability of small and large 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 assets. 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). *Small* is a binary variable equals one if a firm's total assets is smaller than the median of assets in the sample in 2014 and zero otherwise. *Large* is 1-*Small*. *Post* is a dummy variable equals one if the year is after the Alice decision and zero otherwise. The even numbered columns include control variables 1/Assets and Log(Age). 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		$\frac{OperatingIncome}{Assets}$		Tobin's Q	
	(1)	(2)	(3)	(4)	(5)	(6)
Small X Post X Treat	0.066	0.074	-0.109***	-0.107***	-0.461**	-0.413**
	(1.31)	(1.48)	(-3.54)	(-3.53)	(-2.23)	(-2.04)
Large X Post X Treat	0.253***	0.259***	0.026	0.026	1.088***	1.148***
	(3.95)	(4.02)	(1.03)	(1.04)	(3.02)	(3.21)
1/Assets		-4.566***		-4.751***		14.412***
		(-4.72)		(-7.62)		(3.58)
Log(Age)		-0.102***		-0.041**		-0.755***
		(-3.46)		(-2.51)		(-4.92)
Observations	9045	9045	9070	9070	9041	9041
Firm Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Adj. R^2	0.063	0.073	0.044	0.096	0.064	0.080

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/Assets*, 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). *Small* is a binary variable equals one if a firm's total assets is smaller than the median of assets in the sample in 2014 and zero otherwise. *Large* is 1-*Small*. *Post* is a dummy variable equals one if the year is after the Alice decision and zero otherwise. The even numbered columns include control variables 1/Assets and Log(Age). 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:	$\frac{VCF}{Assets}$		TSIMM		Complaints	
	(1)	(2)	(3)	(4)	(5)	(6)
Small X Post X Treat	0.037***	0.038***	11.292***	10.895***	2.793***	2.710***
	(3.50)	(5.54)	(5.62)	(5.63)	(3.20)	(3.13)
Large X Post X Treat	-0.000	0.001	2.436	2.015	0.298	0.213
	(-1.63)	(1.05)	(0.73)	(0.62)	(0.18)	(0.13)
1/Assets		3.315***		-133.145***		-59.719***
		(25.75)		(-4.07)		(-3.84)
Log(Age)		0.004		5.019***		0.796
		(1.32)		(4.82)		(1.28)
Observations	8338	8338	8330	8330	8343	8343
Firm Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Adj. R^2	0.096	0.488	0.122	0.148	0.010	0.017

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 size based on firm assets 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 assets are above the median in the given year, and Small1 indicates firm 1 has below median assets. Size 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	0.080***		
	(11.19)		
Treat2 *X* Post	0.080***		
	(11.19)		
Big1 *X* Treat1 *X* Post		-0.426***	
		(-24.50)	
Small1 *X* Treat1 *X* Post		0.182***	
		(23.93)	
Big2 *X* Treat2 *X* Post		-0.426***	
		(-24.50)	
Small2 *X* Treat2 *X* Post		0.182***	
		(23.93)	
Big1 *X* Big2 *X* Treat1 *X* Post			-0.443***
			(-18.56)
Big1 *X* Small2 *X* Treat1 *X* Post			-0.404***
			(-16.29)
Small1 *X* Big2 *X* Treat1 *X* Post			0.174***
			(17.07)
Small1 *X* Small2 *X* Treat1 *X* Post			0.187***
			(17.13)
Big1 *X* Big2 *X* Treat2 *X* Post			-0.443***
			(-18.56)
Small1 *X* Big2 *X* Treat2 *X* Post			-0.404***
			(-16.29)
Big1 *X* Small2 *X* Treat2 *X* Post			0.174***
			(17.07)
Small1 *X* Small2 *X* Treat2 *X* Post			0.187***
			(17.13)
Observations	11,102,964	11,102,964	11,102,964
Pair Fixed Effects	YES	YES	YES
Year Fixed Effects	YES	YES	YES
R^2	0.123	0.123	0.123

Table 12:
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). *Small* is a binary variable equals one if a firm's total assets is smaller than the median of assets in the sample in 2014 and zero otherwise. *Large* is 1-*Small*. *Post* is a dummy variable equals one if the year is after the Alice decision and zero otherwise. The even numbered columns include control variables 1/Assets and Log(Age). 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)
Small *X* Post *X* Treat	1.324***	1.282**	0.460***	0.454***	1.848***	1.768***
	(2.61)	(2.53)	(2.98)	(2.94)	(3.92)	(3.81)
Large *X* Post *X* Treat	0.514	0.471	-0.155	-0.160	0.359	0.274
	(0.40)	(0.37)	(-0.70)	(-0.72)	(0.59)	(0.46)
1/Assets		-23.762**		-8.983***		-12.068*
		(-2.34)		(-3.43)		(-1.74)
Log(Age)		0.441		0.023		1.067***
		(1.17)		(0.18)		(4.29)
Observations	8343	8343	8343	8343	8343	8343
Firm Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Adj. R^2	0.108	0.112	0.006	0.008	0.092	0.106

Table 13:
Lawsuits and Legal Protection

The table displays panel data regressions examining whether lawsuit metrics of small and large 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). *Small* is a binary variable equals one if a firm's total assets is smaller than the median of assets in the sample in 2014 and zero otherwise. *Large* is 1-*Small*. *Post* is a dummy variable equals one if the year is after the Alice decision and zero otherwise. The even numbered columns include control variables 1/Assets and Log(Age). 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)
Small *X* Post *X* Treat	0.001	0.009	-0.032	-0.021	-0.012	-0.001	-0.215	-0.188	-0.051	-0.038
	(0.02)	(0.15)	(-0.70)	(-0.45)	(-0.26)	(-0.01)	(-0.66)	(-0.58)	(-0.83)	(-0.61)
Large *X* Post *X* Treat	-0.391**	-0.381**	-0.365***	-0.351***	-0.090	-0.074	-1.286**	-1.257**	-0.183	-0.167
	(-2.45)	(-2.38)	(-2.71)	(-2.61)	(-0.57)	(-0.47)	(-2.45)	(-2.40)	(-1.24)	(-1.16)
1/Assets		2.604***		2.211***		3.096***		-11.106*		1.356
		(2.90)		(2.91)		(3.66)		(-1.95)		(1.40)
Log(Age)		-0.111**		-0.171***		-0.177***		-0.453*		-0.202***
		(-2.12)		(-3.58)		(-3.82)		(-1.81)		(-4.41)
Observations	9106	9106	9106	9106	9106	9106	8343	8343	9106	9106
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
Adj. R^2	0.015	0.016	0.013	0.016	0.008	0.012	0.004	0.007	0.004	0.008

Table 14:
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 asset 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). *Small* is a binary variable equals one if a firm's total assets is smaller than the median of assets in the sample in 2014 and zero otherwise. *Large* is 1-*Small*. *Post* is a dummy variable equals one if the year is after the Alice decision and zero otherwise. The even numbered columns include control variables 1/Assets and Log(Age). 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:	$\frac{Acquisitions}{Assets}$		Log(Acquisitions)	
	(1)	(2)	(3)	(4)
Small *X* Post *X* Treat	0.001	0.001	-0.088	-0.093
	(0.09)	(0.09)	(-0.53)	(-0.55)
Large *X* Post *X* Treat	-0.028*	-0.029*	-2.216***	-2.229***
	(-1.81)	(-1.83)	(-2.73)	(-2.75)
1/Assets		-0.478***		-16.000***
		(-3.05)		(-5.14)
Log(Age)		-0.000		0.068
		(-0.05)		(0.23)
Observations	9106	9106	9106	9106
Firm Fixed Effects	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES
Adj. R^2	0.006	0.007	0.003	0.004

Appendix A. Variable definitions

Table 15: Variable definitions

Table 15

Variable	Definition
Panel A: Financial Characteristics	
Assets	Compustat item AT.
Sales	Compustat item SALE
OI/Assets	Compustat OIBDP divided by total assets AT.
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/Assets	Compustat XRD divided by total assets AT. This variable is set to zero if XRD is missing
Log(# of Patents)	Log of one plus number of patent applications.
Patents/Assets	The number of patent applications scaled by total assets.
Acquisitions/Assets	The total amount of acquisitions divided by total assets.
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/Assets	
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.

Appendix B

Table 16:
Patents and R&D (Robustness)

The table displays the robustness tests for the results in Table 8. 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 assets; 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 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). *Small* is a binary variable equals one if a firm's total assets is smaller than the median of assets in the sample in 2014 and zero otherwise. *Large* is 1-*Small*. *Post* is a dummy variable equals one if the year is after the Alice decision and zero otherwise. The even numbered columns include control variables 1/Assets and Log(Age). 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:	$\frac{\#\ of Patents}{Assets}$		Log(# of Patents)		$\frac{R\&D}{Assets}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Small X Post X Treatment	-0.019***	-0.020***	-1.165***	-1.004***	0.119***	0.085**
	(-3.20)	(-3.50)	(-2.99)	(-2.65)	(3.28)	(2.51)
Large X Post X Treatment	-0.035***	-0.035***	-2.747***	-2.749***	-0.008	-0.008
	(-4.23)	(-4.39)	(-3.12)	(-3.12)	(-0.30)	(-0.30)
1/Assets		0.108***		-9.700***		2.054***
		(3.00)		(-5.82)		(7.25)
Log(Age)		-0.009***		-0.131		0.013*
		(-6.62)		(-1.19)		(1.80)
Observations	9215	9215	9215	9215	9215	9215
Firm Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Adj. R^2	0.157	0.168	0.108	0.112	0.022	0.094