Intellectual Property Protection Lost and Competition: An Examination Using Large Language Models

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Abstract

We examine the impact of lost intellectual property protection on innovation, competition, acquisitions, lawsuits, and employment agreements. We consider firms whose ability to protect intellectual property (IP) using patents is weakened following a major Supreme Court decision. We use large language models (LLM) to identify firms' patent portfolios' exposure to this decision and find unequal impact. Large impacted firms benefit as their sales and market valuations increase, their exposure to lawsuits decreases, and they acquire fewer firms. Small impacted firms lose as they face increased competition, product-market encroachment, and lower profits and valuations. They increase R&D and increase secrecy.

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

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What though the field be lost? All is not lost

Paradise Lost, John Milton, 1674.

1 Introduction

Intellectual property protection is at the core of innovation and competition policy. Economic and legal scholars have debated extensively whether intellectual property (IP) protection increases firm incentives to innovate and conduct R&D. A large body of work argues that patents stifle innovation as Boldrin and Levine (2013) summarize in their survey. Examining 60 countries over 150 years, Lerner (2009) also finds limited benefits of increasing patent protection for domestic firms. 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 innovation when commercialization occurs later in order to increase incentives for innovation.

A natural question is how strong to make IP protection? The theories behind optimal IP protection begin with Nordhaus (1969). In that study, the debate is about the trade-off between giving patents to encourage innovation and the cost of reducing subsequent competition resulting from giving the patentee a local monopoly over the life of the patent. There are also issues with the scope of the patent. If patent protection is too broad, new entrants and new innovation may be discouraged as the protected scope of existing innovation might imply high entry barriers. Monopoly profits that arise from IP protection would also be high, harming consumers. If too weak, then firms would be discouraged from engaging in costly innovation as the innovation would be potentially available to all to copy.

Our study examines the consequences of weakened IP protection across multiple industries in a setting that shocked both existing patents and also incentives for *future* innovation and patenting in the U.S. in multiple patent categories - thus changing the dynamics of innovation and competition in large technology areas. We examine entire firms' product spaces when multiple firms' patents in the business methods broad area are exogenously weakened by the Alice Corp v. CLS Bank International, 573 U.S. 208 (2014) Supreme Court decision (Alice, henceforth). 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. The outcome of this decision was in doubt, given prior court decisions, and we show that it had a large impact after the ruling. In the next section, we summarize the extensive lower court disagreements on this case preceding the final Supreme Court ruling.[1]

The Alice decision impacted multiple industries with patenting including data processing, software, finance, games, and measuring or testing in microbiology and enzymology. We document that Alice has had a large impact on patent rejections, and it led to significant decreases in patenting in exposed areas after 2014. 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 20% of the patent subject matter 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. We also conservatively estimate Alice's impact on future patents and find that Alice

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

resulted in at least 3,237 fewer patents being granted per year after Alice.[2]

While the decision had a large ex post impact on patenting, there was and still exists uncertainty about whether an existing or proposed patent transforms an idea sufficiently to be granted patent protection. Given the uncertain impact on each patent, we apply novel machine learning techniques on regulatory and patent textual corpora to assess how much a given firm's patent portfolio is exposed to Alice. Many legal scholars have written about the Alice decision and the difficulties of measuring and deciding whether there is a sufficient transformation of an abstract idea to warrant a patent.[3]

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 fail to provide protection if challenged in a court in the post-Alice period. This is a challenging computational task as there are more than 3.8 million patents granted between 1994 and 2014. We thus focus on the patents with the same primary Cooperative Patent Classification (CPC) as those rejected by the United States Patent and Trademark Office (USPTO) per the 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 large language model (LLM) called Longformer to predict the likelihood that each of the pre-Alice granted patents in the sample may become weakened and patent-ineligible due to the Alice decision. Longformer is a transformer model that is an improvement for long texts on the BERT model, which 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 BERT model is also used in Google search queries, and Google argues that transformer models help Google Search better understand one in ten

[2]We also consider the potential effect other impactful Supreme Court cases that pre-date Alice: Bilski v. Kappos (561 U.S. 593, 2010), Mayo v. Prometheus (566 U.S. 66, 2012), and Association for Molecular Pathology v. Myriad Genetics, Inc. (569 U.S. 576, 2012). See subsequent sections 2.3 and 3.6.

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

searches in the U.S. in English.[4] The breakthrough innovation of models like Longformer and BERT is that they process 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.[5] These models can examine the full context of a word by looking at the words that come before and after it.

We find a large impact of Alice on future patenting and innovation. Our Longformer framework indicates that 111,420 of the 642,678 patents (17.34% of the sample) are likely to lose protection if challenged in court. We verify that ex post patenting by firms whose patent stock is exposed to Alice significantly decreases for all impacted firms. We then split firms by size (and also by market share) as we hypothesize that smaller firms may be hurt more by the lost patent protection as they have fewer resources (managerial, financial and organizational) to defend their product spaces, while large firms are leading firms with more resources who can defend their product areas.[6] When we examine R&D, we find no change for large firms but find a significant increase in R&D for small firms. These results are consistent with small firms' attempting to replenish their innovative portfolio to escape competition from lost IP protection and to rebuild product differentiation. Examining ex-post changes in sales growth and profitability along with firm value, we find unequal impact. Large firms gain and small firms lose. Exposed large firms increase sales and experience insignificant gains in valuation. Small firms whose patent portfolio is exposed to Alice experience a decrease in operating margins and their market valuations.

Our main contribution is to examine who gains and loses after a change in intellectual property protection that impacts whole areas of technology indefinitely for all firms - both large and small. Thus our setting is about the broad inability to patent (present and future) in treated technology areas, which is different from previous studies using random assignments to examine the loss of protection for individual patents.[7] Understanding the

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

[5]We use the Longformer model as it outperforms the BERT model in our context. Our conclusions using Longformer are also fully robust when using the SciBERT model.

[6]In the Internet Appendix, we provide results from classifying firms based on their market shares, and thus by sales shares instead of assets, and the results are qualitatively similar.

[7]Galasso and Schankerman (2015) showed that when larger firms' patents were invalidated, small firms

consequences of invalidating protection for entire areas indefinitely is important as it indicates the likely consequences of future major policy changes that broadly weaken protection.

We show that differential losses for small firms are related to changes in competition relating to decreased IP protection. These small firms face increased competition on a number of different measures. Both large and small firms face increased venture capital financed entry into their product space, but this entry is more severe for small firms. Small firms also complain more about increased competition. We also find using textual analysis of 10-Ks that small firms resort to non-disclosure agreements as an alternative way to protect IP post-Alice. Thus, small firms turn to increased secrecy to defend new IP in the face of lost patent IP protection. This finding shows the importance of disclosure, also noted by Sampat and Williams (2019) in the case of technologies that shift from patentable to unpatentable.

We next examine patent infringement litigation and intellectual property risk. Lemley and Zyontz (2021) descriptively illustrate using filed lawsuits that companies were more likely to lose their patent protection post-Alice than were non-producing entities (NPEs), also called patent trolls.[8] We find using formal difference-in-difference tests that effects are heterogeneous and that large firms experience fewer claims that they infringe on other firms. This decrease is significant for both patent-troll lawsuits and lawsuits by operating companies. This is intuitive as firms would be less likely to sue a deep-pocket firm when the validity of the patents is questionable. Thus, larger firms that previously were sued by NPEs (as documented by Cohen et al. (2019)), benefit from Alice. However, we find only weak results with the opposite sign for small firms.

We also find that large firms decrease their acquisition activity post-Alice. This is consistent with the theoretical arguments and empirical evidence in Phillips and Zhdanov (2013). If a large firm can forecast that a small firm's patent might lose protection post-Alice, there

increased innovation. Farre-Mensa et al. (2020) show that small firms gain from patent protection beyond the value of the idea itself using 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.

[8]One limitation of filed lawsuit analysis is that the primary impact of Alice might be on the number of patent disputes that were *not* filed, as lawsuits are not cost-effective under lost protection.

is less incentive to buy small firms for their technology as they can implement it for free without infringing the smaller firm's patents.

In a review focusing on the role of patents on the incentives to innovate, Williams (2017) proposes three focal channels: disclosure, patent strength, and pre-existing patents. The Alice decision has a direct impact on the latter two: it reduces patent strength both for future and existing patents in entire technological areas that were previously protected. Consistent with protection being important for future innovation, we document a widespread reduction in patenting post-Alice. Yet we do not find corresponding reductions in R&D as smaller firms significantly increase R&D. Disclosure, the 1st channel, was also impacted as small firms shift from disclosed patents to increase non-disclosure agreements.

Overall, our contribution relative to the previous literature is that we examine the impact on both large and small firms when *all* firms lose patent protection in broad areas - different than studies that use the random assignment of patent examiners/judges to examine the grant/loss of protection for a focal firm but where non-treated peers do not change expectations about their ability to patent in the future. In our setup, all firms are randomly treated, with all firms updating their expectations for the future as the court ruling diminishes patent rights for everyone. Our paper is also the first paper in finance and economics to show that large language models can be used to successfully predict the legal validity of patents, thus contributing also to methodology in the law and finance literature.

We find losses in both valuations and competitive positioning for smaller firms suggesting that small firms increase innovation to rebuild their competitive position. Large firms have less patenting, face fewer lawsuits, and their acquisitions of firms with patents also decline.[9] Our results are consistent with large firms having more resources - technological, financial and managerial - which allows them to protect their product market position. We thus conclude that patent protection is particularly important for small firms competing with larger firms. Our paper points to the benefits of increased competition and fewer lawsuits

[9] A recent WSJ article quotes firms that also say Apple has copied extensive features of their software innovations. See "When Apple Comes Calling, It's the Kiss of Death" WSJ, 4/20/23.

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

2 Innovation and Alice *v.* CLS Bank International

There is a substantial debate on how strong to make IP protection. The general academic consensus is summarized by Boldrin and Levine (2013), who state that there is no empirical evidence that patents increase innovation and productivity. They advocate for abolishing patents entirely and using other legislative instruments to increase innovation. Galasso and Schankerman (2015) document that patent invalidation of large patentees triggers follow on innovation by smaller firms. However, these were exogenous invalidations of particular existing patents and these tests are not about indefinite forward-looking changes to entire patent areas as is the case for Alice. Lerner (2002)'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, such expansions of IP protection have been enacted simultaneously with relaxations of trade protections.[10] There is also evidence (see Budish et al. (2015) for example using cancer clinical trials) that maintaining incentives to engage in innovation is important if the ideas take a long time and are costly to develop.

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. Kesan and Wang (2020) review the impact of Alice and document large decreases in 11 patent categories including bioinformatics, business methods, business

[10]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.

methods of finance, business methods of e-commerce, software (in general), databases and file management, cryptography and security, telemetry and code generation, digital cameras, computer networks, and digital and optical communications. They showed significant rejections of patents under Alice based on whether the proposed invention sufficiently transforms an abstract idea or natural law. Section 101 of the Patent Statute specifies four categories of invention that are patent eligible: process, machine, manufacture, and composition of matter. However, there are, three court made exclusions to these categories that limit 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 United States decided a landmark case, Alice Corp *v.* CLS Bank International, 573 U.S. 208 (2014). It had a major effect on patent eligibility across multiple patent categories. 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 does not make it patentable.

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.[11] However, given the case's complexity and its importance for the whole industry, the CAFC vacated the panel's opinion and decided to the hear the case in a full session of all ten judges that then heard the case.[12][13]

The uncertainty in the en banc session was similar to that of the three-judge panel. Five of ten judges upheld the district court's decision that Alice's systems claims were not patent-

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

eligible, and five disagreed. Seven of the ten judges upheld the district court's decision that Alice's method claims were not patent-eligible. However, these seven judges reached their opinions for different reasons. Overall, the judges could not agree on a single standard to determine whether a computer-implemented invention is a patent-ineligible abstract idea.

After the deep division in the CAFC, the Supreme Court of the US granted certiorari and affirmed the en banc decision of the Federal Circuit Court of Appeals.[14] 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 significant stock market reaction. We compute abnormal returns by subtracting the equally weighted CRSP market return. We find a significant negative coefficient at the 1% level for the -1 to +1 event-day window surrounding the Alice decision for the most impacted firms. There is also substantial variation, as at the average of our treatment variable, the excess returns were close to zero at -0.1%. Yet for the top five percent of our treatment variable, this excess return is larger at -0.8%. Thus, while the Alice decision had a small stock market impact for most firms, it had a large impact on some firms.

2.2 Consequences of Lost IP protection

The Alice case had a large impact on ex post patenting. 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 5,831 distinct CPC Subgroups (out of 126,540 total), 919 Groups, 283 Classes, and 8 CPC

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

Sections.

In Table 1, we document the number of patent applications from 2008 to 2017, with the percentage of rejections in parentheses for these industries. We use rejection data provided by Lu et al. (2017) that extends until 2016; therefore the ratio of rejection is assigned NA for 2017. *Change* reports the percentage change from the number of patent applications in 2013 to the average number of patent applications for the 2015-2017 period.

Table 2 provides CPC groups that are impacted by Alice (Panel A) and the industries they belong to (Panel B). Regarding statistics, Kesan and Wang (2020) document that about 17.9% of office action final decisions in bioinformatics 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 afterward, and 72.8% of applications filed after Alice. Additional categories, including computer networks, GUI, document processing, and cryptography and security, also had significant increases in section 101 rejections after Alice. The number of patent applications per month dropped significantly post-Alice by 12-31% across different categories. For example, patent applications in the business method area dropped 29.5%. Kesan and Wang (2020) also 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. The court did not define "abstract" and the court did not define how to decide whether an abstract idea has been transformed sufficiently into an inventive concept by including additional limitations to the patent claim, the basis for rendering claims eligible for patent protection. Given this uncertainty about whether a given patent would be rejected because of Alice, we use a deep learning-based language model called Longformer to predict the likelihood that each of the pre-Alice granted patents in our sample might become ineligible due to the Alice decision. We then study ex post firm decisions and outcomes based on this predicted likelihood.

We split firms by large and small size as we hypothesize that smaller firms might be hurt more by lost patent protection as they have fewer resources (managerial, financial and organizational) to defend their product spaces, while large firms will be the leading firms with more resources who can defend their product area. The differential impact on innovation by leading vs. laggard firms has been modeled, for example by Aghion et al. (2005). In our setting, given the large increase in competition post-Alice, we expect firms left behind will innovate more in order to escape competition from other small firms. Larger firms are predicted to behave more like the Schumpeterian model and will innovate less as laggard firms will preform most innovation with low initial profits or by smaller firms looking to break into the market.

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

2.3 Other Impactful Supreme Court cases

Although the Alice Supreme Court case has been more impactful than other recent cases that weaken patent protection for methods-based inventions, out of an abundance of caution, we also consider the influence of three other impactful Supreme Court cases that pre-date Alice: Bilski v. Kappos (561 U.S. 593, 2010), Mayo v. Prometheus (566 U.S. 66, 2012), and Association for Molecular Pathology v. Myriad Genetics, Inc. (569 U.S. 576, 2012). In section 3.6, we fully describe how we handle these cases and in most tables, we drop all CPC codes that are impacted by these cases.

We also note that these three cases had much less of an impact than Alice (illustrating why our study focuses on Alice). Using the USPTO office actions data from Lu, Myers, and Beliveau (2017), we divide the number of rejections for each case by the number of patent applications filed between the date of the respective Supreme Court decision and the end of 2016. These actual rejections indicate that Bilski had 22.4% of the number of subsequent rejections that Alice had, Mayo had 8.2%, and Myriad had 4.6% of the rejections that Alice subsequently had - despite occurring in the years prior to Alice. These results illustrate the sheer size and impact of Alice, which is our primary motivation for focusing on Alice.

For completeness, we further searched for any additional supreme court cases around the time of Alice and found four additional cases that we note are not relevant to our analysis based on the subject matters they address and their lack of impact on patent application reviews. Medtronic vs. Mirowski (2014) focuses on civil procedure, Icon Fitness vs. Icon Helath (2014) focuses on increasing costs for patent trolls, and Akamai vs. Limelight (2015) focuses on infringement with multiple actors. Nautilus vs Biosig (2014) focuses on clarity of identifying a patent's subject matter but is thought to have had little impact.[15] Most crucial to illustrating non-relevance in our context, unlike the Alice, Bilksi, Mayo and Myriad cases we focus on above, these additional four cases are not coded as relevant data items in the USPTO's Office Action database.

[15] https://www.law360.com/articles/648187/fed-circ-remand-shows-nautilus-may-have-little-impact

3 Data and Methods

We begin by training and validating a model of Alice's impact on lost IP protection at the patent level using the Longformer large language transformer model and patent text. We then aggregate patent-level impact to derive our key firm-level Alice treatment variable used in our study. We then discuss our final sample and present summary statistics.

3.1 Experimental Challenges

Our experiment needs to identify patents that were granted in the pre-Alice period but that would lose protection if they are tested in a court in the post-Alice period. This identification is challenging as there are more than 3.8 million patents granted between 06/19/1994 and 06/19/2014. To make the experiment tractable, we focus on the patents having the same primary CPC as those that were rejected by the USPTO per the Supreme Court's Alice criteria. This filtering leaves us 642,678 patents that we need to score on the likelihood of losing protection. Since manual examination is not feasible, we consider automated models with reliable predictions in this context. Thus, as described below, we train a transformer model using patents applied for prior to Alice but not yet granted. Post-Alice, we have 33,234 patents that were rejected (positives in our testing environment) by the patent examiner where the patent examiner cites the Alice case as the reason for the decision. We also have a large set of granted patents in the same CPC categories that we can use as the negatives (granted patents) in the training of the model. These rejected and granted patents in the same CPC categories thus act as the "ground truth" in our trained large language model.

Basic text-based similarity techniques such as term frequency–inverse document frequency (TF-IDF) have two major shortcomings. First, as technology vocabulary evolves and patents use related but different terms, TF-IDF may have limited power to capture the similarity between two patents. Second, even when two patents use a similar vocabulary, the Supreme Court's Alice decision might affect one but not the other. These challenges motivate us to use an automated system such as the Longformer model, a transformer large language model (LLM), which is capable of catching both syntactic and semantic information.[16]

The primary benefit of transformer models is that they process words in relation to all the other words in a sentence rather than one-by-one or in a fixed-sized sliding window approach. This mechanism is referred to as self-attention, and it provides the capability to understand the intent behind a sentence. To illustrate, we examine two sentences with similar meanings: i) Symptoms of influenza include fever and nasal congestion; ii) A stuffy nose and elevated temperature are signs you may have the flu. While a TF-IDF model that filters the stop words (such as "and") has a similarity score of 0, the BERT and Longformer models find 0.86 and 0.98 similarity scores for these two sentences, respectively.

3.2 The Longformer Model

Transformer-based large language models (LLMs) are neural network models that revolutionized the field of Natural Language Processing (NLP) (Kalyan et al. (2021)). BERT is an early example released by Google in 2019, and it is used in their search engine. BERT also achieves state-of-the-art performance on various NLP tasks (Devlin et al. (2019)). Even though BERT is powerful, a limitation is that it can only process 400 words from any given text. A new transformer-based large language model (LLM) Longformer (Beltagy et al. (2020)), was specifically designed to overcome this limitation, and it can handle longer documents up to 3,200 words. Furthermore, for long documents, Longformer is superior to several LLMs, such as BERT and RoBERTa (Beltagy et al. (2020); Gutiérrez et al. (2020); Xiao et al. (2021); Gupta and Agrawal (2022)). Our results are consistent, as Longformer outperforms these other models.[17] We thus use Longformer to predict the likelihood that

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

[17] We also compare Longformer's out-of-sample prediction performance, and its performance on economic validation tests, to TF-IDF and other computational linguistics methods such as Word2Vec and also to

pre-Alice granted patents might lose IP protection due to the Alice decision.

The Longformer model is pre-trained using text from the Wikipedia, Book Corpus, CC-News, Open Web Text, and Stories datasets. The pre-trained model is then fine-tuned using labeled data.[18] We use descriptions of patent applications to train the model. However, patent descriptions are generally longer than Longformer's 3,200 word limit. The average number of words is 9,173, and only 12.57% of the pre-Alice granted patents in the sample have descriptions less than 3,200 words. We thus use the TextRank automatic summarization tool, which internally uses Google's popular PageRank algorithm, to reduce the text size to 3,200 words (Mihalcea and Tarau (2004), Upasani et al. (2020)).

3.3 Rejected Patent Applications

We first gather patents rejected under 35 U.S.C. §101 from the USPTO website.[19] We then identify the set classified as Alice-rejections based on the method of Lu et al. (2017). This step leaves us with 56,709 rejected patent applications. However, some 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 TF-IDF and tag those with 0.99 similarity score as duplicates, and only keep the one with the latest date. We are left with 33,734 unique rejected patent applications that have a document number and Cooperative Patent Classification (CPC) code. These Alice-rejected patents belong to 5,831 unique CPCs.

BERT. Overall, Longformer outperforms the other models on these validation tests, and we adopt Longformer as our baseline model. Results using SciBERT, which is a version of BERT pre-trained on a scientific corpus, were in an earlier version of the paper and are available from the authors.

[18] Transformer-based language models are fine-tuned for classification tasks as follows. An additional linear layer is appended to the last layer of the language model. The parameters of this new layer, as well as the parameters of the language model, are then fine-tuned using the cross-entropy loss function. The weights of the language model are not frozen. We fine-tune the Longformer model for 5 epochs with a batch size of 32 and a learning rate of $3e^{-}5$ using a linear learning rate scheduler and AdamW optimizer. We use the same fine-tuning parameters for each language model and use the Transformers Library version 4.9.1 (https://huggingface.co/docs/transformers).

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

3.3.1 Training The Longformer Model

There are two phases of training and evaluation. First, we train the system using the text of Alice-rejected patent applications (positives) and texts of applications that were eventually granted (negatives). After training, we evaluate predictions using a hold-out testing sample.

Note we train the model using patents that were rejected because of the Alice court decision, where the patent examiners rejected the patents citing the Alice case. These rejected patents were mainly (over 80%) applied for in the pre-Alice period and then we use the model to evaluate these 642,678 existing pre-Alice granted patents. We also have a very large set of granted patents in the same CPC categories.

In our experiment, we utilize the full set of post-Alice rejected patents in the 3 years after the Alice decision for training and testing to achieve the best possible training for our language model. Table 1 provides statistics regarding the application years of the rejected patents in the top 12 industries with the highest patent rejections. In our overall sample, 80.4% and 80.2% of the Alice-rejected patents used for training and testing, respectively, were applied *before* the Alice decision. Our approach thus allows for optimal sample size and balance regarding both training and testing of the large language model while also ensuring that the overwhelming majority of patents in this sample were submitted pre-Alice or just after Alice when its full consequences were not yet known.

From the set of 33,734 Alice-rejected patent applications, we randomly chose 10,000 patent applications for hold-out testing and use the remaining 23,734 as to train the system. In the language of training, these are the "positive" sample (rejected=yes). Next, we create a sample of rejected = "no" from patents that are successfully granted after 06/19/2014 (the Alice decision). To ensure robustness, we construct the sample of negatives in four different ways based on CPC granularity (which has five levels): i) section; ii) class; iii) subclass; iv) group; and v) main group or subgroup. For example, 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 rejected = "yes", we find a matching rejected

= "no" (in training language the negative cases) that is in the same CPC Group that was granted after 6/19/2014. In samples B, C, and D, we keep adding 23,734 more matching patents to the rejected = "no" pool based on CPC Subclass, Class, and Section, respectively. Therefore, from A to D, each sample has 23,734 more rejected = "no" sample with the newly added ones drawn from broader CPC codes.

3.3.2 Testing Longformer and Other Models

In this section, we compare our trained Longformer Model to SciBERT, BERT, RoBERTa, TF-IDF, and Word2Vec. For TF-IDF and Word2Vec predictions, we combine the model with logistic regression, decision tree, and random forest. In Internet Appendix Section 1, we present a detailed technical comparison of the transformer language models.

For this testing phase, we start with the 10,000 hold-out positives noted above. For each positive, we chose two negatives, giving us 20,000 negatives. This 1:2 ratio balances the fact that the expected rejection ratio is lower than half, and we do not overestimate accuracy for models that do not learn and only predict negative results.[20] To obtain the 20,000 negatives from the 708,115 post-Alice granted patents, we first gather 50,000 negatives that are randomly selected based on the CPC frequency distribution used in our prediction sample (see next section). Finally, from this negative pool, we sample 20,000 negatives 1,000 times to boot-strap the performance of each machine learning model. We then evaluate results using standard performance metrics from computer science: precision, recall, F1 score, and accuracy. These metrics are calculated from a confusion matrix with the following elements: True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN):

$$Precision = \frac{TP}{TP + FP}, \qquad Recall = \frac{TP}{TP + FN}, \tag{1}$$

$$F_1\ Score = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}, \qquad Accuracy = \frac{TP + TN}{TP + TN + FP + FN}. \tag{2}$$

[20] For example, if the ratio of positives to negatives is 1:9, then a model that does not learn but only predicts that all patents are negative would have 90% accuracy.

Table 3 reports the evaluation results. In the last column, we use an ensemble of the two models that have the highest F_1 Score and Accuracy by taking the average of their prediction scores (A has the highest F_1 Score and D has the highest Accuracy). The results show that the ensembled Longformer model is superior to all other algorithms with the highest F1 Score (0.672) and Accuracy (0.804).

3.3.3 Longformer Alice Scores Pre- and Post-Alice

In Internet Appendix Tables IA1 and IA2, we provide lists of sample CPC codes and industries that were highly impacted by Alice. To build more intuition, Table 4 lists the words that are used more frequently in patents with high Longformer Alice scores (≥ 0.5) compared to those with low Longformer scores ($<$0.5). These listed words are intuitive and "open the black box" regarding which words are indicative of Alice exposure.

The nature of Alice is that it will not only impact current patents but also future patents in affected technological areas. While it is hard to estimate this impact, we provide some relevant statistics, and we estimate differences in the patents granted in key technological areas both pre-Alice (2011-2013) and post-Alice in 2017.

Table 5 shows the distributional density of the Longformer Alice Score of granted patents before Alice (2011 to 2013) and after the shock (2017) for the Top 20 technological areas impacted by Alice.[21] 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 granted in 2017, 17,643 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 these 17,643 patents applied for in the post-Alice period. We sort all patents each year into 10 bins based on each patent's Longformer Alice Score. Bins are defined as the ten equal segments in the interval (0,1), which is the range of the Alice Score. For each bin, the density is the number

[21] We redo this analysis for patent applications and present results in the Online Appendix Table IA3.

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 5 shows that, for bins with Longformer Alice scores exceeding 0.5, patenting has declined sharply.[22] In decile 10, the decile with the highest Alice scores, patenting is only 38% 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 granted in 2017 if the Alice judgment had not occurred. In particular, for each bin having materially positive Alice Scores (those greater than 0.3 in Table 5), 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 these bins, and the result is 3,237 patents. This calculation thus estimates that Alice resulted in 3,237 fewer patents per year by 2017 in these 20 technological areas. Because Alice is still in effect, this annual total is likely to accumulate every year, indicating an economically large impact.

The impact of Alice is also shown graphically in Figure 1, which shows the percentage of post-Alice patents granted in 2017 relative to the numbers in 2011-2013 (this is Column (6) of Table 5). The sharp drop-off on the RHS of the figure illustrates that firms greatly reduced patenting in technologies that had the most Alice exposure.

Online Appendix Table IA3 shows robustness of these patterns using patent application distributions instead of patent grants. Column (6) of this table again shows a much larger reduction in patent applications with high Alice scores as compared to those with low Alice scores. These consistent findings for both applications and grants illustrates that companies are not able to easily "game the system" by resubmitting the same patents to USPTO

[22]We find similar results if we use patent applications instead of patent grants (available from authors).

repeatedly with minor adjustments in order to bypass Alice requirements.

3.4 Patent Sample and Treatment Measure

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

$$Treatment_i = \frac{\sum_{j=1}^{N_i} PatentValue_{i,j} \times AliceScore_{i,j}}{Sales_i} \tag{3}$$

$Sales_i$ 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)). We compute an alternative treatment variable where we replace patent value with the number of citations the patent received (discussed below). The treatment variable is computed for each firm in 2014 using all valid granted patents prior to the Alice decision. The patent values in equation (3) are depreciated using an annual 20% rate relative to the base year 2014.[23] Figures are further adjusted for inflation. $AliceScore_{i,j}$ is Longformer's predicted probability that a patent j loses protection if it were to be challenged in a court. N_i is firm i's total patents.

As an alternative to KPSS valuations, we use a citation-based metric to estimate $PatentValue_{i,j}$ in Equation (3). For each patent j, we count the number of granted patents that cite j and have an application date that is within five years of j's grant date. We also depreciate citation-based value using an annual 20% rate relative to the base year 2014.

We estimate all the regressions in our subsequent tables using a difference-in-difference approach where *Post* is the years after Alice, and we interact that with Treatment to allow differential treatment values.[24] We also include a small and large indicator variable interacted with the Treatment variable to allow differences between small and large firms. In the appendix, we also present results for high and low market share firms but use the more

[23]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. Our results are fully robust to using a 15% rate.

[24]In the appendix, given our Treatment value is not binary, we present results using a fuzzy difference-in-difference estimator following (de Chaisemartin and D'Haultfoeuille, 2018) and de Chaisemartin et al. (2019) for implementation in Stata.

general small and large as we use these as a measure of resources organizational resources available to firms. Lastly, we include firm and year fixed effects throughout, and standard errors are clustered by firm. Given the use of these fixed effects, in all of our regressions, the lower-order interactions of our key variables (treatment dummy, large dummy, small dummy and post dummy) are included but are subsumed by the fixed effects.

The justification for examining heterogeneous effects based on firm size follows from Aghion et al. (2005) and is based on the fact that larger firms are more able to defend their product markets given their larger resources - both managerial and financial. We define firms as large or small, respectively, based on whether each firm's assets are above or below the median value among its TNIC-2 industry peers (see Hoberg and Phillips (2016)) in 2013.[25]

For all regression tables that follow, *Post* is an 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 importance of patents to the firm and the extent the firm's patent portfolio is affected by the Alice court decision. Throughout, we use the firm treatment value using each patent's Alice score weighted by the patent's importance to the firm. We present results using two different weights: (1.) using each patent's KPSS weighted value and also (2.) using each patent's citations weighted value. This measure is explained in equation (3), with citations replacing the patent value for the citation-based measure. We note that results are similar across the two weighting methods.

3.5 Sample and Key Variables

We include public firms with at least one patent from a CPC category with a rejected patent. We link patents to public firms using the correspondence provided by Kogan et al. (2017), who extended the data until 2020. 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

[25] In the appendix, we also present results that define large vs. small based on each firm's market share based on TNIC product-text industry peers. These results are fully robust.

competitor network of Hoberg and Phillips (2016). Our sample thus includes 3,402 unique firms: 1,020 Alice-affected firms and also 2,382 competitor firms.

Table 6 displays summary statistics for our main sample of firms. This sample contains 19,135 firm-year observations based on our sample screens noted above spanning the period from 2011 to 2017 (excluding 2014, the treatment year). We briefly describe the variables used in our analysis (full details and a variable list are in Appendix A). Table 6 presents summary statistics for firms both pre-Alice (2011-2013) and post-Alice (2015-2017).

Panel A of Table 6 presents accounting characteristics including the size of firms measured by assets and sales, sales growth, age, and profitability (Operating income / Sales) of firms. We also consider valuation as indicated by the market to book ratio ((market value of equity + book value of debt) / lagged book value of assets). The table shows for example that overall operating margins and sales growth decline. Later, we explore these findings using rigorous models with firm fixed effects.

Panel B presents the innovation, acquisition and legal variables used in our study. Note that all scaled variables are scaled by *lagged* sales or assets. *Treatment Effect* measures the extent a firm's patent portfolio is impacted by Alice as measured using the Longformer model in equation (3). It captures how much a firm is dependent on patents and also the percentage of patents' value that are impacted by the Alice court decision. R&D/Sales is Compustat R&D divided by lagged sales of the firm and is set to zero if R&D is missing for our base tests. We define Acquisitions/Sales as the dollar value of acquisitions scaled by sales. PatTargets/Sales is the dollar value of acquisitions where target has a patent scaled by sales. Acquisitions data is from the Securities Data Corp (SDC) database.

The legal variables we examine are *# Alleged*, *# NPE Alleged*, *# OC Alleged*,*# Accuser*, *IPrisk* and *PatInfringe*. We compute the first four using information in the Public Access to Court Electronic Records (PACER) database, which provides public access to all cases litigated in the U.S. District Courts, and Stanford Non-Practicing Entity (NPE) Litigation Database. For the last two, we use textual queries of each firm's 10-K statement filed with the SEC. *# Alleged* is the number of lawsuits that a firm was alleged for infringing on a patent in that year. *# NPE Alleged* (*# OC Alleged*) refer to the number of lawsuits that the firm was alleged infringing on a patent lawsuit by a Non-Practicing Entity (Operating Company) in that year. *# Accuser* is the number of lawsuits that the firm accused another party for infringing on a patent in that year. *IPrisk* is the total number of paragraphs mentioning "intellectual property" in the risk factor section of the firm's 10-K, scaled by the total number of paragraphs in the 10-K. *PatInfringe* is the total number of 10-K paragraphs containing both a patent word and a word that contains the word root "infringe", also scaled by the total number of paragraphs in the firm's 10-K. The table shows that patents decline and lawsuits and patent infringement all decline post-Alice while IP risk increases.

Panel C of Table 6 presents competition summary statistics. *VCF/Sales* is a measure of VC entry and is total first-round dollars raised by the 25 startups from Venture Expert whose Venture Expert business description most closely matches the 10-K business description of the focal firm (using cosine similarities), scaled by focal firm sales. The next three variables are constructed using the metaHeuristica software package to run high speed queries on 10-Ks filed with the Securities and Exchange Commission. *Complaints* is the number of paragraphs in the firm's 10-K that complain about competition divided by the total number of paragraphs in the firm's 10-K. *Noncompete* is the number of paragraphs in a firm's 10K mentioning "non-compete" agreements, scaled by the total paragraphs in the 10-K. *Nondisclose* is the number of paragraphs mentioning "non-disclose" or NDA agreements in a firm's 10K, scaled by the total paragraphs in the 10-K. The table shows that competition and nondisclosure agreements increase post-Alice.

Our treatment variable is not binary and represents the percentage of a firm's patent portfolio value that is exposed to Alice scaled by sales. Each patent's Alice exposure score is the probability from our Longformer model that the patent will be ruled ineligible if it is challenged in court. For roughly half of the sample, the treatment Alice score is close to 0. The median and average scores of treatment in our sample are 0.001 and 0.062, and the 75^{th}

percentile and 90^{th} percentiles are 0.034 and 0.224, respectively. The standard deviation of treatment variable is 0.025. We show the full distribution of firm-level treatment Alice scores for patenting firms in Figure 2. Panel A shows the histogram for our KPSS valuation-based treatment variable and Panel B for our citation-based treatment variable.

Both panels show that roughly 25% to 30% of our firms have zero Alice scores. Roughly 40% have positive scores that are close to zero. Thus, roughly 65% have Alice scores equal or slightly greater than zero (from 0.0 to .005). About 6% to 7% of firms have very high exposure to Alice with Alice scores in the rightmost bin. Using a continuous treatment score allows us to show how the ex post outcomes vary with the intensity of treatment. Going forward for parsimony, we refer to the Longformer Alice score just as "Alice Score".

Table 7 displays ten examples of large and small firms with high Alice-scores. It presents their most impacted patent and also firm-level characteristics including the final firm-level treatment value. All dollar values are depreciated by our patent depreciation rate and also by the CPI so that values are in 2014 \$. The table shows that both large and small firms have patents impacted by Alice. It also shows that firms that have highly Alice-impacted patents frequently also have many other patents that are not impacted. The observation that larger firms often have many non-Alice impacted patents along with Alice-impacted patents illustrates the depth of knowledge accumulation these firms have, which likely helps to explain why these firms fare better after the Alice shock than do smaller firms.

3.6 Bilski, Mayo, and Myriad Supreme Court Cases

We handle the potential impact of these other patent cases using the following methods. Using the USPTO actions data from Lu, Myers, and Beliveau (2017), we divide the number of rejections for each case by the number of patent applications filed between the date of the respective Supreme Court decision and the end of 2016. These actual rejections indicate that Bilski had 22.4%, Mayo had 8.2%, and Myriad had 4.6% the overall impact of Alice.

Given Bilski was impactful enough to estimate a machine learning model, we apply the same machine learning analyses that we have performed for Alice to separately estimate a Bilski score for each patent in our database. We find that 24,247 of our 642,678 patents would be predicted to lose their protection following the Bilski decision. Yet the impact was in different technological areas as the correlation of Bilski score and our Alice score in a sample of Alice or Bilski affected CPCs is just 9.0%. Moreover, among patents with a Bilski or Alice score higher than 1%, the correlation declines further to essentially zero at 0.4%. This lack of correlation between these scores indicates that the impact of Bilski, while less than Alice in economic terms, is also unlikely to contaminate our inferences as uncorrelated influences are unlikely to result in biased coefficients.

As the total number of rejections for the Mayo and Myriad cases is very low (a full order of magnitude smaller than Alice), we are unable to apply the same ML techniques to these two cases due to data inadequacy for training. For these more narrow cases, which focus on specific issues in biotechnology, we instead identify the top-5 CPC codes for each to assess impacted patents. These top-5 CPC codes are indeed in the biology domain, and each constitutes less than 1% of the Alice-impacted patents.

To be conservative, for all subsequent regression tables examining the impact of Alice in Section 4, we drop all Bilski-related patents (24,247) noted above, and also all patents in the top-5 CPCs from Mayo and Myriad (2,353 for Mayo and 3,803 for Myriad) from our sample of 642,678 patents. This reduced sample forms the sample used in our baseline tables displayed in the paper. Thus, in constructing our firm treatment score per equation (3) used for all regression tables, we omit all patents impacted by these other 3 large pre-Alice cases (Bilski, Mayo, and Myriad). Our economic inferences are fully robust to using the full sample of 642,678 patents (this sample was used in a previous version of the paper, available from the authors). We also conduct additional robustness and placebo tests in Section 4.6.

4 The Impact and Outcomes of Alice

We now analyze the impact of Alice on innovation, firm performance and value, competition, lawsuits, and acquisitions. Throughout this section, we present results for large and small firms, as we find uniformly different treatment effects across these groups. As discussed earlier, the justification for examining heterogeneous effects based on firm size follows from Aghion et al. (2005) and is based on the fact that larger firms are more able to defend their product markets given their larger resources - both managerial and financial.

4.1 Alice and Innovation

We first examine the direct impact of Alice on ex post patents and we examine the number of patents scaled by assets and also by sales. Compared to scaling by assets, scaling by sales has the advantage that it is less subject to accounting differences and in particular differences from accounting for acquisition goodwill that can make scaling by assets more problematic.

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 weaker IP protection. The economic effects are large. For patents relative to sales, using the coefficients in column (3) for our treatment variable scaled by the KPSS patent values, we calculate that large (small) firm patenting decreases by 51% (68%) relative to the pre-Alice mean with a one standard deviation shift in the treatment variable. Using the citation-based measure of treatment, we find similar large effects of 75% (49%) for large (small) firms. We show these results graphically in Figure 3 for small firms (our paper's conclusions pertain most to small firms) to test for pre-trends. The figure shows that patents discretely shifted downwards following Alice.

We also note that our regressions include firm fixed effects, and thus we do not report the lower interactions including the individual variables (Large, Small, and Treat) as these are absorbed by firm fixed effects given that they are defined in the treatment year. Additionally, although we cluster standard errors by firm, we also note that our results are robust to more stringently clustering by industry, illustrating that our results are not driven by any industry differences in the distribution of Alice-affected patents.

4.2 Alice and Competition

Unlike some existing studies, which focus on the impact of individual patent invalidations, our study examines the impact of a technology-area-wide loss in IP protection. Such a market-wide shock impacts both existing patents and also the incentives to patent more in the future. These shifts furthermore affect the incentives 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. We also examine the most broad measure of competition as the intensity at which firms complain about competition in their 10-Ks. Finally, given our strong firm-year results, we examine measures of product market encroachment at the firm-pair level to specifically examine if large firms or small firms move "closer" together in the product space post-Alice (using firm-pair product similarity scores).

Columns (1) and (2) of Table 9 examine venture capital entry into a firm's local product market. The dependent variable, *VCF/Sales*, is the total first-round dollars raised by the 25 startups from Venture Expert whose Venture Expert business description most closely matches the 10-K business description of the focal firm (using cosine similarities), scaled by focal firm sales (see Hoberg, Phillips and Prabhala 2014). 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. Finally, we examine investment in R&D/Sales in columns (7) and (8).

Economically, Table 9's results indicate that entry by VC-backed firms into small firm markets increases by 105% (66%) with a one standard deviation increase in our KPSS-treatment (citation-based treatment) measure relative to the average entry pre-Alice. This is significantly higher than that for large firms. Complaints about increased competition also increase significantly more for small firms than for large firms. Complaints by small firms increase by 2.2%. We also present the VC results graphically in Figure 4 for small firms where we allow each pre- and post-year to have its own indicator variable.

The results for R&D in columns (6)-(7) show that small firms increase R&D after Alice, while there is no significant change for large firms. Using the coefficient from column (5), we calculate that small firms' R&D increases by 93% relative to the mean R&D of small firms with a one standard deviation in treatment relative to the mean pre-Alice. Using the citation-based measure of treatment in column (6), R&D increases by 56% relative to the mean R&D of small firms pre-Alice.

The R&D results are consistent with small firms trying to increase R&D to make up for the lost intellectual property and higher competition we document above. In contrast, large firms do not increase R&D, indicating they were impacted by the shock in a different way in which more R&D was not seen as a necessary response. This muted response by larger firms echoes our consistent finding that larger firms (presumably due to deep pockets and deeper knowledge capital) were less impacted by Alice than smaller firms.

We now examine local pairwise product market encroachment post-Alice in Table 10. *Delta TNIC Score* is computed as the change in the TNIC similarity of the pair of firms from year $t-1$ to year t. A high value indicates encroachment (increased similarity and thus higher competition within the pair) and a decrease indicates the two firms are becoming more differentiated. Our panel for this test is a large firm-pair-year panel.

The variable "Treat x Post" is the sum of the Alice treatment variable of the two firms in the given pair multiplied by the post-Alice dummy. The results in column (1) of Table 10 intuitively show that firm pairs jointly experiencing a large Alice treatment, on average, experience increased product market encroachment at the pair level. This is consistent with weaker IP protection resulting in rivals adopting the patented technologies of rivals and products of the pair becoming more similar. These results are highly significant despite the inclusion of firm-pair fixed effects and clustering standard errors by firm-pair.

Column (2) of Table 10 examines if treatment effects are different for small and large firms. We find that small firms are particularly prone to encroachment after Alice. This is consistent with these firms holding narrower advantages in the product market, and any losses in protection might be catastrophic as rivals would have free access to their technologies. In contrast, larger firms experience modest increases in product differentiation (lower pairwise similarity) post-Alice. This is consistent with these firms having broad patent portfolios that span technology areas, making it harder for rivals to enter.

The final column (3) in Table 10 examines four-way interactions of size for the two firms in the pair. The results indicate that positive encroachment only occurs when there is a small firm in the pair that is treated by Alice. Indeed, Small×Large×Treat Small×Post has a positive coefficient as does Small×Small×Treat Small×Post. However, once the treated firm is a large firm, the coefficient magnitude shrinks by roughly 70% and flips to negative, indicating that larger firms experience much different outcomes. Indeed many scholars argue that patent protection could either be harmful or helpful, and our findings illustrate that firm size is a significant mediator of this outcome.

4.3 Alice and Firm Performance

We now examine the profitability of firms post-Alice. Table 11 displays panel data regressions that examine whether the sales, profitability and market value of large vs. small firms were differently affected by the Alice decision. In columns (1)-(2), the dependent variable is *Sales Growth*, calculated as the natural logarithm of total sales in the current year t divided by total sales in the previous year $t-1$. In columns (3) and (4), the dependent variable is *Operating Income/Sales*. In columns (5)-(6), the dependent variable is the *M/B Ratio* (market value of equity plus book debt and preferred stock, all divided by book value of assets).

Table 11 shows that large firms whose patent portfolios are exposed to Alice experience sales growth and positive but insignificant gains in profitability and valuation (measured using M/B Ratio) post-Alice. Their sales growth goes up by 1.2 percentage points (1.3 percentage points) which is 14% (15%) of their 2013 average growth rate, for the KPSS-based (citations-based) treatment measure. Thus, large firms appear to benefit some when they are operating in technology markets that experience market-wide losses in patent protection. As our earlier results illustrated, these gains at least partially come at the expense of small firms, as large firms face less competition when their smaller rivals scale back.

Consistent with this view, Table 11 shows that small firms indeed experience losses after Alice in the form of decreased operating margins and also losses in their market valuations. These results are significant at the 1% level. Economically, using the KPSS-based treatment measure results from column (3), small firms' operating margins go down by 30.9 percentage points. Using the citation-based treatment measure results from column (4), small firms' operating margins go down by 18.6 percentage points. Using the results from Columns (5) (Column (6)), small firms' M/B ratios decline by 0.23 (.19) which is 13.0 (10.6) percent of their pre-Alice M/B Ratio with a one standard deviation increase in treatment.

4.4 Legal Impact: Contractual Provisions and Lawsuits

Intellectual property protection is inherently a matter of legal protection, and it is a means of reducing the risk that rival firms will expropriate a focal firm's technological advantage. Thus we examine how the legal situation changes for large and small firms post-Alice.

We start with two important aspects of firm legal outcomes: the intensity at which they disclose the 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 the results. 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, scaled by the total paragraphs in the 10-K. *Nondisclosure* is the total number of 10-K paragraphs mentioning "non-disclose" or NDA agreements, scaled by the total paragraphs in the 10-K.

The results in Table 12 show that small firms disclose significantly more information about increased intellectual property risk in the risk section of their 10-K, economically increasing by 7.34 percent of their pre-Alice mean. 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-disclosure agreements - economically increasing the mention of these by 45.6 percent of their pre-Alice mentions (although they do not significantly increase non-compete agreements). 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 use alternative contracts to protect their IP after Alice.

In Table 13, we next examine whether patent lawsuits involving small and large firms were differentially affected by the Alice decision. As described in Section 3.5, we use the Stanford Non-Practicing Entity (NPE) Litigation Database to find NPE and operating company (OC) initiated lawsuits. We also measure complaints and patent infringements using the words from a firm's 10-K. In contrast to earlier findings of strong results for small firms, Table 13 shows that lawsuits are different. We find that lawsuits including small firms weakly increased in some specifications, which is opposite the widespread and highly significant decrease we observe for large firms. The result for small firms, especially when viewed alongside the greater IP risk and increased use of non-disclosure agreements post-Alice for these firms, is consistent with the broader "losing-ground scenario" we document. These firms are likely forced to test IP boundaries more (thus disclosing more IP risk and increasing lawsuite exposure), and they also attempt to replace lost patent protection using other contracts such as NDAs.

The results are different for large firms, whose lawsuit exposure significantly *decreases* across the board after Alice. Large firms are less likely to be alleged to infringe on other firms and their exposure to lawsuits also decreases for lawsuits by non-performing entities (patent trolls) post-Alice. These results are intuitively interpreted through two impacts of Alice. First, Alice reduced IP protection, resulting in lawsuits becoming 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 might be more limited, were less able to achieve this outcome as noted above. Overall our evidence again shows that large firms appear to benefit, and small firms lose ground, following the Alice ruling.

4.5 Alice and Acquisitions

We now examine the impact of Alice on firm acquisitions by small and large firms. Our hypothesis is that large-firm acquisitions will decline after Alice given the theory of Phillips and Zhdanov (2013) and empirical support of Caskurlu (2022). 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 are less incentives for large firms to continue paying to buy these small firms for their patents, as they can more cheaply copy the unprotected innovation or hire employees away if they are not covered by a non-compete agreement. 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 dollars spent on acquisitions both unscaled and also scaled by sales.

The results are displayed in Table 14. Across most specifications, we indeed find that large firm acquisitions decrease significantly post-Alice. Although we do not find significant results for total unconditional acquisitions scaled by sales in columns (1) and (2), we do find the predicted results in columns (3) and (4) when we only consider acquisitions in which the target firm has at least one patent (our hypothesis only applies to patented technologies). We also find results for the log of the dollar amount of acquisitions in columns (5) and (6). Our results are economically significant. Acquisitions/Sales of firms with patents decrease by 19.2% (23.3%) for the KPSS-based (citations-based) treatment measure. Log acquisitions go down by 9.2% (9.7%) for these measures, respectively.

In contrast, we find no impact on small firms. Our results are overall consistent with the predictions of Phillips and Zhdanov (2013) and Caskurlu (2022) that decreased patent protection leads to decreased bargaining power for small target firms, and thus large firms acquire less and pay less for any firms they do acquire. These results once again point to potential gains by large firms post-Alice (who save by spending less on acquisitions), and additional losses for smaller firms (who have fewer options for monetizing IP through M&A).

4.6 Robustness and Placebo Tests

Table 3 shows that Longformer outperforms other linguistic models in predicting patent rejections. We first re-estimate all of our regression econometric tests (Tables 7 - 13) using the SciBERT model, which came out second-best. Our economic robustness tests indicate that its overall results are quite similar to Longformer. These tables were included in a previous version of the paper and are available from the authors.

We also estimate our results separately using the TF-IDF method and a simple binary dummy variable model for the CPC category (see Section 4 in the Online Appendix). For the TF-IDF method, in the treatment calculation depicted in equation (3), we use a TF-IDF score instead of a Longformer score. The binary CPC method sets exposure equal to one if the patent's primary CPC code belongs to one of the top-20 CPCs with the most frequent Alice rejections. We then aggregate over patents as before to get a total firm exposure. We expect and find material improvements using transformer models such as Longformer and SciBERT relative to less-advanced methods such as TF-IDF or CPC dummies. For example, Tables IA10 and IA12 display patenting results using these alternative methods, respectively.

Overall, across these tests, the signs are similar to our main Longformer model results. Yet we also find gains to using the more accurate Longformer model, as we lose some significance for patenting for small firms using TF-IDF. We also lose significance for several of the competition variables for small firms using either of these two less sophisticated methods. Given these findings and the higher out-of-sample prediction accuracy shown in Table 3 for the Longformer model versus the other methods, we conclude that the gains associated with using the deep learning neural network Longformer model are important.

Our Alice Score treatment variable is estimated using machine learning techniques and thus is measured with some noise. Although noise generally results in findings being understated, recent work in econometrics (de Chaisemartin and D'Haultfoeuille, 2018) indicates a new technique for estimating a fuzzy difference-in-differences model that is applicable in our setting. In Table IA14 and Table IA15, we report the local average treatment effect (LATE) indicated by the authors using the fuzzydid model (see de Chaisemartin et al. (2019) for implementation in Stata). Although power is somewhat reduced in this setting, we find that most of our results are robust in this specification.

We also consider a number of placebo tests that we report in online Appendix Tables IA16, IA17, IA18 and IA19. In IA16 and IA17, we randomly swap the firm-level treatment variable among all firms in our sample. In IA18 and IA19, we replace the firm-level treatment variable with random draws from a standard uniform distribution in odd-numbered columns and we replace the firm treatment variable with random draws from a uniform distribution over the range [0,0.13] (the max treatment value in the sample) in the even-numbered columns. Results for all of these tests show insignificant "placebo" treatment effects for both large and small firms indicating our results are valid.

Finally, we provide sensitivity analysis for our differences-in-differences analysis using the technique developed in Rambachan and Roth (2023). Instead of requiring that parallel trends hold exactly, the authors impose restrictions on how different post-treatment violations of parallel trends can be from the pre-treatment differences ("pre-trends"). To conduct this analysis, we need to apply a binary treatment. We thus transform our continuous treatment variable into a binary variable by defining treated=0 when the treatment is zero, and treated=1 otherwise. Figures IA1, IA2, IA3 present results for patent applications and competition measures for KPSS and Cites-based treatments. In these analyses, it is imposed that the post-treatment violation of parallel trends is no more than some constant (Mbar) larger than the maximum violation of parallel trends in the pre-treatment period. For example, if Mbar=2, post-treatment violation of parallel trends is no more than twice that in the pre-treatment period. The figures show that the post-treatment violations are robust to a maximum violation in the pre-treatment in our experiments.

5 Conclusions

We examine the impact of lost intellectual property protection on firm innovation, performance, competition, and acquisitions. We examine firms whose existing granted patents would likely lose protection if challenged following 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 non-novel transformation. It impacted multiple areas including business methods, software, and bioinformatics. The outcome of this decision was very much in doubt and unanticipated.

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 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 as predicted by Aghion et al. (2005). Examining ex-post changes in sales growth and profitability along with firm value, we find an asymmetric impact of Alice on firms whose patent portfolio is exposed to Alice. Large firms gain and small firms lose. Exposed large firms gain in sales. Exposed small firms experience a decrease in operating margins and their market valuations decline.

We show that these differential losses by small firms can be explained by changes in competition and limited legal options to replace lost IP protection. Small firms face increased competition across many measures, while large firms are only minimally impacted. In the post-Alice period, small affected firms face increased venture capital financed entry into their product space, they increase their complaints about increased competition, and they face more product market encroachment from rivals. Consistent with trying to protect IP that has lost protection, small firms resort more to non-disclosure agreements with their employees post-Alice. In contrast, large firms appear to relatively gain as they face fewer lawsuits from both operating companies and non-producing entities ("patent trolls"), and decreased competition from small firms. They also acquire fewer target firms, especially those with patents.

Overall, our focus and contribution relative to the previous literature in that we examine the impact on both large and small firms when *all* firms lose patent protection in broad areas - different than studies that examine what happens to individual firms that use the random assignment of patent examiners where non-treated firms do not change their expectations for the future. In our setup, all firms are randomly treated, with all firms updating their expectations for the future as the court ruling diminishes patent rights for everyone. Our results illustrate an uneven impact of lost IP protection across firms. Our results overall show the costs and benefits of decreased IP protection.

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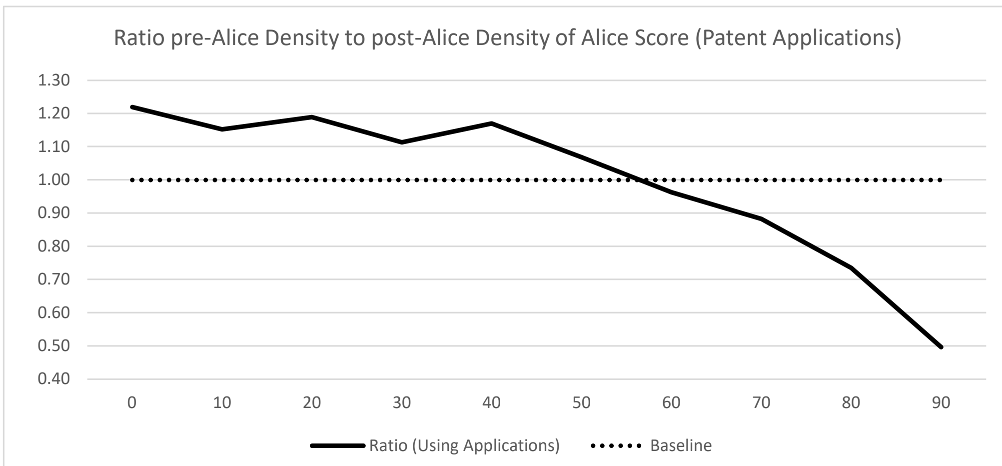
Figure 1: Ratio of Post-Alice Density to Pre-Alice Density

The figure illustrates whether there is a decrease in applications and grants of patents with high Alice scores after the Supreme Court decision (the final column of Table 5). We compute the density of the Alice score based on ten bins (increments of .1) from zero to unity both before Alice (2011 to 2013) and post Alice (2017). The figure reports the ratio of the density for each bin. The values below unity for the rightmost bins below indicate that many fewer patents with high Alice scores were applied for (Panel A) and granted (Panel B) after the Alice Supreme Court decision.



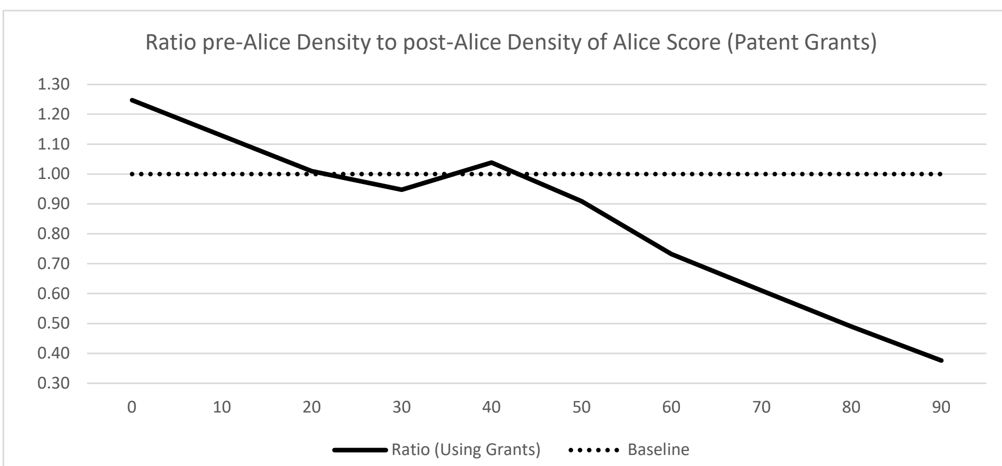
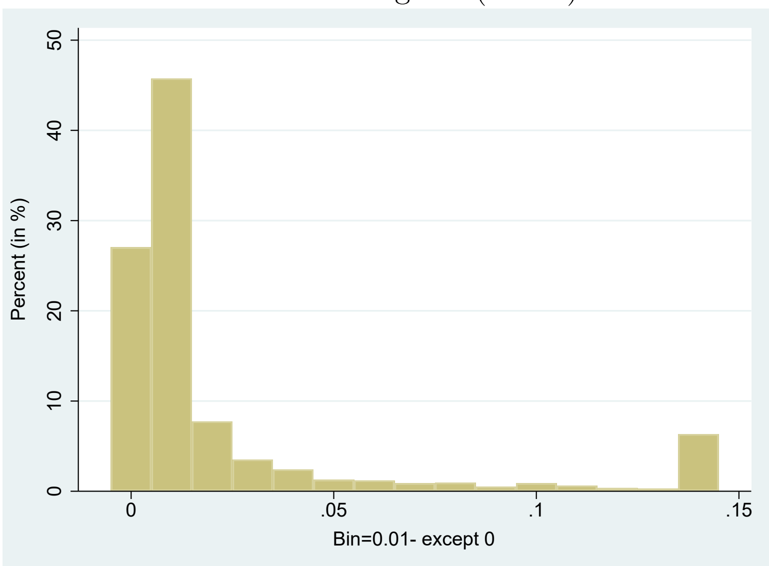


Figure 2: Histogram For Treatment

This figure shows the histogram for the treatment variables for firms with patents. In Panel A, the treatment is based on KPSS, and it is based on citation in Panel B. The bin width is 0.01 and y-axis is the percentage of treatment falls into the bin.

Panel A: Histogram (KPSS)



Panel B: Histogram (Cites)

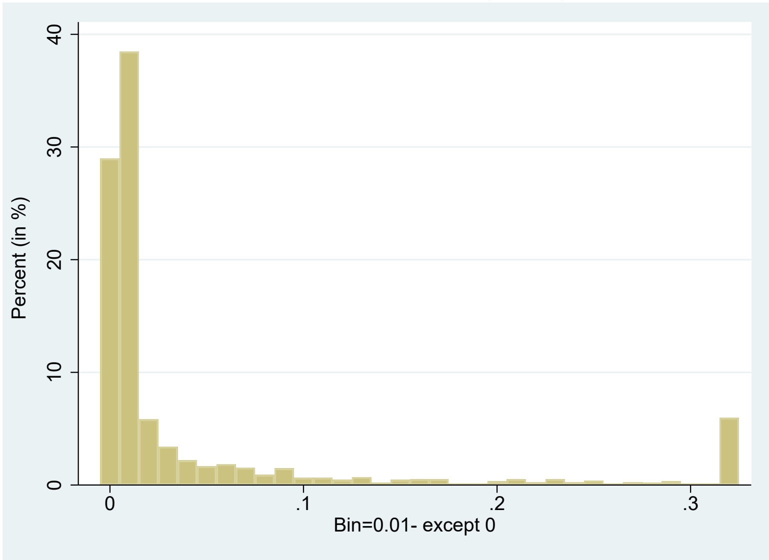
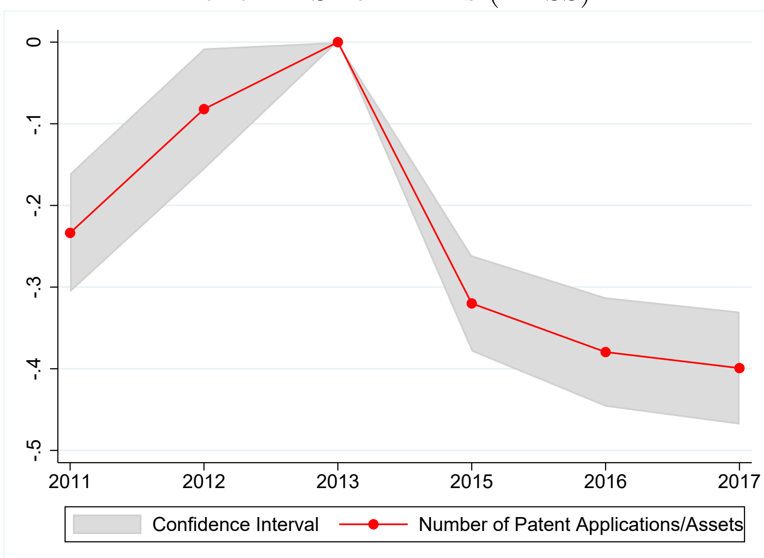


Figure 3: Patent Applications For Small Firms

This figure reports the point estimates per year for $Small \times Treatment$ from Table 8, where the dependent variable is Patents/Assets$_{t-1}$. The regression specification is the same as those reported in columns (1) and (2) of Table 8, except that $Small \times Treatment$ is allowed to vary by year, and 2013 is chosen as the reference year. The treatment is calculated by using the KPSS values in Panel A, and it is calculated by citations in Panel B. The gray line indicates the 90% confidence interval.

Panel A: Small Firms (KPSS)



Panel B: Small Firms (Cites)

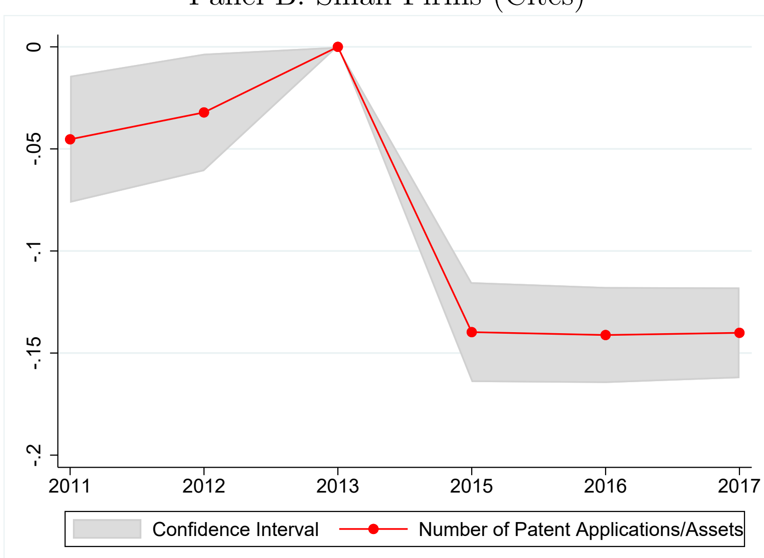
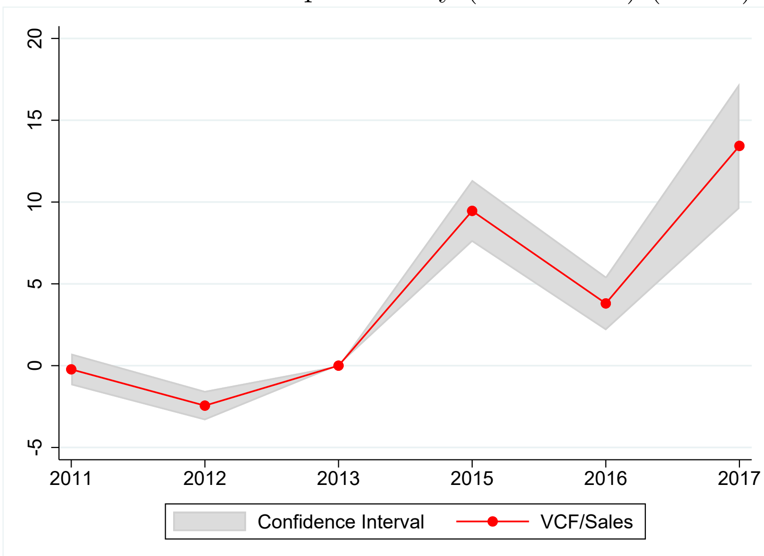


Figure 4: Competition For Small Firms

This figure reports the point estimates per year for $Small \times Treatment$ from Table 9 columns (1) and (2) where the dependent variable is VCF/Sales. The regression specifications are the same as those reported in columns (1) and (2) of Table 9, except that $Small \times Treatment$ is allowed to vary by year, and 2013 is chosen as the reference year. The treatment is calculated by using the KPSS values in Panel A, and it is calculated by citations in Panel B. The gray line indicates the 90% confidence interval.

Panel A: Venture Capital Entry (VCF Score) (KPSS)



Panel B: Venture Capital Entry (VCF Score) (Cites)

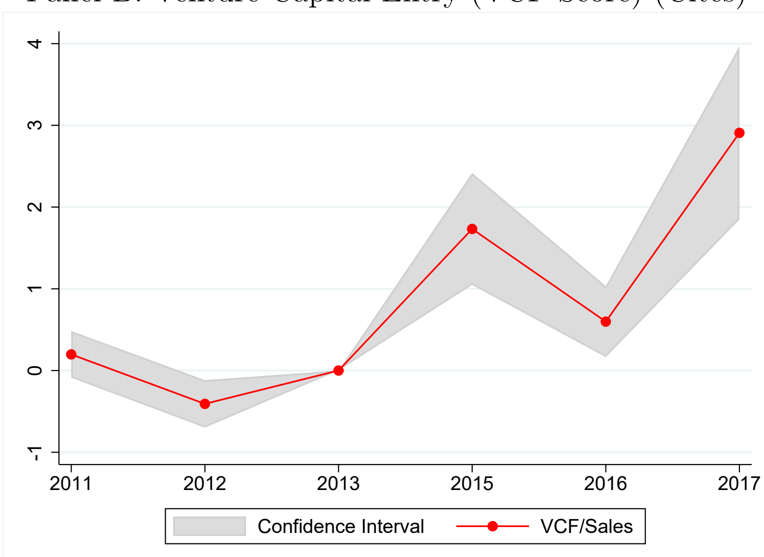


Table 1: Annual Patent Applications and Post-Alice Rejections By Industry

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

Table 2: CPC Descriptions by CPC group and Industry

This table provides descriptions for largest CPC patent subgroups for which we run the Longformer 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 Longformer vs. Other Models

This table compares predictions of Longformer (Beltagy et al. (2020)), SciBERT (Beltagy et al. (2019)), BERT (Devlin et al. (2019)), RoBERTa (Liu et al. (2019)), TF-IDF (Robertson (2004)) and Word2Vec models (Mikolov et al. (2013)) based on F_1 Score and Accuracy. F_1 Score is the harmonic mean of recall and precision, which are defined in Equation (1). Accuracy is the ratio of correctly predicted observations to the total observations. 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 (rejected patent applications), we find a matching negative (a patent application that is granted) that is in the same CPC Group. In sample B, C, and D, without replacement, we keep adding 23,734 more matching granted 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 selected from a broader CPC. In the last column of the table, we use an ensemble of the two models that have the highest F_1 Score and Accuracy by taking the average of their prediction scores. The use of this ensemble is motivated by the fact that A typically has the highest F_1 Score and D has the highest Accuracy. For the testing, we only use applications and granted patents not used in the training. In the testing, we have 10,000 positives in the sample of applications and for each positive, we choose two negatives. This 1:2 positives to negatives ratio is consistent with with the expected rejection ratio having more negatives than positives, while not overestimating accuracy for models that do not learn but only predict negative outcomes. From the negatives pool, we thus sample 20,000 negatives 1,000 times and boot-strap performance of the models. The table below then reports the average F_1 Score and Accuracy for each model.

	A		B		C		D		$\frac{A+D}{2}$	
Model Name	F_1 Score	Accuracy	F_1 Score	Accuracy	F_1 Score	Accuracy	F_1 Score	Accuracy	F_1 Score	Accuracy
Longformer Finetune	0.647	0.745	0.624	0.765	0.618	0.785	0.639	0.800	0.672	0.804
SciBERT Finetune	0.651	0.735	0.634	0.749	0.632	0.767	0.638	0.777	0.669	0.778
BERT Finetune	0.623	0.733	0.598	0.739	0.614	0.764	0.624	0.774	0.642	0.775
RoBERTa Finetune	0.600	0.716	0.555	0.740	0.540	0.756	0.515	0.758	0.592	0.765
TF-IDF + Logistic Regression	0.547	0.643	0.599	0.634	0.613	0.670	0.550	0.719	0.559	0.679
TF-IDF + Decision Tree	0.503	0.602	0.554	0.552	0.558	0.584	0.491	0.690	0.409	0.697
TF-IDF + Random Forest	0.628	0.743	0.368	0.717	0.263	0.696	0.209	0.689	0.387	0.723
Word2Vec + Logistic Regression	0.606	0.731	0.418	0.732	0.377	0.732	0.358	0.730	0.497	0.755
Word2Vec + Decision Tree	0.492	0.607	0.456	0.645	0.461	0.687	0.461	0.702	0.365	0.707
Word2Vec + Random Forest	0.619	0.747	0.439	0.746	0.387	0.739	0.365	0.735	0.500	0.766

Table 4: Most Frequently Used Words in Longformer Predictions

The table lists words that are used mostly frequently in patents with high Longformer scores (≥ 0.5) compared to those with low Longformer scores (<0.5). We first label patents with a Longformer score ≥ 0.5 as "high" and the remaining patents as "low". We remove non-alphabetic characters from patent texts, apply lemmatizing to each word, and calculate the number of high and low patents that each word appears in. We then filter out words that do not appear in at least 1% of the high patents. For each word w, we first assign it to the CPC Group with the Largest ratio of the number high patents in the CPC that contain the word to the total number of low patents in that CPC. Finally, we sort the words selected into each CPC according to their appearance ratio, defined as $\frac{Count_w^H}{1 + Count_w^L}$, where $Count_w^H$ and $Count_w^L$ are high and low number of patents a word w appears in, respectively. The table reports the top 15 words sorted according to their appearance ratio.

Industry	Top Fifteen Words
Commerce (Digital Data Processing)	rebate, bidder, bidding, seller, auction, discounted, sponsor, referral, incentive, purchaser, solicitation, purchasing, solicit
Administration (Digital Data Processing)	interview, consultant, procurement, forecasting, accountability, contractor, consultation, planner, deadline, strategic, forecast, audit, objectively, finalized, logistics
Finance (Digital Data Processing)	underwriting, liquidity, lender, financing, equity, investor, treasury, debt, hedge, earnings, earning, owed, investing, insurer, mortgage
Payment Systems (Digital Data Processing)	settlement, refund, debited, credited, clearinghouse, transacting, approving, dispute, crediting, enroll, deducted, debiting, ach, paying, approves
Coin-freed Facilities or Services (Coin-freed or Like Apparatus)	rewarded, earn, payouts, payoff, redeem, earned, redeemed, redemption, awarding, betting, dealer, profitability, payout, wagered, wager
Information Retrieval (Digital Data Processing)	vowel,phoneme, docket, adjective, ranked, spelling, noun, categorizing, categorization, linguistic, verb, vocabulary, alphabetical, sentence, utterance, searchable
Video Games (Games)	opponent, contest, fun, participated, team, him, town, vote, himself, herself, war, personality, story, thinking, arena
Specialized For Sectors (Digital Data Processing)	hire, attorney, affiliate, reputation, qualification, prospective, pursue, teacher, education, affiliation, court, posting, historic, invited, submitting
Computer Security (Digital Data Processing)	netlist, royalty, licensing, confidential, licensed, license, denied, verilog, denies, creator, vhdl, unlimited, privilege, enforcing, granting
Network Security (Transmission of Digital Information)	certification, certified, certificate, confidentiality, signing, logon, expire, password, signed, violation, username, privacy, violate, someone, denial
Network Specific Applications (Transmission of Digital Information)	publish, subscription, cookie, subscribing, uploaded, uploads, publishes, apache, wap, subscribe, downloading, downloads, movie, activex, url
Measuring or Testing Processes (Microbiology & Enzymology)	institutional, enrolled, lifestyle, consent, smoking, logistic, percentile, multivariate, gender, emotional, exam, younger, college, whom, disability

Table 5: Comparison of Patent Grants Alice Longformer Scores in the Pre- and Post-Period

This table shows the distributional density of the Longformer 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 granted patents in 2011, 2012, and 2013 are 21,404; 26,607; and 31,249, respectively. In 2017, we only consider the patents applied for after the Alice decision, and there are 17,643 granted patents that fit to this description. We sort all patents in each year into 10 bins based on each patent's Longformer Score. Bins are defined as the ten equal segments in the interval (0,1), which is the range of the Longformer 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.

Longformer Score	2011	2012	2013	2011- 2013	2017	Ratio
(LFS)	(1)	(2)	(3)	(4)	(5)	(6)
$0.0 \leq$ LFS < 0.1	0.3627	0.3619	0.3775	0.3683	0.4595	1.2476
$0.1 \leq$ LFS < 0.2	0.1032	0.1017	0.1017	0.1021	0.1152	1.1283
$0.2 \leq$ LFS < 0.3	0.0749	0.0742	0.0715	0.0733	0.0740	1.0095
$0.3 \leq$ LFS < 0.4	0.0734	0.0714	0.0688	0.0709	0.0672	0.9478
$0.4 \leq$ LFS < 0.5	0.1048	0.1080	0.1062	0.1064	0.1105	1.0385
$0.5 \leq$ LFS < 0.6	0.0751	0.0757	0.0763	0.0758	0.0689	0.9090
$0.6 \leq$ LFS < 0.7	0.0413	0.0426	0.0406	0.0414	0.0303	0.7319
$0.7 \leq$ LFS < 0.8	0.0361	0.0374	0.0364	0.0367	0.0224	0.6104
$0.8 \leq$ LFS < 0.9	0.0434	0.0427	0.0421	0.0427	0.0209	0.4895
$0.9 \leq$ LFS < 1.0	0.0850	0.0843	0.0789	0.0824	0.0310	0.3762

Table 6: 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. *, **, 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.)	19135	3402	855.097	9639.602	1313.830	1255.058	11392.650	1394.299	
Sales (in mil.)	19135	3402	408.887	3678.559	271.414	553.080	4029.535	273.673	
OI/Sales	18304	3266	0.161	0.052	0.014	0.149	-0.053	0.022	***
M/B Ratio	19020	3399	1.115	1.525	0.023	1.162	1.518	0.021	
Sales Growth	19135	3402	0.065	0.088	0.003	0.037	0.033	0.003	***
Age	19135	3402	18.000	21.723	0.277	22.000	25.526	0.280	***
Panel B: Innovation, Acquisition & Lawsuit Characteristics									
R&D/Sales$_{t-1}$	19135	3402	0.000	0.104	0.006	0.000	0.143	0.010	***
Patents/Sales$_{t-1}$	19135	3402	0.000	0.013	0.001	0.000	0.008	0.000	***
Patents/Assets$_{t-1}$	19135	3402	0.000	0.006	0.001	0.000	0.003	0.000	***
Acquisitions/Sales$_{t-1}$	19135	3402	0.000	0.057	0.003	0.000	0.054	0.002	
PatTargets/Sales$_{t-1}$	19135	3402	0.000	0.002	0.000	0.000	0.001	0.000	***
Log(Amt. of Acq.)	19135	3402	0.000	0.798	0.023	0.000	0.765	0.023	
# Alleged	19135	3402	0.000	0.281	0.013	0.000	0.227	0.010	***
# NPE Alleged	19135	3402	0.000	0.164	0.008	0.000	0.154	0.007	
# OC Alleged	19135	3402	0.000	0.102	0.005	0.000	0.048	0.003	***
# Accuser	19135	3402	0.000	0.035	0.002	0.000	0.031	0.002	
IPrisk (10-K)	19056	3402	0.592	2.903	0.070	1.233	3.429	0.078	***
Patinfringe (10-K)	19056	3402	0.000	1.344	0.043	0.000	1.293	0.040	***
Panel C: Competition Measures (Text-based measures from 10-Ks)									
VCF/Sales$_{t-1}$	19053	3402	0.013	0.117	0.005	0.012	0.195	0.012	***
Complaints	19056	3402	13.492	14.553	0.117	13.607	14.706	0.116	
Noncompete	19056	3402	0.000	0.597	0.023	0.000	0.557	0.021	
Nondisclose	19056	3402	0.000	0.460	0.029	0.000	0.572	0.040	**

Table 7: Sample of Alice-Impacted Patents and Owner Characteristics

This table provides a representative selection of patents exhibiting a high Alice-score, accompanied by firm characteristics pertaining to the patent owners. Panel A presents data concerning large firms within our sample classification, while Panel B offers corresponding information for small firms. After the first column (company name), the next four columns contain information about the company's most-exposed patent to Alice (as indicated by the high Patent Alice-Score). The final four columns display firm characteristics summarizing patenting intensity and the firm-wide Alice treatment value.

Company Name	Patent Number	Patent Description	Patent Alice-Score	KPSS Disc. Patent Value (2014 $M)	Firm's Total Number of Patents	Firm's # Alice-Impacted Patents	Firm's Total Patent Value (2014 $M)	Firm Treatment Value
Panel A: Large Companies								
MOTOROLA SOLUTIONS	5987486	A data processing system of the present invention analyses input data for statistical similarities in time.	0.99	1.10	57,857	438	12508.88	0.17
MICROSOFT CORP	8484577	A framework provided for obtaining window information, which can be applied to different assignment modelss.	0.99	30.66	84,016	2638	229155.30	0.26
JPMORGAN CHASE & CO	6502080	A method of predicting a net reserve for a vehicle leased by a lessee from a lessor in accordance with a lease.	0.99	44.06	1,702	309	124149.20	0.30
QUALCOMM INC	7458003	Methods and apparatuses to encode and decode information.	0.99	12.96	27,750	442	37833.32	0.13
CISCO SYSTEMS	8175156	A method of video coding/decoding that includes transforming to/from transform coefficients and residual pixel data in moving pictures by a set of vectors.	0.99	14.87	32,153	788	96276.10	0.21
Panel B: Small Companies								
COMMVAULT SYSTEMS INC	7596586	The present invention provides systems and methods for extending media retention.	0.98	3.33	865	13	1537.70	0.19
DIGIMARC CORP	8306811	A method of embedding data into an audio signal and computing masking thresholds for the audio signal from a frequency domain transform of the audio signal.	0.98	0.74	1,422	79	119.24	0.70
APPLIED MICRO CIRCUITS	8244143	A system and method are provided for calibrating orthogonal polarity in a multichannel optical transport network	0.95	2.67	1,493	16	216.58	0.12
MULTIMEDIA GAMES	8574064	Method, apparatus, and program product for displaying gaming results through variable prize progressions	0.93	1.91	308	55	206.18	0.19
STAMPS.COM INC	8612361	System and method for handling payment errors with respect to delivery services	0.97	5.73	403	23	110.10	0.10

Table 8:
Effects of Alice on Patent Applications (Longformer)

The table displays panel data regressions in which patent applications scales by assets and sales are dependent variables. In columns (1)-(2), the dependent variable is the number of patent applications in year *t* divided by assets in year *t-1*; and in columns (3) and (4), the dependent variable is the number of patent applications in year *t* divided by sales in year *t-1*. *Treatment* is the relative impact of the Alice decision on the firm's patent portfolio measured using KPSS dollar values or citations scaled by sales (see equation (3) for the formula). In the odd and even numbered columns, respectively, we use the KPSS and the number of citations approach to compute the *Patent Value* treatment. *Small* is a binary variable equal to one if a firm's total assets are smaller than the median total asset of its TNIC peers in 2013, and it is zero otherwise. *Large* is 1-*Small*. *Post* is a dummy variable that equals one if the year is after the Alice decision and zero otherwise. All variables are described in detail in the variable list in Appendix A. All regressions include firm and year fixed effects. Standard errors are clustered at the firm level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

Dependent Variable:	$\frac{\#\ of Patents}{Assets_{t-1}}$		$\frac{\#\ of Patents}{Sales_{t-1}}$	
	(1)	(2)	(3)	(4)
Small × Post × Treatment	-0.216***	-0.070***	-0.483***	-0.147***
	(-9.10)	(-8.08)	(-8.85)	(-7.65)
Large × Post × Treatment	-0.078***	-0.055***	-0.142***	-0.099***
	(-5.48)	(-4.85)	(-4.46)	(-4.06)
Log(Assets)	-0.004***	-0.004***		
	(-8.82)	(-9.33)		
Log(Sales)			-0.009***	-0.009***
			(-7.55)	(-7.45)
Log(Age)	-0.002*	-0.002*	-0.000	-0.001
	(-1.72)	(-1.93)	(-0.17)	(-0.60)
Observations	19135	19135	19135	19135
Firm Fixed Effects	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES
Treatment Calculation	KPSS	Citation	KPSS	Citation
Adj. R^2	0.113	0.117	0.100	0.098

Table 9:
Competition and Patent Protection (Longformer)

The table displays panel data regressions in which competition variables are the dependent variables. In columns (1)-(2), the dependent variable, *VCF/Sales*, is the a measure of VC entry in a given firm's product market and is the total first-round dollars raised by the 25 startups from Venture Expert whose Venture Expert business description most closely matches the 10-K business description of the focal firm (using cosine similarities) in year *t*, scaled by focal firm sales in yeart-1. 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. R&D/Sales is R&D expenses in year *t* scaled by sales in year *t-1*. *Treatment* is the relative impact of the Alice decision on the firm's patent portfolio measured using KPSS dollar values or citations scaled by sales (see equation (3) for the formula). In the odd and even numbered columns, respectively, we use the KPSS and the number of citations approach to compute the *Patent Value* treatment. *Small* is a binary variable equal to one if a firm's total assets are smaller than the median total asset of its TNIC peers in 2013, and it is zero otherwise. *Large* is 1-*Small*. *Post* is a dummy variable that equals one if the year is after the Alice decision and zero otherwise. All variables are described in detail in the variable list in Appendix A. All regressions include firm and year fixed effects. Standard errors are clustered at the firm level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

Dependent Variable:	$\frac{VCF}{Sales_{t-1}}$		Complaints		$\frac{R\&D}{Sales_{t-1}}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Small × Post × Treatment	10.190***	2.054***	15.572***	3.711**	7.508***	1.436***
	(7.45)	(5.29)	(3.28)	(2.48)	(5.89)	(4.30)
Large × Post × Treatment	0.309*	0.135	-7.519*	-2.445	-0.142	-0.151
	(1.91)	(1.40)	(-1.80)	(-0.98)	(-0.83)	(-1.09)
Log(Sales)	-0.395***	-0.398***	0.148	0.141	-0.173***	-0.176***
	(-14.61)	(-14.63)	(1.58)	(1.50)	(-10.02)	(-9.96)
Log(Age)	0.335***	0.366***	-0.196	-0.148	0.173***	0.197***
	(6.21)	(6.65)	(-0.61)	(-0.46)	(5.04)	(5.53)
Observations	19053	19053	19056	19056	19135	19135
Firm Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Treatment Calculation	KPSS	Citation	KPSS	Citation	KPSS	Citation
Adj. R^2	0.259	0.227	0.008	0.007	0.175	0.128

Table 10:
Firm Level Competition and Encroachment (Longformer)

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 as the change in pairwise TNIC similarity (see Hoberg and Phillips 2016) from year t-1 to year t. A large value indicates increased similarity and product market encroachment. To compute the RHS variables, we first sort firms into above and below median sales (relative to TNIC-2 peers) in 2013. We refer to above and below median firms as large and small, respectively. The variable Treat × Post is the sum of the Alice Scores for the two firms in the pair. Analogously, Large × Treat × Post is the sum of Treat × Post when either firm in the pair is large, and is zero otherwise. Small × Treat × Post is analogously defined for when either firm in the pair is small. The last four variables focus on properties of the pair. Large × Large × Treat Large × Post is the sum of Treat × Post for both firms in the pair when both are large (and is zero otherwise). Small × Small × Treat Small × Post is analogously defined when both are small. Large × Small × Treat Large × Post is Treat x Post for the large firm in the pair when the pair has one large firm and one small firm. Small × Large × Treat Small × Post is analogously defined using the small firm's treatment. We note that all level effects and Smaller-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)
Treat × Post	0.477***		
	(13.32)		
Large × Treat × Post		-0.439***	
		(-9.40)	
Small × Treat × Post		1.673***	
		(33.42)	
Large × Large × Treat Large × Post			-0.382***
			(-6.31)
Large × Small × Treat Large × Post			-0.534***
			(-8.12)
Small × Large × Treat Small × Post			1.776***
			(27.28)
Small × Small × Treat Small × Post			1.592***
			(22.40)
Observations	6,724,112	6,724,112	6,724,112
Pair Fixed Effects	YES	YES	YES
Year Fixed Effects	YES	YES	YES
R^2	0.091	0.091	0.091

Table 11:
Profitability (Longformer)

The table displays panel data regressions that examine whether the profitability of large and small 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.; and in columns (3) and (4), it is operating income scaled by sales. In columns (5)-(6), the dependent variable is the M/B Ratio, calculated as the market to book ratio (market value of equity plus book debt and preferred stock, all divided by book assets). *Treatment* is the relative impact of the Alice decision on the firm's patent portfolio measured using KPSS dollar values or citations scaled by sales (see equation (3) for the formula). In the odd and even numbered columns, respectively, we use the KPSS and the number of citations approach to compute the *Patent Value* treatment. *Small* is a binary variable equal to one if a firm's total assets are smaller than the median total asset of its TNIC peers in 2013, and it is zero otherwise. *Large* is 1-*Small*. *Post* is a dummy variable that equals one if the year is after the Alice decision and zero otherwise. All variables are described in detail in the variable list in Appendix A. All regressions include firm and year fixed effects. Standard errors are clustered at the firm level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

Dependent Variable:	Sales Growth		$\frac{Operating\ Income}{Sales_{t-1}}$		M/B Ratio	
	(1)	(2)	(3)	(4)	(5)	(6)
Small × Post × Treatment	0.557	0.046	-13.783***	-2.629***	-10.398***	-2.684***
	(1.20)	(0.40)	(-5.06)	(-3.74)	(-2.99)	(-2.86)
Large × Post × Treatment	0.491***	0.323***	0.267	0.339	0.921	1.161
	(2.98)	(2.95)	(0.80)	(1.23)	(0.72)	(1.39)
Log(Sales)	-0.206***	-0.206***	0.496***	0.501***	-0.347***	-0.344***
	(-26.97)	(-26.97)	(11.14)	(11.14)	(-6.52)	(-6.47)
Log(Age)	-0.023	-0.020	-0.628***	-0.675***	-1.111***	-1.137***
	(-1.06)	(-0.96)	(-6.83)	(-7.20)	(-7.12)	(-7.25)
Observations	19135	19135	18304	18304	18658	18658
Firm Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Treatment Calculation	KPSS	Citation	KPSS	Citation	KPSS	Citation
Adj. R^2	0.168	0.167	0.160	0.134	0.075	0.073

Table 12:
Firm IP Risk and Legal Protections (Longformer)

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 the relative impact of the Alice decision on the firm's patent portfolio measured using KPSS dollar values or citations scaled by sales (see equation (3) for the formula). In the odd and even numbered columns, respectively, we use the KPSS and the number of citations approach to compute the *Patent Value* treatment. *Small* is a binary variable equal to one if a firm's total assets are smaller than the median total asset of its TNIC peers in 2013, and it is zero otherwise. *Large* is 1-*Small*. *Post* is a dummy variable that equals one if the year is after the Alice decision and zero otherwise. All variables are described in detail in the variable list in Appendix A. All regressions include firm and year fixed effects. Standard errors are clustered at the firm level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

Dependent Variable:	IP Risk		Noncompete		Nondisclosure	
	(1)	(2)	(3)	(4)	(5)	(6)
Small × Post × Treatment	12.945***	3.872***	1.278*	0.446	14.581***	2.369***
	(4.18)	(4.37)	(1.65)	(1.35)	(4.32)	(3.21)
Large × Post × Treatment	2.658	1.367	-0.896	-0.332	-0.354	-0.421
	(1.01)	(0.78)	(-1.32)	(-0.99)	(-0.52)	(-1.02)
Log(Sales)	0.020	0.019	0.043**	0.043**	0.004	-0.003
	(0.38)	(0.36)	(2.04)	(2.02)	(0.09)	(-0.07)
Log(Age)	-0.274*	-0.249	-0.083	-0.080	0.181*	0.230**
	(-1.73)	(-1.57)	(-1.00)	(-0.97)	(1.92)	(2.33)
Observations	19056	19056	19056	19056	19056	19056
Firm Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Treatment Calculation	KPSS	Citation	KPSS	Citation	KPSS	Citation
Adj. R^2	0.070	0.069	0.002	0.002	0.048	0.024

Table 13:

Lawsuits and Legal Protection (Longformer)

The table displays panel data regressions examining whether lawsuit metrics of large and small firms were differently affected by the Alice decision. In columns (1)-(2), the dependent variable, *# Alleged*, is the number of lawsuits that a firm was alleged in that year. In columns (3) to (4), *# NPE Alleged* is the total number of lawsuits that the firm was alleged by a non-practicing entity in that year. In columns (5) to (6), *# OC Alleged* is the number of lawsuits that the firm was alleged by a operating company in that year. In columns (7)-(8), *Patinfringe* refers to the total number of paragraphs containing both the word root "patent*" and "infringe*" in 10-K documents, scaled by the total number of paragraphs in the 10-Ks. In columns (9)-(10), *# Accuser* is the number of lawsuits that the firm accused any party in a patent lawsuit in that year. *Treatment* is the relative impact of the Alice decision on the firm's patent portfolio measured using KPSS dollar values or citations scaled by sales (see equation (3) for the formula). In the odd and even numbered columns, respectively, we use the KPSS and the number of citations approach to compute the *Patent Value* treatment. *Small* is a binary variable equal to one if a firm's total assets are smaller than the median total asset of its TNIC peers in 2013, and it is zero otherwise. *Large* is 1-*Small*. *Post* is a dummy variable that equals one if the year is after the Alice decision and zero otherwise. All variables are described in detail in the variable list in Appendix A. All regressions include firm and year fixed effects. Standard errors are clustered at the firm level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

Dependent Variable:	# Alleged		# NPE Alleged		# OC Alleged		Patinfringe		# Accuser	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Small × Post × Treatment	0.539*	0.021	0.441**	0.039	0.020	-0.045	-0.147	-0.663	0.412	0.179
	(1.94)	(0.17)	(2.43)	(0.43)	(0.14)	(-0.71)	(-0.06)	(-0.84)	(1.03)	(1.57)
Large × Post × Treatment	-4.582***	-1.983***	-2.050***	-1.059**	-2.529***	-0.890***	-4.257***	-3.207***	-0.451	-0.416**
	(-4.56)	(-3.17)	(-2.96)	(-2.51)	(-5.08)	(-2.81)	(-2.81)	(-3.20)	(-1.57)	(-2.45)
Log(Sales)	0.040***	0.038***	0.023***	0.022***	0.012***	0.011**	0.025	0.022	-0.017***	-0.017***
	(4.57)	(4.40)	(3.88)	(3.75)	(2.71)	(2.51)	(0.73)	(0.66)	(-2.68)	(-2.69)
Log(Age)	0.144***	0.150***	0.066**	0.069**	0.066***	0.069***	-0.153	-0.147	-0.369***	-0.369***
	(3.66)	(3.77)	(2.45)	(2.56)	(3.24)	(3.35)	(-1.47)	(-1.40)	(-14.54)	(-14.60)
Observations	19135	19135	19135	19135	19135	19135	19056	19056	19135	19135
Firm Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Treatment Calculation	KPSS	Citation	KPSS	Citation	KPSS	Citation	KPSS	Citation	KPSS	Citation
Adj. R^2	0.021	0.017	0.015	0.014	0.029	0.022	0.004	0.006	0.051	0.052

Table 14:
Acquisitions and Legal Protection (Longformer)

The table displays panel data regressions in which acquisition variables are the dependent variables. In columns (1)-(2), the dependent variables are dollar value spent on acquisition scaled by sales. In columns (3)-(4), the dependent variables are dollar value spent on acquisition of targets that have at least patent scaled by sales. In columns (5)-(6), the dependent variables are log of one plus total value spent on acquisitions in that year. *Treatment* is the relative impact of the Alice decision on the firm's patent portfolio measured using KPSS dollar values or citations scaled by sales (see equation (3) for the formula). In the odd and even numbered columns, respectively, we use the KPSS and the number of citations approach to compute the *Patent Value* treatment. *Small* is a binary variable equal to one if a firm's total assets are smaller than the median total asset of its TNIC peers in 2013, and it is zero otherwise. *Large* is 1-*Small*. *Post* is a dummy variable that equals one if the year is after the Alice decision and zero otherwise. All regressions include firm and year fixed effects. Standard errors are clustered at the firm level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

Dependent Variable:	$\frac{Acquisitions}{Sales_{t-1}}$		$\frac{Targets\ With\ Patents}{Sales_{t-1}}$		Log(Acquisitions)	
	(1)	(2)	(3)	(4)	(5)	(6)
Small × Post × Treatment	0.108	0.007	0.003	-0.002	0.529	-0.011
	(0.82)	(0.19)	(0.72)	(-0.68)	(0.62)	(-0.04)
Large × Post × Treatment	0.023	-0.026	-0.017*	-0.013*	-4.389***	-2.907***
	(0.17)	(-0.29)	(-1.80)	(-1.95)	(-2.58)	(-2.96)
Log(Sales)	-0.037***	-0.037***	-0.001***	-0.001***	-0.137***	-0.139***
	(-6.77)	(-6.78)	(-3.28)	(-3.35)	(-3.82)	(-3.87)
Log(Age)	0.004	0.005	0.001*	0.001*	0.197	0.201
	(0.31)	(0.33)	(1.83)	(1.89)	(1.53)	(1.56)
Observations	19135	19135	19135	19135	19135	19135
Firm Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Treatment Calculation	KPSS	Citation	KPSS	Citation	KPSS	Citation
Adj. R^2	0.009	0.009	0.008	0.008	0.004	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/Sales$_{t-1}$	Compustat OIBDP divided by lagged total sales.
M/B Ratio	Compustat sum of market equity (CSHO * PRCC$_F$), DLC, DLTT, PSTKL, all scaled by lagged book assets.
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 a weighted average of a firm's patent values multiplied by the Alice Score and scaled by sales. For a firm's patent portfolio, we gather all patents that are valid by the third quarter of 2014. Firm's patent value is calculated in two ways: i) dollar amount provided by KPSS; ii) citations that the patent received. The mathematical notation is provided in equation (3).
R&D/Sales$_{t-1}$	Compustat XRD divided by lagged total sales. This variable is set to zero if XRD is missing
Patents/Sales$_{t-1}$	The number of patent applications scaled by lagged firm sales.
Acquisitions/Sales$_{t-1}$	The total amount of acquisitions divided by lagged firm sales.
PatTargets/Sales$_{t-1}$	The dollar value of acquisitions where target has a patent scaled by lagged sales.
Log(Acq. Amt.)	Log of one plus total amount of acquisitions.
# Alleged	It is the number of lawsuits that the firm was alleged for infringing a patent.
# NPE Alleged	It is the number of lawsuits that the firm was alleged by an NPE for infringing a patent.
# OC Alleged	It is the number of lawsuits that the firm was alleged by an OC for infringing a patent.
# of Accuser	It is the number of lawsuits that the firm alleged another party for infringing its patent.
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 both the word root "patent*" and "infringe*" in 10-K documents, scaled by the total number of paragraphs in the 10-Ks.
Panel C: Competition Measures	
VCF/Sales$_{t-1}$	A measure of VC entry in a given firm's product market computed as the total first-round dollars raised by the 25 startups from Venture Expert whose Venture Expert business description is most similar to the 10-K business description of the focal firm (using cosine similarities), scaled by focal firm lagged sales.
Complaints	The number of paragraphs in the firm's 10-K that mention competition divided by the total number of paragraphs in the firm's 10-K.
Noncompete	#10K paragraphs mentioning "non-compete" agreements, all scaled by the total paragraphs in the 10-K.
Nondisclose	#10K paragraphs mentioning "non-disclose" or "NDA" agreements, all scaled by the total paragraphs in the 10-K.

Online Appendix B: Not for publication

1 Technical Comparison of Models

Among the transformer-based language models, the main differences are sourced from the attention mechanism, tokenization, pre-training task, and pre-training data. Table 16 documents these characteristics for BERT (Devlin et al. (2019)), SciBERT (Beltagy et al. (2019)), RoBERTa (Liu et al. (2019)), and Longformer (Beltagy et al. (2020)) models. In the text below, we explain the attention mechanisms, tokenization, and the pre-training procedure in detail.

BERT, SciBERT, and, RoBERTa process all words in a single iteration rather than one-by-one or in a fixed-sized sliding window approach. In these models, the context of a word depends not only on the words that come before it, but depends on the relative position to each other word in the text. The amount of attention given to each word is decided by the internal dynamics of these models. The mechanism where all words in the text have to be paid attention to is referred as the *full-attention* mechanism. In this mechanism, since there is a pairwise attention between words, memory usage is quadratic with respect to the number of words in the text, limiting the usage to 512 tokens (roughly 400 words).

In contrast, the Longformer model uses a sparse-attention mechanism. In this mechanism, for each word, the model does not use pairwise attention between each words in the text. Instead, for each token, the model pays attention only to the 256 tokens that come before and after it, and to a few special tokens. Therefore, memory usage is close to linear with respect to the number of words in a text. Overall, there is a trade-off between full-attention vs. sparse-attention models: the BERT, SciBERT, and, RoBERTa models have more precision for gathering context while the Longformer model can incorporate more tokens.

What is the relation between a word and a token and how the tokenization is different between the four models? While most of the words are converted to a single token, some words can be converted to more than one token. For instance, the word "embodiment" can be converted to the tokens "emb","-od", and "-iment", while the word "transistor" can be converted to the tokens "trans" and "-istor". The way the words will be tokenized depends on the model. The BERT and SciBERT models use WordPiece algorithm and the RoBERTa and Longformer models use the byte-level BPE algorithm for tokenization. It is worth noting that the resulting token of the same word may not be exactly the same even when the same algorithm is used since the pre-training data used for each model is different. Despite the differences in the tokenization algorithm and pre-training data, in general terms, 512 tokens correspond to 400-430 words.

Models	Attention Mechanism	Tokenization Algorithm	Pre-training Tasks	Pre-training Data
BERT	Full-attention	WordPiece	MLM, NSP	Wikipedia, Book Corpus
SciBERT	Full-attention	WordPiece	MLM, NSP	Scientific Articles
RoBERTa	Full-attention	Byte-level BPE	MLM	Wikipedia, Book Corpus, CC-News, Open Web Text, Stories
Longformer	Sparse-attention	Byte-level BPE	MLM	Wikipedia, Book Corpus, CC-News, Open Web Text, Stories, Realnews

Table 16: Comparison of the models

The pre-training procedure of BERT and SciBERT consists of two different tasks: Masked Language Modelling (MLM) and Next Sequence Prediction (NSP). In the Masked Language Modelling task, some randomly selected tokens are masked, and the models try to predict them. In the Next Sequence Prediction task, two sequences are given to the model, and the model predicts whether these two sentences follow each other. The pre-training procedure of RoBERTa and Longformer only use the Masked Language Modelling task. However, they are trained on a much larger dataset than the ones for BERT and SciBERT.

While the BERT is trained on a dataset that contains text from Wikipedia and Book Corpus (Zhu et al. (2015)), SciBERT is trained on a dataset that contains research articles obtained from Semantic Scholar (Ammar et al. (2018)). RoBERTa is trained on a dataset that contains the text used in the pre-training of BERT and some additional text, which is sourced from newsletters (Nagel (2016)), texts crawled from the URLs that are shared on Reddit and have at least three upvotes (Gokaslan and Cohen (2019)), and Stories dataset (Trinh and Le (2018)) in which every entry forms a story.

The Longformer model begins its pre-training from the already pre-trained RoBERTa model, and it is further pre-trained so that it can learn the new sparse-attention mechanism. The second-phase of the pre-training data incorporates additional text from Realnews dataset (Zellers et al. (2019))

As a separate note, the fine-tuning procedure is not dependent on the model, but it is dependent on the task. Therefore, in our paper, we use the same fine-tuning procedure for all of the models.

2 Additional Statistics on CPC codes and Industries with High Longformer Scores

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

The results in Table IA1 show that 111,420 of the 642,678 patents (17.34% of the sample) have a Longformer score (predicted Alice rejection score) of 0.5 or higher, our threshold of a high likelihood of losing protection if challenged in court.[26]

Panel B of Table IA1 provides the list of CPCs that have the highest number of patent applications that were rejected by the USPTO and the list of CPCs for patents that have a Longformer score of 0.5 or higher.[27] There is large overlap across these two lists. Eight of the top ten CPCs for Alice-rejected patents are also in the high Longformer score list.

In Table IA2 we provide further industry and year analysis. We present these by industry for the top 10 industries along with the percentage of patents our Longformer model predicts would be rejected (those with Longformer scores ≥ 0.5). The table shows that, among the granted patents in these industries, multiple industries have over 25% of granted patents with Longformer scores ≥ 0.5. These patents would likely lose protection post-Alice. Corresponding CPCs for each industry are provided in Table 2. These percentages are similar to those for the post-Alice rejected patents shown in Table 1.

[26] Note that 47.2% of these 111,420 patents are owned by public firms (our focus), suggesting that the impact of Alice on private firms (not studied here) might also be significant.

[27] Note in our actual regressions, we use the actual Longformer scores and not just those greater than .5.

Table IA1: Summary of Longformer Prediction Statistics

This table reports statistics from Longformer model predictions for the set of patents that are examined for lost protection. A patent is included in the examination set if it is granted between 06/19/1994 and 06/19/2014 and shares 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 larger than 0.5 as the Longformer score. In our sample, 111,420 patents that have larger than Longformer Score of 0.5 have 114,885 primary CPCs (one patent can have more than one primary CPC). In Panel B, the percentages for patent applications show the total number of rejected patents in that CPC divided by all the rejected patents in all CPCs. The percentages for granted patents show the total number of predicted rejections in that CPC divided by all the predicted rejections in all CPCs.

Panel A: Longformer Predictions For Different Thresholds

Threshold	Percentage of Patents $\geq$ Threshold (%)	Number of Patents $\geq$ Threshold	Number of Unique CPCs
0.5	17.34	111,420	4,979
0.6	11.50	73,934	4,591
0.7	8.87	57,001	4,316
0.8	6.72	43,200	3,980
0.9	4.32	27,786	3,407

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

Alice Rejections (For Patent Applications)			**Longformer Predictions (For Granted Patents)**		
Most Frequent CPCs	Count	Percentage(%)	Most Frequent CPCs	Count	Percentage(%)
G06Q30/02	1185	3.49	G06Q30/02	2898	2.52
G06Q40/04	675	1.99	G06Q10/10	2133	1.86
G06Q10/06	486	1.43	G06Q10/06	1992	1.73
G06Q40/08	397	1.17	G06Q30/06	1638	1.43
G06Q40/06	383	1.13	G06Q40/04	1563	1.36
G06Q10/10	370	1.09	G06Q40/02	1381	1.20
G06Q30/06	343	1.01	G06Q40/06	865	0.75
G06Q40/02	293	0.86	G07F17/32	841	0.73
G06Q30/0631	248	0.73	G06Q40/00	753	0.66
G06Q30/08	247	0.73	G06Q40/08	717	0.62

Table IA2: Patent Grants and Predicted Longformer 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 Longformer model. The years in the table start from 19th of June and end on 18th of June. The numbers in parentheses show the percentage of patents in that industry and period with a Longformer score of 0.5 or larger. Corresponding CPCs for each industry are provided in Table 2.

Patent Grants and Predicted Longformer Rejections

	Number of Patent Grants & Ratio of Longformer Cases (≥ 0.5)			
Industry	1994-1999	1999-2004	2004-2009	2009-2014
Commerce (Data Processing Methods)	355 (52.7%)	1460 (53.2%)	3536 (52.3%)	10389 (50.5%)
Administration (Data Processing Methods)	665 (50.1%)	2001 (45.1%)	4447 (42.2%)	11467 (40.1%)
Finance (Data Processing Methods)	204 (68.1%)	473 (66.8%)	1253 (65.1%)	6387 (66.2%)
Payment Systems (Data Processing Methods)	263 (37.3%)	565 (37.7%)	1175 (35.0%)	3411 (43.8%)
Coin-freed Facilities or Services (Coin-freed or Like Apparatus)	445 (32.6%)	1126 (37.7%)	1483 (36.9%)	4486 (38.4%)
Information Retrieval (Digital Data Processing)	1238 (20.1%)	3823 (17.1%)	5894 (14.3%)	15811 (15.2%)
Video Games (Games)	336 (25.6%)	912 (33.6%)	708 (29.5%)	2598 (31.6%)
Specialized For Sectors (Data Processing Methods)	21 (61.9%)	72 (44.4%)	220 (33.6%)	936 (38.0%)
Computer Security (Digital Data Processing)	509 (27.5%)	1176 (24.7%)	2965 (22.0%)	8659 (22.0%)
Network Security (Transmission of Digital Information)	242 (26.4%)	1109 (23.2%)	3742 (20.5%)	9003 (22.7%)
Network Specific Applications (Transmission of Digital Information)	98 (28.6%)	950 (17.9%)	2943 (14.5%)	7565 (18.8%)
Measuring or Testing Processes (Microbiology & Enzymology)	1369 (9.2%)	2107 (13.4%)	1887 (16.1%)	3749 (24.2%)

Table IA3: Comparison of Patent Applications Alice Longformer Scores in the Pre- and Post-Period

This table reports robustness regarding the results in Table 5 based on patent applications instead of patent grants. In particular, this table shows the distributional density of the Longformer 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 applied in that year in the Top 20 technological areas. The number of patent applications in 2011, 2012, 2013, and 2017 are 31,726; 35,551; 40,590; and 37,786, respectively. We sort all patents in each year into 10 bins based on each patent's Longformer Score. Bins are defined as the ten equal segments in the interval (0,1), which is the range of the Longformer Score. For each bin, the density is the number of patent applications in the given bin in the given year divided by the total number of patent applications 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.

Longformer Score (LFS)	2011 (1)	2012 (2)	2013 (3)	2011- 2013 (4)	2017 (5)	Ratio (6)
$0.0 \leq \text{LFS} < 0.1$	0.2444	0.2323	0.2325	0.2359	0.2877	1.2196
$0.1 \leq \text{LFS} < 0.2$	0.0808	0.0881	0.0882	0.0860	0.0991	1.1523
$0.2 \leq \text{LFS} < 0.3$	0.0662	0.0632	0.0659	0.0651	0.0774	1.1889
$0.3 \leq \text{LFS} < 0.4$	0.0679	0.0674	0.0674	0.0675	0.0751	1.1126
$0.4 \leq \text{LFS} < 0.5$	0.1164	0.1150	0.1155	0.1156	0.1352	1.1696
$0.5 \leq \text{LFS} < 0.6$	0.0919	0.0940	0.0928	0.0929	0.0992	1.0678
$0.6 \leq \text{LFS} < 0.7$	0.0520	0.0545	0.0527	0.0531	0.0511	0.9623
$0.7 \leq \text{LFS} < 0.8$	0.0490	0.0495	0.0494	0.0493	0.0435	0.8824
$0.8 \leq \text{LFS} < 0.9$	0.0636	0.0644	0.0650	0.0644	0.0473	0.7345
$0.9 \leq \text{LFS} < 1.0$	0.1677	0.1716	0.1705	0.1700	0.0844	0.4965

3 Longformer Model (Firms Categorized by Market Shares)

Table IA4:
Effects of Alice on Patent Applications (Firms Categorized By Market Share) Longformer

The table displays panel data regressions in which patent applications scales by assets and sales are dependent variables. In columns (1)-(2), the dependent variable is the number of patent applications in year *t* divided by assets in year *t-1*; and in columns (3) and (4), the dependent variable is the number of patent applications in year *t* divided by sales in year *t-1*. *Treatment* is the relative impact of the Alice decision on the firm's patent portfolio measured using KPSS dollar values or citations scaled by sales (see equation (3) for the formula). In the odd and even numbered columns, respectively, we use the KPSS and the number of citations approach to compute the *Patent Value* treatment. *Small* is a binary variable equals one if a firm's TNIC market share is lower than the median industry-year market share in 2013 and zero otherwise. *Large* is 1-*Small*. *Post* is a dummy variable that equals one if the year is after the Alice decision and zero otherwise. All variables are described in detail in the variable list in Appendix A. All regressions include firm and year fixed effects. Standard errors are clustered at the firm level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

Dependent Variable:	$\frac{\#\ of Patents}{Assets_{t-1}}$		$\frac{\#\ of Patents}{Sales_{t-1}}$	
	(1)	(2)	(3)	(4)
Small × Post × Treatment	-0.201***	-0.072***	-0.442***	-0.151***
	(-8.76)	(-8.06)	(-8.11)	(-7.62)
Large × Post × Treatment	-0.069***	-0.047***	-0.121***	-0.084***
	(-5.58)	(-5.52)	(-5.25)	(-4.64)
Log(Assets)	-0.004***	-0.004***		
	(-8.62)	(-9.21)		
Log(Age)	-0.002*	-0.002**	-0.001	-0.001
	(-1.90)	(-1.99)	(-0.32)	(-0.61)
Log(Sales)			-0.009***	-0.009***
			(-7.40)	(-7.41)
Observations	19135	19135	19135	19135
Firm Fixed Effects	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES
Treatment Calculation	KPSS	Citation	KPSS	Citation
Adj. R^2	0.112	0.118	0.099	0.099

Table IA5:
Competition and Patent Protection (Firms Categorized By Market Share) Longformer

The table displays panel data regressions in which competition variables are the dependent variables. In columns (1)-(2), the dependent variable, *VCF/Sales*, is the a measure of VC entry in a given firm's product market and is the total first-round dollars raised by the 25 startups from Venture Expert whose Venture Expert business description most closely matches the 10-K business description of the focal firm (using cosine similarities) in year t, scaled by focal firm sales in yeart-1. 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. R&D/Sales is R&D expenses in year t scaled by sales in year *t-1*. *Treatment* is the relative impact of the Alice decision on the firm's patent portfolio measured using KPSS dollar values or citations scaled by sales (see equation (3) for the formula). In the odd and even numbered columns, respectively, we use the KPSS and the number of citations approach to compute the *Patent Value* treatment. *Small* is a binary variable equals one if a firm's TNIC market share is lower than the median industry-year market share in 2013 and zero otherwise. *Large* is 1-*Small*. *Post* is a dummy variable that equals one if the year is after the Alice decision and zero otherwise. All variables are described in detail in the variable list in Appendix A. All regressions include firm and year fixed effects. Standard errors are clustered at the firm level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

Dependent Variable:	$\frac{VCF}{Sales_{t-1}}$		Complaints		$\frac{R\&D}{Sales_{t-1}}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Small × Post × Treatment	8.575***	2.061***	11.248***	3.639**	6.153***	1.382***
	(6.87)	(5.37)	(2.62)	(2.48)	(5.31)	(4.12)
Large × Post × Treatment	0.185	-0.001	-7.064	-3.188	-0.053	-0.062
	(1.20)	(-0.01)	(-1.52)	(-1.22)	(-0.57)	(-0.96)
Log(Sales)	-0.400***	-0.401***	0.143	0.142	-0.176***	-0.177***
	(-14.76)	(-14.70)	(1.53)	(1.52)	(-10.12)	(-10.00)
Log(Age)	0.343***	0.365***	-0.265	-0.232	0.180***	0.198***
	(6.38)	(6.70)	(-0.84)	(-0.73)	(5.23)	(5.59)
Observations	19053	19053	19056	19056	19135	19135
Firm Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Treatment Calculation	KPSS	Citation	KPSS	Citation	KPSS	Citation
Adj. R^2	0.252	0.228	0.008	0.008	0.160	0.126

Table IA6:
Profitability (Firms Categorized By Market Share) Longformer

The table displays panel data regressions that examine whether the profitability of high and low market share firms were differently affected by the Alice decision. In columns (1)-(2), the dependent variable is 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; and in columns (3) and (4), it is Operating Income scaled by sales. In columns (5)-(6), the dependent variable is M/B Ratio, calculated as the market to book ratio (market value of equity plus book debt and preferred stock, all divided by book assets). *Treatment* is the relative impact of the Alice decision on the firm's patent portfolio measured using KPSS dollar values or citations scaled by sales (see equation (3) for the formula). In the odd and even numbered columns, respectively, we use the KPSS and the number of citations approach to compute the *Patent Value* treatment. *Small* is a binary variable equals one if a firm's TNIC market share is lower than the median industry-year market share in 2013 and zero otherwise. *Large* is 1-*Small*. *Post* is a dummy variable that equals one if the year is after the Alice decision and zero otherwise. All variables are described in detail in the variable list in Appendix A. All regressions include firm and year fixed effects. Standard errors are clustered at the firm level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

Dependent Variable:	Sales Growth		$\frac{OperatingIncome}{Sales_{t-1}}$		Market-to-Book	
	(1)	(2)	(3)	(4)	(5)	(6)
Small × Post × Treatment	0.619	0.038	-11.285***	-2.543***	-8.460***	-2.870***
	(1.52)	(0.33)	(-4.63)	(-3.60)	(-2.73)	(-3.08)
Large × Post × Treatment	0.392***	0.175**	0.083	0.174	1.113	1.765**
	(2.77)	(2.16)	(0.40)	(1.39)	(0.91)	(2.36)
Log(Sales)	-0.205***	-0.205***	0.502***	0.503***	-0.337***	-0.338***
	(-26.97)	(-26.92)	(11.24)	(11.18)	(-6.32)	(-6.36)
Log(Age)	-0.042**	-0.040*	-0.646***	-0.681***	-1.144***	-1.157***
	(-2.00)	(-1.91)	(-7.08)	(-7.33)	(-7.22)	(-7.31)
Observations	19135	19135	18304	18304	18658	18658
Firm Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Treatment Calculation	KPSS	Citation	KPSS	Citation	KPSS	Citation
Adj. R^2	0.173	0.172	0.152	0.133	0.073	0.073

Table IA7:
Firm IP Risk and Legal Protections (Firms Categorized By Market Share) Longformer

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 the relative impact of the Alice decision on the firm's patent portfolio measured using KPSS dollar values or citations scaled by sales (see equation (3) for the formula). In the odd and even numbered columns, respectively, we use the KPSS and the number of citations approach to compute the *Patent Value* treatment. *Small* is a binary variable equals one if a firm's TNIC market share is lower than the median industry-year market share in 2013 and zero otherwise. *Large* is 1-*Small*. *Post* is a dummy variable that equals one if the year is after the Alice decision and zero otherwise. All variables are described in detail in the variable list in Appendix A. All regressions include firm and year fixed effects. Standard errors are clustered at the firm level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

Dependent Variable:	IP Risk		Noncompete		Nondisclosure	
	(1)	(2)	(3)	(4)	(5)	(6)
Small × Post × Treatment	10.998***	3.760***	0.356	0.408	11.457***	2.090***
	(3.13)	(4.15)	(0.44)	(1.29)	(3.76)	(2.79)
Large × Post × Treatment	2.412	1.888	-0.357	-0.469	0.136	0.053
	(1.12)	(1.13)	(-0.54)	(-1.13)	(0.37)	(0.25)
Log(Sales)	0.007	0.010	0.044**	0.044**	-0.003	-0.006
	(0.14)	(0.18)	(2.06)	(2.09)	(-0.06)	(-0.13)
Log(Age)	-0.205	-0.188	-0.105	-0.107	0.181*	0.217**
	(-1.27)	(-1.18)	(-1.28)	(-1.31)	(1.91)	(2.21)
Observations	19056	19056	19056	19056	19056	19056
Firm Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Treatment Calculation	KPSS	Citation	KPSS	Citation	KPSS	Citation
Adj. R^2	0.066	0.066	0.002	0.002	0.042	0.024

Table IA8:

Lawsuits and Legal Protection (Firms Categorized By Market Share) Longformer

The table displays panel data regressions examining whether lawsuit metrics of high and low market share firms were differently affected by the Alice decision. In columns (1)-(2), the dependent variable, *is Alleged*, is a dummy variable that 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 that 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 that 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 both the word root "patent*" 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 the relative impact of the Alice decision on the firm's patent portfolio measured using KPSS dollar values or citations scaled by sales (see equation (3) for the formula). In the odd and even numbered columns, respectively, we use the KPSS and the number of citations approach to compute the *Patent Value* treatment. *Small* is a binary variable equals one if a firm's TNIC market share is lower than the median industry-year market share in 2013 and zero otherwise. *Large* is 1-*Small*. *Post* is a dummy variable that equals one if the year is after the Alice decision and zero otherwise. All variables are described in detail in the variable list in Appendix A. All regressions include firm and year fixed effects. Standard errors are clustered at the firm level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

Dependent Variable:	Alleged #		Alleged # by NPE		Alleged # by OC		Patinfringe		# of Sueing	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Small × Post × Treatment	0.837	0.090	0.816**	0.102	-0.158	-0.065	-1.768	-0.768	0.233	0.140
	(1.56)	(0.64)	(2.00)	(0.91)	(-0.69)	(-0.90)	(-0.74)	(-0.97)	(0.63)	(1.20)
Large × Post × Treatment	-5.691***	-2.332***	-2.768***	-1.352***	-2.820***	-0.887***	-3.362**	-2.824***	-0.413	-0.311*
	(-5.61)	(-4.11)	(-4.09)	(-3.99)	(-5.22)	(-2.84)	(-2.10)	(-2.83)	(-1.39)	(-1.83)
Log(Sales)	0.039***	0.037***	0.024***	0.023***	0.010**	0.010**	0.021	0.020	-0.017***	-0.017***
	(4.52)	(4.30)	(3.98)	(3.80)	(2.41)	(2.20)	(0.64)	(0.58)	(-2.74)	(-2.74)
Log(Age)	0.128***	0.142***	0.050*	0.057**	0.066***	0.071***	-0.125	-0.124	-0.368***	-0.367***
	(3.30)	(3.60)	(1.87)	(2.14)	(3.20)	(3.42)	(-1.21)	(-1.18)	(-14.45)	(-14.47)
Observations	19135	19135	19135	19135	19135	19135	19056	19056	19135	19135
Firm Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Treatment Calculation	KPSS	Citation	KPSS	Citation	KPSS	Citation	KPSS	Citation	KPSS	Citation
Adj. R^2	0.025	0.019	0.018	0.016	0.030	0.022	0.004	0.005	0.051	0.051

Table IA9:
Acquisitions and Legal Protection (Firms Categorized By Market Share) Longformer

The table displays panel data regressions in which acquisition variables are the dependent variables. In columns (1)-(2) and (3)-(4), the dependent variables are dollar value spent on acquisition scaled by sales and log of one plus total value spent on acquisitions in that year. *Treatment* is the relative impact of the Alice decision on the firm's patent portfolio measured using KPSS dollar values or citations scaled by sales (see equation (3) for the formula). In the odd and even numbered columns, respectively, we use the KPSS and the number of citations approach to compute the *Patent Value* treatment. *Small* is a binary variable equals one if a firm's TNIC market share is lower than the median industry-year market share in 2013 and zero otherwise. *Large* is 1-*Small*. *Post* is a dummy variable that equals one if the year is after the Alice decision and zero otherwise. All regressions include firm and year fixed effects. Standard errors are clustered at the firm level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

Dependent Variable:	$\frac{Acquisitions}{Sales_{t-1}}$		$\frac{Targets\ With\ Patents}{Sales_{t-1}}$		Log(Acquisitions)	
	(1)	(2)	(3)	(4)	(5)	(6)
Small × Post × Treatment	0.024	-0.008	0.001	-0.002	0.073	-0.032
	(0.16)	(-0.18)	(0.09)	(-1.11)	(0.07)	(-0.12)
Large × Post × Treatment	0.067	0.004	-0.024**	-0.011	-5.030***	-2.970***
	(0.59)	(0.05)	(-2.27)	(-1.60)	(-2.77)	(-2.94)
Log(Sales)	-0.038***	-0.038***	-0.001***	-0.001***	-0.143***	-0.144***
	(-6.81)	(-6.81)	(-3.57)	(-3.66)	(-3.96)	(-4.02)
Log(Age)	0.005	0.005	0.002***	0.002***	0.207	0.215*
	(0.33)	(0.34)	(3.04)	(3.15)	(1.60)	(1.66)
Observations	19135	19135	19135	19135	19135	19135
Firm Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Treatment Calculation	KPSS	Citation	KPSS	Citation	KPSS	Citation
Adj. R^2	0.009	0.009	0.007	0.007	0.004	0.004

4 TF-IDF and CPC Models Instead Of Longformer

Table IA10:
Patents (Alice Scores Calculated by TF-IDF Instead of Longformer Model)

The table displays the robustness tests for the results in Table 8. In this table, in the calculation of the treatment variable depicted in equation (3), we use TF-IDF instead of Longformer Model. In columns (1)-(2), the dependent variable is the number of patent applications in that year divided by sales; and in columns (3) and (4), it is one plus log of the number of patent applications in the respective year. In columns (5)-(6), the dependent variable is R&D expenses scaled by sales. In the odd and even numbered columns, KPSS and the number of citations that a patent received are used for *Patent Value* in calculation of the treatment, respectively. *Small* is a binary variable equal to one if a firm's total assets are smaller than the median total asset of its TNIC peers in 2013, and it is zero otherwise. *Large* is 1-*Small*. *Post* is a dummy variable that equals one if the year is after the Alice decision and zero otherwise. All variables are described in detail in the variable list in Appendix A. All regressions include firm and year fixed effects. Standard errors are clustered at the firm level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

Dependent Variable:	$\frac{\#\ of Patents}{Assets_{t-1}}$		$\frac{\#\ of Patents}{Sales_{t-1}}$	
	(1)	(2)	(3)	(4)
Small × Post × Treatment	-0.296***	-0.075***	-0.631***	-0.150***
	(-6.52)	(-5.36)	(-5.64)	(-4.54)
Large × Post × Treatment	-0.104***	-0.072***	-0.182***	-0.124***
	(-5.37)	(-5.17)	(-4.47)	(-4.06)
Log(Assets)	-0.004***	-0.004***		
	(-8.56)	(-8.82)		
Log(Sales)			-0.009***	-0.009***
			(-7.21)	(-7.19)
Log(Age)	-0.002*	-0.002**	-0.001	-0.002
	(-1.87)	(-2.19)	(-0.47)	(-0.87)
Observations	19135	19135	19135	19135
Firm Fixed Effects	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES
Treatment Calculation	KPSS	Citation	KPSS	Citation
Adj. R^2	0.097	0.089	0.084	0.075

Table IA11:
Competition and Patent Protection (Alice Scores Calculated by TF-IDF Instead of Longformer Model)

The table displays the robustness tests for the results in Table 9. In this table, in the calculation of the treatment variable depicted in equation (3), we use TF-IDF instead of Longformer Model. In columns (1)-(2), the dependent variable, *VCF/Sales*, is the a measure of VC entry in a given firm's product market and is the total first-round dollars raised by the 25 startups from Venture Expert whose Venture Expert business description most closely matches the 10-K business description of the focal firm (using cosine similarities) in year *t*, scaled by focal firm sales in yeart-1. 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. R&D/Sales is R&D expenses in year *t* scaled by sales in year *t-1*. *Treatment* is the relative impact of the Alice decision on the firm's patent portfolio measured using KPSS dollar values or citations scaled by sales (see equation (3) for the formula). In the odd and even numbered columns, respectively, we use the KPSS and the number of citations approach to compute the *Patent Value* treatment. *Small* is a binary variable equal to one if a firm's total assets are smaller than the median total asset of its TNIC peers in 2013, and it is zero otherwise. *Large* is 1-*Small*. *Post* is a dummy variable that equals one if the year is after the Alice decision and zero otherwise. All variables are described in detail in the variable list in Appendix A. All regressions include firm and year fixed effects. Standard errors are clustered at the firm level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

Dependent Variable:	$\frac{VCF}{Sales_{t-1}}$		Complaints		$\frac{R\&D}{Sales_{t-1}}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Small × Post × Treatment	11.311***	2.526***	26.156***	6.724**	7.150***	1.796***
	(4.95)	(3.88)	(3.36)	(2.47)	(3.87)	(3.49)
Large × Post × Treatment	0.468*	0.163	-8.110	-2.212	-0.002	-0.020
	(1.69)	(1.14)	(-1.20)	(-0.51)	(-0.01)	(-0.18)
Log(Sales)	-0.403***	-0.402***	0.135	0.136	-0.179***	-0.178***
	(-14.72)	(-14.63)	(1.44)	(1.45)	(-9.99)	(-9.93)
Log(Age)	0.355***	0.372***	-0.190	-0.147	0.191***	0.202***
	(6.46)	(6.70)	(-0.59)	(-0.46)	(5.36)	(5.60)
Observations	19053	19053	19056	19056	19135	19135
Firm Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Treatment Calculation	KPSS	Citation	KPSS	Citation	KPSS	Citation
Adj. R^2	0.227	0.215	0.008	0.006	0.123	0.113

Table IA12:
Patents (CPC Dummy Variable Instead of Alice Score)

The table displays the robustness tests for the results in Table 8. In this table, in the calculation of the treatment variable depicted in equation (3), we use CPC dummy instead of Alice Score. CPC dummy equals one if a patent's primary CPC belongs to one of the top-20 CPCs that have the most frequent Alice rejections and zero otherwise. In columns (1)-(2), the dependent variable is the number of patent applications in that year divided by sales; and in columns (3) and (4), it is one plus log of the number of patent applications in the respective year. In columns (5)-(6), the dependent variable is R&D expenses scaled by sales. *Treatment* is the relative impact of the Alice decision on the firm's patent portfolio measured using KPSS dollar values or citations scaled by sales (see equation (3) for the formula). In the odd and even numbered columns, respectively, we use the KPSS and the number of citations approach to compute the *Patent Value* treatment. *Small* is a binary variable equal to one if a firm's total assets are smaller than the median total asset of its TNIC peers in 2013, and it is zero otherwise. *Large* is 1-*Small*. *Post* is a dummy variable that equals one if the year is after the Alice decision and zero otherwise. All variables are described in detail in the variable list in Appendix A. All regressions include firm and year fixed effects. Standard errors are clustered at the firm level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

Dependent Variable:	$\frac{\# \ of Patents}{Assets_{t-1}}$		$\frac{\# \ of Patents}{Sales_{t-1}}$	
	(1)	(2)	(3)	(4)
Small × Post × Treatment	-0.159***	-0.039***	-0.320***	-0.079***
	(-8.59)	(-6.46)	(-7.87)	(-6.02)
Large × Post × Treatment	-0.047***	-0.027***	-0.080***	-0.046***
	(-4.68)	(-4.40)	(-3.79)	(-3.52)
Log(Assets)	-0.004***	-0.004***		
	(-8.72)	(-9.09)		
Log(Sales)			-0.009***	-0.009***
			(-7.09)	(-7.19)
Log(Age)	-0.002*	-0.002**	-0.001	-0.002
	(-1.80)	(-2.35)	(-0.45)	(-1.01)
Observations	19135	19135	19135	19135
Firm Fixed Effects	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES
Treatment Calculation	KPSS	Citation	KPSS	Citation
Adj. R^2	0.110	0.101	0.091	0.084

Table IA13:
Competition and Patent Protection (CPC Dummy Variable Instead of Alice Score)

The table displays the robustness tests for the results in Table 9. In this table, in the calculation of the treatment variable depicted in equation (3), we use CPC dummy instead of Alice Score. In columns (1)-(2), the dependent variable, *VCF/Sales*, is the a measure of VC entry in a given firm's product market and is the total first-round dollars raised by the 25 startups from Venture Expert whose Venture Expert business description most closely matches the 10-K business description of the focal firm (using cosine similarities) in year t, scaled by focal firm sales in yeart-1. 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. R&D/Sales is R&D expenses in year t scaled by sales in year *t-1*. *Treatment* is the relative impact of the Alice decision on the firm's patent portfolio measured using KPSS dollar values or citations scaled by sales (see equation (3) for the formula). In the odd and even numbered columns, respectively, we use the KPSS and the number of citations approach to compute the *Patent Value* treatment. *Small* is a binary variable equal to one if a firm's total assets are smaller than the median total asset of its TNIC peers in 2013, and it is zero otherwise. *Large* is 1-*Small*. *Post* is a dummy variable that equals one if the year is after the Alice decision and zero otherwise. All variables are described in detail in the variable list in Appendix A. All regressions include firm and year fixed effects. Standard errors are clustered at the firm level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

Dependent Variable:	$\frac{VCF}{Sales_{t-1}}$		Complaints		$\frac{R\&D}{Sales_{t-1}}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Small × Post × Treatment	3.912***	0.735***	10.439***	1.422	1.991**	0.261
	(3.98)	(3.04)	(2.97)	(1.28)	(2.56)	(1.51)
Large × Post × Treatment	0.186*	0.113**	-6.880**	-1.984	-0.099	-0.040
	(1.65)	(2.00)	(-2.37)	(-1.41)	(-0.73)	(-0.48)
Log(Sales)	-0.403***	-0.402***	0.134	0.135	-0.179***	-0.179***
	(-14.62)	(-14.56)	(1.43)	(1.44)	(-9.93)	(-9.88)
Log(Age)	0.366***	0.383***	-0.167	-0.116	0.200***	0.210***
	(6.54)	(6.81)	(-0.52)	(-0.36)	(5.47)	(5.71)
Observations	19053	19053	19056	19056	19135	19135
Firm Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Treatment Calculation	KPSS	Citation	KPSS	Citation	KPSS	Citation
Adj. R^2	0.219	0.210	0.008	0.006	0.109	0.102

5 FuzzyDID

Table IA14:
Fuzzy DID (Panel A) With Longformer Model

This table presents local average treatment effect (LATE) and t-statistics from the Fuzzy DID model developed by de Chaisemartin and D'Haultfoeuille (2018). In columns (1) and (2), the results are displayed for the subsample of Small Firms; and in (3) and (4), they are displayed for Large Firms. A firm is classified as small if its total assets are below the median of its peers in the TNIC database, and it is classified as large otherwise.

	Small		Large	
	(1)	(2)	(3)	(4)
$\frac{\#\ of Patents}{Assets_{t-1}}$	-1.501**	-1.501**	-1.651	-1.651
	(-2.173)	(-2.173)	(-1.476)	(-1.476)
$\frac{\#\ of Patents}{Sales_{t-1}}$	-1.273***	-1.273***	-1.201	-1.201
	(-3.598)	(-3.598)	(-1.451)	(-1.451)
$\frac{R\&D}{Sales_{t-1}}$	42.032***	42.032***	2.794**	2.794**
	(5.412)	(5.412)	(2.511)	(2.511)
$\frac{VCF}{Sales_{t-1}}$	26.927***	26.927***	-3.037*	-3.037*
	(2.789)	(2.789)	(-1.824)	(-1.824)
Complaints	161.406***	161.406***	42.702	42.702
	(2.888)	(2.888)	(0.380)	(0.380)
Sales Growth	7.134**	7.134**	2.000	2.000
	(2.369)	(2.369)	(0.403)	(0.403)
$\frac{OperatingIncome}{Sales_{t-1}}$	-55.079***	-55.079***	9.259	9.259
	(-2.752)	(-2.752)	(1.550)	(1.550)
M/B Ratio	33.190	33.190	85.431**	85.431**
	(1.107)	(1.107)	(2.429)	(2.429)
Treatment Calculation	KPSS	Citation	KPSS	Citation

Table IA15:
Fuzzy DID Continued (Panel B) With Longformer Model

This table presents local average treatment effect (LATE) and t-statistics from the Fuzzy DID model developed by de Chaisemartin and D'Haultfoeuille (2018). In columns (1) and (2), the results are displayed for the subsample of Small Firms; and in (3) and (4), they are displayed for Large Firms. A firm is classified as small if its total assets are below the median of its peers in the TNIC database, and it is classified as large otherwise.

	Small		Large	
	(1)	(2)	(3)	(4)
# Alleged	-3.339	-3.339	-57.756	-57.756
	(-0.693)	(-0.693)	(-1.366)	(-1.366)
# NPE Alleged	0.863	0.863	-3.428	-3.428
	(0.259)	(0.259)	(-0.141)	(-0.141)
# OC Alleged	-6.072***	-6.072***	-49.463	-49.463
	(-2.963)	(-2.963)	(-1.633)	(-1.633)
Patinfringe	-4.145	-4.145	-38.312	-38.312
	(-0.188)	(-0.188)	(-0.806)	(-0.806)
# Accuser	12.192***	12.192***	-9.252	-9.252
	(3.395)	(3.395)	(-1.030)	(-1.030)
IP Risk	256.099***	256.099***	236.715**	236.715**
	(4.055)	(4.055)	(2.464)	(2.464)
Noncompete	2.849	2.849	12.034	12.034
	(0.205)	(0.205)	(0.516)	(0.516)
Nondisclosure	109.403***	109.403***	24.078	24.078
	(3.323)	(3.323)	(0.428)	(0.428)
$\frac{Acquisitions}{Sales_{t-1}}$	-0.630	-0.630	-3.289	-3.289
	(-0.425)	(-0.425)	(-0.573)	(-0.573)
$\frac{Targets\ With\ Patents}{Sales_{t-1}}$	-0.082	-0.082	-0.718*	-0.718*
	(-1.201)	(-1.201)	(-1.699)	(-1.699)
Log(Acquisitions)	-1.349	-1.349	-54.732	-54.732
	(-0.113)	(-0.113)	(-0.580)	(-0.580)
Treatment Calculation	KPSS	Citation	KPSS	Citation

6 Placebo Tests

Table IA16:
Patents (Longformer) With Randomly Swapped Treatment Variables

The table displays the results of placebo regressions for Table 8. In this table, the firm-level treatment variables in Table 8 are randomly swapped among the firms. 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), the dependent variable is the number of patent applications in that year divided by sales. In columns (5)-(6), the dependent variable is R&D expenses scaled by sales. *Small* is a binary variable equal to one if a firm's total assets are smaller than the median total asset of its TNIC peers in 2013, and it is zero otherwise. *Large* is 1-*Small*. *Post* is a dummy variable that equals one if the year is after the Alice decision and zero otherwise. All variables are described in detail in the variable list in Appendix A. All regressions include firm and year fixed effects. Standard errors are clustered at the firm level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

Dependent Variable:	$\frac{\#\ of Patents}{Assets_{t-1}}$		$\frac{\#\ of Patents}{Sales_{t-1}}$	
	(1)	(2)	(3)	(4)
Small × Post × Treatment	-0.009	0.004	-0.034	-0.001
	(-0.45)	(1.02)	(-0.64)	(-0.09)
Large × Post × Treatment	-0.004	-0.005	0.004	-0.006
	(-0.60)	(-1.07)	(0.40)	(-1.03)
Log(Assets)	-0.004***	-0.004***		
	(-8.68)	(-8.71)		
Log(Sales)			-0.009***	-0.009***
			(-7.06)	(-7.08)
Log(Age)	-0.002**	-0.002**	-0.003	-0.003
	(-2.33)	(-2.34)	(-1.05)	(-1.07)
Observations	19135	19135	19135	19135
Firm Fixed Effects	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES
Treatment Calculation	KPSS	Citation	KPSS	Citation
Adj. R^2	0.070	0.070	0.062	0.062

Table IA17:
Profitability (Longformer) With Randomly Swapped Treatment Variables

The table displays panel data regressions that examine whether the profitability of large and small 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.; and in columns (3) and (4), it is operating income scaled by sales. In columns (5)-(6), the dependent variable is M/B Ratio, calculated as the market to book ratio (market value of equity plus book debt and preferred stock, all divided by book assets). *Treatment* is the relative impact of the Alice decision on the firm's patent portfolio measured using KPSS dollar values or citations scaled by sales (see equation (3) for the formula). In the odd and even numbered columns, respectively, we use the KPSS and the number of citations approach to compute the *Patent Value* treatment. *Small* is a binary variable equal to one if a firm's total assets are smaller than the median total asset of its TNIC peers in 2013, and it is zero otherwise. *Large* is 1-*Small*. *Post* is a dummy variable that equals one if the year is after the Alice decision and zero otherwise. All variables are described in detail in the variable list in Appendix A. All regressions include firm and year fixed effects. Standard errors are clustered at the firm level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

Dependent Variable:	Sales Growth		$\frac{Operating\ Income}{Sales_{t-1}}$		M/B Ratio	
	(1)	(2)	(3)	(4)	(5)	(6)
Small × Post × Treatment	0.132	0.107	0.403	0.491	-0.846	0.348
	(0.54)	(1.04)	(0.43)	(0.99)	(-0.44)	(0.43)
Large × Post × Treatment	-0.043	0.008	-0.278	-0.016	-0.433	-0.205
	(-0.29)	(0.11)	(-0.96)	(-0.14)	(-0.58)	(-0.51)
Log(Sales)	-0.206***	-0.206***	0.507***	0.506***	-0.336***	-0.337***
	(-27.00)	(-26.99)	(11.10)	(11.06)	(-6.31)	(-6.32)
Log(Age)	-0.021	-0.020	-0.702***	-0.701***	-1.167***	-1.166***
	(-0.98)	(-0.97)	(-7.36)	(-7.35)	(-7.37)	(-7.37)
Observations	19135	19135	18304	18304	18658	18658
Firm Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Treatment Calculation	Std.	Range	Std.	Range	Std.	Range
Adj. R^2	0.167	0.167	0.119	0.120	0.069	0.069

Table IA18:
Patents Tests With Treatment Variables From Random Distribution

The table displays the results of placebo regressions for Table 8. In this table, the firm-level treatment variables are drawn randomly from standard uniform distribution in odd-numbered columns and from uniform distribution [0,0.13 (the max treatment value in the sample)] in the even-numbered columns. 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), the dependent variable is the number of patent applications in that year divided by sales. In columns (5)-(6), the dependent variable is R&D expenses scaled by sales. *Small* is a binary variable equal to one if a firm's total assets are smaller than the median total asset of its TNIC peers in 2013, and it is zero otherwise. *Large* is 1-*Small*. *Post* is a dummy variable that equals one if the year is after the Alice decision and zero otherwise. All variables are described in detail in the variable list in Appendix A. All regressions include firm and year fixed effects. Standard errors are clustered at the firm level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

Dependent Variable:	$\frac{\#\ of Patents}{Assets_{t-1}}$		$\frac{\#\ of Patents}{Sales_{t-1}}$	
	(1)	(2)	(3)	(4)
Small × Post × Treatment	-0.001	0.005	-0.001	0.004
	(-0.51)	(0.51)	(-0.45)	(0.19)
Large × Post × Treatment	-0.000	0.003	-0.001	0.006
	(-0.76)	(0.74)	(-1.04)	(0.81)
Log(Assets)	-0.004***	-0.004***		
	(-8.70)	(-8.69)		
Log(Sales)			-0.009***	-0.009***
			(-7.07)	(-7.08)
Log(Age)	-0.002**	-0.002**	-0.003	-0.003
	(-2.33)	(-2.32)	(-1.06)	(-1.06)
Observations	19135	19135	19135	19135
Firm Fixed Effects	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES
Treatment Calculation	Std.	Range	Std.	Range
Adj. R^2	0.070	0.070	0.062	0.062

Table IA19:
Profitability (Longformer) With Treatment Variables From Random Distribution

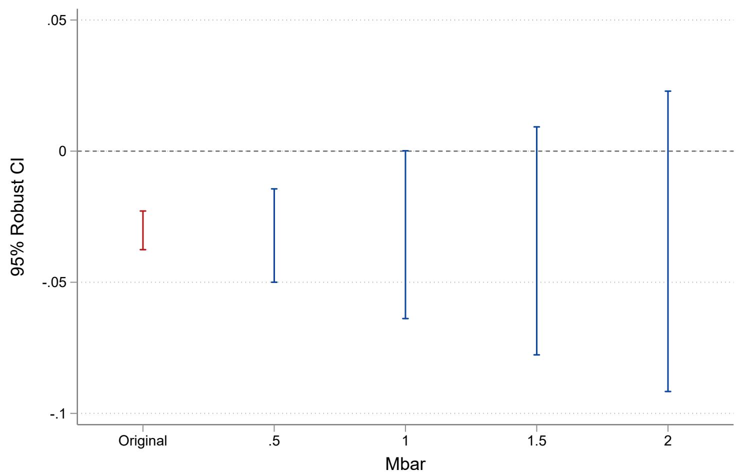
The table displays panel data regressions that examine whether the profitability of large and small firms were differently affected by the Alice decision. In columns (1)-(2), the dependent variable is sales growth, calculated as the natural logarithm of total sales in the current year t divided by total sales in the previous year t-1.; and in columns (3) and (4), it is operating income scaled by sales. In columns (5)-(6), the dependent variable is M/B Ratio, calculated as the market to book ratio (market value of equity plus book debt and preferred stock, all divided by book assets). *Treatment* is the relative impact of the Alice decision on the firm's patent portfolio measured using KPSS dollar values or citations scaled by sales (see equation (3) for the formula). In the odd and even numbered columns, respectively, we use the KPSS and the number of citations approach to compute the *Patent Value* treatment. *Small* is a binary variable equal to one if a firm's total assets are smaller than the median total asset of its TNIC peers in 2013, and it is zero otherwise. *Large* is 1-*Small*. *Post* is a dummy variable that equals one if the year is after the Alice decision and zero otherwise. All variables are described in detail in the variable list in Appendix A. All regressions include firm and year fixed effects. Standard errors are clustered at the firm level. T-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5% and 1% level.

Dependent Variable:	Sales Growth		$\frac{Operating\ Income}{Sales_{t-1}}$		M/B Ratio	
	(1)	(2)	(3)	(4)	(5)	(6)
Small × Post × Treatment	0.006	0.002	0.082	-0.273	-0.091	-0.032
	(0.31)	(0.02)	(1.02)	(-0.42)	(-0.63)	(-0.03)
Large × Post × Treatment	-0.006	-0.047	0.026	0.239	0.023	0.127
	(-0.39)	(-0.38)	(0.97)	(1.09)	(0.37)	(0.24)
Log(Sales)	-0.206***	-0.206***	0.507***	0.507***	-0.337***	-0.337***
	(-27.01)	(-27.00)	(11.09)	(11.09)	(-6.32)	(-6.33)
Log(Age)	-0.020	-0.020	-0.701***	-0.703***	-1.167***	-1.166***
	(-0.97)	(-0.97)	(-7.36)	(-7.36)	(-7.38)	(-7.40)
Observations	19135	19135	18304	18304	18658	18658
Firm Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Treatment Calculation	Std.	Range	Std.	Range	Std.	Range
Adj. R^2	0.167	0.167	0.120	0.119	0.069	0.069

Figure IA1: Patent Applications For Small Firms

This figure presents the sensitivity analysis for differences-in-differences developed in Rambachan and Roth (2023). In this analysis, it is imposed that the post-treatment violation of parallel trends is no more than some constant (Mbar) larger than the maximum violation of parallel trends in the pre-treatment period. For example, if Mbar=2, post-treatment violation of parallel trends is no more than twice that in the pre-treatment period.

Panel A: Small Firms (KPSS)



Panel B: Small Firms (Cites)

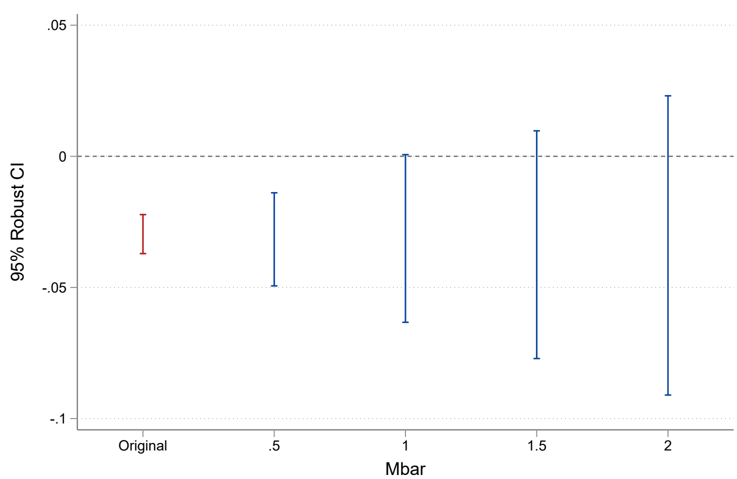


Figure IA2: Competition For Small Firms

This figure presents the sensitivity analysis for differences-in-differences developed in Rambachan and Roth (2023). In this analysis, it is imposed that the post-treatment violation of parallel trends is no more than some constant (Mbar) larger than the maximum violation of parallel trends in the pre-treatment period. For example, if Mbar=2, post-treatment violation of parallel trends is no more than twice that in the pre-treatment period.

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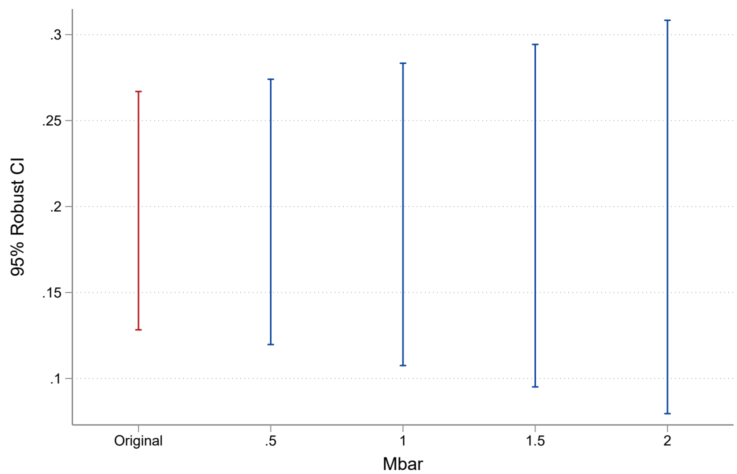
Panel A: Venture Capital Entry (VCF Score) (KPSS)



Panel B: Venture Capital Entry (VCF Score) (Cites)

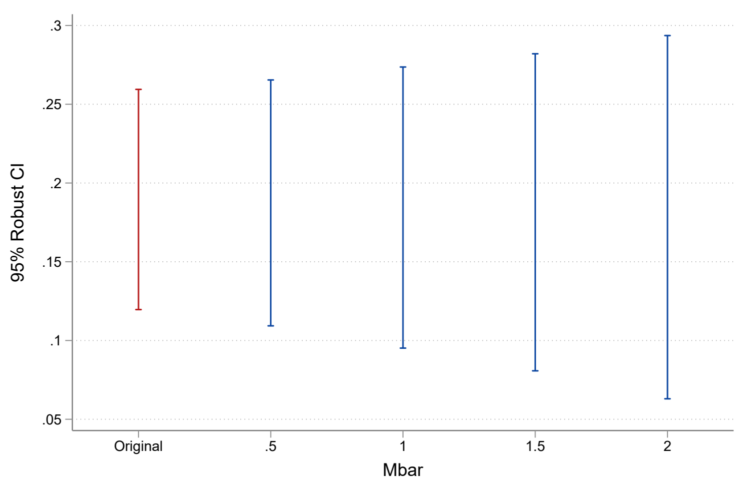


Figure IA3: Competition For Small Firms

This figure presents the sensitivity analysis for differences-in-differences developed in Rambachan and Roth (2023). In this analysis, it is imposed that the post-treatment violation of parallel trends is no more than some constant (Mbar) larger than the maximum violation of parallel trends in the pre-treatment period. For example, if Mbar=2, post-treatment violation of parallel trends is no more than twice that in the pre-treatment period.

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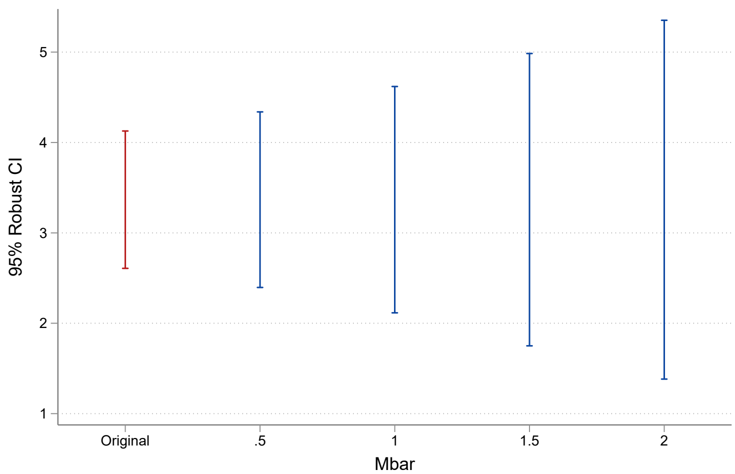
Panel A: Total Similarity (KPSS)



Panel B: Total Similarity (Cites)