Patent Protection and Innovative Entrepreneurship

Natalia Lamberova* and Maxim Ananyev†

Abstract

Does patent protection promote business creation and technological progress? The effect is theoretically ambiguous. We use a unique empirical setup created by Alice Corp. vs. CLS Bank International US Supreme Court ruling, which reduced the strength of software patents, on US startups. Post-decision, software startups faced difficulties securing venture funding and acquisitions, but a decreased rate of non-monetized exits and an increased probability of IPO. This resilience can be attributed to the newfound ability to counter lawsuits. We document a surge in cases seeking patent invalidation specific to software, whereas claims of non-infringement remained constant.

Keywords: patents, start-ups, property rights, access to funding, litigation

JEL Classification: O31, O34, D43

*University of Texas at Dallas, natalia.lamberova@utdallas.edu.

†University of Melbourne, maxim.ananyev@unimelb.edu.au

1. Introduction

Because technological innovation and productivity growth are driven to a large extent by startups (Baumol, 2004; Andrews, Criscuolo and Menon, 2014; Schneider and Veugelers, 2010; Hashai and Markovich, 2017), it is often viewed that the key way in which governments can help foster new inventions is via the mechanism of patenting (Acemoglu, Golosov and Tsyvinski, 2011). The critics of the current patenting system point out that patents are often abused, soak up resources with wasteful "arms races", and unnecessarily shield incumbents from competition (Boldrin, Levine et al., 2008). (Moser, 2005, 2012) shows that the emergence of patent systems did not change the total number and quality of inventions produced in the country, but did shift them from industries with hight costs of imitation to industries where imitation is easy. Giorcelli and Moser (2020) show that the emergence of a different kind of intellectual property rights protection - copyright - is associated with increase in both the number and quality of Italian operas. Currently, patents play an important role in many areas of high-growth entrepreneurship helping secure early-stage venture capital (Amable, Chatelain and Ralf, 2010; Farre-Mensa, Hegde and Ljungqvist, 2020). It is an open question what would happen if the level of patent protection decreases: will it become easier or harder for the start-ups to secure capital and succeed? To answer these questions empirically one needs an institutional context in which, after an exogenous policy change, the level of protection provided by patents changed in some areas but not in others.

In this article, we investigate the role of patents in highly innovative product markets using an exogenous shock to patent protection: 2014 US Supreme Court ruling on *Alice Corporation Pty. Ltd. v. CLS Bank International* case. This ruling effectively decreased the level of protection provided by the software patents, as many of them could be found invalid during the trial (Kiklis, Chen and Zapadka, 2019). The ruling did not significantly affect non-software patents (Lemley and Zyontz, 2021). Such a setting allows for an estimation of the effect of decreased software protection on a variety of firm-level outcomes: venture capital funding, acquisitions, IPOs, and startup closures.

Using a database of U.S. venture funding rounds and a database of patents linked to the firms that own them, we implement synthetic difference-in-differences and trajectory balancing estimations and find that the *Alice* ruling substantially decreased the amount of funding the affected firms secure from the venture capital (VC) firms. The effect is driven by the late-stage funding rounds. We also find a negative effect on the probability of being acquired, a positive effect on the probability of an IPO, and a negative effect on the probability of a firm closure.

We hypothesize that one of the mechanisms through which the *Alice* impacted the probability of survival of a startup is the activity of so-called "patent trolls". Patent trolls are non-practicing entities that acquire a large pool of patents and then approach firms using the technology, predominantly startups, claiming infringement. The *Alice* provided the defense mechanism for the startup from the threats of frivolous lawsuits: the startup could obtain a statement from a court that a patent they are claimed to be infringing upon, was invalid in the first place. We demonstrate that the declaratory judgment regarding the invalidity of software patents increased substantially after the *Alice* ruling, because the declaratory judgments about the invalidity of non-software patterns, as well as about non-infringement of all sorts of patents show no discernible patterns. Additionally, we estimate the synthetic difference-in-differences on the level of a 5-digit patent class and show that the patent classes associated with software patents saw an increase in declaratory judgments claiming patent invalidity as compared with non-software patent classes, and no such change is observed for the declaratory judgement claiming non-infringement.

In sum, our results paint a nuanced picture: for startup firms, exposed to the *Alice* decisions, it became more difficult to get access to venture funding, and their probability of being acquired decreased. However, the probability of having an IPO increased, the survival rate increased, and they were more likely to defend themselves from the "patent trolls". Our results indicate that there's a tradeoff in decreasing the patent protection offered to the new invention by the challenger firms: startups appear to suffer less from the abuse of the system, but also become less attractive to investors.

Most of the studies exploring the effect of intellectual property rights protection assume that the key motive for the technologically lagging firm to innovate is to catch up with the competition, because the key incentive of the technological leader is to escape the competition and increase profits. In their model of "step-by-step" innovation, Aghion et al. (2001) highlight the complementarity of stronger intellectual property rights protection and anti-trust regulation: they find that a little imitation is almost always growth-enhancing, but too much of it is growth-reducing. Acemoglu, Bimpikis and Ozdaglar (2011) model the role of patent protection for experimentation and find that patents may improve the allocation of resources by encouraging it. According to their model, it can also promote the efficient ex-post transfer of knowledge across firms. In a different model, Acemoglu and Akcigit (2012) come to the conclusion that the same degree of protection granted to all firms is inefficient. Instead, they find that optimal policy involves state-dependent IPR protection, with greater protection for technology leaders than for followers. At the same time, Bessen and Maskin (2009) build on the model of sequential innovation and show that patent protection can be harmful to innovation in a dynamic setting. Their model helps to resolve the puzzle of patenting and innovation in the software industry: firms that obtained the most patents reduced their R&D investment relative to sales after patent protection was strengthened. Budish, Roin and Williams (2016) build a model that explores the elasticity of R&D investment to patent term and provide the review of pre-existing emiprcal literature on the topic. Boldrin and Levine (2013) find no empirical evidence that patents serve to increase innovation and productivity. They show that because patents can have a partial equilibrium effect of improving incentives to invent, the general equilibrium effect on innovation can be negative.

Most of these models focus on the incentives of firms to invest in innovation, driven by considerations of product market competition and monopoly rights granted by patents. But firms don't operate in a vacuum. In this article, we consider the incentives of the third parties that emerge from the changes in the strength of patent protection. First, we show that stronger patent protection helps start-ups with patents obtain venture investment. At the same time, start-ups operating in the industry with weaker patents are less likely to be closed and are more likely to achieve a successful exit. These contradictory results can be reconciled if we take into account the fact that both start-ups and software-related firms are more likely to face lawsuits claiming patent infringement. The weakening of patent protection for software-related technology reduces such risk.

Our article contributes to the significant body of literature investigating the relationship between patents and a firm's access to funding. Amable, Chatelain and Ralf (2010) present a theoretical model, showing that using patents as collateral magnifies the effect of innovative rents on investment in research and development. These theoretical findings are in line with empirical findings of Mann (2018), showcasing the fact that patenting companies are likely to use the patent as collateral and that such companies are likely to invest more in R&D [1]. Hochberg, Serrano and Ziedonis (2014) show that annual debt financing of start-ups increases when the secondary market for buying and selling patents grows more liquid [2]. De Rassenfosse and Fischer (2016) analyze the decisions of venture debt lenders and show that the provision of patents as collateral is as important as the provision of tangible assets. Farre-Mensa, Hegde and Ljungqvist (2020) show that start-ups whose patent applications were assigned to more lenient examiners have higher employment and sales growth five years later [3].

[1] The author uses four court decisions from 2002, 2003, 2007 and 2009 that clarified the patent status nationwide and shows that strengthening of the creditor rights to patents led greater ability of companies to raise debt

[2] Using panel data with 1519 start-ups, the authors find the effect to be magnified for the start-ups with less firm-specific patents

[3] They attribute the effect to startups' access to capital (VC funding and debt financing), which is particularly pronounced if startups are founded by the inexperienced entrepreneurs, are located in states where many startups compete for funding or belong to IT industry

There are several distinctive features of this article that allow it to contribute to the literature. First, it examines the role of the structural feature (weaker patent protection) on access to funding, as contrasted to the ability to secure the patent as in Farre-Mensa, Hegde and Ljungqvist (2020) or the rights of the lender with respect to collateralized patents, as in Mann (2018). Unlike Hochberg, Serrano and Ziedonis (2014), where companies with the greater secondary market for patents might be systematically different from those with a weaker secondary market (for example, due to the age of the technology) in a way that impacts access to technology, we rely on the US Supreme Court decision that affected patents irrespective of firm's characteristics that are correlated with the access to funding. Another novelty of our approach is that we connect the *Alice* effect on firms with the effect on patent-related litigations, which is an underappreciated mechanism in the literature.

The closest paper to ours is Acikalin et al. (2022). It used the *Alice* decision to explore the effect of decreased patent protection on public firms. They find that all firms decreased patenting, but the larger firms benefit more from increased competition. Our article is different from Acikalin et al. (2022) in two important respects. First, we look at the emerging firms (startups), whereas Acikalin et al. (2022) explore the established firms. Second, whereas Acikalin et al. (2022) use text-based machine-learning techniques to measure whether a particular patent can be considered invalid by the *Alice* criteria, we posit that the Supreme Court decision affected all software patents by increasing their risk of being invalidated, even though for some patents the risk could have been higher than for the others. Despite these differences, we view our results are consistent with Acikalin et al. (2022). In particular, we find that it became harder for the startups that relied on software patents to secure VC funding. This can be explained by the same mechanism as Acikalin et al. (2022) propose for their smaller firms: without the temporary technological monopoly rewarded by the patents increased competition imperils smaller firms. In addition to that, we argue that startups are more likely to survive due to a higher level of protection from the infringement lawsuits.

2. Background: Property Rights in Software Industry and Alice Decision

On June 19, 2014, the US Supreme Court announced the decision on *Alice Corp. v. CLS Bank International*. The decision put into question the validity of many existing software-related patents and the patentability of the new ones.

Alice Corporation is an Australian company that owned patents on a computerized trading platform that enables financial transactions in which a third party settles obligations between two others to eliminate risk to each party that only one of them will carry its obligation. On May 24, 2007, CLS Bank International (CLS) sued *Alice* and sought a declaratory judgment of non-infringement and invalidity of such patents. *Alice* countersued. After many years and appeals, *Alice*'s patents were found invalid because they were directed at an abstract idea. The US Supreme Court held that *Alice*'s claims did no more than require the generic computer to implement the abstract idea of mediated settlement by performing generic computer functions, which was not enough to transform an abstract idea into a patent-eligible invention.

Thus, the *Alice* two-step test of patenting eligibility was born. According to the *Alice* decision, determining the eligibility of a technology for patent protection involves two steps. First, it is necessary to assess whether the claims are directed toward a patent-ineligible concept, such as a general idea. Second, the claim's elements must be evaluated both individually and as an ordered combination to determine whether they transform the nature of the claims into a patent-eligible application. After *Alice* decision, a patent claim that recites conventional steps at a high level of generality was no longer sufficient to establish the necessary inventive step for patent eligibility.

Because the court decision never cited software patents specifically, the impact of *Al-*

ice was particularly profound for software and computer-implemented technologies, as shown in Lemley and Zyontz (2021). In the first five years after *Alice*, federal courts have invalidated 781 patents either wholly or partially - a 1056% increase in the number of decisions finding ineligible claims compared to five years prior to *Alice* [4].

In 2019, about five years after the *Alice* case was decided, the US patent office released new patent examination guidelines that effectively scaled back the effect of the *Alice* decision (Bae, 2019). Thus, we do not include 2019 and further years in our analysis.

The impact of the *Alice* decision can be decomposed into several components. First, it provides defendants in patent infringement cases with a powerful defense that can be used early on in litigation. In fact, over half of the challenges based on *Alice* were made in early dispositive motions, allowing for a quick resolution of the case (Saltiel, 2019).

Second, invoking the *Alice* defense has proven to be efficient, with the Court of Appeals for the Federal Circuit invalidating most software-related patents it has examined under *Alice*'s "inventive concept" test (T. Vann Pearce and Higgins, 2020). Consequently, enforcement of many software-related patents became risky: after *Alice*, the risk of invalidation of the patent in question increased. In addition, the owner of the patent can face attorney fees (as in Inventor Holdings, LLC v. Bed Bath & Beyond Inc.[5]).

These features have led patent holders to adjust their litigation strategies and reevaluate the value of their software patents (Saltiel, 2019). Acikalin et al. (2022) use machine learning techniques to identify firms' potential exposure to the *Alice* decision in their analysis.

We, on the other hand, assume that the impact was broader. Potential investors might be prejudiced against all software-related patents whereas their enforcement became more uncertain. As a result, potential investors may be hesitant to commit funds to a startup

[4] Invalidation rates related to *Alice* declined over time (Tran, 2019; Lemley and Zyontz, 2021). As noted in (Lemley and Zyontz, 2021), part of this decline can be attributed to the early invalidation of the low-hanging fruit, partly to the Berkheimer, the Federal Circuit court decision in February of 2018

[5] The Federal Circuit has affirmed an award of attorney fees under 35 USC § 285 against a patent owner that pursued its case alleging infringement of a patent after the US Supreme Court decided *Alice Corp. v. CLS Bank Intâl. in June 2014*

even if its patent stands in court when challenged.

Because stronger protection of intellectual property rights can benefit startups by improving their access to funding, it can also threaten them by empowering non-practicing entities ("NPEs" or "patent trolls"). Having lower resources to fight patent infringement cases in courts, startup companies present an easier target.

NPEs have been one of the main contributors to the tenfold increase in patent litigation since 2005 (Cohen, Gurun and Kominers, 2019). However, most instances of NPEs targeting firms with infringement claims don't result in actual litigation (Chien, 2013*b*). Instead, NPEs commonly send "demand letters" with claims of patent infringement. Such letters can target thousands of firms, offering licensing deals to avoid litigation. Appel, Farre-Mensa and Simintzi (2019) cite a case of one company - MPHJ sending demand letters to over 16,000 firms between 2012 and 2013 but never filing a single lawsuit.

Thus, exploring the changes in the number of patent litigation lawsuits against startups is problematic: not only due to statistical problems caused by the rare event data but also because many startups settle after receiving a letter. However, examining the change in strategies startups use given the litigation takes place might be instructive.

Using the patent litigation data from US district court electronic records (1963-2016) (Marco, Tesfayesus and Toole, 2017), Fig 1 illustrates the growth of litigations, focusing on cases of patent declaratory judgment of both non-infringement/invalidity or patent declaratory judgment of Invalidity only (Case types 2 and 4 in Schwartz, Sichelman and Miller (2019)) When a party is threatened with a patent infringement lawsuit, it may preemptively sue the patent owner in a declaratory judgment action and seek to have the patent declared invalid or not infringed. The grounds of declaratory judgment of invalidity or non-infringement may arise when a patent holder informs a prospective company that their product infringes or may infringe on their intellectual property, especially when such discussions are repeated or are not mutually considered to be confidential. Unlike arbitration, a declaratory judgment cannot award any damages or regulate the parties in any way. But patentholder that receives an unfavorable declaratory judgment is unlikely to file a lawsuit, as the suit is much more likely to be dismissed. Declaratory judgment actions are common mechanisms for companies threatened with a patent infringement claim to preemptively file a lawsuit seeking a court ruling declaring the patent invalid or not infringed.

3. DATA

We use data from several sources. First, information on startups, their funding, and exits comes from CrunchBase - a private database maintained by TechCrunch that contains events related to innovative companies. The CrunchBase team aggregates information from the media, as well as information submitted to them by venture capital firms and startups themselves. This database has been widely used in the research on venture capital, startups, and innovation (e.g. Koning, Hasan and Chatterji (2022), van den Heuvel and Popp (2022))

Information on patents comes from The United States Patent and Trademark Office (USPTO). We merge it to Crunchhbase data using the firm's name and location. Importantly, if a firm in the Crunchbase data is not present in the USPTO data, we assume that the number of patents in all the years the firm existed is zero. As a result, our main dataset on start-up funding contains 286 736 observations on a firm-year level between 2012 and 2018.

Because studying exits we chose the unit of observation to be at the category-year level (131 248 observations), where the category is defined in the CrunchBase dataset. Thus, the outcome of interest is the average number of exits (IPOs, acquisitions, and bankruptcies) in a given category in a given year.

The study of a possible mechanism that reconciles the decline in VC funding for software-related start-ups with an increase in successful exits and a decline in closures, we turn to the analysis of patent litigations. Lawsuits regarding intellectual property are notoriously expensive in the USA, and most disputes are settled before the litigation begins. That makes our task very challenging whereas we explore rare events. One of our methods of choice - trajectory balancing - requires a balanced panel for the analysis. In order to satisfy this requirement, we chose our unit of analysis to be patent subclass-year. Patent subclasses outline processes, structural features, and functional features of the subject matter encompassed within the scope of a patent class. We describe the construction of the variables in more detail below.

Software Patents: Classifying patents protecting software is challenging, considering that computer programming is a general-purpose technology. We rely on methods used in prior literature (Graham and Mowery, 2003; Hall and MacGarvie, 2010; Graham and Vishnubhakat, 2013) by inferring whether the patent is a "software patent" based on patent classification. Each patent usually belongs to several patent classes. We designate a patent to be a software patent if at least half of its classifications belong to the "software classes" established in Graham and Vishnubhakat (2013)

Software-reliant category: The CrunchBase database provides a set of short descriptions for most of the firms in the dataset ("enterprise software", "food delivery", "medical instruments" etc.). There are 782 such categories. Each firm can belong to up to six such categories. We define a category to be software-reliant if the share of software-related patents in such category before 2014 exceeded the mean share of software-related patents across all industries.

Software-reliant patent subclass: The original data on patent litigations are built not at the patent subclass level, but at the level of each patent. Each patent can belong to several patent subclasses. Consequently, we treat the patent subclass to be software-related if it contains more than the average number of software patents.

Outcome variables: We are interested in the effect of *Alice* decision on several groups of outcomes of interest. Appendix A1 summarizes the correspondence between outcomes of interest and units of analysis.

Access to funding: We capture the access of startups to funding by looking at the amount of money (in USD) that was raised by the startup per year, the number of investors the firm has attracted during the year and the number of funding events that occurred that year. The level of observation is firm-year.

Exits, Acquisitions, and Closures: We capture the type of exits that happened. We focus on three types of exits: IPO, acquisition, and closure (bankruptcy). We code a binary IPO to be equal to 1 if the firm experienced an IPO in a given year or earlier, and 0 otherwise. Similarly, we create respective binary variables for acquisitions and closures. The unit of observation is category-year.

Litigations: We use the patent litigations data from US district court electronic records (1963-2018) (Marco, Tesfayesus and Toole, 2017), focusing on cases with a declaratory judgment of patent non-infringement and patent declaratory judgment of patent invalidity (Case types 3 and 4 in Schwartz, Sichelman and Miller (2019)).

4. Empirical Specification and Results

In this article, we explore the effects of a decrease in patent protection for software patents on the outcomes of startups. For this, we define firms that hold higher than average amount of software patents as software-reliant. These firms are the ones most affected by the *Alice* decisions. Our analysis proceeds in several stages. First, we explore if the affected firms experienced a change in the funds they raised from VC firms after 2014. Then, we look at the 'exits', such as IPOs and acquisitions (a usual measure of startup success) and closures of firms. Finally, we look at the legal practice: patent-related declaratory judgments. Thus, our results provide a comprehensive picture of the potential impact of the *Alice* decision on statups.

One of the main challenges in such an exercise is that we need to compare firms that rely on software patents (affected by *Alice*) with firms that do not rely on software patents (not affected by *Alice*). These groups are, inherently, hardly comparable: they use different technologies, are subjected to different kinds of technological shocks as well as industry-specific trends. To make sure that the comparisons we make are valid, we employ two flexible methods that use match pre-treatment trajectories of treated and non-treated groups: synthetic difference-in-differences (Arkhangelsky et al. (2021)) and trajectory balancing. (Hazlett and Xu (2018)).

Synthetic difference-in-difference (Arkhangelsky et al., 2021) is an extension of a popular synthetic control method (Abadie, Diamond and Hainmueller, 2010) allowing multiple treated units and using difference-in-differences between the treated and the synthetic counterfactual to estimate the treatment effect. Similarly to the synthetic control methods, the method applies re-weighting and weighting to pre-treatment observations of non-treated units. Similarly to the difference-in-difference method, the results do not depend on potential additive unit-level shifts. The estimator puts more weight on the units that are on average similar to the treated units and and on the periods that are similar to the treated periods. As (Arkhangelsky et al., 2021), this method has competitive or superior performance for the usual applications of the synthetic control and difference-in-difference methods. Another method in this vein is trajectory balancing (Hazlett and Xu (2018)), which also offers a reweighting-based counterfactual, but also implements a kernel expansion thus relaxing a linearity assumption. A more detailed description of the intuition behind those methods is offered in Appendix 5. We also confirm that our results hold if we employ more traditional linear TWFE methods, even though those estimates are unlikely to have causal interpretations. See Appendices B3, B4, B5.

We estimate the equivalent of the following equation:

$$Y_{it} = \alpha + \beta_1 Software_i + \sum_{t=2012}^{2018} \Gamma'(Year_t \times Software_i) + X'_{it}\gamma + \epsilon_{it}$$

Here, Y is an outcome for the relevant unit of analysis i in year t.

As we estimate three different types of outcomes, we use three different types of units of analysis. For the investigation of startup funding, we use firm-level data; when looking at the exit events, we use groups of firms within the thematic classification. Patent declaratory judgments are examined at the patent-class-year level. Consequently, the description of "software-relatedness" adapts in accordance with each unit of analysis. Table A1 in Appendix provides an overview of the units of analysis for each outcome of interest, complemented by the definition of belonging to the treatment group.

Outcomes are the amount of US dollars raised from the venture firms in total, early-stage and late-stage funding. *Software* is an indicator for the firm *i*'s reliance on software patents prior to 2014. It equals 1 if the firm *i* had at least one patent labeled as a software patent by USPTO. Another group of outcomes - "Exits" - includes IPOs, acquisitions, and non-monetized exits. For this group of outcomes, *Software* is an indicator for the category *i*'s reliance on software patents prior to 2014. Thus, our resulting coefficients of interest are given by vector Γ. We expect to be zero before 2014 and have a substantive interpretation after 2014. X_i are the covariates for firm *i*. The third group of outcomes we are declaratory judgments.

The Alice Decision and Funds Raised by a Startup

In this section, we explore if the *Alice* decision affected the amount of funds received by a technological startup from the venture investors. Here, the outcome is the amount of funds raised by a startup from venture capital firms (in USD) in a given year. If the firms had multiple funding events in a year, all the funding raised in those events is aggregated. The results are presented in Table 1. We observe that, for the firms with software patents, the amount of funds they raise goes down after the *Alice* decision by 2.6 mlllion USD with confidence intervals ranging from 530 thousand USD to 4.7 million USD .This signifies that the effect of *Alice* on the ability of software startups to raise funds was large relative to baseline and negative. The corresponding trends are shown on Figure C1 in Appendix C.

Importantly, the CrunchBase data allows us to separate between early-stage and late-stage funding. We consider funding rounds that are labeled by the terms commonly used in the venture capital industry to indicate early funding ("seed", "angel", "round A" etc) to be early-stage, because other types of funding (usually, "round B", "round C" etc) be late-stage.

As we can see from columns "Early" and "Late", the effect is entirely driven by late-stage funding. The effect on early-stage funding is not significant[6]. What can explain such heterogeneity? One of the plausible explanations is that investors consider patent protections an important factor only at the later stages. There is a substantial lag between patent application and patent being granted. approval, so when firms seek funding, they are unlikely to have acquired patents for their technology yet. Thus, it is reasonable to expect that the patents might matter – and thus the *Alice* decision might matter– only for more mature startups. Another possible explanation is that at the early stage, the technology is not fully mature so it is not separable from the inventor, making patent protection less significant. In the meantime, because the later rounds of financing as a rule require that the firm establishes a revenue stream, our results imply that its market presence might be at risk if the patents it relies on face a danger of invalidation, and this danger might be reflected in the VC funding decisions.

We employ two placebo tests for our estimation. The "Placebo Time" retains the treatment group as previously specified, yet dictates that the commencement of the treatment period is in 2012. The selection of this particular year is motivated by its capacity to possibly introduce bias into our results. The year 2012 marks the Supreme Court's ruling in the case of Mayo v. Prometheus where the Court determined that a patent for a diagnostic procedure offered no genuine inventiveness. According to some observers, this decision "created substantial uncertainty with respect to patent eligibility of a large number of issued patent claims" (Holman, 2012). When we relabel 2012 as a treatment year,

[6]It's important to note that each of the outcomes we estimate, in the synthetic difference in differences estimation, requires its own counterfactual. Thus the total result cannot be viewed as convex combination of the results on the subsamples.

the coefficient remains negative but becomes small and not significant. In our second placebo test, shown in the column "Placebo Group", we keep the start of the treatment period at 2014, but drop the treated units from the data, and assign the random firms from the control group treatment status, keeping the proportion of treated units the same as in the original model. It lends robust empirical support to the claim that the *Alice* decision is indeed the driver of the observed change in the funding patterns of start-ups in software-related industries.

We confirm the robustness of the results by estimating the same model using the trajectory balancing approach (Hazlett and Xu (2018)). The results are presented in Table B1 in the Appendix.

The Alice Decision and Startup's Success

How did the *Alice* ruling affect the probability of success of a startup? Following (Wang, Pahnke and McDonald, 2022; Ewens and Marx, 2018), we define success as an "exit": an event where a startup either takes the public route by raising capital via an Initial Public Offering (IPO) or is acquired by another enterprise. We study the probability of a non-monetized exit - a startup's dissolution not instigated by an IPO or acquisition. We perceive this as a measure of startup failure, operating under the assumption that the founder deemed it more prudent to close the startup rather than cultivate it further.

As in the previous section we have shown that software-related startups were able to raise fewer funds from venture capital, especially at the late-stage funding, the expectation was that the weaker patent protection would make them also less attractive for acquisitions and IPOs. We expected to see an increase in non-monetized exits due to limited funding opportunities.

Similar to Section 4, we estimate synthetic difference-in-differences and trajectory balancing. Our unit of observation here is 'category', as delineated in the CrunchBase dataset. A 'category' is a granular representation of the industry in which the startups operate. A key decision in our research design was the criteria to categorize a 'category' as software-related. We exhibit two sets of outcomes: the first where a category is deemed software-related if at least 50% of its startups fall under the software umbrella, and the second where the cutoff is at least 80%. Table 2 reveals the results of the synthetic difference-in-difference estimation using a 50% cutoff, augmented with IPO time and group placebo treatments (columns IPO P.T. and IPO P.G., respectively). [7].

We observe that the frequency of non-monetized exits did not increase for the affected categories. Because the incidence of acquisitions has indeed experienced a downturn, the frequency of IPOs has seen an increase. The aggregate count of exits remained unchanged. These observations propose that the shortfall in late-stage financing, brought on by the dilution of patent protection, did not usher in deleterious effects on the survivability of startups, at least within the time frame of 2014-2018. These conclusions are corroborated in table B2 which presents the results of the trajectory balancing estimation. The placebo tests using 2012 as the treatment year, and a "treated" group randomly selected from non-treated units, display a null effect.

The decrease in the probability of an acquisition is not surprising given that the stock of patents a firm has is often a consideration in the acquisition process. An increase in the IPO probability might be driven by the firms that would otherwise be acquired. In simpler terms, if a firm is no longer a viable target for an acquisition, the only way to secure exit might be an IPO, thus what we observe is some substitution between IPOs and acquisitions.[8]

There is a discrepancy between the trajectory balancing and synthetic difference-in-differences estimation of non-monetized exits (see Appendix 5). Because the trajectory balancing detects a significant decline in non-monetized exits after a small insignificant spike, SDID puts more weight on that initial time period - hence, detecting an insignifi-

[7]The corresponding trends are presented on figures C2-C4

[8]Unfortunately, IPO valuations are not available in the CruchBase dataset for most of the IPOs thus it's impossible to test this mechanism directly.

cant positive effect. This difference is explained by different assumptions of each method regarding the weights of various periods and linearity of the treatment effects: because trajectory balancing allows for the non-linearity of the effects, synthetic difference-in-differences assumes linear effects, placing higher waits on periods closer to the treatment date.

The Alice Decision and Patent Trolls

In the previous section, we have established that the probability of non-monetized exit (company closure) did not increase, and in some specifications was reduced after*Alice*. A reasonable question to ask is why, given that in our other estimations, we have shown that the probability of funding success goes down, this is not reflected in the probability of firm closures. Simply put, there must be some countervailing influences that *help* startups survive.

In this section, we look at the influence of the *Alice* decision on the activity of so-called "patent trolls". Those are non-practicing firms whose business model is to threaten startups with frivolous patent infringement cases, with the startups usually do not have much resources to fight such lawsuits.

Patent trolls present a significant problem for startups' very existence. Chien (2013*a*) analyzed a database of patent litigations from 2006 to 2012 and augmented it with a survey of 223 tech company startups, 79 of which had received a demand from NPEs. According to the study, companies with less than $100M annual revenue constituted at least 66% of unique defendants to NPE suits and at least 55% of unique defendants in troll suits made $10M per year or less. Among the survey respondents, about half of companies making less than $100 million in revenue reported that receiving a patent demand letter had a significant operational impact(business strategy pivot, product change, delay in hiring or meeting an operational milestone, reduction in the value of the company, and/or shutdown of the business), because none of the companies with revenues above

$100 million reported any significant operational impact as a result of receiving a patent demand letter, underscoring the particular danger patent infringement suits pose to start-ups.

NPs have been one of the main contributors to the tenfold increase in patent litigation since 2005 (Cohen, Gurun and Kominers, 2019). However, according to the survey data, most instances of NPEs targeting firms with infringement claims don't result in actual litigation (Chien, 2013*b*). Instead, NPEs commonly send "demand letters" with claims of patent infringement. Such letters can target thousands of firms, offering licensing deals to avoid litigation. Appel, Farre-Mensa and Simintzi (2019) cite a case of one company - MPHJ sending demand letters to over 16,000 firms between 2012 and 2013 but never filing a single lawsuit.

The post-Alice decrease in the patent protection of software patents could have also weakened the power of the "patent trolls" to threaten startups. One way to explore these potential effects is to look at the declaratory judgments. A declaratory judgment is a statement by the court that resolves uncertainty for the potential litigant. For startups, it is a relatively cheap way to fend off a potential frivolous attack by a patent troll.

Figure 2 shows the raw data for declaratory judgments claiming both non-infringement cases and invalidity for the Declaratory judgments related to the patents. Both non-infringement and invalidity judgments help firms defend themselves from frivolous attacks by the NPEs. Non-infringement cases happen, as the name suggests when the firm alleges that it did not infringe on any of the assets in the NPEs pool of patents. If such a claim is successful then the firm is cleared of the charges of the NPE. An invalidity case happens when the firm alleges that the set of patents NPE used to attack the firm was not valid, to begin with. If such a claim is successful then the NPE can no longer use the disputed patent. As we see in Figure 2, declaratory judgments claiming both non-infringement and invalidity cases have risen substantially after the *Alice* decision for software patents but remained roughly on a similar level for non-software patents. It is also instructive that, as shown on Figure 3 there is a spike happened for the invalidity claims alone – whose numbers were close to zero before the *Alice* decision.

Importantly, there appears no change in declaratory judgments claiming non-infringement only: *Alice* decision does not provide an opportunity to infringe on valid patents. Instead, it provides a path to invalidate patents that only claimed novelty due to the use of computer technology.

Thus the evidence appears consistent with the following mechanism behind the longer survival of firms: after the *Alice* decision technological startups become more resilient to the attacks by the NPEs whereas they acquire a stronger means for defense against the opportunistic claims.

We employ a synthetic difference in differences to estimate the effects of *Alice* on the cases where a patent is challenged in court.

We find that the *Alice* decision had a significant impact on the invalidity cases (column 2), increasing them for the software-reliant groups of firms by 0.03 percentage point, which is a 100 percent increase when compared to the baseline. The corresponding trends are presented on Figure C5 in Appendix C. We also find no effect in the placebo estimations.

5. Conclusion

This article explores the effect of patent protection on innovative entrepreneurship. In particular, we explore the effect of the 2014 U.S. Supreme Court decision that significantly loosened the enforceability of software patents because leaving other types of patents intact. Using detailed data on the funding rounds, exits, and lawsuits, we demonstrate several findings. First, startups that relied on software patents started raising less money from venture capital firms, this effect is driven by late funding rounds. Second, we find that the decrease in patent protection increases the probability of IPOs but decreases the probability of an "exit" through an acquisition. Third, we find that company the effect on company closures is negative: more firms survive for longer, and, finally, the effect on the number of court cases claiming patent invalidity is positive.

How can we explain all these findings? Our view is that the loosening of protection of software patents had two main effects: it offered firms a powerful defense mechanism against opportunistic attacks from non-practicing entities (“patent trolls”). Hence, the rise in patent invalidity cases as well as the decrease in company closures. It also made firms less attractive to potential acquirers (because patents are an important part of a company’s value) and thus - to potential venture capital investors. Some of the high-quality firms that would otherwise be acquired are able to secure an IPO.

In sum, we observed two contrasting effects of strengthened patent protection on startups: a decrease in access to VC funding, contrasted with a heightened resilience against patent troll litigation. The question arises as to which effect carries more weight. Unfortunately, our data is limited when it comes to IPOs and acquisitions, which restricts our ability to fully analyze the impact on successful startup exits. However, we do notice a trend of fewer startups folding without financial gain in sectors with weaker patent protection. Whereas VC funding is primarily aimed at fostering startup growth and ensuring a successful exit, we believe that the reduction in these unsuccessful exits is a more critical outcome than the lessened VC funding. This implies that because startups may initially struggle to secure funding, the long-term benefits of stronger patent protection seem to support better outcomes for startups, potentially leading to more successful exits in the long run.

These findings have several implications for policymakers and practitioners. Most importantly, the policy decisions regarding patent protection should take into account the nuanced effects of such protections on innovative entrepreneurship. Policymakers should be aware of the trade-offs between protecting firms from opportunistic attacks by non-practicing entities and limiting the ability of startups to raise venture funding and attract acquirers. The article also shows that patent trolls can pose a significant threat to firms. Therefore, policymakers should consider regulating activities of patent trolls thus promoting a better environment for innovative entrepreneurship.

References

Abadie, Alberto, Alexis Diamond and Jens Hainmueller. 2010. "Synthetic control methods for comparative case studies: Estimating the effect of Californiaâs tobacco control program." *Journal of the American statistical Association* 105(490):493–505.

Acemoglu, Daron, Kostas Bimpikis and Asuman Ozdaglar. 2011. "Experimentation, patents, and innovation." *American Economic Journal: Microeconomics* 3(1):37–77.

Acemoglu, Daron, Mikhail Golosov and Aleh Tsyvinski. 2011. "Political economy of Ramsey taxation." *Journal of Public Economics* 95(7-8):467–475.

Acemoglu, Daron and Ufuk Akcigit. 2012. "Intellectual property rights policy, competition and innovation." *Journal of the European Economic Association* 10(1):1–42.

Acikalin, Utku, Tolga Caskurlu, Gerard Hoberg and Gordon M Phillips. 2022. "Intellectual Property Protection Lost and Competition: An Examination Using Machine Learning." *Available at SSRN 4023622* .

Aghion, Philippe, Christopher Harris, Peter Howitt and John Vickers. 2001. "Competition, imitation and growth with step-by-step innovation." *The Review of Economic Studies* 68(3):467–492.

Amable, Bruno, Jean-Bernard Chatelain and Kirsten Ralf. 2010. "Patents as collateral." *Journal of Economic Dynamics and Control* 34(6):1092–1104.

Andrews, Dan, Chiara Criscuolo and Carlo Menon. 2014. "Do resources flow to patenting firms?: Cross-country evidence from firm level data.".

Appel, Ian, Joan Farre-Mensa and Elena Simintzi. 2019. "Patent trolls and startup employment." *Journal of Financial Economics* 133(3):708–725.

Arkhangelsky, Dmitry, Susan Athey, David A Hirshberg, Guido W Imbens and Stefan Wager. 2021. "Synthetic difference-in-differences." *American Economic Review* 111(12):4088–4118.

Bae, Sangik. 2019. "Overcoming Abstract Idea Exception of Patent Subject Matter Eligibility under 2019 Revised Patent Subject Matter Eligibility Guidance, 18 J. Marshall Rev. Intell. Prop. L. 382 (2019)." *UIC Review of Intellectual Property Law* 18(4):2.

Baumol, William J. 2004. "Entrepreneurial enterprises, large established firms and other components of the free-market growth machine." *Small business economics* 23:9–21.

Bessen, James and Eric Maskin. 2009. "Sequential innovation, patents, and imitation." *The RAND Journal of Economics* 40(4):611–635.

Boldrin, Michele and David K Levine. 2013. "The case against patents." *Journal of Economic Perspectives* 27(1):3–22.

Boldrin, Michele, David K Levine et al. 2008. *Against intellectual monopoly*. Vol. 62 Cambridge University Press Cambridge.

Budish, Eric, Benjamin N Roin and Heidi Williams. 2016. "Patents and research investments: Assessing the empirical evidence." *American Economic Review* 106(5):183–187.

Chien, Colleen. 2013*a*. "Startups and patent trolls." *Stan. Tech. L. Rev.* 17:461.

Chien, Colleen V. 2013*b*. "Patent assertion and startup innovation." *New America Foundation, Open Technology Institute White Paper* .

Cohen, Lauren, Umit G Gurun and Scott Duke Kominers. 2019. "Patent trolls: Evidence from targeted firms." *Management Science* 65(12):5461–5486.

De Rassenfosse, Gaétan and Timo Fischer. 2016. "Venture debt financing: Determinants of the lending decision." *Strategic Entrepreneurship Journal* 10(3):235–256.

Ewens, Michael and Matt Marx. 2018. "Founder replacement and startup performance." *The Review of Financial Studies* 31(4):1532–1565.

Farre-Mensa, Joan, Deepak Hegde and Alexander Ljungqvist. 2020. "What is a patent worth? Evidence from the US patent âlotteryâ." *The Journal of Finance* 75(2):639–682.

Giorcelli, Michela and Petra Moser. 2020. "Copyrights and creativity: Evidence from Italian opera in the Napoleonic age." *Journal of Political Economy* 128(11):4163–4210.

Graham, Stuart JH and David C Mowery. 2003. "Intellectual property protection in the US software industry." *Patents in the Knowledge-based Economy* 219:231.

Graham, Stuart and Saurabh Vishnubhakat. 2013. "Of smart phone wars and software patents." *Journal of Economic Perspectives* 27(1):67–86.

Hall, Bronwyn H and Megan MacGarvie. 2010. "The private value of software patents." *Research Policy* 39(7):994–1009.

Hashai, Niron and Sarit Markovich. 2017. "Market entry by high technology startups: The effect of competition level and startup innovativeness." *Strategy Science* 2(3):141–160.

Hazlett, Chad and Yiqing Xu. 2018. "Trajectory balancing: A general reweighting approach to causal inference with time-series cross-sectional data." *Available at SSRN 3214231* .

Hochberg, Yael V, Carlos J Serrano and Rosemarie H Ziedonis. 2014. Patent collateral, investor commitment, and the market for venture lending. Technical report National Bureau of Economic Research.

Holman, By Christopher M. 2012. "Preliminary Thoughts on Mayo v. Prometheus: The Implications for Biotechnology.".

Kiklis, Micheal, Shu Chen and Matthew Zapadka. 2019. "Lessons Learned Five Years after Alice." *Managing Intell. Prop.* 283:20.

Koning, Rembrand, Sharique Hasan and Aaron Chatterji. 2022. "Experimentation and Start-up Performance: Evidence from A/B Testing." *Management Science* .

Lemley, Mark A and Samantha Zyontz. 2021. "Does Alice Target Patent Trolls?" *Journal of Empirical Legal Studies* 18(1):47–89.

Mann, William. 2018. "Creditor rights and innovation: Evidence from patent collateral." *Journal of Financial Economics* 130(1):25–47.

Marco, Alan C, Asrat Tesfayesus and Andrew A Toole. 2017. "Patent litigation data from US district court electronic records (1963-2015).".

Moser, Petra. 2005. "How do patent laws influence innovation? Evidence from nineteenth-century world's fairs." *American economic review* 95(4):1214–1236.

Moser, Petra. 2012. "Innovation without patents: Evidence from Worldâs Fairs." *The Journal of Law and Economics* 55(1):43–74.

Saltiel, Joseph. 2019. "In the courts: five years after Alice - five lessons learned from the treatment of software patents in litigation.".

Schneider, Cédric and Reinhilde Veugelers. 2010. "On young highly innovative companies: why they matter and how (not) to policy support them." *Industrial and Corporate change* 19(4):969–1007.

Schwartz, David L, Ted M Sichelman and Richard Miller. 2019. "USPTO Patent Number and Case Code File Dataset Documentation.".

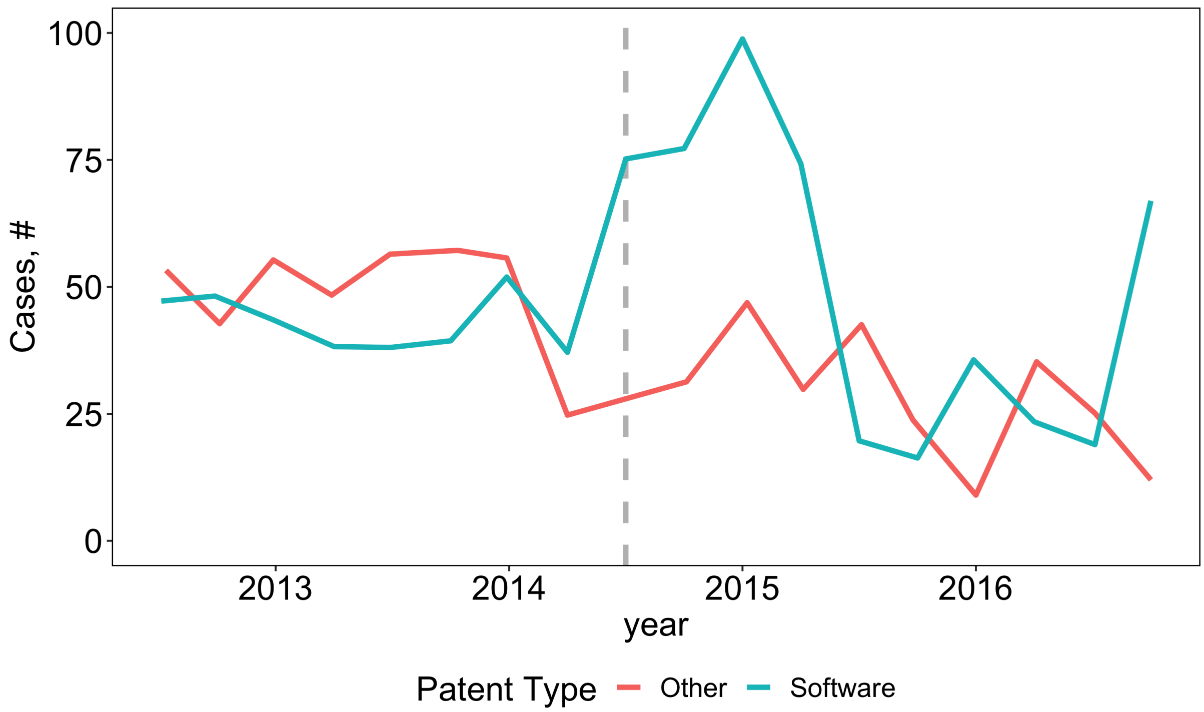
T. Vann Pearce, Jr. and Christopher Higgins. 2020. "The Effect of Alice and Its Progeny in 2020 on Software and 3D Printing Patents.". https://www.orrick.com/Articles/The-Effect-of-the-Alice-Decision-on-Software-and-3D-Printing-Patents.

Tran, Jasper L. 2019. "Alice at Seven." *J. Pat. & Trademark Off. Soc'y* 101:454.

van den Heuvel, Matthias and David Popp. 2022. The Role of Venture Capital and Governments in Clean Energy: Lessons from the First Cleantech Bubble. Technical report National Bureau of Economic Research.

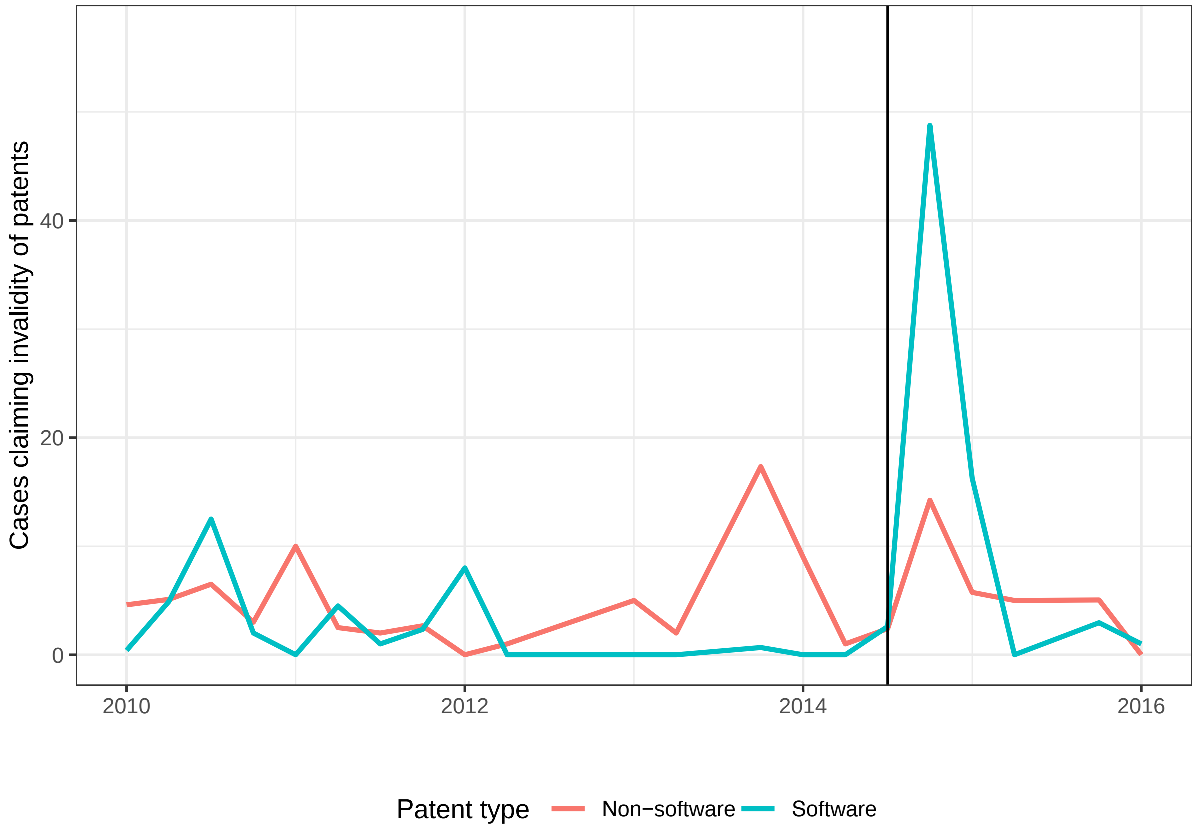
Wang, Dan, Emily Cox Pahnke and Rory M McDonald. 2022. "The past is prologue? Venture-capital syndicatesâ collaborative experience and start-up exits." *Academy of Management Journal* 65(2):371–402.

Figure 1: Quarterly number of cases claiming non-infringement and patent invalidity or invalidity of patent



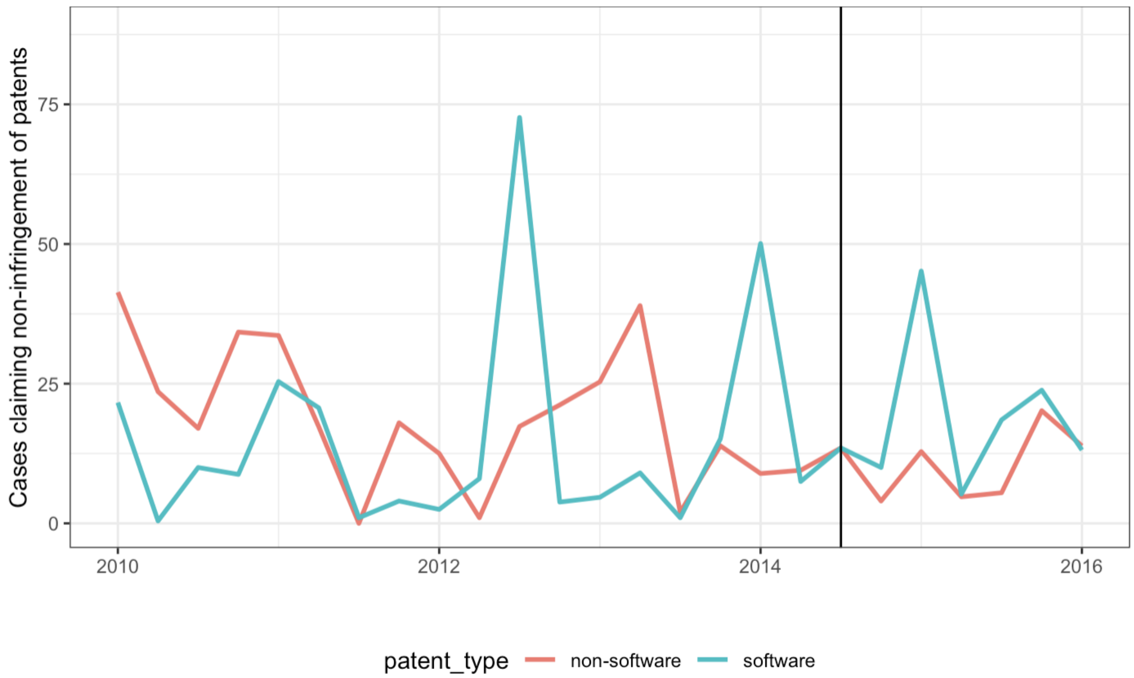
Note: The data source is: Schwartz, Sichelman and Miller (2019). The dashed vertical line shows second quarter of 2014.

Figure 2: Submissions for a declaratory judgement claiming invalidity of a patent



Note: The data source is: Schwartz, Sichelman and Miller (2019). The dashed vertical line shows second quarter of 2014.

Figure 3: Submissions for a declaratory judgement claiming non-infringement of a patent



Note: The data source is: Schwartz, Sichelman and Miller (2019). The dashed vertical line shows second quarter of 2014.

Table 1: Alice decision and VC funding: synthetic difference-in-differences approach

	Total	Early	Late	Placebo Time	Placebo Group
ATE	-264.9	6.934	-259.063	-55.23	27.897
CI	-476.66, -53.15	-1.3; 15.18	-267.3, -250.8	-186.05, 75.59	-147.75; 203.53
Baseline	191.7	12.7	137	144.5	180
N obs	154467	154467	154467	68652	147771
Years	2010-2018	2010-2018	2010-2018	2008-2014	2010-2018
N firms	17163	17163	17163	17163	16419
N firms treated	744	744	744	744	711

Notes: Dependent variable is USD (in 10,000). Jackknife estimation is used for calculations of 90 percent confidence intervals. Placebo Time is 2012, Placebo Group is randomly chosen from the control group to preserve the proportion of "treated" units in the dataset. Placebos are calculated for total funding. Source: Crunchbase. Calculations have been performed with R package synthdid.

Table 2: The *Alice* Decisions and Exits: Synthetic Difference on Differences approach, 50% cutoff

	Total	IPO	Acquired	NM Exit	IPO P.T.	IPO P. G.
ATE	-0.81	0.14	-0.05	0.05	0.09	0.09
CI	-0.17; 0.08	0.54; 0.22	-0.25; 0.1	-0.5;0.6	-0.04;0.2	-0.04;0.002
N obs	178222	178222	178222	178222	61649	46584
Years	2009-2018	2009-2018	2009-2018	2009-2018	2008-2014	2010-2018
N	36050	36050	36050	36050	8807	5176
Treated	18025	18025	18025	18025	4914	2950

Notes: Dependent variable is the percent of relevant exits per "category", as defined in CrunchBase dataset. A category is deemed software-related if at least 50% of its startups fall under the software umbrella. Jackknife estimation is used for calculations of 90 percent confidence intervals. NM Exit denotes the results for non-monetized exit. IPO P.T. denotes the results of placebo test, where "treatment" time is set to 2012 IPO P.G. denotes the results of placebo analysis where threatment group is removed from the data, and the random group of untreated companies is denoted as "treated", preserve the proportion of "treated" units in the dataset. Placebo extemations are calculated for an IPO as an outcome variable. Source: Crunchbase. Calculations have been performed with R package synthdid.

Table 3: Alice Decision and Patent Litigations, 50% cutoff

	Invld + Non-Inf	Invalidity	Non-Infringement	Placebo Time	Placebo Group
ATE	-0.0032	0.0029	-0.0005	0.0012	0.0020
CI	-0.0220, 0.0156	0.0005, 0.0052	-0.0013, 0.0002	-0.0007, 0.0032	-0.0021, 0.0061
N obs	89138	89138	89138	89138	89138
Years	2010-2016	2010-2016	2010-2016	2010-2016	2010-2016
Baseline	0.0112	0.0027	9.07e-04	0.0027	0.0027
N classes	14217	14217	14217	14217	14217
N treated	2353	2353	2353	2353	2353

Notes: Dependent variable is the percent of declaratory judgment cases per patent subclass (at 5 letters of patent classification). A patent subclass is deemed software-related if at least 50% of its patents have "software" designation. Jackknife estimation is used for calculations of 90 percent confidence intervals. Placebo Time is 2012, Placebo Group is randomly chosen from the control group to preserve the proportion of "treated" units in the dataset. Placebos are calculated for Invalidity DJs. Source: Crunchbase. Calculations have been performed with R package synthdid.

Appendices

Appendix A: Variable description

Table A1: Outcome Variable Definitions and the Units of Analysis

Outcome type	Unit of analysis	Definition of Treatment status
Funding	Firm-level	S=1 if more than 50% of its patents are in software 2014
Exits	Industry-level	S=1 if category (as defined by CrunchBase) has more than average software-related firms
DJs	Patent-class level	S=1 if a patent class has more than 80% patents software-related

Appendix B: Alternative Specifications

Trajectory Balancing Approach, Intuition

We seek to estimate the effect of the *Alice* decision on the success of technological startups where when success is measured by the amount of raised funds from the VC firms and by successful exits (IPOs and acquisitions)[9]. The main advantage of the chosen method is that it balances treated and non-treated units on their pre-treatment trajectories and not on the period averages. The balance is achieved by applying mean-balancing weights to the units, and weights themselves are calculated using the kernel the expansions of the covariates.

The intuition behind the method can be understood as follows: assume that both the outcome and treatment depend on omitted time-varying variables as well as some fixed variables. If this is the case, then, once we apply such a weighting to the control units that their pre-treatment trend looks exactly like the trend of the treated unit, those unobserved confounders are automatically adjusted for,

The weights applied to the control units follow the formula:

$$\frac{1}{N_{tr}} \sum_{G_i=1} \phi(Y_{i,pre}) = \sum_{G_i=0} w_i \phi(Y_{i,pre}), \tag{1}$$

For the control group, $\sum_{G_i=0} w_i = 1, w_i > 0$. The choice of ϕ is achieved with a Gaussian kernel $k(Y_i, Y_j) = exp(-||Y_i - Y_j||^2/h)$.

Then, under a set of general assumptions the Average Treatment Effect on the treated is calculated as follows:

[9] As we observe the same firms over multiple years, our data is longitudinal in nature. It has been customary to use the two-way fixed effects (TWFE) approach for the estimation but such an approach can suffer from multiple issues when there is a reason to expect heterogeneous treatment effects and multiple nonlinearities. Therefore, we do not use the TWFE approach for our main estimation. Instead, we used an approach based on non-parametric trajectory balancing (Hazlett and Xu (2018)).

$$\widehat{ATT}_t^k = \frac{1}{N_{tr}} \sum_{G_i=1} Y_{it} - \sum_{G_i=0} w_i Y_{it} \tag{2}$$

.

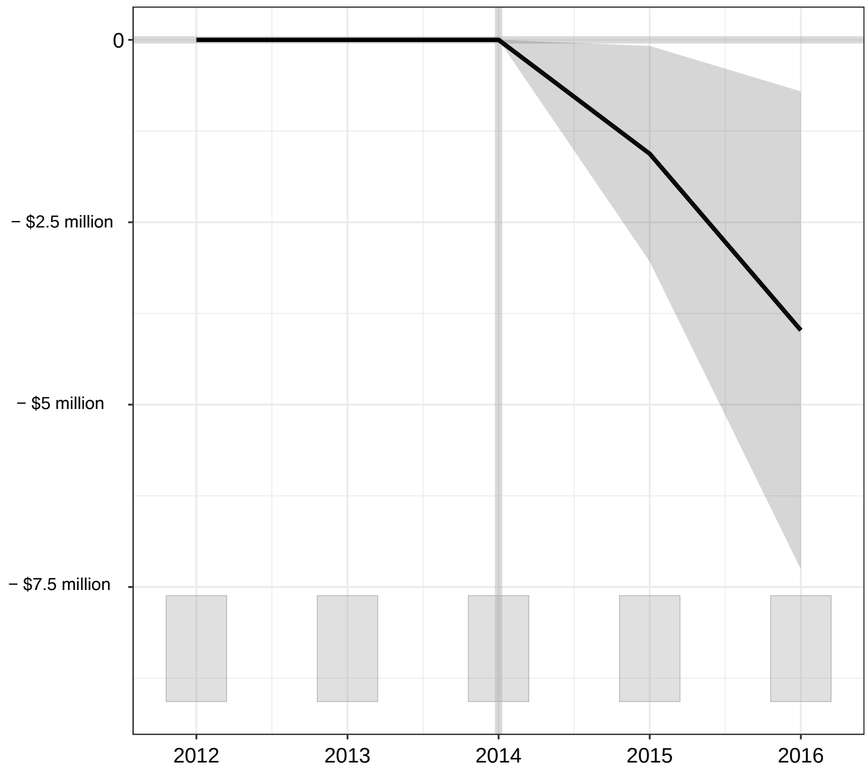
Trajectory Balancing Approach: Funding and Exits

Table B1: Funds raised by start-ups: TJBAL approach

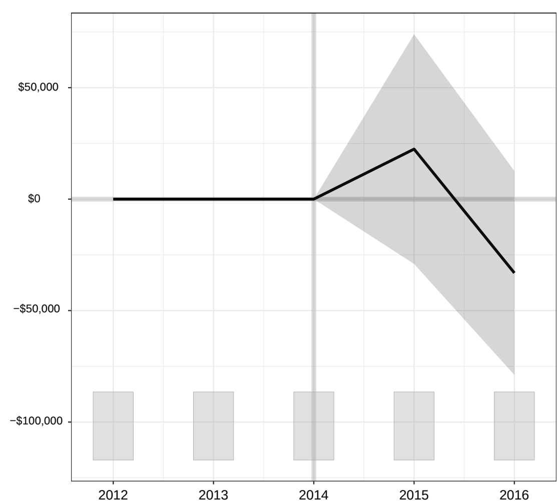
0000 USD	Total	Early	Late	Placebo Time	Placebo Group
ATE	-221	-6.89	-188.7	712	878
CI	-4286;-132	-16; 2	-347; -29	-77; 219	-56; 232
Baseline	191.7	12.7	137	144.5	180
N obs	154467	154467	154467	68652	147771
Years	2010-2018	2010-2018	2010-2018	2008-2014	2010-2018
N firms	17163	17163	17163	17163	16419
N firms treated	744	744	744	744	711

Table B2: Exits, TJBAL approach, 50% cutoff

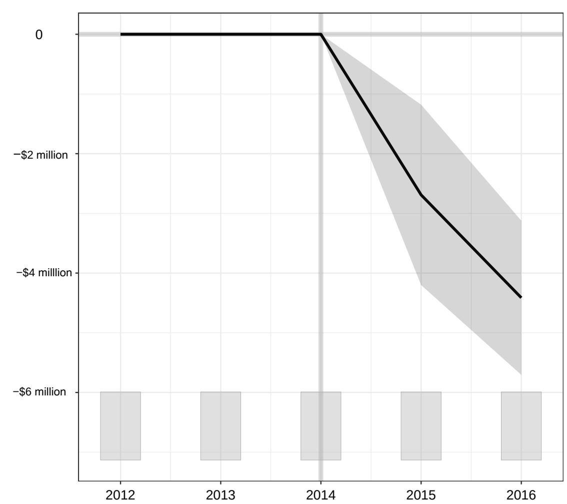
	Total	IPO	Acquired	Closed	IPO P. T.	IPO P. G.
ATE	-0.0011	0.0003	-0.0017	0.0008	-0.0006	0.001
CI	-0.0023;2e-04	1e-04;5e-04	-0.0031; -0.0004	-0.0021;0.0037	-0.0014;0.0002	-4e-04;0.0023
N obs	109269	109269	109269	109069	61257	46314
Years	2010-2018	2010-2018	2010-2018	2010-2018	2008-2014	2010-2018
N cat	12141	12141	12141	12141	8751	5146
N cat tr	6965	6965	6965	6965	4894	2933



(a) All funds

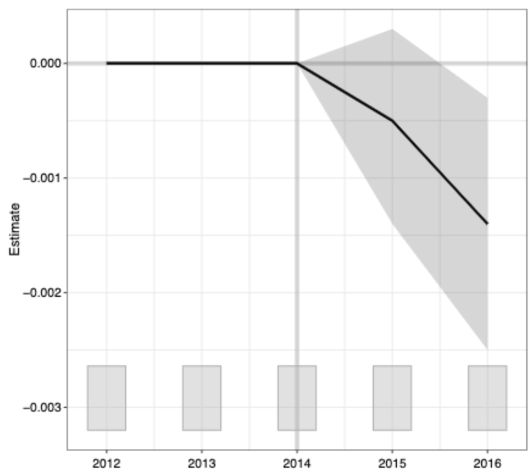


(b) Early funds

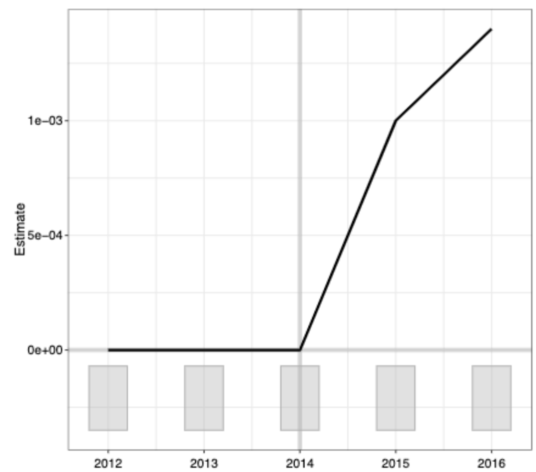


(c) Late funds

Figure B1: Trajectory-balancing estimation of funding changes for software start-ups



(a) Acquisitions



(b) IPOs

Figure B2: Trajectory-balancing estimation of successful exits of software start-ups

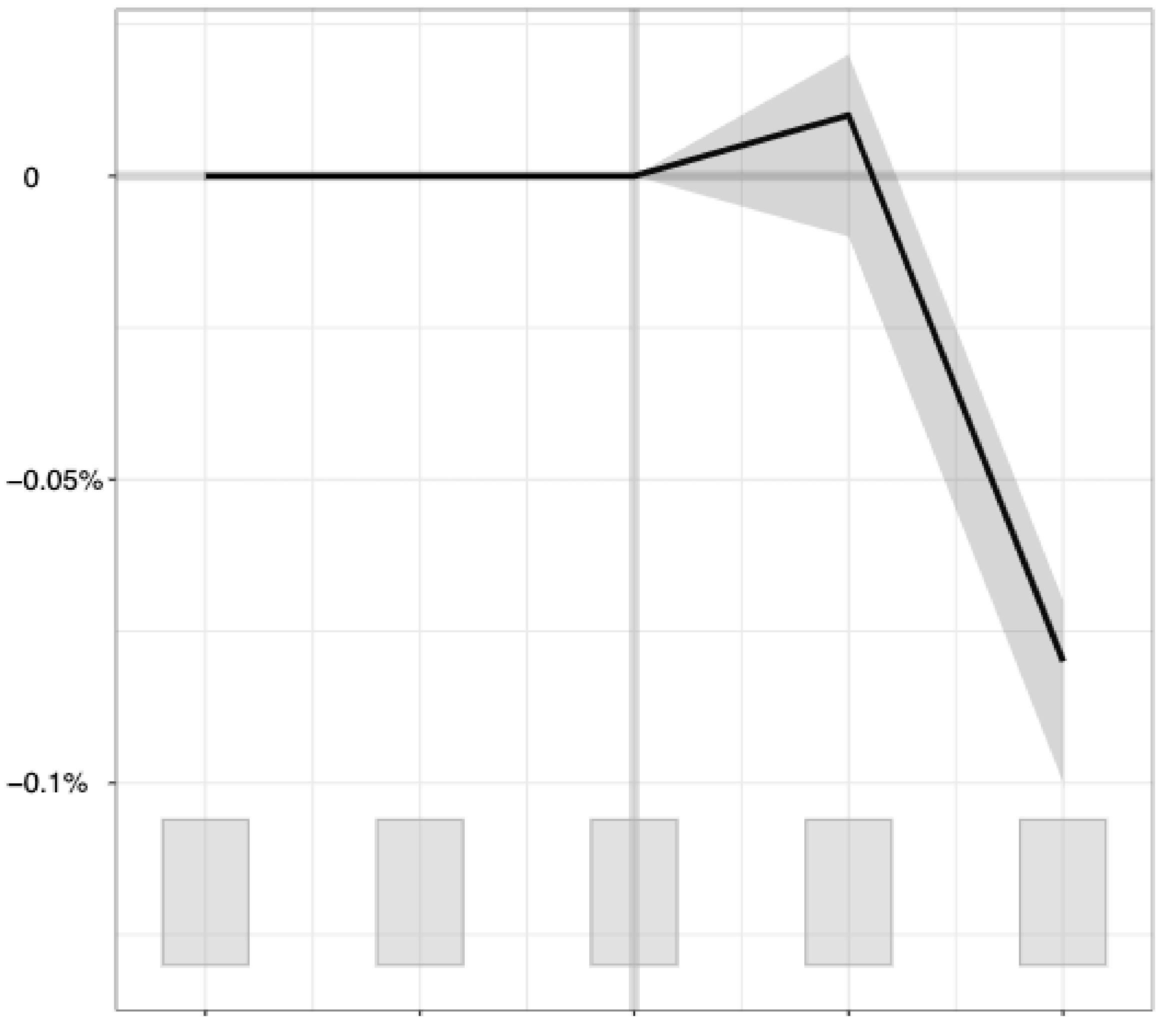


Figure B3: Trajectory-balancing estimation of unsuccessful exits of software start-ups

Two-way Fixed Effects Specifications

Table B3: Exits, TWFE approach, 50% cutoff

	Acquired	IPO	Closed	Exit
Treated	-0.006	0.004	-0.002	-0.003
	(0.003)	(0.001)	(0.001)	(0.001)
N	96866	96866	96866	96866
R2	0.842	0.797	0.756	0.731
FE: Year	X	X	X	X
FE: Category	X	X	X	X

Table B4: Funding, TWFE approach, 50% cutoff

	Early	Late	Total
Treated	-173.895	166.960	-24.548
	(22.358)	(227.211)	(259.466)
N	35029	35029	35029
R2	0.159	0.383	0.396
FE: Year	X	X	X
FE: Category	X	X	X

Table B5: Declaratory judgments, TWFE approach, 80% cutoff

	Non-infr + Invalidity	Invalidity	Non-Infringement
Treated	-0.000264	3.4e-05**	3e-05*
	(0.000134	(0.000145)	(1.5e-05)
N	99519	99519	99519
FE: Year	X	X	X
FE: Category	X	X	X

Appendix C: Synthetic difference-in-differences figures

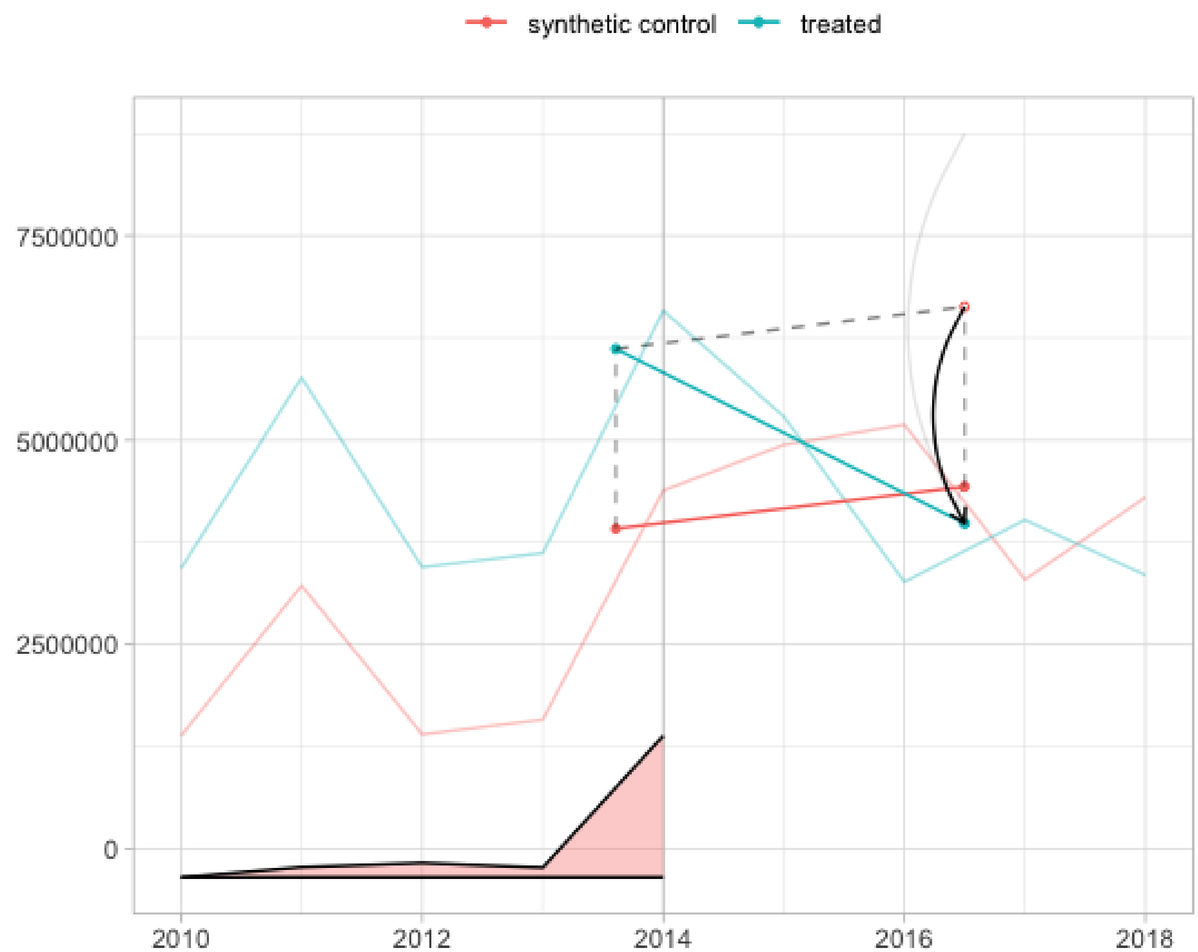


Figure C1: Synthetic difference-in-differences estimate of the effect of the Alice decision on funds raised.

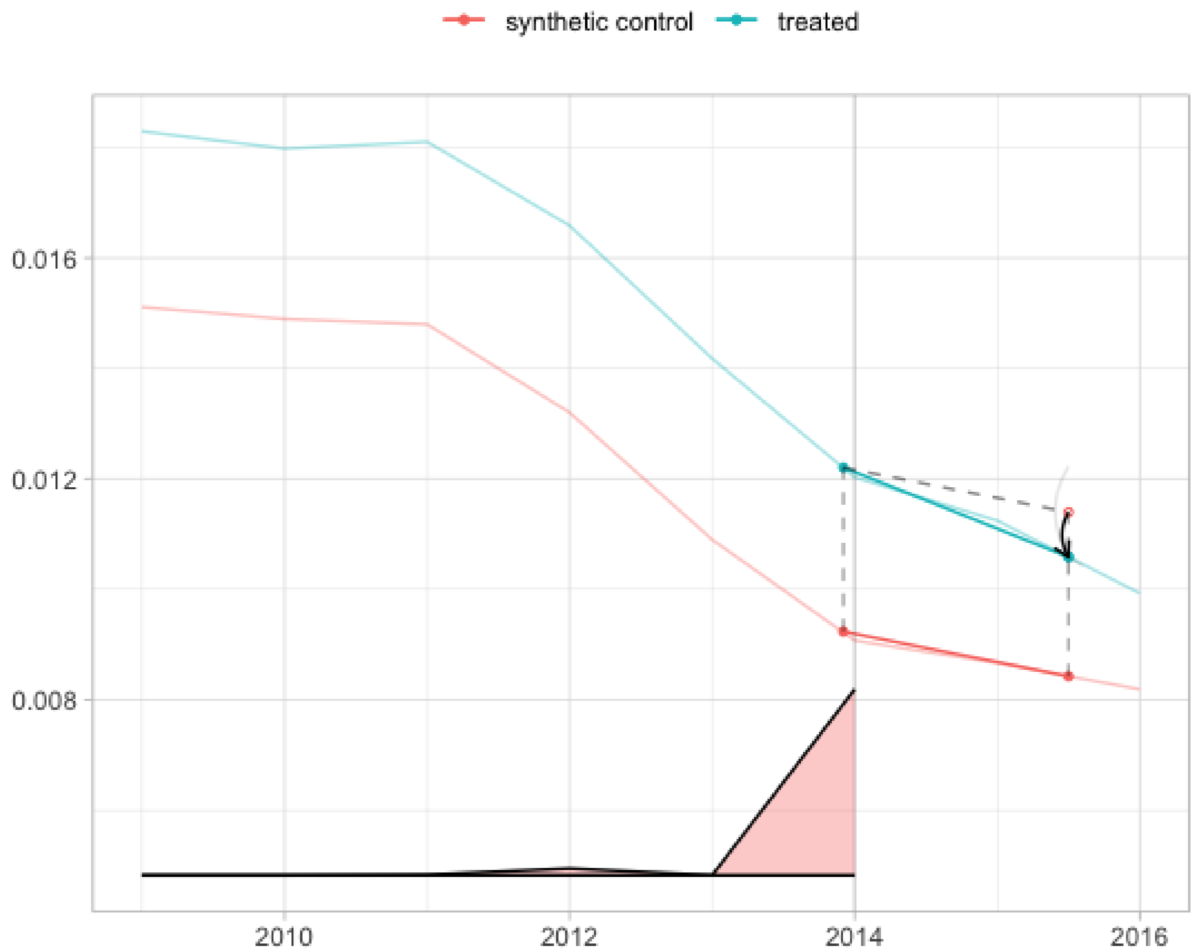


Figure C2: Synthetic difference-in-differences estimate of the effect of the Alice decision on the probability of an exit.

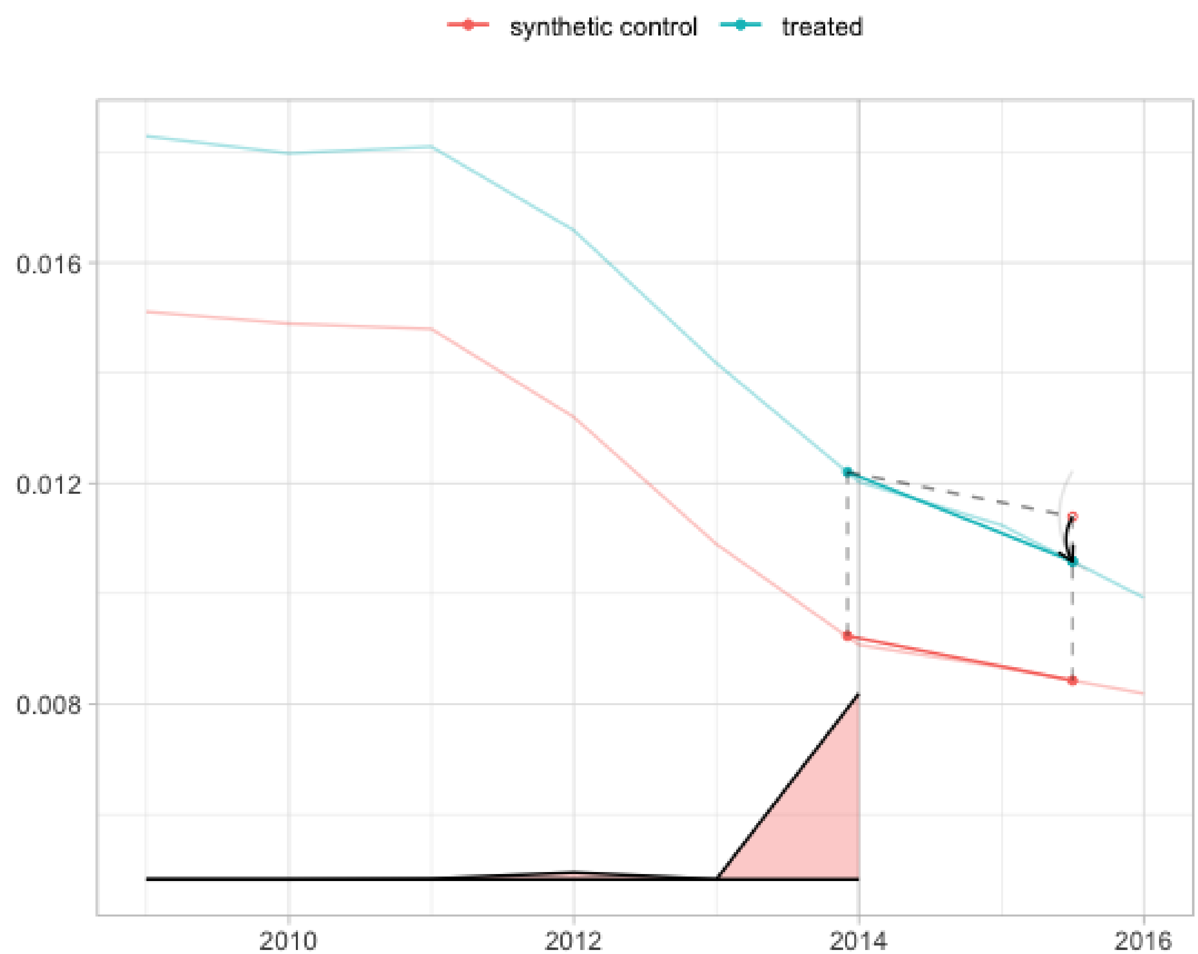


Figure C3: Synthetic difference-in-differences estimate of the effect of the Alice decision on the probability of an IPO.

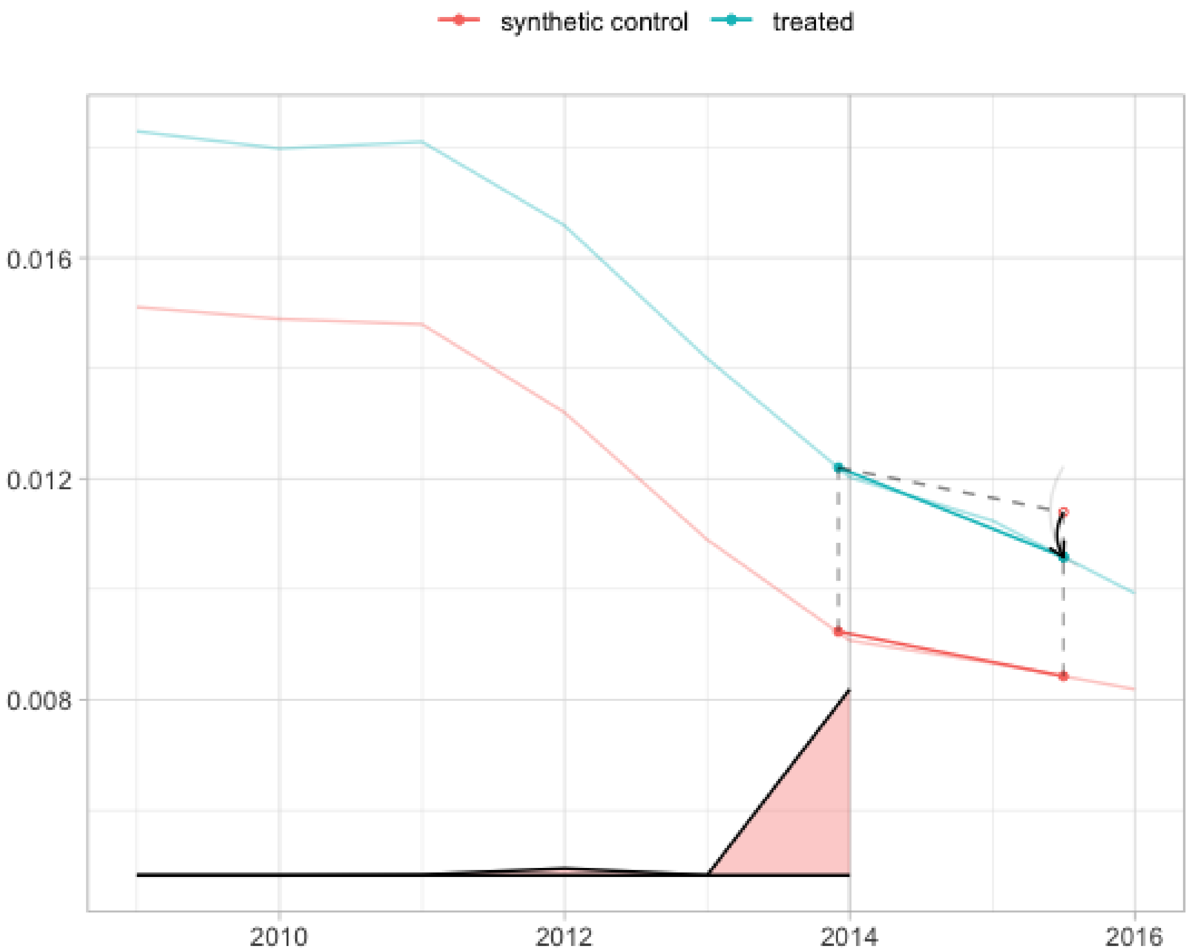


Figure C4: Synthetic difference-in-differences estimate of the effect of the Alice decision on the probability of nonmonetized exit.

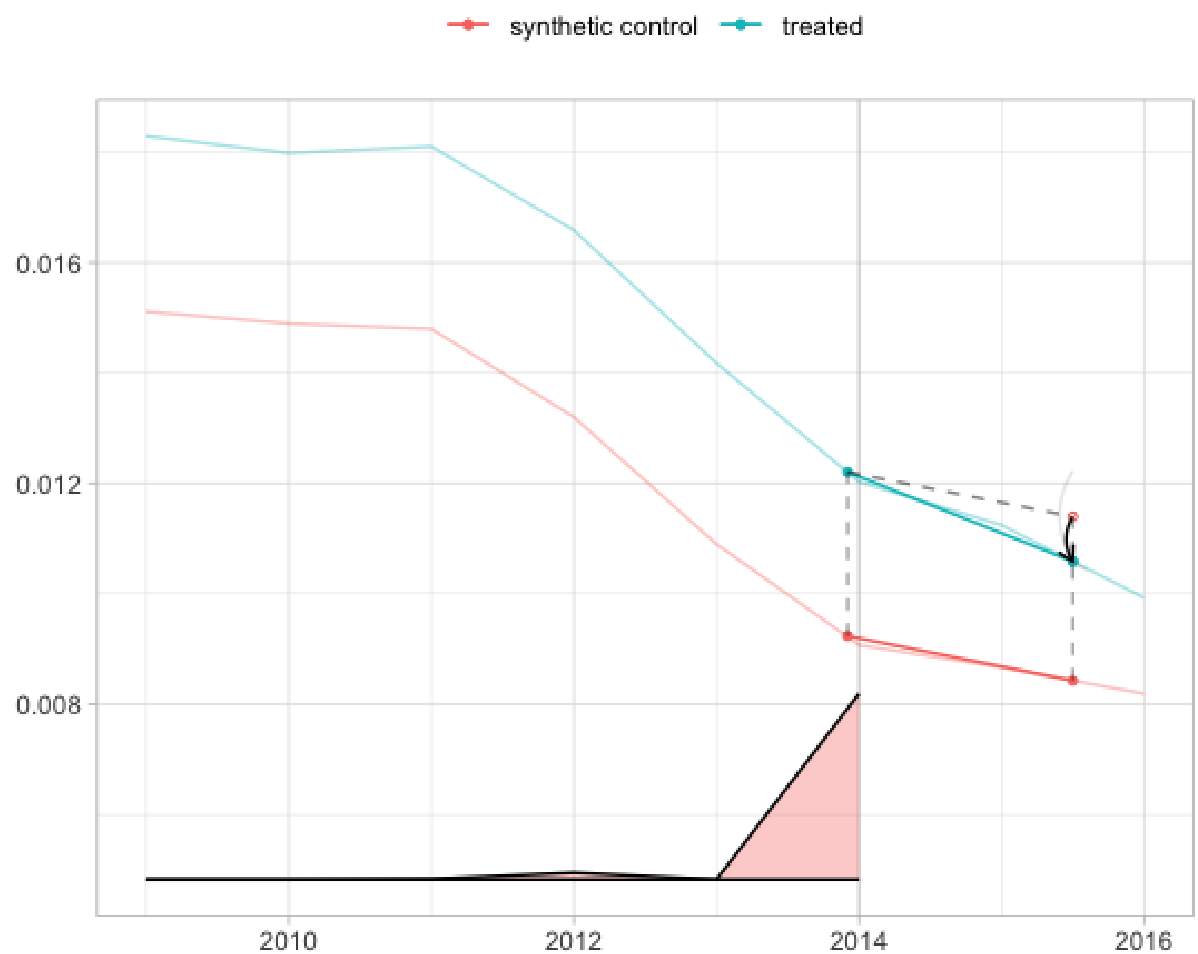


Figure C5: Synthetic difference-in-differences estimate of the effect of the Alice decision on the probability of a patent invalidity case.