How Does Patent Protection Affect Venture Capital Investment?

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Abstract

We study how patent protection affects venture capital (VC) investment in startups by exploiting the *Bilski v. Kappos* Supreme Court decision, which unexpectedly narrowed patent eligibility. Using variation in industry exposure to the ruling, we find that more exposed industries experienced larger increases in initial VC investment after the decision. The effect reflects a divergence in investment responses: exposure to *Bilski* is associated with more investment in startups without patents but less investment in startups with pre-*Bilski* patents. Our findings suggest that weaker patent protection lowers barriers to VC-backed entry and reallocates capital toward startups previously constrained by incumbent patents.

Keywords: Venture capital, innovation, intellectual property, patents, startups, Bilski
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1 Introduction

Patent protection is the primary legal mechanism through which inventors appropriate returns from innovation. By defining the scope and strength of the rights it confers, the patent system can shape how investors allocate capital to startups. Yet the direction of this influence remains contested. One view posits that patent protection enables startups to use patents to attract capital by signaling stronger appropriability and control over future returns from innovation (Arrow, 1962; Kitch, 1977). A second view argues that patent protection enables incumbents to use patents strategically to erect legal barriers that raise the entry costs for startups, thereby reducing investor interest in new entrants (Gilbert and Newbery, 1982). A third view suggests that patent protection has limited influence on startup funding because companies frequently rely on alternative appropriability mechanisms like lead time and secrecy (Mansfield, Schwartz, and Wagner, 1981; Cohen, Nelson, and Walsh, 2000).

The venture capital (VC) industry provides a natural setting to study the relationship between patent protection and startup funding. As professional intermediaries allocating capital on behalf of limited partners, venture capitalists are highly responsive to shifts in legal and institutional environments (Gompers, 1994). Moreover, VC-backed startups disproportionately drive innovation (Kortum and Lerner, 2000) and account for about half of recent IPOs (Ritter, 2025). VC firms' response to changes in patent protection is therefore informative about the broader economic consequences of changes in the patent system.

To identify the effect of patent protection on VC investment, we use the Supreme Court's *Bilski v. Kappos*, 561 U.S. 593 (2010) decision (henceforth *Bilski*) as a quasi-natural experiment. The ruling unexpectedly narrowed the scope of patent eligibility for certain types of inventions, creating cross-industry variation in exposure to the change. Exploiting this variation, we provide novel evidence on the relation between patent protection and VC investment.[1] Specifically, we find that industries more exposed to *Bilski* experienced larger

[1]While prior research shows that startups holding patents secure more VC funding (e.g., Hsu and Ziedonis, 2013 and Farre-Mensa, Hegde, and Ljungqvist, 2020), much less is known about how patent protection more broadly affects the allocation of VC investment. We discuss this literature in greater detail below.

increases in initial funding but not in follow-on funding. Investor responses to *Bilski* varied systematically with patent holdings: exposure to *Bilski* is associated with higher investment in startups without patents but lower investment in startups with pre-*Bilski* patents. Taken together, our results suggest a more nuanced link between patent rights and entrepreneurship than is commonly assumed: under some conditions, weaker patent protection can redirect capital toward less patent-intensive startups by reducing barriers to VC-backed entry.

To motivate our identification strategy, we briefly describe *Bilski* and its implications for patent protection. The case concerned whether a method for hedging risk in commodities trading qualified as patentable subject matter under §101 of the Patent Act. Historically, §101 excludes "abstract ideas" from eligibility – a category that encompasses a broad array of software and business-method innovations central to the startup economy. Prior to *Bilski*, the Federal Circuit relied on the "machine-or-transformation" test as the primary criterion for eligibility. This framework provided a clear pathway for protecting process-based innovations, effectively supporting a broad boundary for patentable subject matter in the digital and financial sectors.

The Supreme Court's decision in *Bilski* significantly altered these boundaries. While the Court invalidated the specific patent at issue, its broader impact lay in its refusal to maintain the "machine-or-transformation" test as a sufficient standard for eligibility, instead reaffirming the abstract-idea exclusion as a central constraint. This shift narrowed the domain of patentable innovation, particularly for business methods and software-adjacent technologies. The decision applied immediately to the existing stock of patents – whose enforceability became subject to renewed scrutiny – as well as to new patent applications facing higher rejection risk. As a result, the decision shifted expectations about the scope of patent protection and the returns to innovation in affected technologies (Delulio, 2010; Mills, 2010; Lemley, Risch, Sichelman, and Wagner, 2011).

This shift in patent protection standards translated into measurable changes in patent examination outcomes. In the two years following the decision, over 14% of all subject-matter

rejections for applications filed before *Bilski* cited the ruling. Exposure to rejections varied sharply across industries: Capital Markets/Institutions, Automation/Workflow Software, and Retail faced rates exceeding 20%, whereas Building Products, Energy Services, and Surgical Devices faced rates below 5%. This cross-industry variation forms the basis of our empirical strategy to identify the impact of patent protection on VC investment. While our identification leverages variation in new application outcomes, we separately show that *Bilski* also affected the enforceability of existing patents, consistent with a broad-based contraction in patent protection.

Using a difference-in-differences framework, we estimate how exposure to *Bilski* affected industry-level VC investment, as measured by total VC funding amounts (i.e., total VC dollars) and total VC funding rounds (i.e., total number of VC deals). We find that industries more affected by *Bilski* experienced significantly larger increases in both measures in the years following the decision. The magnitudes are economically meaningful: a one standard deviation increase in exposure corresponds to a 26% larger increase in total funding amounts and a 22% larger increase in total funding rounds. When we decompose total funding into initial and follow-on funding, we find that these effects are driven almost entirely by increases in initial funding. We confirm that these effects are not explained by pre-event trends or changes in entrepreneurial entry, remain robust to alternative sample construction and variable definition choices, and are driven by economically significant industries.

Since our sample overlaps with the Great Recession, one concern is that the estimates reflect differential post-crisis recovery rather than the change in patent eligibility. However, our results are similar when we exclude finance-related industries, which experienced particularly sharp contraction and rebound, or software-oriented industries, which were both highly exposed to *Bilski* and central to the VC recovery. The findings also persist when we exclude industries that experienced the strongest post-crisis increases in VC funding. Together, these tests indicate that our estimates are unlikely to be driven by sector-specific recovery dynamics.

The positive relation between exposure to *Bilski* and changes in VC funding reflects the net effect of two opposing forces induced by weaker patent protection. We outline a simple conceptual framework to clarify these mechanisms and guide interpretation of our results. First, weaker patent protection reduces incumbent deterrence, which lowers entry barriers and increases expected operating profits for all entrants. Second, weaker patent protection reduces the private value of patents, which diminishes the ability of patent-reliant startups to appropriate returns from innovation. For initial funding, the reduction in deterrence dominates: industries more exposed to *Bilski* experience significantly larger increases in entry-stage investment. For follow-on funding, the two forces largely offset: industries more exposed to *Bilski* experience economically small net effects.

The framework implies cross-sectional heterogeneity in the treatment effect. If the deterrence channel dominates, weaker patent protection predicts a reallocation of capital toward startups that rely less on patent-based appropriation. Consistent with this prediction, we find that in more exposed industries, VC investment increases for startups without patents and declines for startups holding pre-*Bilski* patents. The reallocation operates along both the extensive and intensive margins: non-patenting startups receive more funding rounds and larger investments per round, whereas patent-holding startups experience declines along both dimensions. These results indicate that the average treatment effect conceals economically meaningful compositional changes in the allocation of entrepreneurial finance.

Our paper contributes to the literature on patents and VC by examining how changes in patent protection affect the market-level allocation of VC investment. A large body of prior work emphasizes company-level mechanisms through which patents facilitate financing, including signaling stronger appropriability and control over future returns from innovation (Lemley, 2001; Mann, 2005; Graham and Sichelman, 2008; Conti, Thursby, and Thursby, 2013; Hsu and Ziedonis, 2013) and documents that startups holding patents are more likely to receive venture funding (Baum and Silverman, 2004; Engel and Keilbach, 2007; Caselli, Gatti, and Perrini, 2009; Haeussler, Harhoff, and Mueller, 2014; Farre-Mensa et al., 2020).

We complement this literature by studying how an exogenous weakening of patent protection influences aggregate VC investment and its distribution across startups within an industry.

Specifically, we show that weaker patent protection is associated with an increase in total initial VC investment at the industry level, alongside a reallocation of funding away from patent-holding startups and toward startups without patents. These patterns are difficult to reconcile with a partial-equilibrium interpretation that holds entry conditions and the competitive environment fixed. Instead, they are consistent with a setting in which changes in patent protection relax barriers to VC-backed entry and reallocate capital across companies, even as the private value of patents declines for individual startups.

Our paper also contributes to the literature on patent protection and market entry. One view emphasizes that strong patent protection can facilitate entry by supporting licensing and access to external finance (Hall and Ziedonis, 2001; Arora and Merges, 2004). Another highlights that patent protection may deter entry by strengthening incumbent positions and raising strategic barriers to competition (Boldrin and Levine, 2002, 2008, 2013; FTC, 2003, 2011). Our findings suggest that both forces operate simultaneously but have different implications for capital allocation. While strong patent protection benefits startups that rely on patents to appropriate returns, weaker patent protection is associated with increased VC investment in less patent-intensive startups, consistent with a reduction in strategic entry barriers. In this sense, patent protection shapes not only the level of entrepreneurial activity but also its composition.

Finally, we contribute to a growing literature on the economic consequences of changes in patent protection. Acikalin, Caskurlu, Hoberg, and Phillips (2025) study the Supreme Court's *Alice Corp. v. CLS Bank International* decision and show that weakened patent protection affected competition and firm value among public companies. Specifically, they find that large public companies experienced higher valuations and sales, while small public companies faced lower valuations and increased product-market competition from VC-backed startups. Whereas their analysis focuses on how weakened patent protection reshaped out-

comes in public equity markets, we show that related effects were already emerging after the earlier *Bilski* decision through adjustments in VC investment allocation. By documenting how patent eligibility rulings influence VC funding allocation, our analysis highlights that judicial shifts in patent protection have important implications for entrepreneurial finance and the organization of innovation at the entry stage.

The remainder of the paper proceeds as follows. Section 2 provides background on the *Bilski* decision. Section 3 introduces a conceptual framework. Section 4 describes the data, and Section 5 outlines the empirical strategy. Sections 6 and 7 present aggregate and compositional results, respectively. Section 8 presents average funding amount results. Section 9 concludes.

2 *Bilski v. Kappos*

This section describes the Supreme Court's *Bilski v. Kappos* (2010) decision, which we exploit as an exogenous shock that weakened patent protection of certain types of inventions. We first summarize how the ruling redefined the legal standard for subject-matter eligibility and why it created a discrete decline in the scope of patentable subject matter. We then situate *Bilski* within subsequent decisions to clarify the boundaries of our empirical interpretation.

2.1 Legal background and economic implications

The *Bilski* case examined whether a method of hedging risk in commodities trading was patentable under §101 of the Patent Act. §101 enumerates four categories of patentable subject matter – "process, machine, manufacture, [and] composition of matter" – but courts have long recognized three judicial exceptions: laws of nature, physical phenomena, and abstract ideas (Mills, 2010).

In 2008, the Federal Circuit rejected Bilski's application under the "machine-or-transformation" test, which required that a process be tied to a specific machine or transform a physical art-

icle into a different state. When the Supreme Court reviewed the case in 2010, it unanimously affirmed the rejection but limited the test's authority, describing it as a "useful and important clue" rather than the exclusive standard (Lemley et al., 2011). The Court reaffirmed that abstract ideas are unpatentable but declined to define what constitutes an "abstract idea," instead leaving its application to lower courts (Delulio, 2010).

From an economic perspective, the decision narrowed patent protection for software and business-method inventions – two domains that had expanded rapidly in the late 1990s and 2000s (Bessen and Hunt, 2007). By reinforcing the abstract-idea exclusion and limiting reliance on a bright-line eligibility test, *Bilski* reduced the set of inventions likely to qualify for patent protection and raised the effective bar for both existing patents and new applications (Mills, 2010). Since the ruling was largely unanticipated and applied immediately, it generated a plausibly exogenous contraction in patent protection. We exploit this ruling to examine how reduced patent protection affects VC investment.

2.2 Information transmission

The Supreme Court's decision in *Bilski* was issued amid heightened debate over the scope of patent protection for business-method and software-related inventions. In the years preceding the ruling, rapid growth in patenting activity in these domains, together with increasing judicial scrutiny under §101, had raised questions about the durability of existing patents and the eligibility of new claims. Against this backdrop, *Bilski* was immediately perceived as a potentially consequential shift in the patent landscape, with implications for the effective protection available to innovation-intensive companies.

These implications were rapidly communicated to market participants through extensive contemporaneous coverage in both mainstream business media and technology-focused outlets. Reporting in *The New York Times*,[2] *The Wall Street Journal*,[3] and *The Wash-*

[2] *New York Times*, "Justices Take Broad View of Business Method Patents," June 28, 2010.
[3] *Wall Street Journal*, "On Bilski: A Business-Method Patent is Dead, Though They Live On," June 28, 2010.

ington Post[4] framed the decision in economic terms, emphasizing its relevance for patent strategy, intellectual property valuation, and innovation incentives rather than treating it as a purely technical clarification of patent doctrine. Technology-oriented outlets echoed this interpretation with greater emphasis on software and internet firms, highlighting that while the Court rejected overly abstract claims, it declined to impose categorical exclusions on business-method and software patents.[5,6,7]

In parallel with this media coverage, major law firms with substantial technology, innovation, and VC practices circulated client alerts advising firms and startups to reassess patent strategies in light of the ruling. Fenwick & West LLP, a firm with deep roots in Silicon Valley and a longstanding focus on technology clients, issued a detailed alert outlining the decision's implications for business-method and software patents and its practical consequences for patent portfolios.[8] Cooley LLP, headquartered in Palo Alto and widely known for advising VC investors and emerging technology companies, similarly disseminated an alert analyzing the decision's implications for patent eligibility under §101.[9] Additional alerts from large, nationally prominent law firms with substantial technology and corporate practices further broadened dissemination among corporate, startup, and investor clients.[10,11,12] These communications were issued promptly following the June 2010 ruling and originated from firms with strong ties to technology markets and VC-backed companies.

[4] *Washington Post*, "High court relaxes limits on patents," June 29, 2010.
[5] *Wired*, "Supreme Court Balks at Redrawing Patent Rules," June 28, 2010.
[6] *CNET*, "Supreme Court hedges on business method patents," June 28, 2010.
[7] *Techdirt*, "Supreme Court Rules Narrowly in *Bilski*; Business Method & Software Patents Survive," June 28, 2010.
[8] Fenwick & West LLP, "Patent Alert: Supreme Court Unanimously Rejects Bilski Patent Application but Narrowly Upholds Business Method Patents," June 28, 2010.
[9] Cooley LLP, "Bilski v. Kappos: A Divided Supreme Court Holds That at Least Some Business Methods are Patentable, and Unanimously Rejects Bilski's Claims Because They Attempt to Patent Abstract Ideas," July 2, 2010.
[10] Pillsbury Winthrop Shaw Pittman LLP, "Supreme Court Broadens Test for Patentable Subject Matter," June 28, 2010.
[11] Goodwin Procter LLP, "Supreme Court's *Bilski* Decision Soundly Rejects Call to Outlaw Business Methods Patents," June 30, 2010
[12] Proskauer Rose LLP, "*Bilski v. Kappos*: The Supreme Court Clarifies the Test for Patent-Eligible Processes," June 29, 2010.

Taken together, the breadth and speed of this information flow imply that VC investors were likely exposed to the economic implications of *Bilski* shortly after the decision, either directly or through founders and legal counsel. Since VC firms routinely rely on such intermediaries for intellectual property strategy in technology-intensive sectors, the ruling plausibly shifted expectations regarding the strength and enforceability of software and business-method patents. This expectation shift underlies our identification strategy: *Bilski* generated an immediate and plausibly exogenous change in perceived patent protection with the potential to influence VC investment decisions in affected industries.

2.3 Other rulings

Although *Bilski* was the first major Supreme Court case in decades to revisit subject-matter eligibility, several subsequent decisions refined related doctrines. Due to its timing, the most relevant for our setting is *Mayo Collaborative Services v. Prometheus Laboratories, Inc.*, 566 U.S. 66 (2012) (*Mayo*), which held that a patent must do more than restate a law of nature and instruct a reader to "apply it" (Aboy, Crespo, Liddell, Minssen, and Liddicoat, 2019). While both *Bilski* and *Mayo* restrict eligibility under §101, they apply to different exceptions: *Bilski* limits patents on abstract ideas, and *Mayo* limits patents on laws of nature. Consistent with this distinction, the two decisions affected largely non-overlapping industries. In robustness tests, we show that our results are unchanged when we exclude industries most likely influenced by *Mayo*.

One year after *Mayo*, *Association for Molecular Pathology v. Myriad Genetics, Inc.*, 569 U.S. 576 (2013) (*Myriad*), held that isolated DNA segments are not patentable because they constitute products of nature rather than human inventions. *Myriad* thereby reinforced and broadened the application of existing §101 exclusions, contributing to a further contraction in the scope of patentable subject matter. Together, *Mayo* and *Myriad* generated doctrinal changes that persisted into 2014, when *Alice* extended similar reasoning to software and business-method patents.

By the time of *Alice*, §101 doctrine reflected the cumulative effects of several recent eligibility rulings, making it difficult to isolate the impact of any single ruling. The sequence of *Mayo*, *Myriad*, and *Alice* progressively expanded the reach of §101 exclusions across software, business methods, products of nature, and diagnostic techniques.

We therefore focus on *Bilski* as the cleanest setting. Its timing predates these later decisions, providing a well-defined pre-event period and minimizing contemporaneous confounds. Although *Alice* ultimately affected a larger number of patents and applications than *Bilski* (Acikalin et al., 2025), its timing makes it less suitable for our empirical design.[13]

3 Conceptual framework

This section provides a parsimonious framework illustrating how changes in patent protection affect VC investment.[14] The framework highlights how patent eligibility shapes expected returns to VC investment through both appropriability and competitive effects.

Throughout the framework, we use the term "entrant" to denote a prospective startup evaluated by venture capitalists prior to receiving initial VC funding. Patent protection affects potential entrants through two main forces. First, stronger protection increases the private value an entrant can capture from securing its own patents (i.e., the appropriable economic value of patent ownership rather than the private benefits unrelated to cash flows). Second, stronger protection strengthens the deterrent effect of incumbents' patent portfolios. The relative strength of these forces determines how a shift in patent eligibility affects VC investment across industries.

[13] To be clear, we do not believe using *Alice* poses a problem for Acikalin et al. (2025), who study the effect of patent protection on competition among publicly-traded companies. They address potential confounds by removing patents plausibly affected by *Bilski*, *Mayo*, and *Myriad*. However, startups hold far fewer patents than publicly-traded companies, so applying the same exclusions would eliminate a potentially large share of the relevant sample. Such removals would be overly restrictive, which is why we instead rely on *Bilski*.

[14] This framework draws on prior work on key mechanisms linking patents and venture capital. In particular, we build on studies of patents' role in startup valuation and VC screening (Hsu and Ziedonis, 2013; Conti, Thursby, and Rothaermel, 2013), the probabilistic and strategic nature of patent rights (Lemley and Shapiro, 2005; Farrell and Shapiro, 2008), incumbents' use of patents to deter entry (Gilbert and Newbery, 1982; Green and Scotchmer, 1995), and the fundamental economics of VC investment based on expected post-entry returns (Gompers and Lerner, 2004; Hall and Lerner, 2010).

3.1 Industry environment

Consider an industry with many potential entrants and a representative incumbent whose patent portfolio shapes the entry barriers faced by new companies. Entrants rely on external financing to begin operations. Let s denote the strength of patent protection implied by prevailing eligibility standards. A reduction in s affects entrants through two channels: it lowers the private value of patenting and weakens the deterrent force of the incumbent's patent portfolio.

To formalize these channels, let $\phi(s)$ denote the private value of patenting for an entrant, with $\phi'(s) > 0$. A higher s increases the return an entrant can capture from its innovation and raises the informativeness of patents as signals of appropriability and expected private returns. Let $\ell(s)$ denote the strength of incumbent deterrence, with $\ell'(s) > 0$. A higher $\ell(s)$ reflects stronger litigation threats, greater bargaining power in licensing, and broader ability to block commercialization by others. For tractability, assume that all entrants in an industry face the same change in incumbent deterrence and that all patent-reliant entrants experience the same change in private patent value.

3.2 Entrant profits

An entrant's expected post-entry payoff depends on a baseline operating profit π and the value of the patent-related forces described above. These payoffs represent expected post-entry profits, which VC investors capitalize when making pre-entry financing decisions. A non-patenting entrant earns $\Pi_0(s) = \pi - \ell(s)$, and a patenting entrant earns $\Pi_1(s) = \pi + \phi(s) - \ell(s)$. When patent protection declines, both types of entrants benefit but only patenting entrants lose private patent value.

3.3 VC financing

A VC investor funds an entrant when the expected return exceeds the cost of investment. We assume that conditional on funding, the capital invested to an entrant increases in its expected post-entry profits. Changes in patent protection shift expected post-entry profits by affecting both the private value of patenting and the deterrent force of incumbents, thereby altering which projects clear the investment threshold.

3.4 The *Bilski* shock

Bilski weakened patent protection to heterogeneous degrees across industries. In the framework, this appears as a reduction in the effective strength of protection,

$$s' = s + \Delta s, \qquad \Delta s < 0,$$

which induces declines in both private patent value and incumbent deterrence:

$$\Delta\phi \equiv \phi(s') - \phi(s) < 0, \qquad \Delta\ell \equiv \ell(s') - \ell(s) < 0.$$

Industries differ in the magnitudes of $\Delta\phi$ and $\Delta\ell$, generating heterogeneous effects on expected entrant profits and thus on VC investment.

3.5 Predictions

Let industries be indexed by i, with P_i denoting the set of patent-reliant entrants and A_i the set of all entrants. Aggregating across entrant types, the change in industry-level patent-related profit is

$$\Delta V_i = \sum_{j \in P_i} \Delta\phi \; - \; \sum_{k \in A_i} \Delta\ell.$$

Since VC investment increases in aggregate entrant profits, it responds monotonically to changes in ΔV_i.

Prediction 1a (Private patent value dominates): If the loss in private patent value for patent-reliant entrants is larger than the benefit from the decline in incumbent deterrence faced by all entrants, the industry's patent-related profit and VC investment both fall:

$$\sum_{j \in P_i} \Delta\phi \; < \; \sum_{k \in A_i} \Delta\ell \quad \Rightarrow \quad \Delta V_i < 0 \quad \Rightarrow \quad \Delta VC_i < 0.$$

Prediction 1b (Incumbent deterrence dominates): If the loss in private patent value for patent-reliant entrants is smaller than the benefit from the decline in incumbent deterrence faced by all entrants, the industry's patent-related profit and VC investment both rise:

$$\sum_{j \in P_i} \Delta\phi \; > \; \sum_{k \in A_i} \Delta\ell \quad \Rightarrow \quad \Delta V_i > 0 \quad \Rightarrow \quad \Delta VC_i > 0.$$

Prediction 1c (Neither private patent value nor incumbent deterrence dominates): If the loss in private patent value for patent-reliant entrants is equal to the benefit from the decline in incumbent deterrence faced by all entrants, the industry's patent-related profit and VC investment remain unchanged:

$$\sum_{j \in P_i} \Delta\phi \; = \; \sum_{k \in A_i} \Delta\ell \quad \Rightarrow \quad \Delta V_i = 0 \quad \Rightarrow \quad \Delta VC_i = 0.$$

The next prediction concerns how weaker protection affects the composition of funded entrants. The drop in incumbent deterrence applies to all entrants, but the drop in private patent value applies only to patenting entrants. Profits therefore shift asymmetrically across entrant types.

Prediction 2: Weaker patent protection reallocates VC funding toward non-patenting entrants and away from patent-reliant entrants in more exposed industries.

The resulting profit changes are:

$$\Delta\Pi_0 = \Pi_0(s') - \Pi_0(s) = -\big(\ell(s') - \ell(s)\big) = -\,\Delta\ell,$$

$$\Delta\Pi_1 = \Pi_1(s') - \Pi_1(s) = \big(\phi(s') - \phi(s)\big) - \big(\ell(s') - \ell(s)\big) = \big(\Delta\phi - \Delta\ell\big),$$

$$\Delta\Pi_0 - \Delta\Pi_1 = \big(-\,\Delta\ell\big) - \big(\Delta\phi - \Delta\ell\big) = -\,\Delta\phi.$$

Since $\Delta\phi < 0$, it follows that $\Delta\Pi_0 > \Delta\Pi_1$. This is a relative comparison: non-patenting entrants experience a more favorable change in expected profits than patent-reliant entrants, although $\Delta\Pi_1$ may be positive or negative. VC funding therefore shifts toward non-patenting entrants in more exposed industries.

Taken together, the framework predicts heterogeneous effects of weaker patent protection on VC activity. The overall level of investment depends on the balance between reduced private patent value and reduced incumbent deterrence. Since weaker protection increases profits for non-patenting entrants relative to patenting entrants, funding shifts toward non-patenting entrants, leading to corresponding changes in the composition of funded startups.

3.6 Follow-on funding

While our framework focuses on initial investment decisions, it is natural to ask whether the same mechanisms apply to follow-on funding. This distinction matters because industry characteristics play an important role in initial investment decisions (Gompers, Gornall, Kaplan, and Strebulaev, 2020), whereas follow-on investments are typically contingent on startups achieving pre-determined milestones (Sahlman, 1990; Kaplan and Stromberg, 2001). By weakening patent protection, *Bilski* reduced expected appropriability and altered competit-

ive conditions, plausibly leading VC investors to reassess the environment for already-funded startups. These changes affect the continuation value of VC-backed startups – including those that have met technical or commercial milestones – and therefore enter the option value calculation underlying follow-on funding decisions. Since follow-on funding decisions are made conditional on prior investment and revealed startup-level performance, industry-level changes in patent protection operate on a narrower margin. As a result, while the same patent-related mechanisms remain relevant, we expect their net effects on follow-on funding to be more muted than for initial investment.

4 Sample

4.1 Data sources

We obtain VC funding data from PitchBook. This dataset includes detailed information on startups (e.g., industry, location), funding rounds (e.g., amounts, dates), and investors (e.g., assets under management, year founded). Since our empirical setting centers on a U.S. Supreme Court decision, we restrict our sample to U.S.-based startups.

We obtain patent data from PatentsView, which is maintained by the USPTO's Office of the Chief Economist, and the Orbis Intellectual Property database. Orbis includes standard patent information – such as the applicant, assignee, filing and grant dates, location, and technology class – and is particularly useful for our analysis because it directly matches patent applications and grants to their corporate owners and tracks ownership transfers.

4.2 Sample construction

We begin by matching VC-backed startups in PitchBook to patenting companies in Orbis using fuzzy matching on company names and exact matching on city and country. We then aggregate the resulting dataset, which includes all VC-backed startups regardless of patent status, into an industry–year panel.

PitchBook organizes industries into a three-tier hierarchy comprising 7 broad sectors, 41 intermediate groups, and 214 detailed codes in our sample. Since startups are unevenly distributed across these categories, we create a custom classification that balances granularity with representativeness. For any intermediate group with more than 100 companies holding active patents as of *Bilski*, we use the more detailed codes. We then apply two filters. First, we drop industries with fewer than 20 companies holding active patents at that time, which ensures sufficient observations for constructing the treatment variable. Second, we drop industries with fewer than 10 funded startups in the preceding decade, which ensures sufficient data for constructing dependent variables. This process yields 87 distinct industries for analysis. Robustness tests show that our results are not sensitive to alternative industry thresholds or aggregation rules.

The sample spans fiscal years 2007 through 2013, providing four pre-event and three post-event years. Since *Bilski* was decided at the end of June, we use fiscal years as July 1 through June 30. Table 1 reports summary statistics of our dependent variables and highlights the skewness in industry-level investment outcomes. For follow-on investment variables, we only include post-first-round funding from startups first funded before *Bilski*, since startups with initial funding after *Bilski* may have been affected differentially by the decision. This restriction allows us to cleanly separate the effects of *Bilski* on initial and follow-on investments.

5 Empirical strategy

5.1 Unit of analysis

We conduct our analysis at the industry–year level because this unit plausibly corresponds to how VC investors form expectations about legal and technological risk, particularly at early stages of investment. *Bilski* represents a change in patentability that applies broadly to technological domains rather than to individual startups. In early-stage financing, information about startup-specific patent quality is limited, making it difficult for investors to assess

exposure at the startup level. As a result, especially for initial financing decisions, investors are likely to rely on more systematic, domain-level assessments of patent risk (Kortum and Lerner, 2000; Gompers, Lerner, and Scharfstein, 2005). An industry-level design therefore provides a reasonable approximation to the information set relevant for VC decision-making.

This level of aggregation also has important implications for identification and inference. Our difference-in-differences strategy, which we discuss in detail below, relies on cross-industry variation in exposure to *Bilski* derived from patent examination outcomes. Since most startups hold few or no patents, mapping this variation to individual startups would create substantial measurement error, leaving startup-level treatment intensity noisy or undefined and mechanically attenuating estimated effects. Aggregating to the industry–year level pools information across startups, reduces noise, and improves inference when treatment intensity is measured with error (Bertrand, Duflo, and Mullainathan, 2004).

Moreover, a startup-level design would necessarily limit the analysis to follow-on funding rounds of pre-*Bilski* entrants. Aggregating at the industry level allows us to also study effects on initial funding – the key margin for entry in our framework – while capturing the broader market response to the ruling.[15]

5.2 Specification

To examine how patent protection affects VC investment across industries, we estimate a difference-in-differences model using Poisson pseudo-maximum likelihood (PPML). Let $Investment_{it}$ denote the total, initial, or follow-on VC investment received by all startups in industry i in fiscal year t. We specify the conditional mean of investment as

$$\mathbb{E}[Investment_{it} \mid X_{it}] = \exp(\alpha + \beta_1 \, Treatment_i \times Post_t + \eta_i + \delta_t) \, . \tag{1}$$

[15] In unreported tests, we find qualitatively similar results using the industry-level treatment variable in panel regressions at the startup level.

$Treatment_i$ measures the intensity of exposure to *Bilski* for industry i and is normalized to have mean zero and unit standard deviation; we describe its construction in the next subsection. $Post_t$ is an indicator equal to one for fiscal years 2011 through 2013 and zero for fiscal years 2007 through 2010. The specification includes industry fixed effects (η_i) and fiscal year fixed effects (δ_t), which absorb the main effects of $Treatment_i$ and $Post_t$. We cluster standard errors at the industry level, which corresponds to the level of treatment variation.

Under the PPML framework, the coefficient of interest, β_1, is interpreted as a semi-elasticity of the conditional mean (McConnell, 2024). It captures the proportional change in expected VC investment associated with a one standard deviation increase in treatment intensity in the post-treatment period.[16]

5.3 Treatment

To construct our treatment variable, we use the USPTO office actions data from Lu, Myers, and Beliveau (2017). This dataset has almost 4.4 million office actions from March 2008 to July 2017 and covers 2.2 million unique patent applications. We focus only on §101 rejections, which are given when an application claims patent-ineligible subject matter. These are the types of rejections affected by *Bilski*.

To focus on the effect of *Bilski*, we restrict the sample to patent applications filed before the decision on June 28, 2010. All patents in the sample were filed before the law, so the underlying technology and the decision to seek patent protection are predetermined.[17] The decision affected patent examination through an administrative channel: on July 27, 2010, the USPTO issued its Interim *Bilski* Guidance and required examiners to apply the new

[16] PPML is well suited for non-negative outcomes with zero values and delivers consistent estimates of multiplicative conditional mean models under general forms of heteroskedasticity (Santos Silva and Tenreyro, 2006). In contrast, log-linear OLS transformations can change the estimand and alter the effective sample in difference-in-differences settings (Cohn, Liu, and Wardlaw, 2022; Chen and Roth, 2024). In our data, up to six percent of industry-year observations have zero values for some outcome variables. We nonetheless obtain qualitatively similar estimates in unreported results using OLS with (i) $\log(Investment_{it})$ while dropping observations with zero values and (ii) $\log(Investment_{it} + 1)$.

[17] To further alleviate concerns about strategic patenting behavior in response to the case, we later show that the results are robust to defining treatment using only applications filed before the Supreme Court agreed to hear the case.

eligibility standard to all pending applications. We therefore study applications with final decisions issued on or after July 27, 2010. We end the sample on June 19, 2014, the date of *Alice*. *Alice* operationalized and intensified the abstract-idea framework introduced in *Bilski* and became the primary legal standard for patent eligibility in this area (Kesan and Wang, 2020; Gruner, 2022). Ending the sample at this date ensures that our treatment variable captures only the impact of *Bilski*. To summarize, we construct our treatment variable using patent applications filed before the *Bilski* decision of June 28, 2010 and with a final decision between the *Bilski* guidance date of July 27, 2010 and the *Alice* decision of June 19, 2014.

Using this filtered sample, we first compute, for each of the 2,445 Cooperative Patent Classification (CPC) main groups, the fraction of §101 rejections that explicitly cite *Bilski*. CPC main groups are defined as all characters appearing before the forward slash in a CPC subgroup. We then assign each pre-*Bilski* startup-owned patent the *Bilski*-related rejection share of its primary CPC group. Finally, we construct our industry-level treatment variable by averaging these rejection shares across all active patents in the corresponding industry.

The intuition behind this measure is that it shows how much an industry was exposed to the legal change from *Bilski* before the event happened. An industry gets a higher treatment score if its patents are in technology areas that saw a bigger share of subject matter rejections after the *Bilski* ruling. In other words, our treatment variable is a measure of an industry's vulnerability to the change in patent law, not a measure of how it reacted.

Table 2 provides descriptive statistics on patent rejections and industry exposure related to *Bilski*. Panel A shows that *Bilski* accounted for over 11% of all §101 rejections in each of the four years after the case and negligible rejection rates thereafter. That is, *Bilski* had significant effects on patent examination outcomes until the *Alice* ruling at the end of fiscal year 2014. Panel B shows that the most affected industries had exposure rates of over 20%. Given that the case centered on a patent application for a method of hedging risk in commodities trading, it is natural that the most affected industries were Capital Markets/Institutions and Automation/Workflow Software.

As a validation that *Bilski* also influenced existing patents, not just new applications, we also examine changes in infringement suits using USPTO Patent Litigation Docket Reports.[18] For each classification, we compute the log change in infringement suits between the three years before and after the decision. There are several reasons why litigation could increase when patent protection weakens. First, even patents with reduced expected enforceability can generate positive settlement value, making litigation a viable strategy for rights holders (Lemley and Shapiro, 2005; Chien, 2009). Second, initiating litigation can serve as a commitment device, allowing patent owners to assert residual exclusionary rights and deter entry in closely related technological spaces (Lanjouw and Lerner, 2000). Third, when future patenting becomes more difficult – as reflected in higher rejection rates – the existing stock of patents becomes more valuable, making litigation the primary tool for monetization (Hall and Ziedonis, 2001; Bessen and Meurer, 2008).

Panel C shows that changes in infringement suits are positively correlated with rejection rates at the class and subclass levels, but close to zero at the more granular subgroup and main group levels, where litigation activity is sparse. Restricting to classifications with above-median litigation activity yields positive correlations across all levels. In short, post-*Bilski* increases in infringement suits move closely with rejection rates of subsequent applications. This pattern is consistent with patent holders adapting rationally to weaker protection.

6 Aggregate effect

In this section, we examine the aggregate effect of *Bilski* on VC investment. Guided by our conceptual framework, we begin by estimating the average treatment effect and testing

[18] For example, in *CyberSource Corp. v. Retail Decisions, Inc.*, 654 F.3d 1366 (Fed. Cir. 2011), the Federal Circuit invalidated a pre-*Bilski* patent covering a method for detecting online credit-card fraud, holding that the claims amounted to an abstract mental process implemented on a computer. In *Dealertrack, Inc. v. Huber*, 674 F.3d 1315 (Fed. Cir. 2012), the court struck down an existing patent on a computer-assisted system for processing automobile loan applications, reasoning that automating a longstanding business practice did not render it patent eligible. Similarly, in *Fort Properties, Inc. v. American Master Lease LLC*, 671 F.3d 1317 (Fed. Cir. 2012), claims directed to structuring tax-advantaged real estate investment arrangements were invalidated as abstract financial concepts despite their computerized implementation.

for pre-event trends. We then examine whether the effects reflect increased entrepreneurial entry rather than a reallocation of VC funding across industries. Finally, we evaluate the robustness of our findings to alternative sample constructions, treatment definitions, and industry exclusions.

6.1 Average treatment effect

Table 3 presents results from estimating Equation 1. In the first three columns, the dependent variable is funding amounts. The first column shows that total funding increases more in industries more affected by *Bilski*. The coefficient of 0.233 (z-score of 3.79) implies that a one standard deviation increase in treatment is associated with a 26% larger increase (i.e., $(e^{0.233}\text{-}1)\times 100\%$) in total funding after *Bilski*. The second and third columns show that this effect is driven primarily by larger increases in initial funding.

In the last three columns of Table 3, the dependent variable is funding rounds. The results closely parallel those for funding amounts: industries more affected by *Bilski* see a significantly larger increase in total funding rounds, again driven by initial rather than follow-on funding.

Table 3 shows that industries more exposed to the eligibility change experienced larger increases in VC investment. These increases are concentrated in initial financing. More exposed industries receive larger first-round investments and attract more startups at entry. This pattern is consistent with Prediction 1b of our framework, in which reductions in entry barriers more than offset the decline in private patent value for patent-reliant entrants. In contrast, we find no effect on follow-on funding, implying that these opposing forces are of similar magnitude for incumbent startups, consistent with Prediction 1c.

6.2 Dynamic treatment effects

We next explore the dynamic relationship between treatment intensity and VC investment around *Bilski* to assess the validity of the parallel trends assumption and to trace how the

effect of weaker patent protection evolves over time. To do so, we estimate a version of Equation 1 in which we replace the *Post* dummy with a full set of event-time dummies.

Figure 1 plots the estimated coefficients on the interaction between the treatment variable and event-time dummies. The estimates show no evidence of a differential trend prior to *Bilski* for any of the dependent variables, with investment trajectories remaining parallel across treatment groups through 2008 and 2009. This absence of pre-trends indicates that our results are unlikely to be driven by recession-era dynamics.

Following *Bilski*, we observe a sharp and significant increase in both total and initial funding for more affected industries. The discrete jump following the decision, rather than a gradual trend, reinforces our interpretation that the observed effects reflect the impact of *Bilski* itself and not macroeconomic recovery. Consistent with the conceptual framework, this discontinuity reflects a decline in patent protection that immediately weakens both private patent value and incumbent deterrence, triggering a reallocation of early-stage capital toward industries more directly exposed to weaker patent protection.

6.3 Reallocation versus entry

Building on this increase in VC funding for more exposed industries, we next examine whether this response reflects active reallocation by investors or increased entrepreneurial entry. In our conceptual framework, an increase in investment does not require an increase in the number of entrants. The decline in incumbent deterrence raises expected profits for both existing and new startups. Distinguishing between these channels is important: if the larger increase in funding among more exposed industries was driven primarily by entry, the estimated treatment effect would capture shifts in the composition of startups rather than changes in investor behavior.

To isolate the investor margin, we restrict the sample to startups founded before *Bilski*. For these startups, we aggregate funding at the industry level over the post-event period and regress these outcomes on treatment intensity. Since all startups in this sample predate

the ruling, any treatment effects must arise from changes in how investors allocate capital rather than from entry. If our main results are driven solely by entrepreneurial entry, they should disappear once the sample is limited to pre-existing startups. This design follows the logic of prior studies that distinguish investor reallocation from company creation (Kortum and Lerner, 2000; Ewens, Nanda, and Rhodes-Kropf, 2018).

Table 4 shows that the effects persist within the pre-*Bilski* cohort. We find positive and statistically significant effects on both initial funding amounts and initial funding rounds, with magnitudes only slightly below our baseline estimates. The persistence of these effects rules out an explanation based exclusively on new company formation and indicates that investor reallocation plays a meaningful role. More broadly, they are consistent with an equilibrium adjustment in which both investor behavior and entry respond to the new legal environment.

6.4 Robustness

Our analysis relies on several design choices, including how industries are defined and how exposure to *Bilski* is measured. To verify that our findings do not hinge on any one of these decisions, we conduct a series of robustness checks that vary the industry classification schemes, modify the level of aggregation used to calculate exposure, and alter the definition of the treatment variable itself.

Panel A of Table 5 reports estimates based on alternative industry definitions. The first row restates the baseline estimate from Table 3. The next two rows re-aggregate startups using Pitchbook's group-level and code-level classifications, both of which yield results consistent with the baseline. The final two rows of Panel A vary the minimum number of funded startups required for an industry to be included in the sample, using thresholds of five and twenty instead of the baseline cutoff of ten, and the resulting estimates remain similar in magnitude and statistical significance.

Panel B of Table 5 reports robustness checks based on alternative constructions of the treatment variable. In the baseline, treatment is measured as the share of §101 rejections attributable to *Bilski* for each of the 2,445 CPC main groups, which are then aggregated to the industry level. To test whether the results depend on this choice, we compute rejection shares at three other aggregation levels: 118 CPC classes, 504 CPC subclasses, and 8,046 CPC subgroups. The first three rows show that these alternative choices yield similar estimates.

The baseline analysis uses a continuous measure of treatment intensity, which effectively assumes that funding responds in proportion to an industry's exposure to *Bilski*. To check whether this assumption matters, we re-estimate the model using a simple above-median indicator that distinguishes more-exposed from less-exposed industries. This coarser measure serves as a basic threshold test and helps reveal whether the baseline results are driven by a handful of highly exposed industries or by the linear structure of the continuous treatment. As shown in the fourth row of Panel B, the estimates change little, suggesting that the main findings do not depend on the specific functional form.

Finally, we consider the possibility that applicants may have adjusted their filing behavior not only after the *Bilski* decision was released but as soon as the Supreme Court agreed to hear the case. To address this concern, we re-define treatment using only applications filed before the certiorari grant on June 1, 2009. This timing restriction ensures that exposure is measured without capturing any applicant responses to the Court's decision to take up the case. As reported in the final row of Panel B, the resulting estimates are qualitatively similar to the baseline, indicating that the main findings do not depend on whether treatment is defined using all pre-decision applications or only those filed prior to the certiorari stage.[19]

[19] These regressions exclude six additional industries. The additional omissions are due to each having fewer than twenty companies with active patents as of June 1, 2009, leaving the treatment variable undefined.

6.5 Alternative explanations

We next consider whether the estimated effects of *Bilski* reflect other forces at work during our sample period. Table 6 reports estimates from a series of regressions in which we exclude particular subsets of industries, each chosen to probe a different alternative explanation.

Our sample period overlaps with the Great Recession, raising the concern that our estimates reflect differential post-crisis recovery across industries rather than a change in patent eligibility. If industries more exposed to *Bilski* also experienced stronger cyclical rebounds, our results could simply capture correlated recovery dynamics.

We address this concern in three steps. First, since finance-related industries experienced particularly sharp contraction and rebound, we re-estimate our baseline specification excluding all four of them – Capital Markets and Institutions, Financial Software, Insurance, and Other Financial Services. The first row of Table 6 shows that our results remain economically and statistically similar when excluding them.

Second, since software-oriented industries – among the most exposed to *Bilski* – were also central to the post-crisis VC recovery, we re-estimate our baseline specification excluding all fifteen software-related industries. The second row of Table 6 shows that our results remain positive and statistically significant when excluding them, indicating that the estimates are not driven by unusually strong post-recession investment in core software sectors. Instead, this pattern is consistent with the notion that *Bilski* shifted expectations about the patent protection of software-implemented and computer-assisted technologies in ways that affected a broad range of industries, rather than the results being driven by a sector-specific upswing unrelated to the ruling.

Finally, to more directly account for differential recovery regardless of sector, we compute each industry's percentage change in total VC funding over 2011 through 2013 relative to 2007 through 2010 and exclude the ten industries with the largest increases. The third row shows that our results remain positive and statistically significant when doing so. Taken together, the first three rows of Table 6 suggest that our findings are unlikely to be driven by

sector-specific recovery patterns and instead reflect an effect operating through the timing and scope of the *Bilski* decision.

We also consider whether the results are driven by a small group of industries especially exposed to *Bilski*. If the effect was concentrated entirely in these industries, the broader interpretation of the results would be more limited. We therefore exclude the ten most-exposed industries. The fourth row of Table 6 shows that the estimates shrink somewhat, which is consistent with these industries experiencing a stronger shock, but the effects remain positive and economically meaningful.

A related concern is that the results are shaped by industries that are unusually small or have low levels of patent activity. To explore this possibility, we re-estimate the model after excluding, in turn, the one-third smallest industries and the one-third least patent-intensive industries. In both cases, the estimated effects remain stable and statistically significant, suggesting that neither industry size nor patent intensity is driving the main result.

Next, we consider whether our findings are confounded by *Mayo* (March 2012), which altered the patent-eligibility doctrine for a subset of technologies during our study period. We identify the ten industries most likely to be affected by *Mayo* (i.e., industries with *Mayo* exposure of 5% or above) and implement two tests: first, we drop their observations in event-time years 2 and 3 (removing the months immediately after *Mayo*), and second, we drop these industries entirely. The last two rows of Table 6 show the estimated effects remain positive and statistically significant in both cases, indicating that the main results are not driven by industries exposed to the *Mayo* decision.

Finally, in unreported analyses, we verify that no single industry drives the results by re-estimating the baseline equation while excluding each industry in turn. The findings remain similar across all 87 regressions.[20]

[20] An additional concern is that our post-*Bilski* period overlaps with the implementation of the Leahy-Smith America Invents Act (AIA), enacted in September 2011 and implemented in stages through March 2013. Key provisions included new post-grant and inter partes review procedures (effective September 2012) and the transition to a first-inventor-to-file priority system for applications filed on or after March 2013. While these reforms could affect patent value in general, they differ fundamentally from *Bilski*. The AIA primarily introduced procedural and priority changes that applied broadly across technologies, rather than altering

7 Compositional effect

The second prediction in our conceptual framework states that weaker patent protection should shift VC funding toward non-patenting entrants and away from patent-reliant entrants. The mechanism is asymmetric: the decline in incumbent deterrence benefits all entrants, but the decline in private patent value affects only patent-reliant entrants. This asymmetry implies larger profit gains for non-patenting entrants. To test this prediction empirically, we estimate industry-level treatment effects separately for startups without patents at the time of funding and for startups with patents at the time of funding.

7.1 Startups without patents at funding

We begin by examining startups that held no patents at the time of funding. Panel A of Table 7 re-estimates the main specification using industry–year VC flows constructed solely from investments in non-patenting startups. Consistent with the interpretation that *Bilski* relaxed barriers to entry, non-patenting startups in more exposed industries experience significantly larger post-*Bilski* increases in initial VC investment, both in terms of capital invested and number of rounds.

A potential concern is that these results may reflect mechanical reclassification rather than genuine changes in investor behavior. Since patent eligibility narrowed more sharply in highly exposed industries after *Bilski*, some startups may appear in the non-patenting group simply because obtaining a patent became more difficult, not because their underlying patenting strategies changed. Under this interpretation, the estimated treatment effects could capture shifts in which startups qualify as non-patenting rather than a true relaxation of entry barriers.

subject-matter eligibility under §101 or generating cross-industry variation in exposure. Moreover, our treatment is constructed entirely from pre-*Bilski* applications, so neither the passage nor implementation of the AIA affects treatment assignment. Consistent with this interpretation, Lerner, Speen, and Leamon (2015) find no economically meaningful effect of the AIA on VC investment. Moreover, our treatment is constructed entirely from pre-*Bilski* applications, so neither the passage nor implementation of the AIA affects treatment assignment.

To address this concern, Panel B of Table 7 restricts the sample further to startups founded before *Bilski* that held no patents as of *Bilski*. Since this cohort's patent status is fixed in advance, this subsample allows us to isolate the effect of changes in incumbent deterrence from changes in the private value of patents. We aggregate all post-*Bilski* investment within each industry and regress these outcomes on treatment intensity in a cross-sectional design. Despite the substantially smaller sample, we find positive and statistically significant correlations between treatment exposure and initial funding.

Overall, Table 7 shows that non-patenting startups in more exposed industries experienced larger post-*Bilski* increases in initial VC investment, and that this pattern is not entirely driven by endogenous shifts in patenting behavior. Together, these findings support the interpretation that the reduction in patent protection relaxed VC-backed entry barriers.

7.2 Startups with patents at funding

We next examine startups that held patents at the time of funding. Since patent eligibility standards tightened following *Bilski*, the ruling differentially affected patents depending on when they were issued. Pre-*Bilski* patents were granted under a more permissive eligibility regime and therefore experience a reduction in effective legal protection following the decision. For startups holding these patents, changes in investment reflect the combined effects of declining private patent value and changes in incumbent deterrence. Patents issued post-*Bilski*, by contrast, had already undergone a more rigorous examination process and were far less exposed to the shift in standards. As a result, investor responses may differ depending on whether a startup's patent portfolio included pre-*Bilski* patents.

We begin by re-estimating the main specification on the sample of patent-holding startups. This specification pools startups with both pre- and post-*Bilski* patents, so the treatment effect reflects the average exposure of all patenting startups within an industry-year. Since startups holding only post-*Bilski* patents should be largely unaffected by the ruling, their inclusion alongside startups holding more vulnerable pre-*Bilski* patents will attenuate

any differential response. As a result, the expected treatment effect in this pooled sample is ex ante ambiguous. Consistent with this reasoning, Panel A of Table 8 shows that the interaction between treatment intensity and post-*Bilski* investment is small and statistically indistinguishable from zero across all outcomes.

To isolate the startups whose patent positions were actually weakened by the ruling, we restrict attention to startups founded before *Bilski* that held at least one pre-*Bilski* patent. For this group, a portion of the patent portfolio is predetermined prior to the decision, which substantially reduces concerns about endogenous patenting responses or changes in examination standards. In the context of the conceptual framework, these startups are precisely those for whom the decline in private patent value applies.

As in the preceding subsection, we aggregate all post-*Bilski* investment within each industry and regress these outcomes on treatment intensity in a cross-sectional design. Panel B of Table 8 shows strong negative correlations between industry exposure and post-decision VC investment for startups with pre-*Bilski* patents. This pattern is consistent with the relaxation of VC-backed entry barriers. As pre-*Bilski* patents lost value, startups whose competitive advantage relied on patent protection became less able to sustain barriers to entry, reducing the expected returns to patent-dependent investment strategies.

Taken together, the results in Tables 7 and 8 show a clear shift in who receives VC funding after the decision. More exposed industries see greater investment in startups that do not rely on patents. Conversely, funding declines for startups whose pre-*Bilski* patents lost value. These patterns indicate that weaker eligibility standards changed the relative appeal of different types of entrants and redirected capital accordingly. Importantly, these compositional results also hold for follow-on funding, which shows that the insignificant net effect in Table 3 masks heterogeneous effects by startup patent status. Overall, the findings in Tables 7 and 8 support Prediction 2 in our conceptual framework.

8 Intensive margin effects

The preceding results show that exposure to *Bilski* increases aggregate VC investment, primarily through initial funding, and reallocates capital toward non-patenting startups and away from startups holding pre-*Bilski* patents. We now examine whether the ruling also affected the intensive margin of VC investment by testing whether *Bilski* changed the average amount invested per funding round and whether these effects differ by startup patent status.

Since the amount invested conditional on funding increases with expected post-entry profits, the same mechanisms that drive the extensive-margin results should also affect average funding amounts. In particular, weaker patent protection reduces incumbent deterrence and therefore raises expected profits for non-patenting entrants. For patent-reliant entrants, however, the effect on profits is ambiguous because weaker protection also reduces the private value of their patents. The framework therefore predicts larger investments per round for non-patenting startups in more exposed industries, while the effect for patent-reliant startups remains ambiguous.

8.1 Aggregate effect

To examine how *Bilski* affected the intensive margin of VC investment, we re-estimate the main specification using average funding amount as the dependent variable, defined as total VC investment divided by the number of funding rounds with non-missing amounts. This measure captures capital raised per round within an industry–year and isolates intensive-margin adjustments from changes in deal counts. The results are presented in Table 9.

Panel A shows that industries more exposed to *Bilski* experience a significantly larger increase in average initial funding amounts. The coefficient of 0.484 implies that a one standard deviation increase in treatment is associated with a 62% larger increase in average initial funding per round after the ruling. In contrast, we find no significant results on average funding amount for total or follow-on funding. These patterns mirror the aggregate res-

ults in Section 6: initial funding increases in more exposed industries, which is consistent with Prediction 1b, and follow-on funding shows little net effect, which is consistent with Prediction 1c.

8.2 Compositional effect

Panel B of Table 9 estimates regressions of average funding amount separately for non-patenting and patent-holding startups using the cross-sectional specification restricted to pre-*Bilski* cohorts. The estimation approach matches that used in Tables 7 and 8.

The results show that in more exposed industries, average initial funding amounts increase for non-patenting startups and decrease for patent-holding startups. These intensive-margin results are similar to the compositional results in Section 7 and are consistent with Prediction 2 of the conceptual framework.

Overall, the results in Table 9 indicate that the reallocation of VC investment following *Bilski* also operates along the intensive margin. In more exposed industries, VC investors allocate larger investments per round to non-patenting startups and smaller investments per round to patent-reliant startups. Together with the earlier evidence on funding rounds, our findings reinforce the interpretation that weaker patent protection reshapes not only which startups are funded but also the scale at which they are financed.

9 Conclusion

In this paper, we provide evidence that weaker patent protection lowers barriers to VC-backed entry. Exploiting variation in industry exposure to the Supreme Court's *Bilski* decision, we find that more exposed industries had larger gains in initial VC investment. The composition of investment also shifted: funding expanded for startups without patents, while startups holding pre-*Bilski* patents received less investment. These patterns point to a reallocation of capital toward entrants previously constrained by strong incumbent patent positions.

Our results show that adjustments in patent protection can have broad consequences for the flow of entrepreneurial finance. They also carry policy implications. Patent rules influence not only companies' incentives to innovate but also the availability of external capital for young companies and, ultimately, the intensity of competition in affected markets. The welfare implications of these shifts, however, are not one-sided. More entry can increase competition and reduce deadweight loss, while weaker appropriability may lower incumbents' incentives to invest in R&D. Understanding the relative strength of these forces remains an important task for future work.

Finally, our findings should not be read as evidence that weaker patent protection is desirable across the board. They reflect the effects of a marginal reduction in protection starting from an already strong regime – one in which incumbent patent positions appear to have constrained entry meaningfully. The optimal level of protection depends on the technological environment, the distribution of patent holdings, and the underlying strength of the regime. In settings where protection is already weak or imitation risk is high, further erosion of rights may discourage investment rather than support it. Recognizing this state dependence helps place our results in the broader discussion of how patent systems shape innovation, entry, and the allocation of capital.

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Figure 1. Dynamic treatment effects

This figure shows the dynamic treatment effects of *Bilski* on VC investment. Each panel plots the difference-in-differences coefficients from Equation 1 estimated by event time. *Total investment* is the sum of all VC funding. *Initial investment* is the sum of all first rounds of VC funding. *Follow-on investment* is the sum of all post-first-round VC funding, calculated only for startups whose initial round occurred before *Bilski*. *Treatment* is a measure of exposure to the *Bilski* ruling, calculated as the average share of §101 rejections weighted by the distribution of an industry's active patents across technology classes. Panels A and B show results for total funding amounts and total funding rounds, respectively. The unit of analysis is at the industry-fiscal year level. Confidence intervals are at the 95% level and are adjusted for clustering at the industry level.

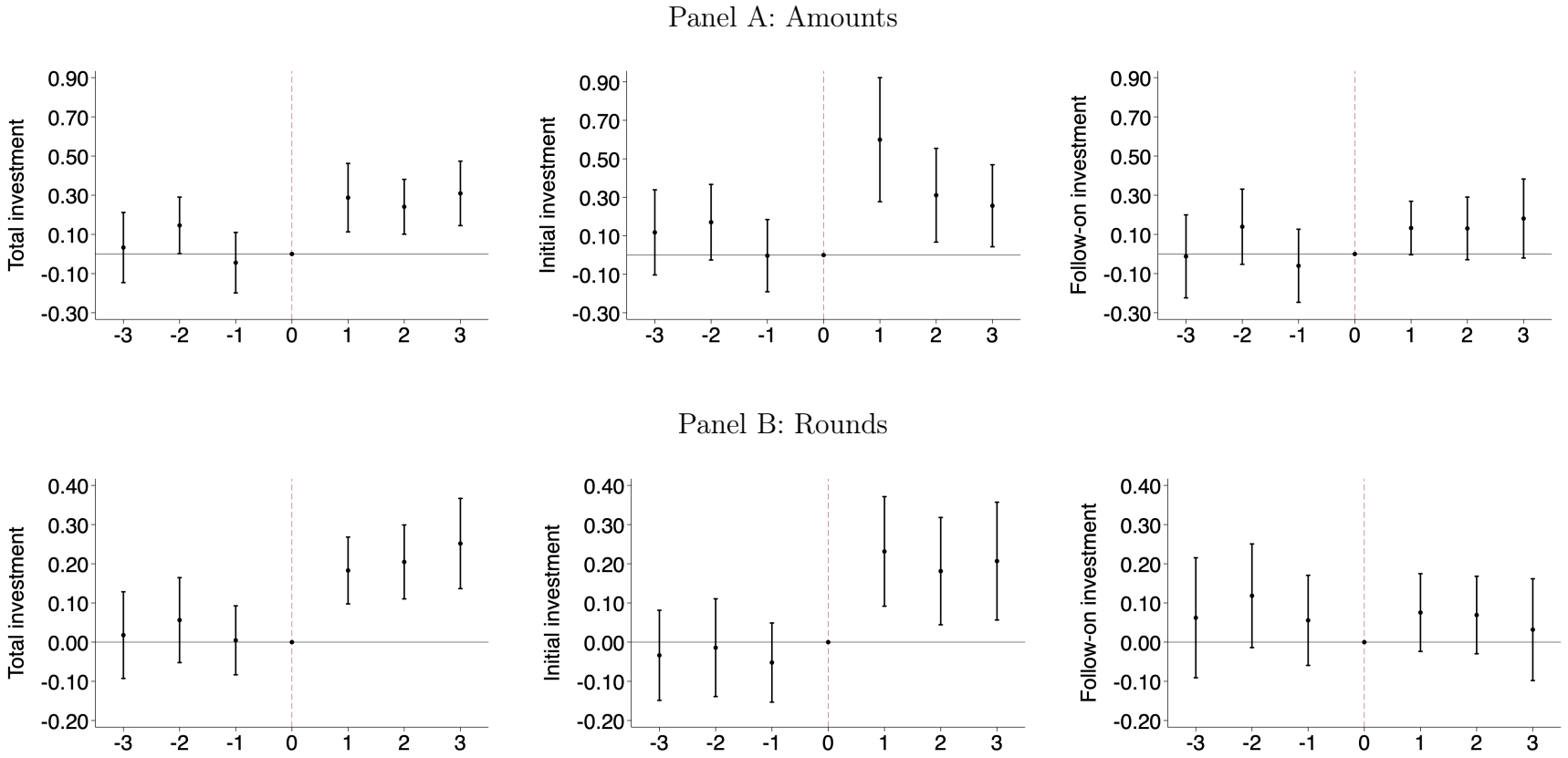


Table 1. Summary statistics

This table presents summary statistics of our dependent variables. Panel A presents the distribution of total funding amounts, deflated by CPI (in millions). Panel B presents the distribution of total funding rounds. *Total investment* is the sum of all VC funding. *Initial investment* is the sum of all first-round VC funding. *Follow-on investment* is the sum of all post-first-round VC funding, calculated only for startups whose initial round occurred before *Bilski*. The unit of analysis is at the industry-fiscal year level. Our sample spans fiscal year 2007 through 2013.

Panel A: Millions of dollars

	Mean	Std. dev.	p10	p25	p50	p75	p90	Obs.
Total investment	128	176	9.16	23.3	68.1	150	349	609
Initial investment	32.8	48.2	0.69	5.08	15.9	41.7	84.1	609
Follow-on investment	87.6	122	2.15	13.9	42.3	103	248	609

Panel B: Number of rounds

	Mean	Std. dev.	p10	p25	p50	p75	p90	Obs.
Total investment	31.5	50.1	4	7	17	36	73	609
Initial investment	16.2	27.4	1	3	8	18	36	609
Follow-on investment	12.9	17.9	1	3	7	15	30	609

Table 2. Descriptive statistics

This table presents statistics on patent rejections and industry exposure related to *Bilski*. Panel A shows the number of patent application rejections that cite *Bilski*, along with the share of such rejections as a percentage of all §101 rejections, based on the fiscal year in which the rejection was mailed. Panel B reports industry-level exposure to *Bilski*. *Startups* denotes the number of distinct startups in each industry that received VC funding in the ten years preceding *Bilski*. *Treatment* is a measure of exposure to the *Bilski* ruling, calculated as the average share of §101 rejections weighted by the distribution of an industry's active patents across technology classes. Panel C shows the correlation for each CPC classification between *Bilski*-based rejection rates and the log change in infringement suits between the three years before and after the decision. *Above-median suits* includes only those CPCs with above-median number of suits in the years surrounding *Bilski*.

Panel A: Annual *Bilski*-based rejections

	2011	2012	2013	2014	2015	2016	2017
Count	4,421	5,758	2,535	1,056	222	59	34
Rate	15.51%	13.63%	11.18%	11.70%	1.83%	0.95%	1.25%

Panel B: Industry exposure to *Bilski*

Most affected industries	Startups	Treatment	Least affected industries	Startups	Treatment
Capital Markets/Institutions	36	23.83%	Building Products	26	2.19%
Automation/Workflow Software	146	21.76%	Agriculture	15	2.51%
Retail	95	20.35%	Restaurants, Hotels and Leisure	44	2.82%
Medical Records Systems	47	18.51%	Pharmaceuticals	219	3.13%
Enterprise Systems (Healthcare)	77	18.19%	Other Materials	13	3.33%
Insurance	23	17.79%	Containers and Packaging	11	3.37%
Other Information Technology	17	15.32%	Chemicals and Gases	61	3.83%
Media and Information Services (B2B)	586	13.88%	Energy Services	82	3.85%
Monitoring Equipment	71	13.58%	Surgical Devices	224	4.22%
Commercial Transportation	13	13.15%	Consumer Non-Durables	108	4.39%

Panel C: Correlation between rejection rates and change in infringement suits

	Class	Subclass	Subgroup	Main group
Correlation: Overall	32.39%	11.40%	-2.19%	-1.19%
Observations	74	189	353	523
	Class	Subclass	Subgroup	Main group
Correlation: Above-median suits	41.29%	25.64%	15.75%	4.56%
Observations	37	94	178	252

Table 3. Average treatment effect

This table reports the effect of *Bilski* on VC investment. The dependent variable is either total funding amounts (first three columns) or total funding rounds (last three columns). *Total investment* is the sum of all VC funding. *Initial investment* is the sum of all first-round VC funding. *Follow-on investment* is the sum of all post-first-round VC funding, calculated only for startups whose initial round occurred before *Bilski*. *Treatment* is a measure of exposure to the *Bilski* ruling, calculated as the average share of §101 rejections weighted by the distribution of an industry's active patents across technology classes. *Post* is zero for fiscal years 2007 through 2010 and one for fiscal years 2011 through 2013. The unit of analysis is at the industry-fiscal year level. z-scores below coefficients are adjusted for clustering standard errors at the industry level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***.

	Amounts			Rounds		
	(1) Total	(2) Initial	(3) Follow-on	(4) Total	(5) Initial	(6) Follow-on
Treatment × Post	0.233***	0.298***	0.117	0.195***	0.229***	0.000
	(3.79)	(4.23)	(1.56)	(3.88)	(3.90)	(0.00)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.840	0.737	0.801	0.849	0.802	0.740
Observations	609	609	609	609	609	609

Table 4. Reallocation versus entry

This table reports the effect of *Bilski* on VC investment in an industry cross-section aggregating VC funding rounds of startups founded prior to *Bilski*. The dependent variable is either total funding amounts (first three columns) or total funding rounds (last three columns), summed over the entire post period (fiscal years 2011 through 2013). *Total investment* is the sum of all VC funding. *Initial investment* is the sum of all first-round VC funding. *Follow-on investment* is the sum of all post-first-round VC funding, calculated only for startups whose initial round occurred before *Bilski*. *Treatment* is a measure of exposure to the *Bilski* ruling, calculated as the average share of §101 rejections weighted by the distribution of an industry's active patents across technology classes. The unit of analysis is at the industry level. z-scores below coefficients are adjusted for heteroskedasticity-robust standard errors. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***.

	Amounts			Rounds		
	(1) Total	(2) Initial	(3) Follow-on	(4) Total	(5) Initial	(6) Follow-on
Treatment	0.036	0.218**	-0.073	0.169	0.212**	0.059
	(0.31)	(2.32)	(-0.53)	(1.55)	(2.11)	(0.46)
Pseudo R^2	0.001	0.039	0.004	0.021	0.032	0.002
Observations	87	87	87	87	87	87

Table 5. Robustness

This table reports the effect of *Bilski* on VC investment after varying key design choices in the baseline specification (Equation 1). The dependent variable is either total funding amounts (first three columns) or total funding rounds (last three columns). *Total investment* is the sum of all VC funding. *Initial investment* is the sum of all first-round VC funding. *Follow-on investment* is the sum of all post-first-round VC funding, calculated only for startups whose initial round occurred before *Bilski*. Panel A reports estimates obtained after modifying how startups are assigned to industries or after altering the minimum number of startups required for an industry to be included. The specifications labeled *Groups classification* and *Codes classification* use Pitchbook's groups and codes industry classifications, respectively. Panel B reports estimates based on alternative constructions of the treatment variable. *Class treatment*, *Subclass treatment*, and *Subgroup treatment* compute exposure at the CPC class, subclass, and subgroup levels prior to aggregation. *Treatment dummy* equals one if an industry's *Treatment* value is above the median. *Pre-certiorari treatment* reports estimates based on treatment defined using applications filed before the Supreme Court agreed to hear *Bilski*. *Treatment* measures exposure to the *Bilski* ruling as the average share of §101 rejections weighted by the distribution of an industry's active patents across technology classes. The unit of analysis is at the industry–fiscal year level. z-scores below coefficients are adjusted for clustering at the industry level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***.

Panel A: Alternative industry definitions

	Amounts			Rounds			
	(1) Total	(2) Initial	(3) Follow-on	(4) Total	(5) Initial	(6) Follow-on	Observations
1. Main results	0.233***	0.298***	0.117	0.195***	0.229***	0.000	609
	(3.79)	(4.23)	(1.56)	(3.88)	(3.90)	(0.00)	
2. Industry groups classification	0.378***	0.424***	0.225***	0.260***	0.286***	-0.002	231
	(5.36)	(4.30)	(3.11)	(3.09)	(2.67)	(-0.04)	
3. Industry codes classification	0.247***	0.272***	0.145	0.201***	0.220***	0.023	805
	(3.35)	(3.62)	(1.63)	(3.90)	(3.56)	(0.38)	
4. Drop industries <5 startups	0.235***	0.299***	0.118	0.198***	0.232***	0.000	644
	(3.77)	(4.19)	(1.55)	(3.90)	(3.91)	(0.00)	
5. Drop industries <20 startups	0.237***	0.298***	0.125*	0.199***	0.230***	0.012	567
	(3.91)	(4.27)	(1.70)	(3.99)	(3.92)	(0.20)	

Panel B: Alternative treatment measures

	Amounts			Rounds			
	(1) Total	(2) Initial	(3) Follow-on	(4) Total	(5) Initial	(6) Follow-on	Observations
1. Class treatment	0.194***	0.287***	0.081	0.176***	0.243***	-0.029	609
	(2.71)	(4.23)	(0.98)	(3.23)	(4.30)	(-0.52)	
2. Subclass treatment	0.238***	0.266***	0.148**	0.230***	0.251***	0.050	609
	(4.26)	(3.92)	(2.16)	(5.85)	(4.80)	(0.94)	
3. Subgroup treatment	0.226***	0.300***	0.104	0.192***	0.222***	0.008	609
	(3.42)	(3.95)	(1.37)	(3.46)	(3.63)	(0.14)	
4. Treatment dummy	0.360***	0.559***	0.164	0.377***	0.494***	-0.002	609
	(2.71)	(3.93)	(1.10)	(3.76)	(4.69)	(-0.02)	
5. Pre-certiorari treatment	0.162**	0.255***	0.061	0.117**	0.152**	-0.050	567
	(2.42)	(3.32)	(0.79)	(2.04)	(2.44)	(-0.81)	

Table 6. Alternative explanations

This table reports the effect of *Bilski* on VC investment after excluding industry subsets that may confound the estimated effect of *Bilski*. *Drop finance industries* removes industries directly exposed to the Great Recession. *Drop software industries* removes industries with 'software' in the name. *Drop top 10 recovery industries* removes industries with the highest percentage increase in total VC funding from 2011 through 2013 relative to 2007 through 2010. *Drop top 10 treated industries* excludes those with the highest *Treatment*, which is as measure of the exposure to the *Bilski* ruling as the average share of §101 rejections weighted by the distribution of an industry's active patents across technology classes. *Drop smallest industries* and *Drop patent-poor industries* remove, respectively, the smallest one-third of industries (by pre-*Bilski* startup counts) and the least patent-intensive one-third of industries. *Mayo: drop years 2 and 3* removes observations for industries plausibly affected by *Mayo* in the two event-time years following the ruling. *Mayo: drop all years* excludes all observations from those industries throughout the sample. The unit of analysis is at the industry–fiscal year level. z-scores below coefficients are adjusted for clustering at the industry level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***.

	Amounts			Rounds			
	(1) Total	(2) Initial	(3) Follow-on	(4) Total	(5) Initial	(6) Follow-on	Observations
1. Drop finance industries	0.218***	0.251***	0.115	0.201***	0.243***	-0.007	581
	(3.17)	(3.46)	(1.43)	(3.72)	(3.81)	(-0.11)	
2. Drop software industries	0.207***	0.278***	0.095	0.165***	0.188***	-0.004	504
	(4.19)	(3.79)	(1.40)	(3.44)	(3.91)	(-0.06)	
3. Drop top 10 recovery industries	0.192**	0.281***	0.076	0.208***	0.264***	-0.008	539
	(2.45)	(3.29)	(0.83)	(3.43)	(3.96)	(-0.11)	
4. Drop top 10 treated industries	0.196***	0.261***	0.103	0.170***	0.232***	-0.031	539
	(2.68)	(3.71)	(1.21)	(2.79)	(3.68)	(-0.50)	
5. Drop smallest industries	0.223***	0.248***	0.130*	0.219***	0.253***	0.033	406
	(3.63)	(3.54)	(1.84)	(4.59)	(4.37)	(0.59)	
6. Drop patent-poor industries	0.134*	0.352***	-0.027	0.120**	0.236***	-0.114	406
	(1.85)	(3.77)	(-0.29)	(2.32)	(5.31)	(-1.44)	
7. Mayo: drop years 2 and 3	0.226***	0.302***	0.108	0.189***	0.219***	0.006	589
	(3.88)	(3.86)	(1.59)	(3.73)	(3.59)	(0.09)	
8. Mayo: drop all years	0.219***	0.305***	0.085	0.200***	0.237***	-0.008	539
	(3.50)	(3.66)	(1.19)	(3.62)	(3.49)	(-0.11)	

Table 7. Startups without patents at funding

This table reports the effect of *Bilski* on VC investment in startups without patents at the time of funding. The dependent variable is either total funding amounts (first three columns) or total funding rounds (last three columns). *Total investment* is the sum of all VC funding. *Initial investment* is the sum of all first-round VC funding. *Follow-on investment* is the sum of all post-first-round VC funding, calculated only for startups whose initial round occurred before *Bilski*. *Treatment* is a measure of exposure to the *Bilski* ruling, calculated as the average share of §101 rejections weighted by the distribution of an industry's active patents across technology classes. Panel A focuses on investments in startups without patents at the time of investment. The unit of analysis is at the industry-fiscal year level, and the sample period is fiscal 2007 through fiscal 2013. *Post* is zero for fiscal years 2007 through 2010 and one otherwise. z-scores below coefficients are adjusted for clustering standard errors at the industry level. Panel B restricts the sample further to those startups founded prior to *Bilski*. The unit of analysis is at the industry level, with dependent variables summed over the entire post period (fiscal years 2011 through 2013). z-scores below coefficients are adjusted for heteroskedasticity-robust standard errors. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***.

Panel A: All startups without patents at funding						
	Amounts			Rounds		
	(1) Total	(2) Initial	(3) Follow-on	(4) Total	(5) Initial	(6) Follow-on
Treatment × Post	0.305***	0.320***	0.215**	0.202***	0.220***	0.052
	(4.54)	(4.32)	(2.54)	(3.68)	(3.58)	(0.85)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.827	0.735	0.776	0.854	0.805	0.741
Observations	609	609	609	609	609	609
Panel B: Startups founded prior to *Bilski* without patents at funding						
	Amounts			Rounds		
	(1) Total	(2) Initial	(3) Follow-on	(4) Total	(5) Initial	(6) Follow-on
Treatment	0.188*	0.297***	0.103	0.239**	0.242**	0.176
	(1.81)	(3.40)	(0.81)	(2.24)	(2.41)	(1.44)
Pseudo R^2	0.026	0.069	0.007	0.039	0.040	0.019
Observations	87	87	87	87	87	87

Table 8. Startups with patents at funding

This table reports the effect of *Bilski* on VC investment in startups with patents at the time of funding. The dependent variable is either total funding amounts (first three columns) or total funding rounds (last three columns). *Total investment* is the sum of all VC funding. *Initial investment* is the sum of all first-round VC funding. *Follow-on investment* is the sum of all post-first-round VC funding, calculated only for startups whose initial round occurred before *Bilski*. *Treatment* is a measure of exposure to the *Bilski* ruling, calculated as the average share of §101 rejections weighted by the distribution of an industry's active patents across technology classes. Panel A focuses on investments in startups with patents at the time of investment. The unit of analysis is at the industry-fiscal year level, and the sample period is fiscal 2007 through fiscal 2013. *Post* is zero for fiscal years 2007 through 2010 and one otherwise. z-scores below coefficients are adjusted for clustering standard errors at the industry level. Panel B restricts the sample further to those startups founded prior to *Bilski* that held at least one pre-*Bilski* patent. The unit of analysis is at the industry level, with dependent variables summed over the entire post period (fiscal years 2011 through 2013). z-scores below coefficients are adjusted for heteroskedasticity-robust standard errors. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***.

Panel A: All startups with patents at funding						
	Amounts			Rounds		
	(1) Total	(2) Initial	(3) Follow-on	(4) Total	(5) Initial	(6) Follow-on
Treatment × Post	0.013	0.099	-0.032	-0.003	0.176	-0.082
	(0.13)	(0.43)	(-0.29)	(-0.04)	(1.52)	(-1.12)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.737	0.499	0.716	0.573	0.352	0.541
Observations	609	609	609	609	609	609
Panel B: Startups founded prior to *Bilski* with pre-*Bilski* patents at funding						
	Amounts			Rounds		
	(1) Total	(2) Initial	(3) Follow-on	(4) Total	(5) Initial	(6) Follow-on
Treatment	-0.530***	-0.704***	-0.514***	-0.322**	-0.327**	-0.325**
	(-3.30)	(-3.63)	(-3.10)	(-2.22)	(-2.13)	(-2.19)
Pseudo R^2	0.127	0.121	0.114	0.053	0.034	0.050
Observations	87	87	87	87	87	87

Table 9. Average funding amounts

This table reports the effect of *Bilski* on average VC funding amounts. The dependent variable is average funding amounts. *Average total investment* is the sum of all VC funding amounts divided by the count of VC funding rounds with non-missing amounts. *Average initial investment* is calculated similarly using first VC funding rounds. *Average follow-on investment* uses all post-first VC funding rounds for startups whose initial round occurred before *Bilski*. *Treatment* is a measure of exposure to the *Bilski* ruling, calculated as the average share of §101 rejections weighted by the distribution of an industry's active patents across technology classes. Panel A uses the full sample. The unit of analysis is at the industry-fiscal year level, and the sample period is fiscal 2007 through fiscal 2013. *Post* is zero for fiscal years 2007 through 2010 and one otherwise. z-scores below coefficients are adjusted for clustering standard errors at the industry level. Panel B restricts the sample to those startups founded prior to *Bilski* and without (with pre-*Bilski*) patents at the time of investment in the first three (last three) columns. The unit of analysis is at the industry level, with dependent variables being averages calculated using the sum (count) of funding amounts (rounds) over the entire post period (fiscal years 2011 through 2013). We assign an average funding amount value of zero to industry-fiscal years with no funding rounds and include an untabulated dummy variable equaling one for these observations in all regressions. Importantly, results are identical when excluding these observations instead. z-scores below coefficients are adjusted for heteroskedasticity-robust standard errors. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***.

Panel A: All startups

	(1) Total	(2) Initial	(3) Follow-on
Treatment × Post	0.143	0.484***	0.071
	(1.00)	(2.67)	(1.40)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Pseudo R^2	0.224	0.381	0.291
Observations	609	609	609

Panel B: Startups founded prior to *Bilski*

	Without patents at funding			With pre-*Bilski* patents at funding		
	(1) Total	(2) Initial	(3) Follow-on	(4) Total	(5) Initial	(6) Follow-on
Treatment	0.169	0.424*	-0.033	-0.142	-0.471***	-0.130
	(1.09)	(1.80)	(-0.70)	(-1.04)	(-3.18)	(-1.11)
Pseudo R^2	0.066	0.168	0.097	0.200	0.385	0.308
Observations	87	87	87	87	87	87