PATENT COLLATERAL, INVESTOR COMMITMENT, AND THE MARKET FOR VENTURE LENDING[*]

Yael V. Hochberg
Rice University, MIT & NBER

Carlos J. Serrano[†]
Universitat Pompeu Fabra & Barcelona GSE

Rosemarie H. Ziedonis
Boston University & Stanford University

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ABSTRACT

This paper investigates the market for lending to technology startups (i.e., venture lending) and examines two mechanisms that facilitate trade within it: (1) the 'salability' of patent collateral; and (2) the credible commitment of existing equity investors. We find that intensified trading in the secondary patent market increases the annual rate of startup lending, particularly for startups with more redeployable patent assets. Moreover, we show that the credibility of venture capitalist commitments to refinance and grow fledgling companies is vital for startup debt provision. Following a severe and unexpected capital supply shock for VCs, we find a striking flight to safety among lenders, who continue to finance startups with investors better able to credibly commit to refinance their portfolio companies but withdraw from otherwise-promising projects that may have needed their funds the most. The findings are consistent with predictions of incomplete contracting and financial intermediation theory. (JEL: L14, L26, G24, O16, O3.)

1. Introduction

Entrepreneurial activity is vital for technological progress and long-term productivity growth (Acs and Audretsch, 1990; Aghion and Howitt, 1992; Davis, Haltiwanger, and Schuh, 1998; Haltiwanger, Jarmin and Miranda, 2013). Yet entrepreneurs seeking to commercialize unproven technologies can find it difficult to attract external capital, particularly through debt channels (Leland and Pyle, 1977; De Meza and Webb, 1987). The market value of startup companies often rests on intangible assets that are hard to value ex ante and sell ex post. Equally challenging, the path to commercialization is risky and fraught with hazards. Even though loans would allow entrepreneurs to avoid additional dilution of their ownership stakes, external debt is widely cast as an unlikely way to fund risky projects absent tangible assets or stable cash flows to secure a loan (Hall and Lerner, 2010).

Although technology startups and outside debt may seem poorly suited for one another in theory, a large and growing industry is supplying loans to early-stage companies. Ibrahim (2010) estimates that "venture lenders," including leader Silicon Valley Bank and specialized non-bank lenders, supply roughly $5 billion to startups annually.[1] In a recent survey, Robb and Robinson (2014) similarly report a "surprisingly high" debt reliance by startups with external equity owners, with loans representing 25 percent of the startup capital for 200 growth-oriented companies.

This paper investigates the market for venture lending and factors that facilitate trade within it. Drawing on incomplete contracting and financial intermediation theory, we explore two mechanisms that could reduce informational and contracting frictions in venture lending: (1) increased liquidity in the secondary market for patent assets, which could alter lender expectations

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[1] Venture loans are typically arm's length (formal) loans supplied by banks and other for-profit financial institutions to science and technology startups. Ibrahim's market size estimates therefore do not include loans from government agencies or "insiders" (e.g., bridge loans from investors or alliance partners).

of salvage value, and (2) the ability of an intermediary (i.e., a venture capitalist) to credibly convey to a lender that he/she will refinance and grow the fledgling company.

The effects of patent-market trading on innovative activity is a topic of heated academic and policy debate as illustrated by recent reports from the U.S. Federal Trade Commission (2011) and U.S. White House (2013). The main concern is that patent sales could stifle innovation incentives if rights are re-allocated to entities that extract "excessive" rents through litigation and hold-up. If thicker trading in the secondary patent market expands entrepreneurial financing opportunities, it is of paramount importance to this debate. We take a first step toward investigating this relationship and quantifying its effect. Governments worldwide also are experimenting with ways to stimulate lending to technology startups (Harhoff, 2009). Understanding the micro-underpinnings of the venture debt market could inform the design of such initiatives.

Prior empirical research on venture lending has been impaired by a lack of reliable data: information about the loans and the parties involved is very sparsely reported.[2] We use an indirect route and identify startup-level lending through patents, a common form of collateral used to secure the loans. Venture lenders typically require a blanket lien on assets, including but not limited to patents (Gordon, 2013). When the collateral includes patents, lenders have strong incentives to record the security interest with the U.S. Patent and Trademark Office (USPTO). Doing so establishes secured-lender status, thus ensuring that the lender is first in line to be paid if assets are liquidated, and reveals that status to other potential lenders (Haemmeli, 1996; Mann, 1997). We use this paper trail of recordation to map startups to loans, thus revealing lending activity at the startup level that is difficult to glean from other sources.[3]

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[2] As Ibrahim (2010) notes, venture lenders are not required by regulators to disclose such information. Since the borrowing companies are small and private, the deals are underreported in lending databases such as DealScan. Our conversations with lenders further suggest that these transactions are insufficiently captured in standard VC databases.

[3] An obvious caveat, the approach requires a sample of companies with patents at risk for use in lending.

Our descriptive evidence reveals a widespread use of loans to finance technology startups, even in early stages of their development. The sample is drawn from the population of venture capital (VC)-backed companies founded from 1987 through 1999 in three innovation-intensive sectors: computer software, semiconductors, and medical devices.[4] Among the 1,519 startups with patents, 36 percent received venture debt by 2008 or prior to exit as evidenced by the USPTO security interest records. The annual likelihood of receiving venture debt climbs steadily over time, is lower prior to first receipt of a VC equity infusion (independent of startup age), and is higher if top-tier investors are involved as would be expected.

Turning to friction-reducing mechanisms in the market, we find that venture lending is stimulated both by thicker trading in the secondary patent market and by VC-level factors. To test effects through the collateral channel, we exploit a ramp up in patent sales over the past few decades that is largely driven by shifts in the legal environment and a corresponding rise in the assertion of patents in information technology-related fields (USFTC, 2011; Hagiu and Yoffie). Employing a novel measure we construct from patent sales data, we find that thicker trading in the secondary market for patent assets increases the annual likelihood that a startup will receive a loan (i.e., the annual debt rate). The estimates control for numerous time varying and permanent startup characteristics (e.g., wealthy founders) that could affect the likelihood of lending, and are not spuriously explained by time-varying opportunity shocks within sectors. Importantly, we also discern a clear and distinctive pattern predicted in incomplete contract theory—the collateral market effect is amplified when startups have patents that are more redeployable to alternative uses or users (Williamson 1988; Shleifer and Vishny, 1992; Benmelech and Bergman 2008, 2009; Gavazza, 2011). At the mean "redeployability" value, a one-percent increase in patent trading

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[4] Our research design requires the inclusion of startups in information technology (IT)-related sectors (represented by semiconductors and software) as well as the life sciences (represented by medical devices). Including all IT and life science startups was infeasible due to manual cleaning of the patent assignment records.

boosts the predicted debt rate by 1.14 percentage points, or 15 percent of the average annual debt rate in our sample. The magnitude of the effect dissipates when startups own patents that are highly firm-specific and is amplified at the upper-distribution of redeployment value. Also consistent with a salvage-value interpretation, observable characteristics of a startup's patents (re-deployable or firm-specific) have an economically meaningful impact on the debt rate only when the collateral asset market is liquid.

Finally, we find that the credibility of a VC's commitment to support a startup is vital for debt provision. To test this intermediary role (formalized in Holmstrom and Tirole 1997), we exploit differences in VC fundraising cycles when the U.S. "technology bubble" collapsed in early 2000, which led to an unexpectedly severe and prolonged decline in the supply of institutional capital to the VC asset class (Townsend, 2012). Given lumpiness in the VC fundraising cycle, this shock should impose more binding near-term constraints for VCs that had not recently closed a new fund at the time of the collapse. We therefore use the age of the most-recently raised funds managed by a startup's investors in early 2000 as a source of variation in capital constraints that affects the credibility of VC commitment and implicit promise to repay lenders for reasons plausibly exogenous to the quality of a startup previously selected for VC funding.

The results are striking. Following the technology bubble's collapse, lending to startups with less capital-constrained investors (i.e., those that had recently closed funds as of early 2000) continued apace, increasing slightly to a per annum rate of 13 percent by 2002. In sharp contrast, lending to startups with more constrained investors (i.e., those that had not recently fundraised at the time of the collapse) plummeted, from an average rate of 17 percent in the three-year run-up period to a mere 1.5 percent three years following the crash. The estimates are based on IT startups active and independent in the six-year window surrounding the shock, and therefore are not explained by differences in time to exit. In more formal difference-in-difference (DD) tests, we

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show that the before-and-after shift in lending is large in magnitude and statistically significant. The annual debt rate of IT startups backed by VCs with relatively old funds at the time of the crash declined by 18 percentage points post-shock relative to startups backed by VCs with more recent funds, even allowing for permanent and time-varying startup characteristics to affect the likelihood of lending.[5] In a "flight-to-safety," lenders continued to finance startups backed by less capital-constrained investors in the post-crash period, but withdrew from otherwise-promising projects that may have needed their funds the most. Our findings suggest that business cycles may depress funding for innovation-based startups not only by limiting future economic prospects and reducing the supply of available VC funding, but also indirectly, by reducing the credible commitment of equity investors and limiting access to debt financing.

This paper provides the first systematic evidence of startup-level activity in the market for venture lending. In contemporaneous work, Mann (2014) reports that debt secured by patents is an important source of financing for R&D performed by established firms. We document similar lending in a context where its use is particularly surprising—young innovation-oriented companies. In doing so, we contribute to a small but emerging literature on venture debt, much of which is conducted by legal scholars (Mann, 1997; Ibrahim, 2011). We trace startup-level lending over a three-decade period, and provide novel evidence on the micro-underpinnings of the market.

The study contributes to a related literature on the role of VCs as intermediaries in the development of startups with risky projects. Considerable evidence shows that venture capitalists help guide and professionalize young firms (e.g., Lerner, 1995; Hellmann and Puri, 2002) and provide access to superior resource networks (e.g. Hsu, 2004; Hochberg et al., 2007). Complementing this work, we highlight an intermediary role of VCs that has received limited

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[5] The two groups of startups exhibit comparable trend-lines in the annual rate of lending in the pre-shock period. Also reassuring for our empirical strategy, placebo tests reveal differential sorting only when differences in VC fundraising cycles are likely to bind near-term capital sourcing.

empirical attention—opening access to debt channels of financing—and devise a lever for identifying its effects.

Finally, we contribute to a broader literature on trading frictions and the mechanisms used to reduce them. The most compelling evidence that lender decisions are affected by conditions in the collateral resale market is based on physical assets in mature industries such as railroads (Benmelech, 2009) and commercial aircraft (Benmelech and Bergman, 2008, 2009; Gavazza 2011). Whether a similar effect arises in friction-filled markets for patents is unexamined in prior work, largely due to data limitations and the difficulty of quantifying secondary-market activity for intangible assets. We introduce new measures and data sources that allow a first look into this issue. Separately, Lamoreaux and Sokoloff (1999) report that historic markets for buying and selling patents allowed inventors to specialize in the generation of new ideas sold to others for commercialization, potentially leading to efficiency gains in technology production.[6] Serrano (2010) and Galasso et al. (2013) document active trading in the modern market for patents, particularly for inventions originating from individuals and small firms. The implications of patent trading for innovation financing is unexplored in prior research, a gap that this study helps fill.

The remainder of this paper is organized as follows. We first discuss relevant insights from the incomplete contracting literature and their relevance for venture lending. We then describe the sample and data sources. Finally, we present and discuss our empirical analysis and findings.

2. Theoretical Framework and Background

An extensive theoretical literature suggests that financing the innovation activities of new firms through formal debt is problematic. A common reason is financial frictions between lenders and debtors due to information asymmetries, which can reduce access to debt (Leland and Pyle, 1977;

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[6] For related arguments, see Arora, Fosfuri and Gambardella (2001), Serrano (2011), Akcigit, Celik and Greenwood (2014), and Czarnitzki et al. (2015).

Stiglitz and Weiss, 1981). Among the mechanisms for reducing such frictions, collateral posting and financial intermediation have received prominent theoretical attention.

Turning first to collateral posting, lenders typically demand collateral because the threat of asset liquidation can increase the debtor's motives to avoid default, reducing the risk of the loans (Johnson and Stulz, 1985). If the debtor fails to repay the loan, lenders also have the legal right to seize and sell the collateral assets to offset losses. The amount that creditors expect to recover upon seizure of the collateral (i.e., the expected "liquidation" or "salvage" value of the assets) should thereby affect their incentives to lend (Williamson, 1988; Shleifer and Vishny, 1992).

The incomplete contracting literature typically assumes that lender expectations of salvage value are shaped by two inter-related factors: (1) trading conditions in the secondary market for collateral assets such as the number of potential buyers and the costs associated with finding them; and (2) whether the assets pledged are firm-specific (e.g., tied to the human capital or commercial pursuits of the debtor) or likely to retain value if redeployed to alternative uses or users (Williamson, 1988). To elaborate, Benmelech and Bergman (2008, 2009) and Gavazza (2011) show that thicker trading (increased "liquidity") in the collateral resale market increases liquidation values and, in turn, stimulates lending. When buyers are few and/or costly to locate, trading frictions reduce the gains anticipated from exchange and lower asset prices. In thicker markets, matching between sellers and buyers is more efficient; in turn, lenders expect more value to be retained in the event of exchange (Gavazza, 2011). If assets are highly firm-specific, however, their redeployment value is more limited by definition (Williamson, 1988). In this event, the effects of trading activity in the broader resale market should diminish. Consistent with this view, Benmelech (2008) finds that railroad companies with standard-width rather than site-specific track gauges (i.e., with more redeployable assets for use as collateral) were better able to obtain debt financing during

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the mid-1870s economic depression. Similarly, Benmelech and Bergman (2009) report a higher debt capacity for U.S. airlines that operate less specialized (more redeployable) fleets.

A second mechanism—an intermediary's credible commitment to support a risky venture, including financially—can also alleviate informational frictions with lenders. Holmstrom and Tirole (1997) model lending transactions that involve firms (entrepreneurs), informed intermediaries (venture capitalists), and uninformed outsiders (lenders). The entrepreneur's borrowing capacity is limited as is the intermediary's capital. The entrepreneur may lack the skills or incentives to manage projects diligently. Although the intermediary (VC) can monitor and guide the entrepreneur, his/her efforts are unobservable to the lender, thus creating a moral hazard problem. As Holmstrom and Tirole (1997) show, an injection of capital by the intermediary is required to credibly convey to the lender that he/she will exert the effort to monitor the company: the intermediary, in seeking a return on its investment, has an incentive to engage in the unobservable effort to build and oversee the project. In Williamson (1983, 1988), equity infusions serve a similar incentive-alignment function, by "credibly committing" contracting parties to an endeavor. In turn, financial frictions arising from information asymmetries between the entrepreneur and uninformed outsider (lender) are reduced.[7]

Of particular importance for our analysis, Holmstrom and Tirole (1997) further show that a negative shock to the capital supply, in which the availability of capital to financial intermediaries is reduced for reasons largely beyond their control, will limit debt access for entrepreneurial firms backed by those intermediaries. The intuition is simple. Less capital can be injected into the companies because the supply of capital to intermediaries is limited. As a result, financial intermediaries will find it more difficult to credibly convey to the lenders that they will continue to support the portfolio company, thus making it more difficult for the company to secure a loan.

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[7] In a recent model, Nanda and Rhodes-Kropf (2014) use similar reasoning to explain how a financial intermediary's implicit promise to support the venture can affect lender expectations of loan repayment.

Implications for Venture Lending

The use of formal debt to finance startups with risky projects is a situation rife with informational and contracting frictions. Success rests on entrepreneurial and managerial effort that is difficult for lenders to specify ex ante and monitor ex post, and commercialization requires upfront investments in projects likely to fail. As Ljungqvist and Richardson (2003) report, the average VC fund raised between 1981 and 1993 wrote-off more than 75 percent of its portfolio-company investments.

Challenges aside, parties involved in a typical venture lending transaction, lenders and the entrepreneurs and/or their investors, have much to gain from striking a deal. Venture lenders stand to earn interest on the loans, with bank-lenders earning additional fees for banking services rendered.[8] For entrepreneurs and their investors, the main attraction is funding that does not require costly dilutions of equity. In turn, they gain added financial cushion, potentially increasing their abilities to maneuver in the event of commercialization setbacks or milestone delays. As depicted in Figure 1, venture debt is therefore marketed as a way to "extend the financial runway" of a startup (Gordon, 2013). The obvious drawback is the need to repay the loans, plus accumulated interest, within an agreed-upon time frame. In the event of default, entrepreneurs also stand to lose control over assets used to secure the loan, including patented inventions.

What mechanisms facilitate trade in the venture lending market? Industry descriptions and case studies highlight the importance of VC involvement (Mann, 1997; Ibrahim, 2010). Hardymon, Lerner and Leamon (2005, p4) aptly describe the VC role as follows:

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[8] Non-bank organizations in the venture debt landscape include specialized lenders like Lighthouse Capital, Hercules Technology Growth Capital, and Western Technology Investment. Banks tend to provide smaller loans, typically ranging up to $2-3 million, at lower interest rates than non-banks. As Ibrahim (2010) reports, banks typically require borrowers to deposit cash and use other financial services, thus producing a secondary source of revenues from fees while providing a monitoring function (of tracking changes in burn rates) for VC investors. Non-banks face less stringent regulatory restrictions than banks. In turn, specialized non-bank lenders typically incur higher risk, charge higher interest rates, and have higher maximum loan packages reaching the tens of millions.

"Lenders rel[y] both on the investors' ability to choose good firms and on their presumed willingness to support the investments with future funding, and thus tried to maintain a good relationship with the best venture capitalists. Further reducing the risk, the loan usually closed just after a major equity infusion, increasing the possibility that the debt would be paid off before the company's money ran out."

As in our conversations with lenders, Hardymon et al. (2005) report that lenders outsource much of the due-diligence and valuation process to VCs, both for the applicant startup and its intangible assets. The quote further suggests that VC reputation (skill) is informative for lenders, both for ex ante (ability to identify and attract more promising startups) and ex post (ability and willingness to support the startup once funded) reasons. In either case, this discussion suggests that venture capitalists help "harden" soft assets—technologies, skills, and other intangibles like patents—that startups would find more difficult to borrow against on their own. Ironically, venture lenders also may lower risks by funding startups in earlier stages of development, when VCs are more likely to secure follow-on resources for the company.

Whether lending activity is shaped by expectations of the salvage value of patent collateral is more ambiguous. As an asset class, intangibles are more difficult to value and trade than tangibles like commercial aircraft. Indeed, the intangibility of a firm's assets is a common proxy for low salvage value in the corporate finance literature. Legal scholars nonetheless report that lenders consider the tradable (salvage) value of patents when crafting loans, despite obvious valuation challenges (Mann, 1997; Ibrahim, 2010; Menell, 2007). Fischer and de Rassenfosse (2011) report similar findings in a survey of lenders.

Anecdotal evidence further suggests that the secondary market for buying and selling patents has grown more active in the past few decades, an effect largely driven by shifts in the legal environment and a corresponding rise in the assertion of patents in information technology-related fields (Hall and Ziedonis, 2001; U.S. FTC, 2011). In 1999, Intel Corporation launched its first patent purchasing program, formalizing the process by which it acquired patents either as

standalone assets or through corporate takeovers (Chernesky, 2009). Intellectual Ventures (IV), the largest patent "aggregator" formed to date, was founded in the year 2000. By 2012, IV had spent over $2 billion to amass one of the world's largest portfolios of 35,000 patents, primarily covering software, semiconductor and mobile computing inventions (Hagiu and Yoffie, 2013). Hagiu and Yoffie (2013: 60) assert that, "[b]ecause of its size, Intellectual Ventures can single-handedly create liquidity in the market." The patent-market liquidity measure we utilize, described below, indirectly captures this effect by tracking the intensity of patent trading in different invention classes, including semiconductors and software (where IV is particularly active) and medical devices (where it is not).

To summarize, the incomplete contracting and financial intermediation literature yield three testable predictions in the venture-lending context. First, if increased liquidity in the secondary patent market is altering lender expectations of the salvage value, the likelihood that a startup will receive a loan should increase with thicker trading in the market for buying and selling patents, particularly when a startup's patents are more redeployable to alternative uses or users (less firm-specific). Second, the likelihood of lending should increase following a startup's first VC equity infusion, especially when reputable (skillful) VCs are involved. Finally, the likelihood of lending should depend on the ability of VC intermediaries to convey to lenders a credible commitment to monitor and support the risky project.

3. Data Sources and Descriptive Findings

As noted earlier, reliable startup-level data on venture loans is lacking. Novel to the field, our approach identifies loans to startups through patent collateral, thus revealing transactions difficult to glean from other sources. The approach requires a focus on startups with one or more patent assets at risk of being used to secure a loan; otherwise, the presence or absence of a loan is unobservable. The remainder of this section describes our "patenting startup" sample (Section 3.1),

defines key variables and data sources (Section 3.2), and shows patterns revealed in the data (Section 3.3). We discuss identification challenges in Section 4.

3.1. Sample Construction

Our sample is drawn from the universe of U.S. venture capital-backed firms reported in Dow Jones' VentureSource (aka "VentureOne") database in three innovation-intensive sectors: software, semiconductor devices, and medical devices. Focusing on startups that eventually receive VC financing allows us to observe when each company first received a VC equity infusion and from whom they received such investment. We then select all startups founded from 1987, the first year of comprehensive reporting in VentureOne, through 1999. The latter cut-off captures the youngest cohort at risk of being affected by the market crash in early 2000, and provides a common decade-long window for tracking the startups' activities and outcomes. To better pinpoint when startups disband and leave the risk pool for lending, we supplement VentureOne data with information from Sand Hill Econometrics on the type and timing of entrepreneurial exits (Hall and Woodward, 2010). Each company is tracked through 2008, our last year of reliable financing data, or until exit. The initial sample comprises 3,414 companies.

To identify startups with patents, we search the Delphion database for U.S. patents assigned to all current and former names listed for each startup as reported in VentureOne. Of the 3,414 startups, 1,519 receive at least one U.S. patent by 2008 or exit, averaging 9.5 patents per company. In the combined set of 14,514 patents, 51 percent are issued to 483 medical devices companies, 23 percent are issued to 197 semiconductor devices companies, and the remaining 26 percent are awarded to 839 software startups. The maximum portfolio size is 199 patents. The summary statistics and analyses below are based on this patenting-startup sample.

The dataset is an unbalanced panel with 1,519 startups and 11,298 startup-year observations, a subset of which is used in our difference-in-differences (DD) analysis. Startups are retained in the sample through 2008 or the year in which they went public, were acquired, or were disbanded.

3.2. Main Variables and Data Sources

Our analysis requires measures of startup-level lending, patent-market activity, and VC investors. Appendix I summarizes these measures, and lists the sources used to compile them.

Startup Receipt of Debt Financing

Our outcome variable, $DEBT_{it}$, indicates if one or more patents owned by a startup is used to secure a loan in a given year. To obtain information on patent security assignments, we extend the method developed in Serrano (2010) and extract records for each of the 14,514 patents from the USPTO Patent Assignment Database. We then identify, on a patent-by-patent basis, all instances where a patent "security interest" is assigned to a third party and is therefore pledged as collateral.[9] For each record, we track the date of the transaction (execute date), the date the transaction was recorded (recorded date), the entity that assigned the security interest (assignor), the entity that received it (assignee), and the patent numbers involved in the transaction.

As expected, Silicon Valley Bank, a specialist in providing banking services for startups, is the most common lien holder. More specifically, Silicon Valley Bank supplies loans to 35.2 percent of the 547 startups with loans in our sample and an even larger share (42 percent) of the subset in IT-related sectors. In total, we identify 239 annual debt deals between Silicon Valley Bank and patenting startups. Of those, only eight (3 percent) are listed in the VentureOne database.

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[9] Common terms used to describe patent security agreements in USPTO patent assignments include "security interest", "security agreement", "collateral assignment", "collateral agreement", "lien", and "mortgage."

Patent Market Liquidity

Lender expectations of the salvage value of patents are unobservable. We therefore compute an indirect proxy, *Patent Market Liquidity$_{it}$,* to capture the annual likelihood that patents in a startup's portfolio will be traded.[10] The measure and the premise behind it follows recent work by Gavazza (2011) on aircraft leasing: in decentralized markets, where buyers and sellers face fixed costs to search for the right trading partner, market thickness should facilitate reallocation to next-best use, thus increasing the salability of collateral assets. Despite the recent rise of aggregators like Intellectual Ventures, the market for buying and selling patents remains highly fragmented (Hagiu and Yoffie, 2013). The analogy therefore applies.

To compute the measure, we first identify the population of patents in each technology sector using the USPTO invention classes and subclasses reported in Appendix I. We then tally the number of U.S. patents awarded in each set of classes by calendar year and, using patent sales data provided by RPX Corporation, the share involved in subsequent transactions.[11] Consistent with Serrano (2010) and Galasso et al. (2013), patent sales are defined broadly to include sales of patents as standalone assets and transfers bundled through corporate acquisitions, a common route through which patent assets are transferred to new owners.[12] Serrano (2010) shows that the likelihood that a patent is sold can differ across patent classes, calendar year ("vintage"), and patent age. Serrano also shows that the vast majority of patent sales occur within eight years of issue and that the likelihood of sale declines over the lifetime of a patent. As a final step, we therefore restrict the pool of potentially tradable patents to those issued eight years prior to year *t.* This provides us with a measure of liquidity for each sector and issue year. We then average across the sectors and

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[10] Patent sales recorded at the USPTO do not include transaction prices.

[11] As per Serrano (2010), the RPX data are drawn from USPTO Assignment data and omit transaction types unrelated to patent sales, including the assignment of legal title from employees to their employers and security agreements with lenders. These data enable us to trace patent sales for U.S. patents over the full sample period.

[12] To illustrate, Berman (2014) estimates that $7 billion of the $12.5 billion Google paid to acquire Motorola Mobility in 2011 was for the company's portfolio of 17,000 patents. Following the takeover, Google divested Motorola Mobility's core product unit (mobile handsets) but retained most of the patents transferred through the deal.

issue years of the startup's patent portfolio and compute *Patent Market Liquidity$_{it}$* as the combined

probability (averaged across patents based on sector and issue year) that a patent in startup *i*'s

portfolio will be traded in year *t*.

Firm-Specificity of Patent Assets

Discerning the firm-specificity (or redeployability) of patent assets is also challenging. The

ideal measure would capture the extent to which patent collateral is likely to retain value if the

company fails and the assets are sold to others. At one extreme, the assets could be perfectly "firm-

specific" in the classic sense of Williamson (1988): rendered worthless if the company fails or the

team disbands. This outcome could arise if the patent rights hold no value absent access to the

underlying human capital. A startup's patents could also be highly "firm-specific" if they cover

inventions that are nonviable on the market and/or hold no value if enforced (e.g., see Galasso et

al., 2010). At the other extreme, the patent rights could be highly redeployable (saleable) if the

company fails. To illustrate, e-commerce patents owned by Commerce One sold for $15.5 million

at the startup's bankruptcy auction in 2005. Novell, an established software company, reportedly

purchased the patents to ensure that they would not be used against it in future license negotiations

or lawsuits (Markoff, 2005).

To capture the firm-specificity of patents assets, we compute the share of citations to a startup's

patents that originate from follow-on patents issued to the focal company (i.e., the proportion of

follow-on patent references that are "self-cites"). More specifically, *Firm-Specificity$_{it}$* is the share

of citations that a startup's patents receive within three years of being granted that are self-citations.

The three-year window is a time-horizon likely to be relevant in startup lending and is consistent

with recent studies (e.g., Lerner et al., 2011). A higher self-cite share is assumed to correlate with

higher "firm-specificity" levels and hence, more limited redeployability of the assets in the

secondary market.[13] The measure is similar in spirit to an internal-focus proxy used in Hoetker and Agarwal (2007)'s study of failed disk drive companies: the authors report a steeper decline in follow-on citations (invention use) following exits of companies with high self-citation shares in the pre-exit period. Marx et al. (2009) use a similar citations-based measure to gauge the firm-specificity of skills among employee-inventors.

VC-Related Variables

We examine the effects of VC involvement from several vantage points and with multiple measures. The first measure, *Post VC$_{it}$*, is an indicator that switches from zero to one in the year that the startup receives its first VC equity infusion. First receipt of VC financing is determined based on close dates reported in VentureOne.

A second measure, *Has Top-Tier VC$_{it}$*, captures whether and when a startup receives funds from a top-tier (highly reputable) VC, thus exploiting heterogeneity among VCs in reputational capital and skill. To identify top-tier VCs, investor names in VentureOne are matched to reputation scores computed by Lee, Pollock, and Jin ("LPJ" 2011).[14] Computed annually for VCs active from 1990 through 2010, the LPJ scores range from 0, for fringe/new investors, to a maximum of 100, with a median value of 5.7 out of 100. Consistent with Gompers et al. (2010), *Has Top-Tier VC$_{it}$* is set to one if a startup has backing from one or more VCs in the top 25 percent of the annual LPJ score distribution given high skew in VC reputation and skill levels. Use of a more stringent top-percentile threshold yields similar results. Of the 1,519 sample startups, 1,075 (71 percent) receive funds prior to exit from a VC with a top 25 percentile score while 444 (29 percent) do not. Kleiner

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[13] Perhaps more intuitively, if a startup's patents are extensively cited by outside parties in follow-on inventions, we assume that it is more likely that those patents could sold in the secondary market if the startup fails than if the startup is the only sole party building on and citing the focal patents.

[14] Each VC's score is a composite measure based on years in operation, the average number of funds managed in the prior 5 years, the number of startups funded in the prior 5 years, the amount of funds invested in the prior 5 years, and the number of companies taken public in the prior 5 years. The scores are posted at: http://www.timothypollock.com/vc_reputation.htm. The scores are slow moving in time. We therefore use a VC's score in 1990 to impute values in years (1987-1989) that pre-date the LPJ series.

Perkins and Sequoia Capital, venerable Silicon Valley investors, both fall in the top percentile of the distribution, with average annual scores of 77 and 62 respectively.

A third VC-related measure, *Recent Fund$_i$*, is required for the DD analysis that exploits variation among VCs in fundraising cycles. The measure, defined more fully in Section 4, is based on the vintage of VC funds most recently raised by the startup's collection of investors as of early 2000, when the technology bubble collapsed. Although VentureOne identifies VC firms investing in a startup and their rounds of participation, it does not track the individual funds from which those investors make investments. To map investors to funds, we obtain supplemental data from Private Equity Intelligence (PREQIN) on the vintage (close year) and size of funds raised by VC investors. According to PREQIN, $72.3 billion in VC funds were raised worldwide between 1987 and 1999. Of that, $67.6 billion (93 percent) matched investors backing startups in our startups. Investors represented in our study thus control the vast majority of VC funds in the industry.

Other Measures

Appendix I lists other control variables and data sources. *Patent Portfolio Size (citation-weighted)$_{it}$* is a time-varying measure of a startup's patent portfolio size in year *t*, weighted by the citations those patents receive within three years post-grant to capture the overall "importance" of those inventions. *Funds Raised Last Equity Round$_{it}$* measures the millions of US dollars raised by the startup in its last equity round, which could affect the need for debt financing. *Founding Year$_i$* is the startup's year of establishment, thus capturing age/cohort effects. *Sector$_{ij}$* indicates whether the startup's primary sector is medical devices, semiconductor devices, or software. Finally, *Time Period$_t$* allows for differences in entrepreneurial funding climates in the pre-boom (1987-1997), boom (1998-1999) and post-boom (2000-2008) periods. As is well-known, entrepreneurial capital was unusually plentiful in the late 1990s, an era known for "money chasing deals."

3.3. Descriptive Findings

Table 1 reveals that debt financing is commonly used among the startups in our sample. As shown in Table 1A, 36 percent of all patenting-startups received at least one loan pre-exit as evidenced by the USPTO patent security records. The percentages are similar across the three sectors. Of the 14,514 U.S. patents awarded to the startups by 2008 or prior to exit, more than 25 percent were involved in one or more security interest agreements. The percentage is highest for software startups, where almost one-third (32 percent) of the patents were used in lending. Panel B further shows that security agreements tend to cover most patents in a startup's portfolio: on average, the startups have liens on 92 percent of their patents by the year of the last reported loan transaction. As noted earlier, venture lenders typically take a blanket lien on all company assets when securing a loan, so this statistic is not surprising.

Table 2 compares observable characteristics of startups that do (n=545) versus do not (n=974) secure loans with their patents. Although the mean age is similar across the groups, startups with loans tend to raise more equity capital than those without, have more (and more highly cited) patents on average, and are more frequently backed by top-tier investors. Nonetheless, the IPO rate for startups with loans is lower than that for those startups without (13 versus 21 percent), and a higher share of debt-financed companies (27 versus 20 percent) remained private by 2008. A similar pattern holds for the subsample of startups founded in the late 1990s. Qualitatively, the pattern in Table 2 resonates with claims that venture lending is particularly useful when VCs seek to "extend the financial runway" of portfolio companies without resorting to new rounds of equity investing. As in media reports (e.g., Tam, 2007), these loans may have enabled VCs to keep otherwise-promising companies afloat during a cold period in the venture capital market.

Patent Market Liquidity and Venture Lending Activity

Table 3 reports patent sales and the intensity of trading (*Patent Market Liquidity*) by sector and time period, alongside the annual debt rates for sample startups. Panel A shows that, between 1987 and 2008, 295,438 patents less than eight years old at the time of transaction were sold across the three sectors. Of those, 212,643 transactions (72 percent) were sold between 2000 and 2008. Patent sales have increased over time in all sectors, but the rise is especially noticeable in software, an effect partly due to disproportionate growth in the patenting of software inventions shown in prior studies (e.g., Cockburn and MacGarvie, 2011).

In Panel B of Table 3, we adjust for the pool of patents available for trading, thus normalizing sector-level differences in the annual supply of patents. The average *Patent Market Liquidity* value is 0.039, which indicates that the combined sample probability that a patent issued within the last eight years will be sold in a given year is 3.9 percent. Estimates range from 5.1 percent in medical devices to 3.8 and 2.7 percent in the software and semiconductor devices sectors, respectively.[15] Again, the upward time trend is most visible in software, where the intensity of patent trading increased by 75 percent (from 2.8 to 4.9 percent) from the pre- to post-boom periods. These patterns are consistent with claims of increased trading activity in secondary patent markets by patent assertion entities and patent aggregators, particularly for software inventions (e.g., Hagiu and Yoffie, 2013).

Finally, Panel C of Table 3 shows the annual rate of lending to sample startups in equivalent time periods. In the frothy entrepreneurial and IPO climate of the late 1990s, industry insiders forecast that the venture lending market would collapse if VC funding became less plentiful (Gates, 1999). Indeed, the growth rate in lending between the pre-boom and boom period in Panel C is

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[15] By comparison, Serrano (2010) reports an annual trade rate that ranges from 2.8 to 1.6 in the first eight years for patents granted to both U.S and foreign individuals from 1985-2000. The higher aggregate trade rate in our IT sectors is likely due to the inclusion of the post-2000 period.

striking. The sample probability that a startup secured a loan in a given year (i.e., the average annual "debt rate") almost doubled, from 4.7 to 9.0 percent. Post-boom, however, the within-sample debt rate remained relatively stable, at 8.4 percent. This persistent reliance on debt financing could stem from multiple factors, including increased demand for non-equity sources of entrepreneurial financing when VC sources dwindled. Regardless, we find no evidence of market collapse following the "money-chasing-deals" era.

In unreported estimates (available upon request), we compute the correlation between the annual patent-market liquidity and annual startup debt rate in each sector. Not surprisingly, given evidence in Table 3, the correlations are positive and significant, ranging from 0.87 in software to 0.54 and 0.37 in medical devices and semiconductors respectively.

VC Investors and Venture Lending Activity

Are lending rates higher following a startup's first VC equity infusion and, conditional on receipt of such financing, for those with top-tier investors? The short answer is "yes." As shown in Figure 2, the average debt rate is much lower for startups before (versus after) first receipt of VC financing, at 3.0 versus 8.4 percent. The gap is wide and visible across the startup-age distribution.

Table 4 further distinguishes startups with top-tier VCs from those backed by lower-tier investors, and revisits time patterns. Conditional on receiving VC financing, the debt rate for startups with top-tier VCs is higher than that of startups backed solely by lower-tier investors, at 9.1 versus 7.1 percent. This pattern is consistent across time, except in the pre-boom (1987-97) period. Interestingly, Table 4 also shows a steady climb over time in the debt rate for sample startups in periods before they receive VC financing, thus suggesting increased activity (albeit at much lower levels) in early phases of the entrepreneurial life cycle.

4. Estimating the effects of patent markets and VC investors on startup lending

Establishing whether patent trading activity and/or venture capitalists *causally* facilitate

startup-level lending poses numerous identification challenges. Prior evidence suggests, for

example, that entrepreneurs with prior IPO exits are more likely to secure external funds for their

new ventures and from highly reputable VCs (Gompers et al., 2010). Such entrepreneurs also are

likely to have better assets and financial resources unobservable to the econometrician that could be

used to guarantee a loan, thus increasing the likelihood of debt financing at their new companies. If

this was the case, the presence of top-tier VC backing and of debt might be correlated, but not

causally related. Similarly, VCs could simply select "higher quality" ventures that in turn are better

candidates for lending. Below, we describe our approaches for dealing with these issues, report

results, and conduct robustness checks with these and other identification challenges in mind.

4.1. Baseline econometric model and results

To start, we estimate the likelihood that a startup will obtain debt financing in a given year with

a simple linear probability model:

$$DEBT_{it} = \beta_1 Patent\ Market\ Liquidity_{it} + \gamma_1 PostVC_{it} + \tau_t + X_{it} + \theta_i + u_{it} \qquad (1)$$

As explained earlier, $DEBT_{it}$ indicates if startup i receives a loan in year t, *Patent Market*

Liquidity$_{it}$ captures the intensity of secondary-market trading for patents owned by startup i in year

t (adjusted by the annual age profile of the portfolio), and *PostVC$_{it}$* switches to one in the year the

startup first receives VC financing. The term τ_t captures period differences in funding climate,

while X_{it} represents time-varying startup characteristics that could affect the baseline probability of

lending, including a company's age, funds raised in its last equity round, and patent portfolio sizes

(citation-adjusted to capture the overall importance of the inventions). u_{it} is the residual component.

The term θ_i in Equation (1) represents startup fixed effects, thus allowing us to difference out

permanent startup characteristics (e.g., unobserved wealth endowments of founders) that might

correlate with lending. In Equation (1), β_1 therefore captures the change in the probability that a startup obtains debt financing in a given year (i.e., its annual debt rate) due to shifts in patent-market trading not otherwise explained by the control variables and the fixed effects. Similarly, the coefficient γ_1 captures the added change in the predicted annual debt rate following first receipt of VC financing that is not explained by the controls. Expanding Equation (1), we then add the *Firm-Specificity* proxy and interact it with *Patent Market Liquidity.* The interaction term tests whether lending is less responsive to patent-market changes when a startup's patent assets are more firm-specific. Finally, we add the *Has Top-Tier VC* indicator to test whether the probability that a startup receives a loan is further heighted by equity infusions from investors that are especially reputable or skillful. Since *PostVC* is in Equation (1), *Has Top-Tier VC* acts as a step-function and captures whether the change in a startup's probability of receiving a loan post-VC financing is significantly higher when top-tier investors are involved, whether initially or in later rounds of financing.

The estimation sample is an unbalanced panel with 1,519 startups and 11,298 startup-calendar year observations. Table 5A shows summary statistics at the startup-year unit of observation. The statistics are in line with evidence reported in prior tables. Table 6 reports OLS estimates of the likelihood that a startup receives a loan in a given year. Columns 1-3 focus on the two main variables in Equation (1), *Patent Market Liquidity* and *PostVC*, and test the robustness of the estimates to different specifications. Columns 4 and 5 further probe the patent market effect, while Column 6 tests for added effects due to top-tier investors. In all regression we cluster the standard errors at the startup level.

The coefficients on *PostVC* and *Patent Market Liquidity* are positive and statistically significant both in Column 1 of Table 6, the parsimonious specification, and Column 2, which adds controls for the entrepreneurial funding climate, the startup's sector, and annual characteristics of each company (startup's founding year, innovative output, and equity funds last raised). Column 3 adds

startup fixed effects, thus identifying effects from within-startup variation. The *PostVC* and *Patent Market Liquidity* coefficients remain positive, significant, and comparable in magnitude. A Hausman test rejects the null hypothesis that the startup effects are random.[16] In robustness tests, we obtain similar results if we use a fixed-effects Logit model to estimate the effects or use calendar-year rather than period-wide controls.

In combination, Columns 1-3 show that—even controlling for numerous time-varying factors and allowing for company-specific differences among startups (e.g., wealthy founders)—the annual debt rate is significantly higher following a startup's first VC equity infusion and when the market for buying and selling patents is more liquid.

Although the observed ramp up in patent transactions has been linked to patent 'trolling' activities –acquisition of patent rights for later use against existing manufacturing firms– (see e.g., Hagiu and Yoffie, 2013), it is natural to question whether the "patent market liquidity" effect is due to an omitted variable that simultaneously drives changes in patent-market trading and affects the likelihood of startup lending. For example, a positive opportunity shock could increase the demand for patents and/or human capital in a sector, thus intensifying trading activity in the market for patents. The same opportunity shock could increase the value of inventions produced by a startup and, in turn, increase the startup's viability as a candidate for lending. Due in part to this concern, our specification includes a time-varying control for the overall "value" of each startup's patent portfolio. As is standard in the innovation literature (e.g., see Hall et al., 2005), patent value is proxied by the total number of citations those patents receive in a given time window. In addition, we include sector-level fixed effects and time period dummies. In supplemental tests (available upon request), we obtain similar findings in specifications that replace the time period dummies

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[16] To perform the test, we run random effects panel regression with covariates. We also run a fixed effect panel regression with the sub-sample of time-variant covariates. The coefficient on VC in the random effects specification is 0.03756 (p-value<0.01). The estimate from the fixed effects specification is 0.0428. A Hausman test rejects that the estimated coefficients are equal (χ =43.73), indicating that a random coefficients estimator would be inconsistent.

with more granular annual fixed effects and that interact the sector and annual effects, thus allowing for sector-specific yearly shocks.[17]

To probe the patent market effect more fully, we exploit differences among startups in the redeployability of their patent assets. If increased liquidity in the secondary market for patents shifts (unobservable) lender expectations of salvage value, we should find a disproportionate boost for startups with patent assets that are more redeployable to alternative uses or users (Williamson 1988; Benmelech and Bergman 2008, 2009). Put differently, lending should be less responsive to collateral-market conditions when patent assets are firm-specific. A priori, it is unclear why an omitted opportunity shock would yield this distinctive pattern.

The evidence in Columns 4 and 5 is consistent with this salvage-value interpretation. In Column 4, the coefficient on *Firm-Specificity* is negative and statistically significant, suggesting that lending rates are lower for startups with more firm-specific (less redeployable) patent assets. More importantly, in Column 5, the coefficient on the interaction, *Firm-Specificity x Patent Market Liquidity*, is negative and statistically significant: startups with firm-specific patent assets experience lower annual debt rates when patent market liquidity is high than startups with patents more likely to retain value if redeployed to alternative uses or users. Interestingly, the main effect of *Firm-Specificity* is trivial in magnitude and statistically insignificant in Column 5. This result is also consistent with a salvage-value interpretation: absent liquidity in the patent market, the specificity (or redeployability) of patent assets should not affect the probability of startup lending.[18]

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[17] Similar results were obtained if *Patent Market Liquidity* measure is based on a four-year window instead.

[18] The results in Table 6 are robust to use of alternative firm-specificity proxies. Instead of a self-citation-based measure, we computed the number of distinct companies citing the patent portfolio of the startup in an equivalent three-year window relative to the startup's patent portfolio size. In the spirit of Shleifer and Vishny (1992), more citing parties are assumed to represent more potential buyers and thus a higher likelihood of redeployment. Given high skew in the patent value distribution within firms (e.g., Hall et al., 2005), we also re-compute firm-specificity based solely on a startup's patents with above-median citation counts that are likely to attract more interest in the resale market. Not surprisingly, the various specificity measures are highly correlated and yield similar findings.

To interpret the magnitude of the interaction effect in Column 5, we calculated the estimated effect of a one percentage point increase in patent-market liquidity from its mean value (0.0448) at different points in the firm-specificity distribution—highly redeployable (bottom 10 percentile of the specificity distribution), average redeployability (mean value), and firm-specific (top 10 percentile)—with controls held at mean values.[19] When redeployability is high, a one percentage point increase in patent-market liquidity predicts an increase in the annual debt rate by 0.0131, or 1.31 percentage points. When patent assets are firm-specific (redeployability is low), the magnitude of the effect is much smaller: an equivalent patent-market change increases the annual debt rate by 0.004, or only 0.4 percentage points. At the mean firm-specificity value, the estimated effect is 0.0114, which is a 1.14 percentage point boost in the annual rate of startup lending. This marginal effect is large, corresponding to about 15 percent of the sample mean of the annual debt rate. In combination, we interpret these results as evidence that increased trading in the secondary market for patent rights is shifting lender expectations of salvage value, expanding the financing opportunities of innovative companies.

Turning more closely to VC effects, Column 6 of Table 6 adds *Has Top-Tier VC* to the specification. The coefficient on *Has Top-Tier VC* is positive and significant, suggesting that the lending likelihood is heightened further by the presence of equity investment by highly reputable VCs. Based on coefficients in Column 6, the first receipt of VC financing (*PostVC*) increases the annual debt rate by 2.8 percentage points, from 5.2 to 8.0 percent, almost doubling the rate predicted at the mean. Backing from a top-tier investor, whether in an early or later round, increases the predicted debt rate by an additional 2.8 percentage points, a large added boost. As before, the results are robust to inclusion of year (versus period) and sector-year effects.

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[19] For the bottom and top percentiles, estimates are based on the mean within-percentile specificity value.

While interesting, these VC-related findings are prone to multiple interpretations. Consistent with financial intermediation theory, VCs could be serving an intermediary role: by credibly committing to build and monitor portfolio companies through equity infusions, VCs could reduce financial frictions originating from information asymmetries between entrepreneurs and lenders. In this view, the relationship between the presence of VCs and startup lending is causal. Relatedly, being selected for funding by a VC, particularly one that is highly reputable or skillful, could alter lender expectations of the otherwise difficult-to-discern quality of the startup, similarly altering expectations of repayment in a causal manner.

Although qualitative accounts of venture lending suggest that VCs serve an economically meaningful intermediary role, non-causal explanations for the VC findings in Table 6 are also plausible. To elaborate, recall the error term u_{it} in Equation (1). VC backing could correlate with this error term in either a negative or positive direction. A negative correlation could arise if a successful but cash-constrained startup suffers a negative shock to patent rights that reduces the tradability of those assets in the secondary market. Absent redeployable assets to pledge as collateral, equity arrangements could offer a more viable financing option, thus increasing the likelihood of VC financing while decreasing the likelihood of debt. Alternatively, and more troublesome given the directionality of our findings, a positive shock to the value of the technology underlying the startup could increase the company's growth opportunities in ways unobservable to us, increasing the likelihood of both debt and VC financing—a possibility that we turn to below.

4.2. Difference-in-Differences Analysis

In a final set of analyses, we develop a novel method for identifying whether VCs serve an intermediary (causal) role in the market for venture lending. Our aim is to test an intermediary function of particular salience in incomplete contracting theory (Holmstrom and Tirole, 1997; Williamson, 1988): By credibly committing to lenders that they will exert future effort to build and

refinance a portfolio company, VCs could facilitate exchange between lenders and startups with risky projects. In this view, VCs add value as intermediaries in debt transactions beyond the ex ante screening of projects, whether via independent due diligence, which is likely, or from updates simultaneously known to lenders.

Identification Strategy and Background

To isolate a potential "VC credible commitment" effect, we exploit an unexpectedly severe and negative shock to the supply of capital to VC firms—the collapse of the technology bubble in early 2000—and differences in VC fundraising cycles at the time of that shock. As explained below, VCs that had not recently closed a new investment fund at the time of the shock should face more binding capital constraints in the post-shock period than VCs with recently closed funds, for reasons unrelated to the quality of a given startup previously selected for funding. We use this plausibly exogenous source of variation among VCs to test a core prediction in the Holmstrom and Tirole (1997) model: following a negative capital-supply shock, financial intermediaries with binding constraints will find it difficult to convey to lenders that they will continue to support and monitor a portfolio company, thus reducing a startup's likelihood of receiving a loan.

The technology bubble's collapse is often pegged to March 2000, when Nasdaq shares plummeted from an unprecedented run-up in prices in the prior two years. Often referred to as the collapse of the "internet" or "dot.com" bubble, the steep fall in valuations had major ramifications across the IT sector. As one example, Cisco Corporation, a large computer networking company, lost more than 80 percent of its market capitalization in the one-year period following the shock. Not surprisingly, new VC investments in IT startups also suffered a precipitous decline. According to data from VentureOne, the amount of VC funds raised by software and semiconductor startups fell from $6.6 billion in Q2 of 2000 to $2.6 billion in Q2 of 2001—a 60 percent one-year drop—

and declined further, to $1.5 billion, by Q2 of 2002.[20] As Townsend (2012) and others document, the bubble's collapse significantly reduced the willingness of pension funds, wealthy individuals, and university endowments to commit funds to the VC asset class, particularly for IT-related investments, thus reducing the supply of institutional capital available for VC investing.

Although shockwaves were felt throughout the IT sector, VCs that had not yet closed a recent fund at the time of the crash should be particularly constrained in the near-term sourcing of capital. VC firms raise legally separate individual funds, typically organized as Limited Partnerships, in overlapping sequences over time. At the start of each fund's life, the VC firm secures lump-sum commitments from institutional investors for investment over an agreed-upon payback period. During the timeframe of our study, the standard lifespan of a VC fund was typically 10-12 years (Dow Jones, 2007). By the end of this period, the VC must realize returns through exits of portfolio companies by selling shares at IPO or to acquirers, and distribute the proceeds back to their institutional investors. Given this finite lifespan for a fund, the Limited Partnership fund agreements typically limit the period for pursuing new investment opportunities (referred to as the "investment period") to 5 years (Dow Jones, 2007). As the investment period of an existing fund draws to a close, VCs begin fundraising for a follow-on fund from which they will undertake future investments over the subsequent five-year period. As a result, VC funds are typically spaced three to five years apart (Gompers and Lerner, 1999; Hochberg et al., 2014).

When an exogenous event—such as the collapse of the technology bubble in early 2000— restricts the ability of the VC firm to close a new fund, the VC's ability to make new investments will be constrained: Investments in the existing fund will face added competition for the remaining dollars from existing portfolio companies and new investment opportunities, as the coffers cannot

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[20] In contrast, VC investments in the life sciences were relatively stable. Medical device and biopharmaceutical startups received $1.3 billion in new VC funds in Q2 of 2000, a comparable $1.29 billion in Q2 of 2001, and a slightly higher $1.6 billion in Q2 of 2002. In medical devices, the amounts were $597 million in Q2 2000, $500 million in Q2 2001 and $577 in Q2 2002. Estimates are quarterly VC funds raised in each sector, as reported in VentureOne.

be replenished. A VC firm that was attempting to fundraise at the time of the bubble's collapse, or that needed to do so in its immediate aftermath, would find it particularly difficult to source capital in the post-bubble period. As noted above, the VC fundraising cycle is largely determined by the timing of prior funds, and the timing and severity of the collapse was unexpected. We thus use heterogeneity in VC fundraising cycles at the time of the crash as a plausibly exogenous source of variation with which to identify the effect of VC credible commitment on startup lending.

Supplemental Fund-Vintage Data, Estimation Sample, and Descriptive Evidence

To implement this methodology, we identify investors in a startup's most recent syndicate prior to the bubble's collapse and compute the age of those investors' most recent VC funds as of the year 2000 using data from PREQIN.[21] We create three versions of a *RecentFund* variable, setting it equal to one when the average age of the most recent funds within the syndicate is less than either two, three or five years in early 2000. This approach allows the capital-constraints introduced by the market's collapse to be less (more) binding when a startup's investors have relatively recent (older) funds at the time of the crash. Since the typical investment period of a VC fund is five years, our main *RecentFund* variable uses the less-than-five-year threshold. As shown below, we find similar results using alternative two- and three-year thresholds that allow for shorter cycle-times in VC fundraising during the boom years of the late 1990s.

Our main analysis focuses on startups that (a) compete in sectors most affected by the technology bubble's collapse (i.e., are in IT-related sectors), (b) have received VC funds prior to early 2000, thus allowing us to observe VC investors and the vintage of funds they manage, and (c) are at risk of receiving a loan over the entire 6-year period surrounding the crash. The last restriction allows us to test differential before-and-after shifts in startup-level lending. In

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[21] PREQIN reports information on all private equity funds raised worldwide, including but not limited to VC funds. Consistent with Hochberg et al. (2014), we classified "VC funds" if the fund focus in PREQIN was listed as startup, early-stage, development, late-stage, or expansion investments, venture capital (general), or balanced.

combination, these criteria yield an estimation sample of 119 semiconductor and software startups at risk of receiving a loan between 1997 and 2002. Of these companies, 96 (eighty percent) had syndicates with funds averaging less than five years old at the time of the crash, while 23 did not. The average age of new funds managed by syndicate partners in these startups was 2.62 (std. dev. 3.23) years at the time of the crash.

As previewed earlier, we find a dramatic shift in startup lending patterns post-shock that correlates with differences in VC fundraising cycles. In the three years prior to 2000, IT startups backed by investors with more recent VC funds at the time of the crash (i.e., with *RecentFund$_i$=1*) had an average annual debt rate of 10 percent. From 2000 through 2002, the annual debt rate for this group of startups increased slightly, to 13 percent. In sharp contrast, the average annual debt rate in the comparison group (i.e., IT startups with *RecentFund$_i$=0*) fell from 17 percent in the 1997-1999 period to 1.5 percent in the post-bubble period, a steep drop of 15.5 percent.

Table 7 suggests that this pattern is not due to simple differences between groups in the presence or absence of top-tier investors. The share with top-tier VCs pre-crash is comparable between groups at 53 (*RecentFund*=1) and 57 (*RecentFund*=0) percent. On average, startups with recent-fund syndicates had raised more equity and received more patent citations in the three years prior to the crash. Table 7 shows, however, that the differences in mean values are not statistically significant. Both a Wilcoxon-Mann-Whitney test, the non-parametric analog of the independent sample t-test, and Kolmogorov- Smirnov test of distributional differences yield similar findings.

Econometric Specification and Results

To test the differential effect of VC fundraising cycles (VC credible commitment) on startup lending more formally, we use a difference-in-differences estimator:

$$Debt_{it} = \delta_1 After_{it} + \delta_2 RecentFund_i + \delta_3 After_{it} * RecentFund_i + \delta_4 W_{it} + \theta_i + v_{it} \quad (2)$$

As above, $DEBT_{it}$ indicates if startup i receives a loan in year t, and $RecentFund$ is an indicator set equal one when the most recent funds managed by startup i's investors are less than five years old on average in early 2000. *After* indicates startup-year observations in the three-year window following the bubble's collapse; the omitted category is a comparable three-year "pre-shock" period. The term W_{it} represents observable time-varying characteristics of startups that could affect the baseline probability of debt financing: *Has Top-Tier VC*, *Patent market liquidity*, *Firm-specificity of patent assets*, *Funds raised* and *Patent portfolio size (citation-weighted)*. As before, startup fixed effects, represented by θ_i, allow for time-invariant, company-specific, differences among startups to influence lending. The effects in Equation (2) are therefore identified from within-startup changes in the annual debt rate during the six-year window.

The coefficient of interest, δ_3, tests for differential changes in the annual debt rate for startups backed by investors with recent versus older funds when the bubble collapsed. Under the assumption that changes in the annual debt rate would be comparable for the startups had the bubble not collapsed, Equation (2) allows us to identify the causal effect of VC credible commitment on the rate of lending. The identification assumption is that VC capital constraints post-crash, as proxied by *RecentFund*, are largely exogenous to unobservables in the debt financing equation. Since the vintage year of a VC firm's most recent fund at the time of the crash is plausibly exogenous, this assumption seems reasonable.

Table 8 reports results of the DD estimator of changes (before versus after the technology bubble's collapse) in startup lending based on the fundraising cycles of VCs at the time of the crash. The unit of analysis is a startup-calendar year estimated in the six-year window surrounding the technology bubble's collapse, with 714 startup-year observations and 119 startups in the IT-related sectors. We cluster the standard errors at the startup level.[22] Column 1 includes time-

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[22] Clustering errors at a more granular startup-before and startup-after level yields similar findings.

invariant startup controls only, while Column 2 uses startup fixed effects and time-varying

covariates.

The difference-in-differences coefficient in Column 2, our preferred specification with fixed-

effects and a full-set of controls, is 0.18. This coefficient indicates that the annual debt rate of

startups backed by VCs with relatively recent funds at the time of the crash (*Recent Fund*=1),

relative to that of the startups backed by VCs with older funds (i.e., with more capital-constrained

investors), increased by 18 percentage points during the post-shock period. Put differently, the

striking shift in the trajectories of pre- versus post-shock lending shown earlier is wide and

statistically significant even controlling for permanent and numerous time-varying startup factors.

Figure 3 plots estimates from a more general empirical specification that allows the treatment

effect to vary on an annual basis, with coefficients normalized to 1999, the year prior to the shock.

In years prior to the collapse, the estimated coefficients are statistically indistinguishable from zero,

thus revealing parallel trends pre-treatment. Following the bubble's collapse, however, the

estimated treatment effects are positive in all three years, which implies a differential shift in

trajectories. The DD coefficient for the year of crash, which includes two months preceding the

crash, is a positive 0.15, but is not statistically significant (p-value=0.14). In the first and second

year immediately following the shock, however, the coefficients are positive 0.19 and 0.21 and are

statistically significant (p-values 0.05 and 0.03, respectively).[23]

In combination, this evidence reveals a dramatic "flight to safety" among lenders in the wake of

the technology bubble's collapse in early 2000. Following the collapse, lending continued apace

and even increased slightly for startups backed by investors with relatively recent funds, but fell

sharply for startups with more capital-constrained investors. The large magnitude of the effect not

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[23] As an added check on the DD identification, we allowed each group to exhibit a different time trend by adding
an interactive dummy between *RecentFund* and the time trend variable in each of the difference-in-differences
regressions. The estimated effect of the DD coefficient is robust to this test.

only highlights the contracting challenge involved in lending to startups but also how investors with relatively recently-raised funds can overcome this problem during a major capital illiquidity event, whereas the more capital-constrained cannot. This result resonates with the predictions in Holmstrom and Tirole (1997): that those investors with less capital, particularly in times when capital is scarce, find it more difficult to credibly convey to the lenders that they will continue to support the portfolio company, thus making it more difficult for the company to obtain a loan. Furthermore, from a macro-economic perspective, our findings suggest that business cycles may depress funding for innovation-based startups in multiple fashions: directly, by limiting future economic prospects and reducing the supply of available VC funding, but also indirectly, by reducing the credible commitment of equity investors, which may act to further limit access to debt financing.

Robustness checks and alternative explanations

In robustness and placebo tests described below, we experiment with alternative measures and estimation samples, and investigate factors unrelated to VC credible commitment that could explain our findings. First, we re-estimate the effects with alternative treatment assignment measures. Because the typical investment period for a VC fund is five years, our benchmark DD estimation assigned *RecentFund$_i$=1* to startups when the mean age of the most recent funds managed by their investors as of the year 2000 was less than five years. It is commonly known that during the late 1990s the time between fund raises for some firms was reduced, as VCs capitalized on the heightened interest of institutional partners in the VC asset class. A potential concern for our identification approach is that the *RecentFund* variable may be simply capturing VC firms that did not raise capital during the five years prior to the bubble collapse due to lower quality or poorer performance. To rule out this concern, Columns 3 and 4 in Table 8 replicate our preferred specification in Column 2 with two- and three-year cutoffs that allow for faster cycle-times in VC

fundraising. The estimated DD coefficients remain positive at 0.11 and 0.10, and are significant at the 5-percent level. While the magnitude of the effect is smaller than the one obtained in the benchmark DD specification in Column 2, the confidence intervals of the coefficients overlap. Thus, the estimates of the model specification with two- and three-year cutoffs do not differ qualitatively from the benchmark specification.

A separate concern is that "smarter" or better-connected CEOs could obtain venture debt regardless of the state of affairs in the VC industry and simultaneously better predict the timing and severity of the market collapse, leading them to seek investors with younger (investment-mode) funds. Although the mainstream view is that the timing and severity of the market's collapse was unexpected, this possibility could explain a positive correlation between startups with access to investors with recently raised funds and higher debt rates in the post-shock period.

To investigate this alternative "smart CEO" explanation for our findings, we reset the treatment assignment ($RecentFund_i=1$) based solely on the fund-raising state of the investors in the startup's first VC financing round. Typically, first-round investors continue to participate in later rounds to preserve ownership stakes and control; if they decide not to reinvest, it casts a negative signal about the prospects of the startup, making it difficult for the startup to raise money. Thus, the capitalization of these initial investors should still matter for the startup's ability to raise debt after the technology market's collapse. At the same time, it is highly unlikely that even "smart" CEOs choose early investors with an eye to capital shortages that they anticipate in an uncertainly timed future post-bubble period. As shown in Column 5 of Table 8, the DD coefficient is a positive 0.13 when *RecentFund* is based on the vintage of funds managed by first-round investors, and remains statistically different than zero (p-value=0.03). The confidence intervals of this coefficient and our baseline DD specification in Column 2 of Table 8 overlap, which is reassuring.

If our results are driven by the abilities of VCs to credibly commit to the continued financing of a startup, we should expect a differential shift in lending only in the aftermath of a negative and severe capital-supply shock and in sectors most affected by the shock. In turn, in the absence of such a shock, differences in the fundraising cycles of VCs should not alter lender expectations of loan repayment. Columns 6 and 7 in Table 8 report placebo tests with this logic in mind.

In Column 6, we replicate the DD estimator for IT startups in non-crisis periods (1992-1997 and 2002-2006).[24] Neither period had a major shock to the supply of institutional capital available for VC investing. The non-overlapping panels are stacked to increase the number of observations available for the estimation. In total, 302 semiconductor and software startups were VC-backed and active in the two periods combined. As Column 6 shows, the DD coefficient in our preferred specification (fixed-effects with controls) is positive and small (0.028) in the non-crisis periods, and is not statistically significant in the non-crisis periods (p-value=0.33). We obtain similar results if the effects are estimated separately for each non-crisis period, albeit with smaller sample sizes.

Finally, Column 7 retains the six-year period surrounding the technology bubble's collapse, but tests effects for startups relatively shielded from the run-up and collapse. As shown earlier, new VC investments in IT startups plummeted in the wake of the bubble's collapse, while new investments in life science startups remained relatively stable. It is unlikely that the IT-driven shock imposed binding constraints in the sourcing of capital for life science startups, including but not necessarily limited to the medical device startups represented in our sample. Column 7 therefore replicates our preferred specification using a placebo sample of medical device startups that were VC-backed by early 2000 and active in the six-year window surrounding the crash (n=99). Reassuringly, the DD coefficient is not significant at conventional levels (p-value=0.46).

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[24] In light of the U.S. banking crisis, which began in 2007 and worsened in 2008, we conservatively restrict the second window to a 5-year period that ends in 2006.

The placebo tests suggest that VC fundraising cycles shift lender expectations only when the capital constraints of the startup's VC investors are likely to be binding. Combined with the parallel pretreatment trend-lines shown in Figure 3, this evidence allays concerns that our main DD results are explained by unobserved time-varying characteristics of startups that could affect lending and investor matching in a non-causal manner: It is unclear why the effect would arise solely for IT startups, and specifically in the crisis period.

5. Conclusion

This study provides novel evidence on the market for venture lending, a surprisingly active yet unexplored arena for innovation financing. Consistent with contract theory, we find that thicker trading in the secondary market for patent assets and intermediation by equity-owners are mechanisms that facilitate lending to startups with risky projects.

We find that the annual debt rate increases when the secondary market for buying and selling patents grows more liquid, particularly for startups with more redeployable (less firm-specific) patents. This result resonates with classic predictions by Williamson (1988), Shleifer and Vishny (1992) and others: lender expectations of salvage value should affect the willingness to supply funds in the presence of contracting frictions. Although prior studies document this effect for tangible assets such as railroads (Benmelech, 2009) and commercial aircraft (Benmelech and Bergman, 2008, 2009; Gavazza, 2011), it is widely assumed that the market for patents is too illiquid to sway lender expectations. Our findings challenge this assumption, and suggest that patent assets and their exchange play a meaningful friction-reducing role in innovation financing.

As is well known, intangible assets underpin the market value of modern U.S. corporations, many of which invest heavily in R&D and patent-related activities. A natural question is whether the increased "salability" of patent assets affects the financing opportunities for this wider swath of companies, and if so, how the magnitude of the effect varies by sector. In the policy arena, the

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emergence of "patent assertion entities" and large "aggregators" such as Intellectual Ventures has fueled concern that the acquisition and enforcement of patents by such organizations is imposing an ex post tax on innovation (U.S. White House, 2013; Hagiu and Yoffie, 2013). If these intermediaries increase the salability of patent assets, by increasing liquidity in the market, innovation-oriented companies could find it easier to borrow against their patents. This ex ante effect on innovation financing should be weighed, ideally with evidence from more companies and sectors, against the ex post distortions that may arise from patent trading and enforcement.

The ability of informed investors to credibly commit to the future support and monitoring of risky projects serves a central contracting function in financial intermediation theory (Holmstrom and Tirole, 1997). Identifying this causal relationship empirically is difficult: intermediaries and lenders may simultaneously see updates unobservable to researchers that increase the attractiveness of projects both for equity financing and lending. Our approach, which exploits differences in VC fundraising cycles at the time of a capital-supply shock, provides a useful lever for discerning this "credible commitment" effect of widespread theoretical interest in the field.

We document a dramatic flight to safety among lenders following the collapse of the U.S. technology bubble in early 2000: they continued to finance startups backed by investors with less binding capital constraints following the collapse, but withdrew from otherwise-promising projects that may have needed the funds the most. A reallocation of risk capital has been shown in response to other unexpected and severe economic shocks (Caballero and Krishnamurthy, 2008). Bernanke (1993), for example, shows that in the Great Depression of the 1930s, banks rushed to compete for safe high-grade assets yet withdrew funds from many borrowers with otherwise good projects. Our analysis reveals a flight-to-safety episode undocumented in prior studies. This finding suggests that the credibility of VC commitment is vital both for venture lending and for policies aimed at stimulating entrepreneurial-firm innovation through debt channels. Absent a well-developed

infrastructure of venture capitalists and institutional investors, our results suggest that the economic

effects of such initiatives will be muted.

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TABLE 1. Patent Security Interests

A.   Startup-Level Analysis

		Sectors		
	All	Medical Devices	Semiconductor Devices	Software
Share of startups with loans secured by patents	0.36	0.36	0.38	0.35
Number of startups	1,519	483	197	839

B.   Patent-Level Analysis

	All	Medical Devices	Semiconductor Devices	Software
Share of all patents awarded to sample startups by 2008 or exit used to secure a loan	0.27	0.26	0.24	0.32
Share of patent portfolio used as collateral by last transaction year (average for startups with loans)	0.92	0.88	0.89	0.94
Total # U.S. patents awarded to sample startups by 2008 or exit year	14,514	7,435	3,288	3,791

TABLE 2.   Summary Statistics: Patenting Startups with vs. without Patent-backed Debt

	All Sample Startups With Patents	Subsample with Patent-backed Debt	Subsample without Patent-backed Debt
Backed by Top-Tier VC (%)	0.71	0.74	0.69
Total VC Funds raised ($ million)	27.1	33.3	23.7
Patent Portfolio Size	9.55	11.7	8.3
Patent Portfolio Size, citation weighted	62.17	73.6	55.8
Founding Year	1994.9	1994.8	1995.0
Startup status as of 2008 (%)			
IPO	0.18	0.13	0.21
Disbanded (Failed)	0.21	0.21	0.20
Still Private	0.22	0.27	0.20
Acquired	0.39	0.40	0.39
Number of Startups	1,519	545	974

Note: The sample includes VC-backed startups in three sectors (medical devices, semiconductor devices, and software) awarded at least one U.S. patent by 2008 or exit. Startups with (without) patent-backed debt have (do not have) at least 1 patent-backed security agreement recorded at the PTO through 2008 or exit. *Backed by Top-Tier VC* is the percentage of startups that eventually receive equity financing from a VC investor with reputation above the top 25 percentile of the annual distribution of scores reported in LPJ2011; *Total VC Funds raised* is the cumulative amount of funds that the startup receives from VC investors through 2008 or exit. Appendix I reports the rest of the variable definitions and data sources.

TABLE 3. Patent Sales, Patent-Market Liquidity, and the Annual Startup Debt Rate Across Time and Technology Sectors

	All years	Pre-boom 1987-1997	Boom years 1998-1999	Post-boom 2000-2008
A. Patent Sales				
Medical devices	46,632	11,994	5,109	29,529
Semiconductors	28,778	3,553	2,451	22,774
Software	220,028	39,359	20,329	160,340
All three sectors	295,438	54,906	27,889	212,643
B. Patent Market Liquidity				
Medical devices	0.051	0.043	0.060	0.060
Semiconductors	0.027	0.018	0.036	0.036
Software	0.038	0.028	0.047	0.049
All three sectors	0.039	0.030	0.048	0.048
C. Annual Startup Debt Rate (within-sample)				
Medical devices	0.069	0.052	0.069	0.080
Semiconductors	0.076	0.041	0.082	0.091
Software	0.080	0.043	0.105	0.085
All three sectors	0.076	0.047	0.090	0.084

NOTE: In Panel A, "Patent sales" is a running stock of U.S. patents less than eight years old that were sold by year t. Sector-level tallies are based on USPTO invention class-subclass lists. In Panel B, "Patent Market Liquidity" adjusts the sales (transactions) counts by the pool of patents available for trading, defined as all U.S. patents issued in the same set of PTO class-subclasses for the sector in the prior eight years. In Panel C, "Annual startup debt rate" is the sample probability that a startup secures patent-backed lending in a given year. See Appendix I for data sources.

TABLE 4. Startup Debt Rate and VC backing: Startups with vs. without Top-Tier VC

	Not Yet VC-Backed	VC backed: Has Top-Tier VC	VC backed: Lacks Top-Tier VC	T-test: Has vs Lacks Top-tier VC (p-value)
Time periods				
Pre-boom (1987-97)	0.022	0.064	0.056	0.50
Boom years (1998-99)	0.041	0.116	0.080	0.06
Post-boom (2000-08)	0.045	0.093	0.073	0.00
All years	0.030	0.071	0.091	0.00

Note: Debt rate is the sample probability that a startup secures a loan in a given year. Has Top-Tier VC is equal to 1 if the startup has already secured VC financing from at least one investor with reputation score in the top 25 percentile of the annual distribution of scores reported in LPJ2011.

TABLE 5. Summary Statistics at the Startup-Calendar Year Unit of Analysis

	Mean	S.D.	Min	Max	# Startups	# Startup-Year Obs.
A. Main Analysis (all three sectors, years = 1987-2008)						
Debt	0.08	0.26	0	1	1,519	11,298
Post VC	0.84	0.36	0	1	1,519	11,298
Has Top-Tier VC	0.55	0.50	0	1	1,519	11,298
Patent Market Liquidity	0.045	0.017	0	0.085	1,519	11,298
Firm-Specificity of Patent Assets	0.089	0.156	0	1	1,519	11,298
Patent Portfolio Size (Citation Weighted)	47.57	133.91	0	3,639	1,519	11,298
Patent Portfolio Size	7.29	12.24	0	199	1,519	11,298
Funds Raised Last Equity Round (million $)	8.82	11.13	0	122	1,519	11,298
Founding Year	1994.81	3.55	1987	1999	1,519	11,298
Primary sector = software	0.52	0.50	0	1	1,519	11,298
Primary sector = semiconductors	0.13	0.34	0	1	1,519	11,298
Primary sector = medical devices	0.35	0.48	0	1	1,519	11,298
Pre-boom period (1987-1997)	0.25	0.43	0	1	1,519	11,298
Boom period (1998-1999)	0.15	0.36	0	1	1,519	11,298
Post-boom period (2000-2008)	0.60	0.49	0	1	1,519	11,298
B. Difference-in-Differences Analysis (semi and software sectors only; years=1997-2002)						
Debt	0.11	0.32	0	1	119	714
Post VC	0.88	0.32	0	1	119	714
Has Top-Tier VC	0.63	0.48	0	1	119	714
Patent Market Liquidity	0.044	0.016	0	0.070	119	714
Firm-Specificity of Patent Assets	0.07	0.11	0	0.67	119	714
Patent Portfolio Size (Citation Weighted)	45.72	77.55	0	648	119	714
Patent Portfolio Size	7.52	11.33	1	86	119	714
Funds Raised (million $)	21.70	23.80	0	144.6	119	714
Founding Year	1994.16	2.94	1987	1999	119	714
Primary sector = software	0.75	0.43	0	1	119	714
Primary sector = semiconductors	0.25	0.43	0	1	119	714
Recent Fund	0.81	0.40	0	1	119	714

NOTE: Appendix I reports variable definitions and data sources.

TABLE 6. Patent Market Liquidity, VC Investors, and the Likelihood of Startup Debt Financing

	1	2	3	4	5	6
Estimation Method	**OLS**	**OLS**	**OLS**	**OLS**	**OLS**	**OLS**
Dependent Variable	**Debt**	**Debt**	**Debt**	**Debt**	**Debt**	**Debt**
Post VC	0.043***	0.037***	0.040***	0.040***	0.040***	0.028***
	(0.006)	(0.007)	(0.009)	(0.009)	(0.009)	(0.010)
Patent Market Liquidity	0.912***	1.264***	1.216***	1.195***	1.306***	1.297***
	(0.137)	(0.163)	(0.200)	(0.200)	(0.214)	(0.213)
Firm Specificity				-0.066**	0.004	0.003
				(0.031)	(0.043)	(0.043)
Firm Specificity * Patent Market Liquidity					-1.811**	-1.865**
					(0.929)	(0.933)
Has Top-Tier VC						0.028**
						(0.012)
Startup Fixed Effects	NO	NO	YES	YES	YES	YES
Patent Portfolio Size (citation-weighted)	NO	YES	YES	YES	YES	YES
Funds Raised Last Equity Round	NO	YES	YES	YES	YES	YES
Period Fixed Effects	NO	YES	YES	YES	YES	YES
Founding Year Fixed Effects	NO	YES	NO	NO	NO	NO
Sector Fixed Effects	NO	YES	NO	NO	NO	NO
No. of Startups	1,519	1,519	1,519	1,519	1,519	1,519
Observations	11,298	11,298	11,298	11,298	11,298	11,298

Note: The unit of analysis is a startup-calendar year, with an unbalanced panel. Debt = 1 if the firm is involved in at least one security interest agreement in a given calendar year. Robust standard errors, clustered at the startup level, are reported in parenthesis. Statistical significance: * 10 percent, ** 5 percent, *** 1 percent.

TABLE 7. "Pre-Shock" Characteristics of Startups backed by Investors with Recent (versus Older) Funds in early 2000

|	All Patenting IT Startups Backed by VC investors	Startups Backed by VC Investors with RecentFund=1	Startups Backed by Investors with RecentFund=0	Diff of Means Between the Two Groups
Has Top-Tier VC	0.54	0.53	0.57	-0.037
Funds Raised (million $)	9.16	9.53	7.63	1.90
Patent Portfolio Size	5.15	5.43	3.94	1.49
Patent Portfolio Size (citation-weighted)	33.5	35.6	25.0	10.6
Firm-specificity of patent assets	0.08	0.07	0.08	-0.01
Patent market liquidity	0.04	0.04	0.04	0.00
Number of Observations	357	288	69	
Number of Startups	119	96	23	

Note: *RecentFund=1* when the average age of the most recent VC funds within the investor syndicate is less than five years in early 2000; it is zero otherwise. *Funds Raised (million $)* is the mean of the total amount of venture capital raised. *Has Top-Tier VC* is the share of startups backed by at least one investor with a reputation score in the top quartile of the annual distribution of scores reported in Pollock et al. (2011). *Patent Portfolio Size* = the mean of the cumulative number of patent succesful applications. *Patent Portfolio Size (citation-weighted)* = the mean of the cumulative number of patent citations received within three years of each patent being granted. *Firm-specificity of patent assets* is the mean across startups of the share of citations that are self-citations. *Patent Market Liquidity* is the mean across startups of the startup-level patent-portfolio combined probability that a patent will be traded in a year. All means are computed across the period 1997-1999. Venture capital round data are from VentureOne. Fund age data are from Preqin. Statistical significance of the difference of the means between two groups: * 10 percent, ** 5 percent, *** 1 percent.

TABLE 8. Difference-in-Differences (DD) of Startup Debt Rate Before and After the Technology Bubble's Collapse in Early 2000:
Startups backed by Investors with Recent (versus Older) Funds at the Time of the Crash

|	Main Results		Robustness Checks			Falsification Tests	
	1	2	3	4	5	6	7
Estimation Method	DD	DD	DD	DD	DD	DD	DD
Dependent Variable	Debt	Debt	Debt	Debt	Debt	Debt	Debt
DD coefficient	0.187***	0.178***	0.112**	0.105**	0.126**	0.030	-0.053
	(0.056)	(0.056)	(0.047)	(0.054)	(0.065)	(0.030)	(0.061)
Startup Fixed Effects	NO	YES	YES	YES	YES	YES	YES
Has Top-Tier VC	NO	YES	YES	YES	YES	YES	YES
Patent Market Liquidity	NO	YES	YES	YES	YES	YES	YES
Firm-specificity of Patent Assets	NO	YES	YES	YES	YES	YES	YES
Funds Raised	NO	YES	YES	YES	YES	YES	YES
Patent Portfolio Size (citation-weighted)	NO	YES	YES	YES	YES	YES	YES
Founding Year Fixed Effects	YES	NO	NO	NO	NO	NO	NO
Sector Fixed Effects	YES	NO	NO	NO	NO	NO	NO
Event Year	2000	2000	2000	2000	2000	placebo years (1995, 2005)	2000
Recent Fund is computed with data of the investors that participated in the…	Last round of VC financing pre-2000	Last round of VC financing pre-2000	Last round of VC financing pre-2000	Last round of VC financing pre-2000	First round of VC financing	Last round of VC financing pre-placebo year	Last round of VC financing pre-2000
Recent Fund = 1 if mean of most recent investor fund is…	< 5 years	< 5 years	< 2 years	< 3 years	< 5 years	< 5 years	< 5 years
Sample	software and semi. startups active 1997-2002 and VC-backed by 2000	software and semi startups active 1997-2002 and VC-backed by 2000	software and semi startups active 1997-2002 and VC-backed by 2000	software and semi startups active 1997-2002 and VC-backed by 2000	software and semi startups active 1997-2002 and VC-backed by 2000	software and semi startups active 1992-97 (2002-06) and VC-backed by placebo year	medical device startups active 1997-2002 and VC-backed by 2000
No. of Startups	119	119	119	119	100	302	99
Observations	714	714	714	714	600	1,572	594

Note: Except in Column 6 (a falsification test), the DD coefficient estimates the change in the annual startup debt rate before versus after the technology bubble's collapse in early 2000. Column 1 and 2 present the DD main results. Column 3, 4 and 5 present robustness analysis. Column 6 shows a falsification test using years (1995, 2005, and corresponding 6-year windows), that did not experience a negative shock to the institutional capital supplied to the VC asset class. Column 7 shows a falsification test using startups in medical devices, a life science sector relatively shielded from the technology bubble's collapse in 2000. *Debt* = 1 if the firm is involved in at least one security agreement in a calendar year. The unit of analysis is a startup-calendar year, with a balanced panel. Robust standard errors, clustered at the startup level, are reported in parenthesis. Statistical significance: * 10 percent, ** 5 percent, *** 1 percent.

Figure 1. Venture Lending as a Way to "Extend the Financial Runway" of a Startup
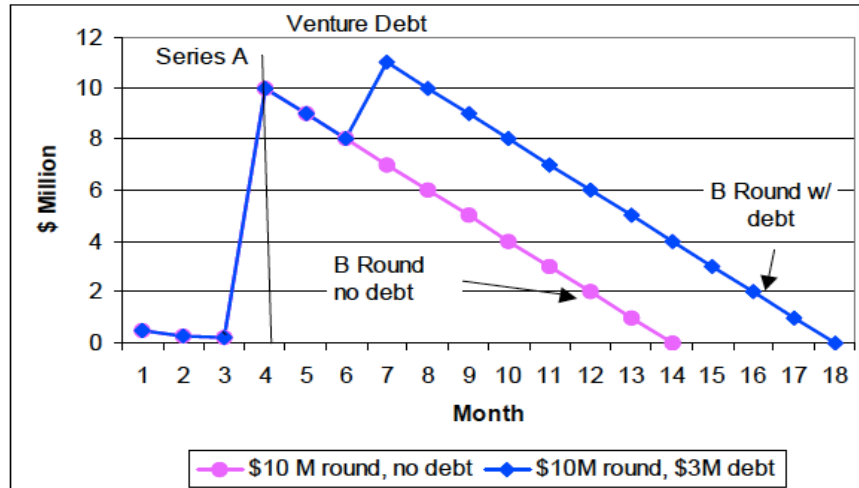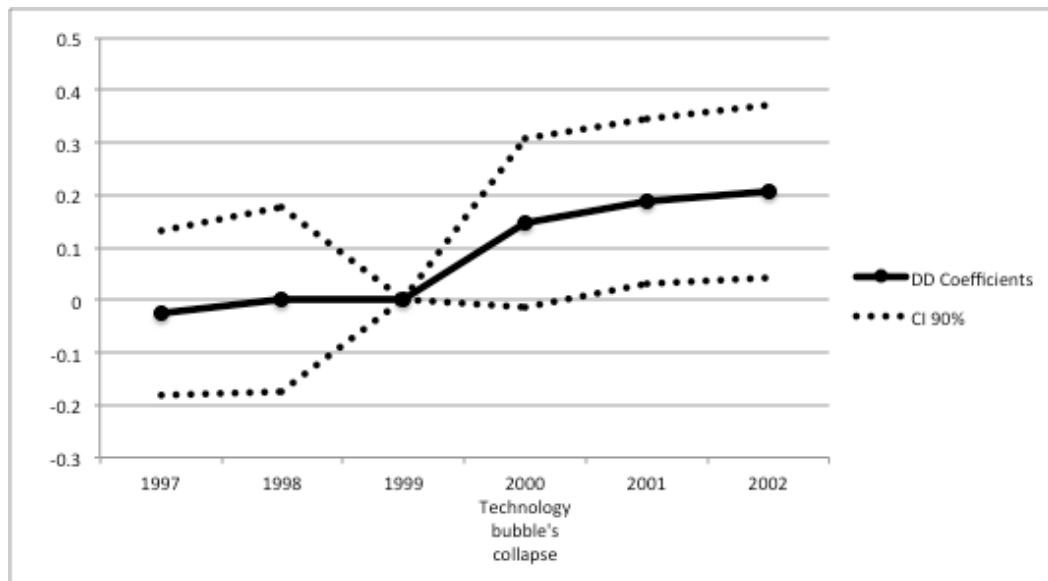

Source: Hardymon, Lerner, and Leamon (2005).

Figure 2. Average annual debt rate before and after first VC equity infusion: overall and by age thresholds
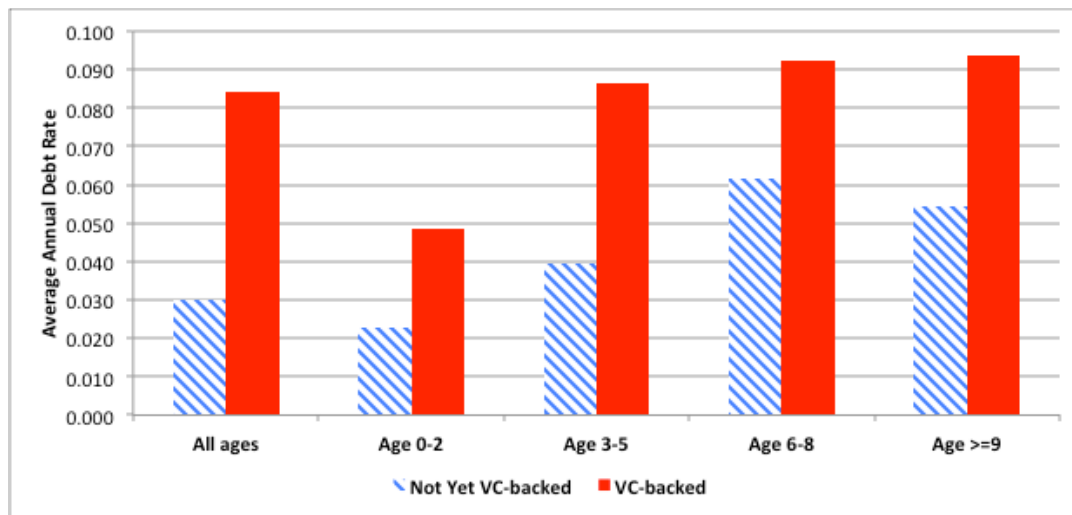
Note: Average annual debt rate is the sample probability of startups securing a loan in a given year.

Figure 3. Non-Parametric Differences in Differences

APPENDIX I
Table A.1. Main Variables and Data Sources

	Definition	Data Source
Dependent Variable		
$DEBT_{it}$	Indicator set to 1 if at least one patent awarded to startup i is involved in a "security interest" agreement (i.e., used to secure a loan) in year t	USPTO Assignments Data
Main Independent Variables		
$Post\ VC_{it}$	Indicator that switches from zero to one in the year that the startup first receives VC financing	VentureOne
$Has\ Top\text{-}Tier\ VC_{it}$	1 if the startup is backed by a VC in the top 25 percent of the annual LJP reputation score distribution (sometimes time-invariant; see notes on output tables)	LPJ2011
$Recent\ Fund_i$	1 if the average age of the youngest funds managed by a startup's investors in the year 2000 is less than 5 years old	PREQIN
$Patent\ Market\ Liquidity_{it}$	startup i's combined probability (averaged across patents in its portfolio as of year t) that patents issued in the prior 8 years in its sector are traded by year t	USPTO Reports[a]; Graham and Vishnubhakat (2013)[b]; RPX Corp
$Firm\text{-}Specificity_{it}$	Proxy for degree to which the value of startup i's patents are "firm-specific"; measured as the share of patents citing startup i's patents within three years that are made by the focal startup (i.e., are "self-cites"). In the few instances where no patents within a startup's portfolio are cited within three years, we set the variable to zero.	USPTO patent data
Additional Startup-Level Covariates		
$Patent\ Portfolio\ Size$ $(citation\ weighted)_{it}$	Cumulative # successful U.S. patent applications of startup i by year t, weighted by the # of citations each patent receives 3-years post-grant	Delphion
$Funds\ raised\ last\ equity$ $round_{it}$	Millions of US\$ raised in startup i's last equity financing round as of year t,	VentureOne
$Founding\ Year_i$	Year startup i was founded	VentureOne
$Sector_i$	Startup i's primary sector: medical devices, semiconductor devices, or software	VentureOne
$Time\ Period_t$	Indicates if year is in pre-boom (1987-1997), boom (1998-1999), or post-boom (2000-2008) period	VentureOne

[a] The list of class-subclass combinations relevant for medical device inventions is available from the USPTO website at: http://www.uspto.gov/web/offices/ac/ido/oeip/taf/meddev.htm. A parallel list for semiconductor devices is at: http://www.uspto.gov/web/offices/ac/ido/oeip/taf/semicon.htm.

[b] The class-subclass list relevant for computer software invention, equivalently compiled by USPTO examiners, is reported in Graham and Vishnubhakat (2013) on page 75, footnote 7.