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

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ABSTRACT

This paper investigates the market for lending to technology startups (i.e., venture lending) and examines two mechanisms that may 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 is strongly related to 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 reinvest in their startups' next round of financing can be critical for startup debt provision. Utilizing the crash of 2000 as a severe and unexpected capital supply shock for VCs, we show that lenders continue to finance startups with recently funded 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.)

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1. Introduction

Entrepreneurial activity is vital for technological progress and long-term productivity growth (Acs and Audretsch, 1990; Aghion and Howitt, 1992; 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 costly dilution of ownership stakes, external debt is widely cast as an unlikely way to fund risky projects absent tangible assets or stable cash flows to secure the loan (Hall and Lerner, 2010).

Although technology startups and outside debt may seem poorly suited for one another in theory, recent evidence suggests that this market for entrepreneurial capital is surprisingly large and active. 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.

In this paper, we investigate 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: (1) increased liquidity in the secondary market for patent assets, which could alter lender expectations 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. 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 to identify startup-level lending—through patents, a common form of collateral used to secure the loans. Venture lenders typically

[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).
[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.

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.

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.[3] 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.

The effect 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. More generally, governments worldwide 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.

To explore the patent 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 (IT)-related fields (USFTC, 2011; Hagiu and Yoffie, 2013). Employing a novel

[3] As discussed below, our research design requires the inclusion of startups in information technology-related sectors (represented by semiconductors and software) and the life sciences (represented by medical devices). Including more sectors was infeasible due to challenges in quantifying secondary patent-market activity and other data limitations. We include startups founded from 1987, our first year of reliable financing data, through 1999, which includes the youngest cohort at risk of being affected by the shock utilized in our empirics.

measure we construct from patent sales data, we find that thicker trading in the secondary market for patent assets is associated with an increase in 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 that could affect the likelihood of lending, and are not spuriously explained by time-varying opportunity shocks or shifts in M&A activity within sectors. Importantly, our analysis further reveals a clear and distinctive pattern predicted in incomplete contract theory—the relationship between lending and increased trading in the collateral market 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 percentage point increase in patent trading is associated with an increase in the predicted debt rate of 1.10 percentage points, or 15 percent of the average annual debt rate in our sample. This relationship 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 relationship to the debt rate only when the collateral asset market is liquid.

As formalized in Holmstrom and Tirole (1997), intermediaries (such as VCs) could reduce frictions in venture lending by credibly committing to refinance and grow early-staged companies. To test this second channel, we exploit differences in fundraising cycles across VC firms when the U.S. "technology bubble" collapsed in early 2000. The collapse of the bubble led to an unexpectedly severe and prolonged decline in the supply of institutional capital to the VC asset class (Townsend, 2015). Given lumpiness in the VC fundraising cycle, the collapse imposed more binding near-term capital constraints on VCs that had not recently closed a new fund at the time of the collapse. We use the heterogeneity in 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 the implicit promise to repay lenders for reasons plausibly exogenous to the quality of a startup previously selected for VC funding.

Our difference-in-difference (DD) results suggest that VCs serve an important intermediary role in the market for venture lending. The annual debt rate of IT startups backed by VCs with relatively old funds at the time of the crash declined by 14 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 lending. The two groups of startups exhibit comparable trend-lines in the annual rate of lending pre-shock. 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. Moreover, the result is stronger for startups backed by investors with greater exposure to the IT sector, where the crash was particularly detrimental to future fundraising (Townsend, 2015). In combination, this evidence suggests a “flight-to-safety” among lenders after the crash, continuing to finance startups backed by less capital-constrained investors but withdrawing from otherwise-promising projects that may have needed their funds the most.

To the best of our knowledge, our study 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 micro-underpinnings of the market.

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

Third, 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. 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.[4] Serrano (2010) and Galasso et al. (2013) document active trading in the modern market for patents originating from individuals and small firms. The implications of patent trading for innovation financing are unexplored in prior research, a gap that this study helps fill.

Finally, the findings in this paper can be interpreted as validation of the financing risk hypothesis put forth by Nanda and Rhodes-Kropf (2013, 2016). Our results show how shifts in financing risk can alter the types of firms that get funded, thus shifting aggregate patterns of innovation. Unlike banks that lend on future cash flow from operations, venture debt is predicated on future cash flows from financing. Financing risk thus plays a key role in determining how vibrant the market for venture lending is likely to be.

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; 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

[4] For related evidence, see Arora et al. (2001), Serrano (2011), Akcigit et al. (2014), and Czarnitzki et al. (2016).

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 were better able to obtain debt financing during 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 and monitor a risky venture—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, frictions arising from information asymmetries between the entrepreneur and uninformed outsider (lender) are reduced.[5]

[5] In a recent model, Nanda and Rhodes-Kropf (2016) use similar reasoning to explain how a financial intermediary's implicit promise to support the venture can affect lender expectations of loan repayment.

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.

Implications for Venture Lending

The use of formal debt to finance startups with risky projects is 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, commercialization requires upfront investment, and the risk of project failure is high. 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.[6] For entrepreneurs and their investors, the main attraction is funding that does not require costly dilution 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 and interest in 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.

[6] Specialized non-bank lenders include 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 revenues from fees while providing a monitoring function. Non-banks face less stringent regulatory restrictions. In turn, non-bank lenders typically incur higher risk, charge higher interest rates, and offer larger loan packages reaching the tens of millions.

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:

> "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."

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 to lenders for ex ante (ability to identify and attract more promising startups) as well as ex post (ability and willingness to support the startup once funded) reasons. Put differently, 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 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. 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). de Rassenfosse and Fischer (2016) report similar findings in a recent survey of lenders.

Anecdotal evidence further suggests that the secondary market for buying and selling patents has grown more active since the late 1990s, an effect largely driven by shifts in the legal environment and a corresponding rise in the assertion of patents in IT-related fields (Hall and Ziedonis, 2001; U.S. FTC, 2011). In 1999, Intel Corporation created a patent purchasing program to manage its increasing volume of deals (Chernesky, 2009). Soon thereafter, Intellectual Ventures (IV) established a fund for buying and aggregating portfolios of patents. Between 2000 and 2012, IV 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 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 literatures yield three testable predictions in the venture-lending context. First, if increased liquidity in the secondary patent market is altering lender expectations of 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 (via follow-on funding) the risky project.

3. Data Sources and Descriptive Findings

As noted earlier, reliable startup-level data on venture loans is lacking. 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 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 receives a VC equity infusion and from whom they receive such investment. We then select all startups founded from 1987, the first year of comprehensive reporting in VentureSource, 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 use supplemental Sand Hill Econometrics data 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 VentureSource. 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 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 disband, go public, or are acquired.

3.2. Main Variables and Data Sources

Our analysis requires measures of startup-level lending, patent-market activity, and VC investors as discussed below. Table A-1 of the Appendix lists our main measures and the sources used to compile them.

Startup Receipt of Debt Financing

The 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 agreements, we extend the method 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.[7] 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. As an example, Silicon Valley Bank, a specialist in providing banking services for startups, is the most common lien holder, with secured interests in 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

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

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 VentureSource database.

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. 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 class-subclass mappings reported in Appendix Table A-1. We then tally the annual number of U.S. patents awarded in each set of classes and, using sales data from RPX Corporation, the share involved in subsequent transactions.[8] Serrano (2010) shows that the likelihood of sale declines over the lifetime of a patent, and that the vast majority of patents are sold within eight years. We therefore restrict the pool of potentially tradable patents to those issued eight years prior to year *t* and average across sectors and issue years of the startup's patent portfolio. *Patent Market Liquidity* thus represents the combined probability (averaged across sectors and issue years) that a patent in startup *i*'s portfolio will be sold in year *t*. 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. To illustrate, Berman (2014) estimates that $7 billion of the $12.5 billion that Google paid to acquire Motorola Mobility in 2011 was for its portfolio of 17,000 patents. Following the takeover, Google divested Motorola Mobility's core product unit (mobile handsets) but retained most of the patents acquired through the deal. All results are robust to alternative measures that omit M&A-driven deals.

[8] As per Serrano (2010), the RPX data are based on USPTO Assignment data and omit transactions unrelated to patent sales, including title transfers from employees to employers and security agreements with lenders. These data enable us to trace patent sales for U.S. patents over the full sample period.

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 collateral is sold to others. At one extreme, patent 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 rights hold no value if de-coupled from the underlying human capital or venture. A startup’s patents could also be highly firm-specific if they cover inventions that are nonviable on the market or hold no value if enforced (e.g., see Galasso et al., 2010). At the other extreme, some patents could be highly redeployable if a 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 litigation (Markoff, 2005).

To capture the firm-specificity of patents assets, we compute the share of citations a startup’s patents receive from follow-on patents issued to the focal company (i.e., the share of “self-cites”). The measure is based on the citations a patent receives within three years of being granted, a time-horizon likely to be relevant in startup lending and that is consistent with recent studies (e.g., Lerner et al., 2011). If a startup’s patents are extensively cited by outside parties in follow-on inventions relative to citations made by follow-on patents by the same startup (i.e., the share of self-cites is relatively low), we assume that the patents are more likely to trade in the secondary market than if the startup is the sole party building on and citing the focal patents. Our *Firm-Specificity* 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}, 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 VentureSource.

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 VentureSource are matched to reputation scores computed by Lee, Pollock, and Jin ("LPJ" 2011).[9] 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 percentile 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 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 investors as of early 2000, when the technology bubble collapsed. To map investors to funds, we use supplemental Private Equity Intelligence (PREQIN) data 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.[10] Of that, \$67.6 billion (93 percent) matched investors backing startups in our sample. Investors in our study thus control the vast majority of VC funds in the industry.

Other Measures

As listed in Appendix Table A-1, we control for numerous factors likely to affect the baseline likelihood of debt financing. *Patent Portfolio Size (citation-weighted)*$_{it}$ weights a startup's patent portfolio size in year t by the citations those patents receive within three years post-grant. As is standard in the literature (e.g., Hall et al. 2005), this variable allows for time-varying differences among companies in the overall "quality" or "importance" of patents in their portfolios. *Funds Raised Last Equity Round*$_{it}$ measures the millions of U.S.

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

[10] Consistent with Hochberg et al. (2014), we classify "VC funds" as those listing an investment focus as startup, early-stage, development, late-stage, or expansion, venture capital (general), or balanced.

dollars raised by the startup in its last equity round, which could affect the need for debt financing. $Profitable_{it}$ indicates whether a startup is profitable in a given calendar year. $Founding\ Year_i$ 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. $Time\ Period_t$ 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." Finally, $Year_t$ captures more granular calendar-year effects.

3.3. Descriptive Findings

Table 1 reveals that debt financing is commonly used by startups in our sample. As shown in Panel A, 36 percent of the patenting-startups receive 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 patents awarded to the startups by 2008 or prior to exit, more than 25 percent are involved in one or more security interest agreements. The share is highest in software, where almost one-third of the patents are 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 (27 versus 20 percent) remains 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 are sold in the three sectors. Of those transactions, 72 percent (212,643) occur between 2000 and 2008. The growth in patent sales is particularly visible in the software sector, an effect partly due to a disproportionate increase in the patenting of software inventions during this period as documented in prior studies (e.g., Cockburn and MacGarvie, 2011).

Panel B of Table 3 normalizes 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 sectors, respectively.[11] Again, the upward time trend is most visible in IT-related sectors. In software, for example, 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 purchasing of software and other IT-related inventions by patent assertion entities and aggregators during this period (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, between the pre-boom and boom period, 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 after 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

[11] 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.

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

As expected, Figure 2 shows that 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. Empirical Analysis

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. In this case, the presence of top-tier VC backing and of debt could 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. The Collateral Channel for Venture Lending

To estimate the likelihood that a startup will obtain debt financing in a given year, we use a simple linear probability model. To start, we regress $DEBT_{it}$, which indicates if startup *i* receives a loan in year *t*, on *Patent Market Liquidity*$_{it}$—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 $PostVC_{it}$, which switches from zero to one in the year the startup first receives VC financing.

The estimation sample is an unbalanced panel with 1,519 startups and 11,298 startup-calendar year observations. Table 5 shows summary statistics at the startup-year unit of observation. The statistics are in line with evidence reported in prior tables.

Table 6 presents OLS estimates of the annual likelihood a startup receives a loan, with standard errors clustered at the startup level. Column 1 shows a naïve regression of the dependent variable on the patent market liquidity and post VC variables. Column 2 adds time-varying startup controls (quality-adjusted patent portfolio size, equity funds last raised, profitable), year fixed effects that capture shifts in general market conditions, as well as fixed effects at the sector and cohort (founding year) level. Column 3 adds fixed effects that allow for permanent startup-specific differences. In all three specifications, the coefficients on *PostVC* and *Patent Market Liquidity* are positive and statistically significant. To interpret, a one standard deviation increase in patent market liquidity is associated with a 2 percentage point increase in the likelihood that a startup raises debt, as compared to the unconditional mean of 7.6. A Hausman test rejects the null that the startup effects are random.[12] In robustness tests, we obtain similar results using a fixed-effects Logit model.

In combination, Columns 1-3 in Table 6 suggest that, controlling for numerous time-varying factors and allowing for startup-specific differences (e.g., wealthy founders), the annual debt rate is significantly higher after a startup's first VC equity infusion and when the market for buying and selling patents is more liquid.

To probe the collateral channel 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, the effect should be amplified for startups with patent assets that are more redeployable to alternative uses or users (Williamson 1988; Benmelech and Bergman 2008, 2009). Similarly, lending should be less responsive to collateral-market conditions when patent assets are more firm-specific. To

[12] 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 0.0333 (p-value<0.01). The estimate from the fixed effects specification is 0.0275. A Hausman test rejects that the estimated coefficients are equal (χ =89.45), indicating that a random coefficients estimator would be inconsistent.

test for this distinctive pattern, we add the *Firm-Specificity* proxy in Column 4 and interact it with *Patent Market Liquidity* in Column 5. Both specifications include year and startup fixed effects.

The estimates in Columns 4 and 5 are consistent with a salvage-value interpretation. In Column 4, the coefficient on *Firm-Specificity* is negative and 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 have lower annual debt rates when patent market liquidity is high than startups with patents more likely to retain value in sales to others. At the same time, the coefficient on *Firm-Specificity* in Column 5 is small in magnitude and statistically insignificant, which is also consistent with a salvage-value interpretation. Absent liquidity in the secondary market, the specificity (or redeployability) of assets should not affect the probability of lending.

To interpret the magnitude of the interaction effect in Column 5, we calculate 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), average redeployability, and firm-specific (top 10 percentile)—with controls held at mean values.[13] When redeployability is high, a one percentage point increase in patent market liquidity is associated with a 1.29 percentage point increase in the annual debt rate. The magnitude of the association is much smaller (at 0.3 percentage points) when patent assets are highly firm-specific. At the mean firm-specificity value, the estimated association is a 1.10 percentage point increase in the annual debt rate—an economic magnitude corresponding to about 15 percent of the average debt rate in the sample.

Robustness Checks and Supplemental Analysis

It is natural to question whether the results in Table 6 are explained by factors unrelated to the patent collateral channel. One concern is that *Firm Specificity* is simply capturing shifts in patent quality rather than expectations of asset redeployment.[14] For example, an unobserved opportunity shock could increase liquidity

[13] For the bottom and top percentiles, we use the mean within-percentile specificity value.
[14] In Table 6, we include controls for time-varying shifts in the overall "quality" of a startup's patent portfolio in light of this general concern; we do so by weighting patent portfolio size in year *t* by the number of citations those patents receive within three years, as is common in the literature (e.g., Hall et al., 2005; Lerner et al., 2011).

in the secondary market and simultaneously increase the value of "good" patents relative to "bad" ones that are not cited by others.

In Appendix Table A-2, we test the robustness of our results to use of alternative controls for patent "quality." To allow for the possibility that a lack of citations by others correlates with low-quality inventions, Column 1 replaces our time-varying control for portfolio quality, *Patent Portfolio Size (citation-weighted)*$_{it}$, with a more restricted version based solely on the number of patent citations received from *other* entities. In a similar spirit, Column 2 replaces the citations-weighted *Patent Portfolio Size* variable with its un-weighted counterpart and controls separately for the average number of patent citations that the startup receives from others. Column 3 re-defines firm-specificity as an indicator set to one for startups with firm-specificity above the sector median, else zero. Finally, Column 4 adds calendar-year*sector fixed effects, to account for sector-specific yearly shocks. In all cases, the estimates are similar to those in Column 5 of Table 6. As noted earlier, our estimates further indicate that when patent-market liquidity is low, characteristics of a startup's patent portfolio appear to be unrelated to the probability that a startup receives a loan. This finding lends further reassurance that our *Firm Specificity* variable is not merely a measure of patent portfolio quality.

A related concern is that an unobserved factor could increase M&A activity in a sector, potentially pulling up our patent-trading measure and stimulating lending for reasons unrelated to the salvageability of patent assets. Regardless of whether our model includes year or year*sector fixed effects, it is still the case that our patent-trading measure includes sales that arise due to M&A activity. We conduct two additional robustness tests to address this concern more directly. First, we add explicit controls for the annual intensity of M&A activity in each sector. Second, we re-run our models using an alternative patent-trading measure that removes patents sold through the M&A channel.

To implement these additional tests, we compile supplemental data from Thomson SDC Platinum on acquisitions involving firms with SIC codes corresponding to the medical devices, semiconductor, or computer software industries. In total, we identify 11,229 acquisitions between 1987 and 2008 involving 1,022 medical device companies, 1,158 semiconductor companies, and 9,201 software firms.[15] Using a name-matching

[15] The sum exceeds the total acquisition count since some deals involve firms from different sectors. We omit bond deals, equity capital transactions, joint ventures, buy backs, exchange offers, recapitalizations, and transfers of partial interest.

algorithm, we are able to match target companies to patent assignees in the USPTO patent grant database for 8,714 (78 percent) of the acquisitions. Unmatched targets include firms that do not receive a U.S. patent within the eight years prior to the transaction. For each matched target, we compile information about its portfolio of patents granted prior to the month and the year of the acquisition. These matched transactions involve 3,717 medical device patents, 3,272 semiconductor patents, and 22,682 software patents.

Appendix Table A-3 shows the M&A-related robustness checks. In Column 1, M&A intensity is based on the annual number of transactions in the sector divided by the number of active companies in the sector that year (*M&A per Firm*). Column 2 uses an alternative measure, *M&A share of patents transacted*, based on the annual number of M&A-driven patent sales in the sector divided by the stock of patents in the sector available for trading that year. Column 3 replicates our original estimation but removes patents sold via M&A from the *Patent Market Liquidity* variable. To compute the alternative measure, we subtract patent sales attributable to M&A from the tallies of sales by sector and issue year provided to us from RPX Corporation. Reassuringly, the coefficients on *Patent Market Liquidity* remain positive, the coefficients on *Patent Market Liquidity * Firm Specificity* remain negative, and the estimates remain statistically significant at conventional levels.

To further bolster the notion that there is a relationship between broader patent-market trading and the salvage value of the patents for a lender, we examine patent sale activity in the subsample of startups that fail (and therefore likely default). In our sample, 275 startups disband by 2008 and have at least one active patent at the time of failure. The average company has six unexpired patents when it fails. In Columns 1 and 2 of Table A-4, we estimate the probability that patents are sold from these failed companies using a linear probability model with time-variant covariates. The unit of observation is a startup-year that begins the year the company fails and ends the year its first patent is sold. (Serrano and Ziedonis (2017) show that when a startup fails, the patent portfolio is typically sold in bulk during the year the first patent is sold.) The estimates suggest that patent trading activity is indeed positively associated with the likelihood that a failed startup's patents are sold: A one percentage point increase in *Patent Market Liquidity* is associated with a 2.8 percentage point increase in the likelihood of sale. A duration analysis (exponential proportional hazard model) in Columns 3 and 4 provides similar qualitative results: the patents from failed startups sell more quickly when the secondary market is more active. To interpret, the estimates suggest that a one percentage point increase in *Patent Market Liquidity* increases the hazard of trade by up to 50 percent. As Table A-4 shows, the estimates are robust to choice of controls and use of either year or year-sector fixed effects.

In combination, our empirical evidence is consistent with the view that increased trading in the secondary market for patent rights shifts lender expectations of salvage value, expanding the financing opportunities of innovative companies.

4.2. The VC Commitment Channel for Venture Lending

To explore whether VCs facilitate exchange in the market for venture lending, we expand on the linear probability estimates in Table 6, and then conduct a more targeted difference-in-difference analysis that helps isolate the credible commitment effect predicted in financial intermediation theory (Holmstrom and Tirole, 1997; Williamson, 1988).

In Columns 6 and 7 of Table 6, we test whether there is an association between a startup receiving a loan and having received equity infusions from investors that are especially reputable or skillful. Since the specification in Column 6 includes *PostVC* in addition to year and startup fixed effects, *Has Top-Tier VC* acts as a step-function when top-tier investors are involved, whether initially or in later rounds of financing. The same patterns (for patent market liquidity, firm specificity, and so forth) persist here as in the previous models, with similar or larger magnitudes. Further, the coefficient on *Has Top-Tier VC* is positive and significant, consistent with the lending likelihood being heightened by the presence of equity investment by highly reputable VCs. Based on coefficients in Column 6, the first receipt of VC financing (*PostVC*) is associated with an increase in the annual debt rate by 1.8 percentage points, from 6.1 to 7.9 percent. Backing from a top-tier investor, whether in an early or later round, is associated with an increase in the predicted debt rate of 2.4 percentage points, a large added boost. As seen in Column 7, these findings are robust to the inclusion of year-sector fixed effects that allow time-varying shifts in a sector to alter the baseline rate of lending.

The VC-related evidence in Table 6, while interesting, is prone to multiple interpretations. As financial intermediation theory (Holmstrom and Tirole, 1997; Williamson, 1988) suggests, exchange between lenders and startups with risky projects could be facilitated by the ability of VCs to credibly commit that they will exert future effort to build and refinance a portfolio company. 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. Relatedly, being selected for funding by a VC, particularly one that is highly reputable or skillful, could affect lender expectations of the otherwise difficult-to-discern quality of the startup, similarly altering expectations of repayment in a causal manner. It is also possible, however, that VC backing correlates with the error term in Columns 6 and 7. A negative correlation could arise if a successful but cash-constrained startup suffers a negative shock to patent rights that reduces the salability of those assets. 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. More troublesome given the directionality of our findings, a positive shock insufficiently captured by our controls could boost the value of a startup's technology and simultaneously increases its attractiveness as a candidate for financing for both lenders and equity investors —a possibility that we turn to below.

In our next set of analyses, we develop a novel method for isolating the potential "VC credible commitment" effect in the market for venture lending. To do so, 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 we explain below in more detail, 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 VentureSource, 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.[16] As Townsend (2015) 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. 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. The typical lifespan of a VC fund is 10-12 years. 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 3-5 years. 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 be replenished.[17] 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

[16] 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 VentureSource.

[17] VCs have conflict-of-interest reasons to avoid "crossover" investments where two or more of their funds invest in the same portfolio company. In periods of crisis, however, Townsend (2015) reports a semi-fungibility in cross-fund investing. Intuitively, some of the capital that would have gone into new projects from the new fund will now come from the old fund, thus leaving current portfolio companies of the older fund competing with new investments for the funds that had been reserved for follow-on investment.

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.

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 the PREQIN data. Our goal is to compare startups with investors with recently-raised funds at the time of the crash (less-constrained) to startups whose investors had not recently raised a fund but were likely to have tried to fundraise soon absent the crash (constrained).

Our main analysis focuses on startups that (a) compete in sectors most affected by the bubble's collapse (i.e., are in IT-related sectors), (b) receive 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 but filters out many startups that fail in the immediate aftermath of the crash. In combination, these criteria yield an estimation sample of 91 semiconductor and software startups at risk of receiving a loan between 1997 and 2002. The average age of new funds managed by syndicate partners in these startups was 1.11 (std. dev. 1.10) years at the time of the crash.

As our main specification, we set the variable *RecentFund* equal to one when the average age of the most recent funds in a startup's syndicate of investors is less than two years in early 2000. We then compare startups in this group with those backed by investors whose most recent funds average between 2 to 4 years when the market collapsed (*RecentFund=0*). We conservatively exclude startups when the syndicate average exceeds 4 years. VCs that had not raised a fund in the five years leading up to the crash may have done so due to low quality or reputation that precluded them from fundraising despite the availability of capital; such low quality or reputation may also affect the ability of the startup to raise venture debt. To more directly address this concern, our specifications further control for whether the startup has a top tier VC investor.

We estimate a difference-in-differences model with the specification:

$$Debt_{it} = \delta_1 After_{it} + \delta_2 RecentFund_i + \delta_3 After_{it} * RecentFund_i + \delta_4 W_{it} + \theta_i + \upsilon_{it}$$

As above, $DEBT_{it}$ indicates if startup *i* receives a loan in year *t,* and *RecentFund* is an indicator set equal to one when the most recent funds managed by startup *i*'s investors are less than two years old on average in early 2000, and zero if between two and four years old. *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, Profitable* and *Patent portfolio size (citation-weighted)*. As before, startup fixed effects, represented by θ_i, allow for time-invariant, company-specific differences to influence lending. The effects 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 both groups of startups had the bubble not collapsed, the difference-in-differences (DD) model 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 7 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 546 startup-year observations and 91 startups in the IT-related sectors. At the time of the crash, 66 startups (seventy-two percent) had syndicates with relatively recent funds (*Recent Fund*=1). Standard errors are clustered at the startup level. Clustering errors at a more granular startup-before and startup-after level yields similar findings. Column 1 includes time-invariant startup controls only, while Column 2 uses startup fixed effects and time-varying covariates.

The results suggest a dramatic shift in startup lending patterns post-shock that correlates with the differences in VC fundraising cycles. The DD coefficient of interest in Column 2, our preferred specification with fixed-effects and a full-set of controls, is 0.148. This coefficient indicates that difference in 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 14.8 percentage points during the post-shock period.

Figure 3 plots estimates from a more general 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 in 2000 is positive and statistically significant 0.27 (p-value=0.02). In the two years immediately following the shock, the coefficients are similarly positive and significant at 0.20 and 0.19.[18]

In combination, the estimates are consistent with a "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 highlights the contracting challenges of lending to startups and resonates with predictions in Holmstrom and Tirole (1997): particularly in times when capital is scarce, investors with less capital 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 startup to obtain a loan. From a macro-economic perspective, this finding suggests that business cycles may depress funding for innovation-based startups both directly, by limiting future prospects and reducing the supply of available VC funding, but also indirectly, by reducing the credible commitment of equity investors and limiting in turn a startup's access to debt financing.

Robustness Checks and Supplemental Analysis

We conduct a number of robustness tests on the main DD specification reported in Columns 1 and 2 of Table 7. First, we check that this pattern is not due to simple differences between groups in the presence or absence of top-tier investors or other startup characteristics. Both the Wilcoxon-Mann-Whitney test (the non-

[18] 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.

parametric analog of the independent sample t-test) and Kolmogorov- Smirnov test of distributional differences yield similar findings: on average, we fail to observe statistically significant differences between startups with recent-fund syndicates and their counterparts without recent-fund syndicates in the year prior to the crash. Regardless, all specifications in Table 7 control for these startup characteristics.

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 3 and 4 in Table 7 report placebo tests with this logic in mind.

In Column 3, we replicate the DD estimator for IT startups in non-crisis periods (1992-1997 and 2002-2006).[19] 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, 148 semiconductor and software startups are VC-backed and active in the two periods combined. As Column 3 shows, the DD coefficient in our preferred specification (fixed-effects with controls) is small (0.037) and is not statistically significant in the non-crisis periods (p-value=0.39). We obtain similar results if the effects are estimated separately for each non-crisis period, albeit with smaller sample sizes.

Column 4 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 4 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=80). Reassuringly, the DD coefficient is not significant at conventional levels (p-value=0.39).

[19] 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.

If capital constraints imposed by VC fundraising challenges is the mechanism affecting a startup's ability to raise venture debt, the effect should be stronger for startups with investors more exposed to the shock. We therefore distinguish between startups whose VCs had relatively high investment exposure to the IT sector at the time of the crash, and startups backed by VCs with more limited exposure. To do so, we compute for startup *i*'s syndicate as of 2000, the total rounds invested in semiconductor and software startups as share of total rounds in all three sectors in our sample. In the spirit of Townsend (2015), we define high (limited) IT exposure using above (below) median values for syndicates in medical device startups, a non-IT sector.

Column 5 estimates a triple differences model that further distinguishes between startups backed by investors with high (above-median) IT exposure at the time of the crash, and startups with less exposed (below-median) investors. The estimation sample now includes both IT and medical device startups. Consistent with the credibility of commitment interpretation, only the triple interaction coefficient (*RecentFund x After x High IT Exposure*) is positive and significant. This finding indicates that the "recent fund effect" is restricted to startups whose investors had recently raised funds and had high exposure to the IT sector. The estimate is similar in magnitude to that in the previous columns (=0.12). To elaborate, the estimated coefficients for *RecentFund x After x High IT Exposure* (=0.12*) and *After x High IT Exposure* (=-0.05) indicate that startups with investors highly exposed to the IT sector and with recent funds are more likely to get loans post-bubble burst than startups with investors highly exposed to the IT sector that had not recently raised funds when the bubble burst. An F-test (p-value==0.06) rejects the null that the two coefficients are equal. In contrast, the coefficients of *After* and *RecentFund* x *After*, which correspond to the effect of *Recent Fund* when investors have more limited exposure to the shock (as is the case for some startups in medical devices), are not significantly different than zero and from each other.

In Column 6, we further strengthen the intuition of this test by repeating the triple-differences estimation, this time restricting the sample to contain only medical device startups that plausibly are affected by the crash only through having investors with IT exposure (Townsend, 2015). The estimates when restricting to this sample are similar, both in pattern and magnitude. Once again, only the triple interaction (*RecentFund x After x High IT Exposure*) has a positive and significant coefficient, indicating that the "recent fund effect" is restricted to medical device startups whose investors had recently raised funds and who were characterized by high exposure to the IT sector. The estimate is of similar magnitude to that estimated in the previous columns (=0.14, p-value 0.10). Here too, the estimate for *After x High IT Exposure* is insignificant, and an F-test shows we can reject (p-value==0.10) the hypothesis that *RecentFund x After x High IT Exposure* and *After x High IT Exposure* are equal. Overall, the estimates in Column 6 suggest that medical device startups backed by VC investors with high exposure to the shock and that had not recently raised a fund at the time of the crash experience a stark drop in lending after the crash, consistent with the VC credible commitment story.

Taken together, this evidence is consistent with the patterns demonstrated in the baseline DD specification. Consistent with the VC credible commitment mechanism, venture lenders continued to finance startups whose investors were less capital-constrained following the technology bubble's collapse in 2000, yet withdrew support from startups with more capital-constrained investors. The estimates further 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 helps to allay 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.

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 potential 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: expectations of salvage value should affect the willingness to lend in the presence of contracting frictions. Although prior studies document this effect for tangible assets (Benmelech, 2009; 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 can play a meaningful friction-reducing role in innovation financing.

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 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 emergence of "patent assertion entities" and "aggregators" 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 entities increase liquidity in the resale market for patents, 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 that, following the collapse of the U.S. technology bubble in early 2000, lenders continued to finance startups backed by investors with less binding capital constraints 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. Consistent with the financing risk hypothesis in Nanda and Rhodes-Kropf (2013, 2016), this evidence suggests that the credibility of VC commitment plays a vital role in venture lending. Our results further suggest that, absent a well-developed infrastructure of venture capitalists and institutional investors, the economic effects of policies aimed at stimulating entrepreneurial-firm innovation through debt channels alone 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

NOTE: A startup receives a loan if at least one patent of the startup is involved in a security interest agreement (pledged as collateral) in a calendar year.

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	0.091	0.071	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
Profitable	0.06	0.23	0	1	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	0.12	0.32	0	1	91	546
Post VC	0.88	0.33	0	1	91	546
Has Top-Tier VC	0.60	0.49	0	1	91	546
Patent Market Liquidity	0.043	0.017	0	0.070	91	546
Firm-Specificity of Patent Assets	0.07	0.11	0	0.64	91	546
Patent Portfolio Size (Citation Weighted)	48.85	84.68	0	648	91	546
Patent Portfolio Size	8.08	12.16	1	86	91	546
Funds Raised (million $)	23.41	24.86	0	144.6	91	546
Profitable	0.06	0.24	0	1	91	546
Founding Year	1994.33	2.99	1987	1999	91	546
Primary sector = software	0.70	0.46	0	1	91	546
Primary sector = semiconductors	0.30	0.46	0	1	91	546
Recent Fund	0.73	0.45	0	1	91	546

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	7
Estimation Method	**OLS**	**OLS**	**OLS**	**OLS**	**OLS**	**OLS**	**OLS**
Dependent Variable	**Debt**	**Debt**	**Debt**	**Debt**	**Debt**	**Debt**	**Debt**
Post VC	0.043***	0.033***	0.027***	0.028***	0.028***	0.018*	0.018*
	(0.006)	(0.007)	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)
Patent Market Liquidity	0.912***	1.247***	1.179***	1.165***	1.294***	1.272***	1.536***
	(0.137)	(0.171)	(0.221)	(0.220)	(0.235)	(0.233)	(0.248)
Firm Specificity				-0.060*	0.019	0.019	0.009
				(0.031)	(0.045)	(0.045)	(0.043)
Firm Specificity * Patent Market Liquidity					-2.142**	-2.154**	-1.880**
					(0.958)	(0.961)	(0.954)
Has Top-Tier VC						0.024**	0.021*
						(0.012)	(0.012)
Funds Raised Last Round		0.000	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Patent Portfolio Size (citation-weighted)		0.000	0.000	0.000	0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Profitable		-0.007	-0.008	-0.008	-0.008	-0.008	-0.008
		(0.012)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Year FE	NO	YES	YES	YES	YES	YES	YES
Year x Sector FE	NO	NO	NO	NO	NO	NO	YES
Startup FE	NO	NO	YES	YES	YES	YES	YES
Founding Year FE	NO	YES	NO	NO	NO	NO	NO
Sector FE	NO	YES	NO	NO	NO	NO	NO
No. of Startups	1,519	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	11,298

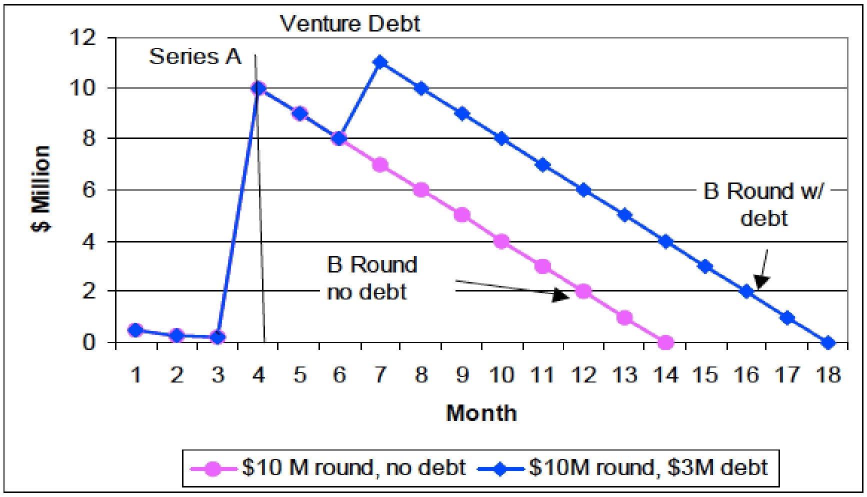
NOTE: The unit of analysis is a startup-calendar year, with an unbalanced panel. Debt = 1 if the firm is involved in at least one security interest agreement in a calendar year. *Post VC* = Indicator that switches from zero to one in the year that the startup first receives VC financing. *Has Top-Tier VC* is an indicator that turns from 0 to 1 in the year that the startup is 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) and remains 1 thereafter. *Patent Market Liquidity* is the startup-level patent-portfolio combined probability that a patent will be traded in a year. *Firm-specificity of Patent Assets* is the share of citations that are self-citations. *Funds Raised Last Round* (million $) is the total amount of venture capital raised in the latest financial round. *Profitable* = 1 if the startup is profitable as of a given calendar year, and 0 otherwise. *Founding Year* is the founding year of the startup. *Patent Portfolio Size (citation-weighted)* is the cumulative number of patent citations received within three years of each patent being granted. Venture capital round data are from VentureOne. Robust standard errors, clustered at the startup level, are reported in parenthesis. Statistical significance: * 10 percent, ** 5 percent, *** 1 percent.

TABLE 7. Difference-in-Differences (DD) of Startup Debt Rate Before and After the Technology Bubble's Collapse in Early 2000

	Main Results		Robustness Tests			
	1	**2**	**3**	**4**	**5**	**6**
Estimation Method	**DD**	**DD**	**DD**	**DD**	**DDD**	**DDD**
Dependent Variable	**Debt**	**Debt**	**Debt**	**Debt**	**Debt**	**Debt**
RecentFund x After	0.141**	0.148**	0.037	0.044	-0.001	-0.045
	(0.056)	(0.060)	(0.043)	(0.051)	(0.047)	(0.051)
RecentFund x After x High IT Exposure					0.122***	0.145*
					0.045	0.087
After x High IT Exposure					-0.048	-0.092
					(0.043)	(0.067)
After					0.035	0.253
					(0.093)	(0.252)
High IT Exposure	NO	NO	NO	NO	YES	YES
Has Top-Tier VC	NO	YES	YES	YES	YES	YES
Patent Market Liquidity	NO	YES	YES	YES	YES	YES
Firm-specificity of Patent Assets	NO	YES	YES	YES	YES	YES
Funds Raised	NO	YES	YES	YES	YES	YES
Patent Portfolio Size (citation-weighted)	NO	YES	YES	YES	YES	YES
Startup FE	NO	YES	YES	YES	YES	YES
Founding Year FE	YES	NO	NO	NO	NO	NO
Sector FE	YES	NO	NO	NO	NO	NO
Profitable	YES	YES	YES	YES	YES	YES
After x Founding Year FE	YES	YES	YES	YES	YES	YES
After x Sector FE	YES	YES	YES	YES	YES	YES
After x Profitable	YES	YES	YES	YES	YES	YES
Event Year	2000	2000	placebo years (1995, 2005)	2000	2000	2000
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 1992-97 (2002-06) and VC-backed by placebo year	medical device startups, active 1997-2002 and VC-backed by 2000	software and semi startups and medical device startups, active 1997-2002 and VC-backed by 2000	medical device startups, active 1997-2002 and VC-backed by 2000
No. of Startups	91	91	148	80	171	80
Observations	546	546	771	480	1,026	480

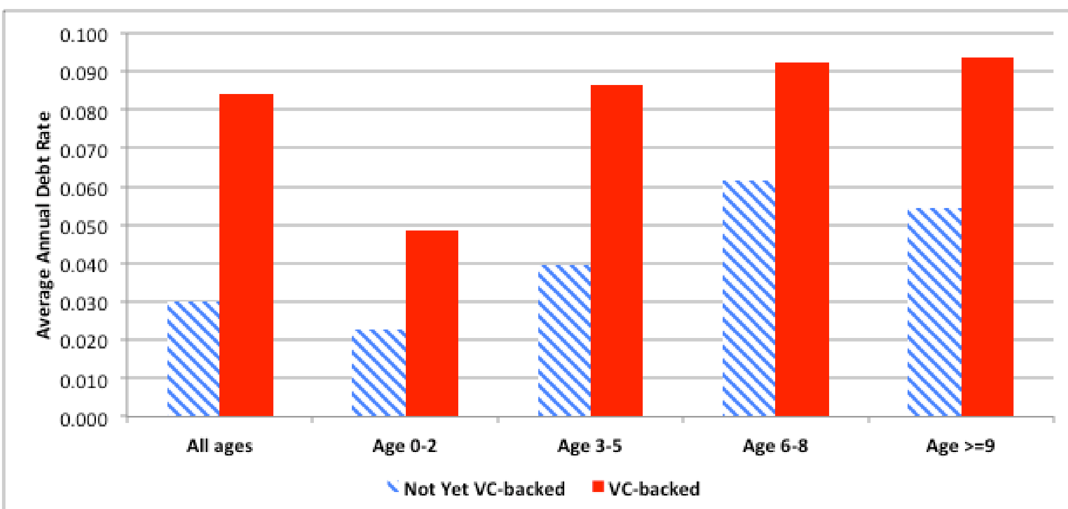
NOTE: Column 1 and 2 present the Differences-in-Differences (DD) main results. DD coefficient *(RecentFundxAfter)* estimates the change in the annual startup debt rate before versus after the technology bubble's collapse in early 2000. *Recent Fund* = 1 (0) if the mean age of the most recent fund raised by the startup's investors is less than two (vs. between two and four) years old in the event year. Column 3 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 4 shows a falsification test using startups in medical devices, a life science sector relatively shielded from the technology bubble's collapse in 2000. Column 5 shows a triple-dif regression using all startups in Semiconductor, Software and Medical Device sector and distinguishes between startups whose investors had high exposure to the IT sector at the time of the crash, and startups backs by VCs with limited exposure to the IT sector at the time of the crash. IT exposure of startup i's syndicate as of 2000 is based on the total rounds invested in semiconductor and software startups as percentage of total rounds in all three sectors in our sample. High (or limited) exposure corresponds to IT exposure that is above (or below) the median exposure of VC syndicates that had invested in Medical Device startups by 2000. Column 6 shows the coefficients of a triple-diff regression for the sample of Medical Device. *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. *Has Top-Tier VC* is an indicator that turns from 0 to 1 in the year that the startup is 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) and remains 1 thereafter. *Patent Market Liquidity* is the startup-level patent-portfolio combined probability that a patent will be traded in a year. *Firm-specificity of Patent Assets* is the share of citations that are self-citations. *Funds Raised* is the total amount of venture capital raised by a given year. *Profitable* = 1 if the startup is profitable as of a given calendar year, and 0 otherwise. *Founding Year* is the founding year of the startup. *Patent Portfolio Size (citation-weighted)* is the cumulative number of patent citations received within three years of each patent being granted. 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



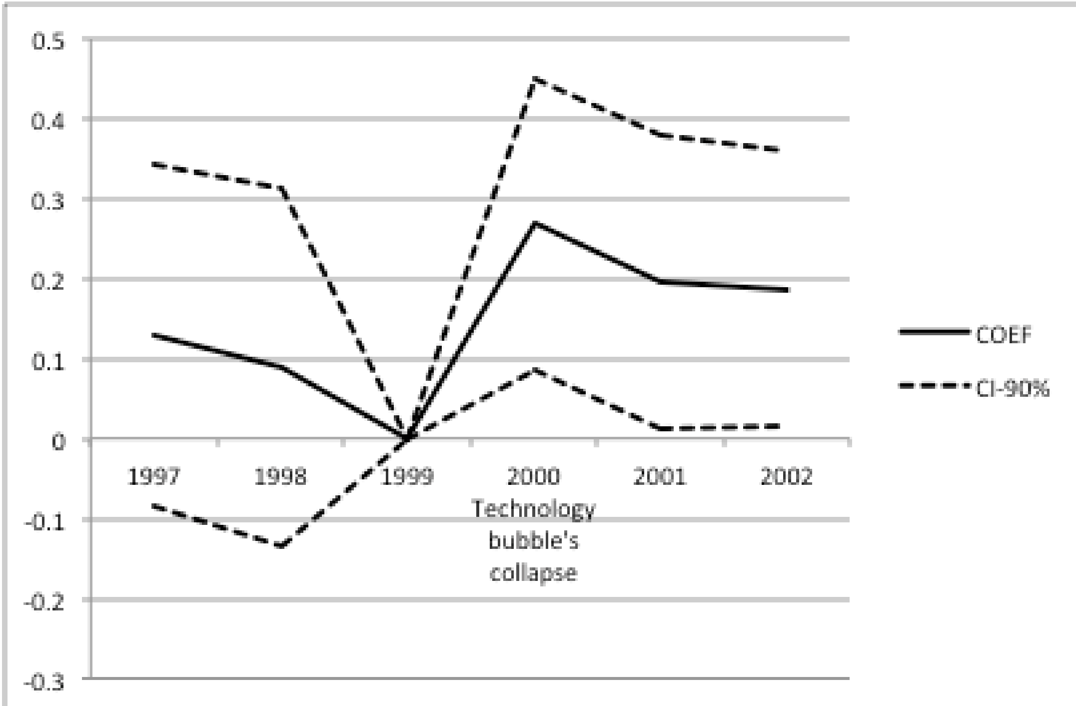
Source: Hardymon, Lerner, and Leamon (2005).

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

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	VentureSource
Has Top-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-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*,	VentureSource
Profitable$_{it}$	1 if the startup is profitable.	VentureSource
Founding Year$_i$	Year startup *i* was founded	VentureSource
Sector$_i$	Startup *i*'s primary sector: medical devices, semiconductor devices, or software	VentureSource
Year$_t$	Indicates calendar year (1987-2008)	VentureSource
Time Period$_t$	Indicates if calendar year is in pre-boom (1987-1997), boom (1998-1999), or post-boom (2000-2008) period.	VentureSource
M&A Intensity Measures		
M&A per Firm	Annual number of M&A transactions in the industry divided by the number of active companies in the industry that year	SDC Platinum
M&A share of patents transacted	Annual number of patents transacted due to M&A activity in a given year and technology sector divided by the stock of patents that could have been traded in that year	SDC Platinum

[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.

TABLE A-2. Firm-specificity: Robustness checks

	1	2	3	4
Estimation Method	**OLS**	**OLS**	**OLS**	**OLS**
Dependent Variable	**Debt**	**Debt**	**Debt**	**Debt**
Post VC	0.028***	0.028***	0.027***	0.027***
	(0.010)	(0.010)	(0.010)	(0.010)
Patent Market Liquidity	1.271***	1.227***	1.360***	1.560***
	(0.234)	(0.233)	(0.246)	(0.251)
Firm Specificity	0.021	0.026		0.008
	(0.044)	(0.045)		(0.043)
Firm Specificity x Patent Market Liquidity	-2.116**	-2.625***		-1.868**
	(0.944)	(0.967)		(0.951)
High Firm Specificity			0.033*	
			(0.020)	
High Firm Specificity x Patent Market Liquidity			-0.624*	
			(0.374)	
Funds Raised Last Round	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Patent Portfolio Size (citation-weighted)	0.000		0.000	0.000
	(0.000)		(0.000)	(0.000)
Patent Portfolio Size		0.001**		
		(0.000)		
Patent Citations Received from Others per Patent		-0.002		
		(0.001)		
Profitable	-0.008	-0.009	-0.008	-0.008
	(0.016)	(0.016)	(0.016)	(0.016)
Robustness Checks	Patent Portfolio Size is weighted by number of patent citations received from *others*	Patent Portfolio Size is unweighted and Patent portfolio quality is based on the average number of patent citations that the patents in portfolio received from *others*	Firm-Specificity is an indicator (1=High Firm Specificity if startup's firm-specificity is above the median firm-specificity of the sector, 0 otherwise)	Year x Sector Effects
Year FE	YES	YES	YES	YES
Startup FE	YES	YES	YES	YES
No. of Startups	1,519	1,519	1,519	1,519
Observations	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 calendar year. *Post VC* = Indicator that switches from zero to one in the year that the startup first receives VC financing. *Profitable* = indicates whether or not the startup is profitable as of a given calendar year. *Patent Portfolio Size (citation-weighted)* is the cumulative number of patent citations received within three years of each patent being granted. *Patent Portfolio Size* is the cumulative number of patents applied for and granted to the startup by a given year. *Firm-specificity* of patent assets is the share of citations that are self-citations. *Patent Market Liquidity* is the startup-level patent-portfolio combined probability that a patent will be traded in a year. *Patent Citations Received from Others per Patent* is the number of patent citations received that the patents of the portfolio of a startup receive from other firms. Robust standard errors, clustered at the startup level, are reported in parenthesis. Statistical significance: * 10 percent, ** 5 percent, *** 1 percent.

TABLE A-3. Patent Market Liquidity: Robustness checks

	1	2	3
Estimation Method	**OLS**	**OLS**	**OLS**
Dependent Variable	**Debt**	**Debt**	**Debt**
Post VC	0.028***	0.028***	0.027***
	(0.010)	(0.010)	(0.010)
Patent Market Liquidity	1.294***	1.404***	0.916***
	(0.235)	(0.236)	(0.311)
Firm Specificity	0.019	0.022	0.005
	(0.045)	(0.045)	(0.047)
Firm Specificity * Patent Market Liquidity	-2.142**	-2.201**	-1.830*
	(0.957)	(0.954)	(1.099)
Funds Raised Last Round	-0.001***	-0.001***	-0.001***
	(0.000)	(0.004)	(0.000)
Patent Portfolio Size (citations-weighted)	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Profitable	-0.008	-0.007	-0.008
	(0.016)	(0.012)	(0.016)
Merger and Acquisition Activity	0.002	-2.091*	
	(0.027)	(1.136)	
Robustness Checks	Merger and Acquisition Activity based on number of merger and acquisition bids per firm	Merger and Acquisition Activity based on patents transacted due to merger and acquisitions	Patent Market Liquidity measure computed excluding patents transacted due to mergers and acquisitions
Year FE	YES	YES	YES
Year x Sector FE	NO	NO	NO
Startup FE	YES	YES	YES
Founding Year FE	NO	NO	NO
Sector FE	NO	NO	NO
No. of Startups	1,519	1,519	1,519
Observations	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 calendar year. *Post VC* = Indicator that switches from zero to one in the year that the startup first receives VC financing. *Funds Raised Last Round* (million $) is the total amount of venture capital raised in the latest financial round. *Patent Portfolio Size (citation-weighted)* is the cumulative number of patent citations received within three years of each patent being granted. *Firm-specificity of Patent Assets* is the share of citations that are self-citations. *Patent Market Liquidity* is the startup-level patent-portfolio combined probability that a patent will be traded in a year. *Profitable* = indicates whether or not the startup is profitable as of a given calendar year. *Founding Year* is the founding year of the startups. Venture capital round data are from VentureOne. Merger and acquisition bids and actual transactions involving companies in a given year and in the same technology sector of the focal startup were obtained from the Thomson Reuters SDC Platinum database. Robust standard errors, clustered at the startup level, are reported in parenthesis. Statistical significance: * 10 percent, ** 5 percent, *** 1 percent.

TABLE A-4. The Sale of Patents of Failed Startups and Patent Market Liquidity

	1	2	3	4
Estimation Method	**OLS**	**OLS**	**Proportional Hazard Model – MLE**	**Proportional Hazard Model – MLE**
	Marginal Effect	**Marginal Effect**	**Hazard Ratio**	**Hazard Ratio**
Dependent Variable	**Sale**	**Sale**	**Sale**	**Sale**
Patent Market Liquidity	2.828***	2.929***	1.359***	1.497***
	(0.715)	(0.747)	(0.095)	(0.136)
Has Top-Tier VC	0.050*	0.048*	1.337*	1.313
	(0.025)	(0.026)	(0.230)	(0.230)
Patent Portfolio Size (citation-weighted)	0.001***	0.001	1.003***	1.003***
	(0.000)	(0.000)	(0.001)	(0.001)
Previously Received a Loan	0.062**	0.061**	1.403**	1.420**
	(0.027)	(0.028)	(0.232)	(0.237)
Founding Year FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Sector FE	YES	YES	YES	YES
Year x Sector FE	NO	YES	NO	YES
No. of Startups	285	285	285	285
Observations	989	989	989	989

NOTE: The first two columns present the coefficients of linear probability models whereas the second two columns show the hazard ratios of an exponential proportional hazard model. The unit of analysis is a startup-calendar year until the year a startup sells its first patent. *Sale* is an indicator that switches from zero to one when the sells its first patent. *Patent Market Liquidity* is the startup-level patent-portfolio combined probability that a patent will be traded in a year. *Has Top-Tier VC* is an indicator that turns from 0 to 1 in the year that the startup is 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) and remains 1 thereafter. *Founding Year* is the startup's founding year. *Patent Portfolio Size (citation-weighted)* is the cumulative number of patent citations received within three years of each patent being granted. *Previously Received a Loan* =1 if the failed startup obtained at least one loan before failure. Standard errors are reported in parenthesis. Statistical significance: * 10 percent, ** 5 percent, *** 1 percent.