NBER WORKING PAPER SERIES

BUILDING RELATIONSHIPS EARLY: BANKS IN VENTURE CAPITAL

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Working Paper 10535
http://www.nber.org/papers/w10535

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
June 2004

We thank Serdar Dinc, Colin Mayer, Bill Megginson, and seminar participants in Chicago (Federal Reserve Conference), Duke, Frankfurt, Georgia Tech, Half Moon Bay (Stanford GSB and NYSE Conference on Entrepreneurial Finance and Initial Public Offerings), LBS, Michigan, New York (Federal Reserve Bank), Notre Dame, Oslo, Oxford, Philadelphia (Federal Reserve Bank), Pittsburgh, Porto, Sydney, Toronto, UBC, UNC, UT Austin, and Yale (First EVI Conference). We also thank Steven Drucker, Jun Ishii and Shu Wu for excellent research assistance and the Center for Entrepreneurial Studies at the Stanford Graduate School of Business and the National Science Foundation for financial support. Puri thanks the Sloan Foundation for partial funding support. All errors are ours. The views expressed herein are those of the author(s) and not necessarily those of the National Bureau of Economic Research.

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NBER Working Paper No. 10535
May 2004
JEL No. G2, L2

ABSTRACT

The importance of an investor's organizational structure is increasingly recognized in modern finance. This paper examines the role of banks in the US venture capital market. Theory suggests that unlike independent venture capital firms, banks can seek complementarities between their venture capital and lending activities. Our empirical analysis suggests that banks use their venture capital investments to build relationships for their lending activities. Banks target their venture investments to companies that are more likely to subsequently raise loans, and having made an investment as a venture capitalist increases a bank's likelihood of providing a loan. Companies may benefit from these relationships through more favorable loan pricing. The analysis suggests that banks are strategic investors in the venture capital market with investment patterns distinct from independent venture capitalists. It also provides a cautionary note for relying on banks for the development of a venture capital industry.

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1. Introduction

Banks are the dominant financial institution in most countries (see Allen and Gale, 2000). Policy makers in many countries want to develop their venture capital market. Their natural instinct is to rely on their incumbent banks for this task (Becker and Hellmann, 2003). From a US perspective this is somewhat surprising, given that the US venture capital market is largely dominated by independent venture capital firms. At the same time, even in the US banks have exploited some loopholes in the Glass-Steagall Act to maintain an active presence in the venture capital market. The question arises of what the role of banks in venture capital is, and how banks differ from independent venture capital firms.

This leads us to an important economic question about the significance of an investor's organizational structure. Different organizational structures may imply that investors pursue different objectives and exhibit different investment patterns. The most fundamental difference between a bank and an independent venture capital firm is that a bank also has its core banking business, selling loans and other financial services.

Our theoretical starting point is that banks as venture capitalists may differ from independent venture capitalists because their venture investments may interact with their other banking activities. Hellmann (2002) provides a general theory of how strategic venture investors differ from independent venture capitalists. He shows that strategic investors will target companies where there are complementarities between the venture capital investments and their other core business. They differentiate themselves by virtue of their complementary assets and they reap benefits from exploiting the synergies between the venture investments and their core business. For banks, the complementary asset would be their lending expertise, which may be of future interest to the portfolio company, and the synergies lie in the potential for banks to leverage relationships from venture capital into the lending market.

To empirically examine the strategic investor hypothesis, we use and augment data from Venture Economics about the investments made by banks and independent venture capitalists over the period 1980-2000. We also gather additional data from

Compustat, Loan Pricing Corporation, and Moody's Manuals. We first establish that banks can indeed be thought of as a distinct type of investors. We show that banks behave differently in the venture capital market. In particular, they invest less frequently in earlier rounds, they syndicate more, and they invest in larger deals. Interestingly, banks are also more likely to make investments in high-debt industries (both in terms of the absolute level of debt and the debt-to-asset ratio). This begins to point us in the direction of strategic investing.

Next, we examine whether banks invest in venture capital to forge relationships with potential future banking clients. We test whether the companies that receive venture capital from banks are more likely to subsequently obtain loan financing. We find a strong relationship between banks making venture investments and companies subsequently raising loans. We show that part of this statistical relationship can be explained by observable deal characteristics: banks invest in deals where the observable characteristics suggest a higher likelihood of future loan activity. Using an estimation approach similar to Chiappori and Salanié (2000), we also find evidence that banks select future loan candidates based on unobservable deal characteristics. Furthermore, we verify that the banks' ability to target future loan candidates is not a by-product of banks simply targeting companies that are more likely to go public.

To further test for strategic complementarities, we go beyond the venture capital market and test whether relationships from venture capital actually affect loan market outcomes. Using both standard and conditional logit approaches, we find that having a prior venture capital relationship significantly increases a bank's chance of becoming a company's lender. This result supports the hypothesis that building relationships in the venture capital market complements the banks' lending business.

Do firms also benefit from using relationships developed in the venture capital market in the lending market? On the one hand there are potential benefits in that companies can use their relationship to signal their quality and lower their pricing terms by obtaining loans from their relationship bank. Alternatively, banks may engage in rent extraction, so that no benefits of better pricing accrue to the firm. We test for this by comparing yields of relationship and non-relationship loans through the use of matching regressions, based on propensity scores, as in Heckman, Ichimura and Todd (1997, 1998). We find that relationship loans have lower yields than non-relationship loans. This difference suggests that relationships have an economic impact, and using these relationships can benefit the firm.

Overall, our evidence provides rich support for the hypothesis that banks strategically invest in the venture capital market, seeking complementarities with their traditional loan business. These results confirm that the organizational form of venture capital matters, affecting the role of the venture capitalist and the kind of investments made.

The paper builds on the literature on relationship banking. Petersen and Rajan (1994), Berger and Udell (1995) examine relationships in small private firms. James (1987), Lummer and McConnell (1989), Best and Zhang (1993), Billett, Flannery and Garfinkel (1995) among others find that new loans, loan renewals, and lender identity carry (positive) private information to the outside equity market about a borrowing company's financial condition. Bharath et. al (2004), Drucker and Puri (2004) show that lending relationships are key for generating other fee based business including underwriting. The literature on universal banking has also long recognized that banks want to lever their client relationships across a variety of financial products (see e.g., Carow and Kane, 2001, Puri, 1996). This debate has generally focused on the cross-selling of different products by the bank at a point of time. However, the intertemporal expansion of banks' activities, in terms of using venture capital to invest in the early stages of a company's life cycle, has received relatively little attention. Our paper takes a first step in this direction. The paper is also related to work that analyzes corporate venture capital (Block and MacMillan, 1993, Gompers and Lerner, 2000, Gompers, 2002) and to Hamao, Packer, and Ritter (2000), who examine bank-affiliated venture capital in the context of underwriting in Japan.

Finally, our analysis provides a cautionary note against relying too much on banks to develop a venture capital industry. Looking at the US evidence, we recognize that banks may be driven by strategic objectives, making them strategic followers, rather than leaders in the venture capital market. Naturally, the lessons from the US may not necessarily translate directly to other countries, but our evidence does provide a first step in understanding banks' incentives when they engage in venture capital (see also Mayer, Schoors and Yafeh, 2001).

The remainder of the paper is organized as follows. Section 2 describes the data and discusses the regulatory environment. Section 3 examines the banks' strategic interest in the venture capital market. Section 4 examines the role of a prior venture relationship in the loan market. Section 5 examines the impact of these relationships on loan pricing. Section 6 provides some further discussion. It is followed by a brief conclusion.

2. The data

In this section we describe the data sources, the variables of interest, and the bank regulation surrounding banks in venture capital.

2.1. Data Sources

The data are compiled from several commercially available data sources, including Venture Economics, Loan Pricing Corporation, Compustat, and augmented by hand-collected data from Moody's Manuals. The main data source is Thomson Financial's Venture Financing database, called Venture Economics (VE henceforth). VE provides information on venture firms (i.e., the investors),[1] the companies in which they invest, and the details of individual financing rounds. We collect all data on U.S. investments for the period 1980-2000.[2] Considerable care is taken in matching these data

[1] Throughout the paper we reserve the word "firm" to the investor, and the word "company" to the investee.

[2] Venture Economics began tracking venture deals in 1970. Their coverage in the early years is believed to have been sparse. Moreover, the reinterpretation of the ERISA 'prudent man' standard in 1979 is widely believed to mark the beginning of the modern venture market. We therefore take 1980 as the beginning of our sample period.

from the different databases since there is no unique ID that corresponds across all of these datasets.

The Venture Economics database contains information on individual financing rounds, such as the company receiving the financing, the different investors providing the financing, the date and round number of individual financing rounds, and the total dollar amount raised by the company (see also Kaplan, Sensoy and Strömberg, 2004).

Since we are interested in venture capital financing of start-ups or private companies, we exclude all leveraged buyout deals. For each investor the VE database tracks its organizational form and affiliations. With this data we can identify whether a venture capital firm is bank-owned, independent or other. In order to have a clean comparison of organizational types, we exclude the deals by all investors that are neither banks nor independent venture capitalists.

While VE identifies bank venture capitalists, its classification is not reliable. Apart from omissions and coding errors, their bank category includes entities other than commercial banks, such as finance companies and foreign banks without a U.S. banking charter affiliate. We therefore verified every venture capital firm manually, using Moody's Bank and Finance Manuals. We classified a firm as a bank venture capitalist if it was a commercial bank, a bank holding company, or a subsidiary of a bank. Moreover, the bank had to be chartered in the U.S. For every venture capital firm we considered the most recent issue of Moody's Bank and Finance Manual. If a firm was not listed, we also consulted Moody's index, which lists all past entries for (at least) the last ten years. If necessary, we also went back to the appropriate Moody's issue ten years prior, to further look for past entries. Classifying venture capitalists with this approach, and also taking into account bank mergers (see discussion below), we identified 50 bank venture capitalists for the entire dataset. For independent venture capitalists, we use all funds that are listed as "Independent Private Partnership" and where the venture capitalist is listed as "Private Firm Investing Own Capital."

Our unit of analysis is a venture deal, which is the unique match of an investor with a company. Thus, if in a particular round there exists more than one investor, we count each investor as a separate observation. If, for example, a bank and two independent venture capitalists co-invest in the same round, this allows us to recognize the presence of each of these three distinct investors. Our unit of analysis, however, does not count repeated interactions between a particular investor and company as a separate observation. If there are two investors, and one of them prefers to commit the money in several stages, whereas the other prefers to commit all the money at once, we do not count them as making a different number of deals. This definition of the deal is appropriate to study the portfolio structure of the different types of ventures. It allows us to identify all interactions between investors and companies without introducing any double counting that might arise from an investor's preference to stage the commitment of financing (see Gompers, 1995, Kaplan and Strömberg, 2001, 2003, 2004 or Sahlman, 1990). Our definition also eliminates a potential data problem in VE, namely that even within a single round there may be staging of disbursements, which could be mistaken as separate rounds (see Lerner, 1995). Finally, we use clustered standard errors (see Rogers, 1993) that recognize the interdependence of errors for the same company. Our data contains 10583 companies that generate 24659 deals.[3]

We obtain lending information for bank-financed portfolio companies from the Loan Pricing Corporation's (LPC) DealScan Database. LPC contains all loans reported in SEC filings. The data extend from January 1987 to June 2001, though full coverage in the LPC data did not begin until 1989. To identify prior relationships between companies and bank venture capitalists, we also need to account for acquisitions and mergers among banks. We track these changes manually using the Moody's Bank and Finance Manuals. We classify banks according to their end of sample merger status. For a company that received venture financing from a bank that was later acquired, we further check that the loan by the acquiring bank was not made prior to the bank merger.

Venture Economics maintains an industry classification (called VE codes) that is more suited to the venture industry than the standard SIC codes. Most venture deals fall into a small number of four digit SIC codes, and at the one digit level, SIC codes have

[3] As a robustness check we also reran all of our results using the round as unit of observation, even though we think of it as conceptually less satisfying. Using rounds requires calling a round a bank round when it contains a bank investor, irrespective of whether the round also contains an independent venture capitalist. All results are very similar.

inappropriately broad aggregations, such as grouping computer equipment and electronics in the same category as the manufacturing of textiles and furniture. The VE codes group industries into somewhat more meaningful and detailed categories. At the one digit level, for example, the VE codes are Communications, Computer Related, Other Electronics (including semiconductors), Biotechnology, Medical/Health Related, Energy Related, Consumer Related, Industrial Products, and Other Services and Manufacturing. Whenever possible, we use the VE codes.

2.2. Data variables

Table 1 contains the descriptive statistics. The variables we use are as follows:

BANK is a dummy variable that takes the value 1 if the investor in the deal is a bank, 0 otherwise. Being a bank means that the deals were done by the bank itself or by a venture fund that is affiliated to the bank or bank holding company.

IPO is a dummy variable that takes the value 1 if the company went public, 0 otherwise

LOAN is a dummy variable that takes the value 1 if a company obtained a loan in LPC, 0 otherwise. This variable is obtained from LPC.

ORIGINATION is a dummy variable that takes the value 1 if the deal is the company's first round, 0 otherwise.

ROUND 2 (3,4) is a dummy variable that takes the value 1 if the deal is the company's second (third, fourth) round, 0 otherwise.

EARLY STAGE is a dummy variable that takes the value of 1 if the company received seed or first stage financing at the time of the round, 0 otherwise.

SYNDICATION is a dummy variable that takes the value 1 if the round had more than 1 investor, 0 otherwise.

CLUSTER is a dummy variable that takes the value 1 if the company is in California or Massachusetts, 0 otherwise.

AMOUNT is the natural logarithm of the total amount invested by all investors in a particular round.

YEAR controls relate to the year that the VC deal is made.

YEAR1st controls correspond to the year of the first VC round for the company.

LOANYEAR1st controls relate to the year that the first loan deal is made.

INDUSTRY controls are the Venture Economics industry categories.

DEBT is the natural logarithm of the average industry debt level for each portfolio company. In Compustat this corresponds to Data Item 9 + Data Item 34. Total debt is calculated for all companies in Compustat using the first 3 years of data. The industry average is the mean for each two-digit SIC code.

DEBT/ASSET ratio is the average industry debt to asset ratio for each portfolio company. In Compustat this corresponds to (Data Item 9 + Data Item 34) / Data Item 6. The debt to asset ratio is calculated for all companies in Compustat using the first 3 years of data. The industry average is the mean for each two-digit SIC code.

From the LPC data set we identify all companies that obtain loans and that previously received venture financing from banks.

PORTFOLIO PARTICIPATION for bank i is a ratio. The numerator counts the number of companies that received both a loan and venture financing from bank i. The denominator counts the number of companies in our LPC sample that received venture financing from bank i.

MARKET PARTICIPATION for bank i is a ratio. The numerator counts the number of companies that received a loan from bank i. The denominator counts the total number of companies in our LPC sample.

LENDER is a dummy variable that takes a value of 1 if the bank participated in a loan to the company, 0 otherwise.

PRIOR VC is a dummy variable that takes a value of 1 if the bank made a prior venture investment in the company, 0 otherwise.

YIELD SPREAD is the yield of the loan, quoted in basis points over LIBOR. In LPC, the yield spread is the called the “all-in spread drawn,” which includes all fees in the yield calculation.

2.3. Background on regulation

Venture investments involve private equity participation. The Gramm-Leach-Bliley Act, passed in November 1999, allows banks to engage in various activities though the financial holding company. However, during our sample period, banks were yet to take advantage of this provision. Prior to Gramm-Leach-Bliley, the Glass-Steagall Act of 1933 prohibited banks from buying stock in any corporation and from buying “predominately speculative” securities. Nonetheless, there are two loopholes through which banks can make private equity investments, which are relevant for our sample period.

First, there is a government program administered by the Small Business Administration (SBA), which allows for the creation of “Small Business Investment Corporations” (SBICs). These SBICs can make equity investments and they may receive financial leverage from the SBA. The Small Business Act of 1958 authorized bank and bank holding companies to own and operate SBICs. A bank may place up to 20% of its capital in an SBIC subsidiary (10% at the holding company level). These investments are governed by the rules of the SBA and subject to regulatory review by that organization. An SBIC is also reviewed by the bank’s regulators as a wholly owned subsidiary. SBA provisions include a limitation on the amount of the SBIC’s funds that can be placed in a single company (less than 20%). Further, SBIC investments are subject to certain size restrictions. Currently, the SBA considers a business small when its net worth is $18 million or less and average annual net after-tax income for proceeding 2 years is not more than 6 million. See also Brewer and Genay (1994), Kinn and Zaff (1994) or SBIC (2003). Second, bank holding companies can make equity investments subject to some limitations. Under Section 4(c)(6) of the Bank Holding Company Act of 1956, bank holding companies may invest in the equity of companies as long as the position does not exceed more than 5% of the outstanding voting equity of the portfolio company. Some banks also invest in limited partnerships directly at the bank holding company level. Unlike SBICs, which are regulated by both the SBA and relevant bank regulators, bank holding companies are regulated only by the bank regulators. See also Fein (2002) or FDIC (2003).

3. Banks' strategic interest in venture capital: evidence from the venture capital market

3.1. What kind of venture deals do banks do?

We begin our inquiry by asking whether our base premise, that bank investors are a distinct type of investor, is empirically valid. For this we examine whether banks as venture capitalists have a distinct investment pattern, relative to their independent counterparts. Table 1 shows statistically significant differences in terms of univariate comparisons. Table 2 reports the results of a Probit regression where the dependent variable is BANK, and the independent variables are deal characteristics. Both the univariate and multivariate comparisons show that banks are different in a number of dimensions. First and foremost, banks invest less frequently in origination rounds and other early rounds. While this finding might be intuitive for those familiar with the institutional details of venture capital, it contrasts with the usual argument in the banking literature (see e.g., Greenbaum and Thakor, 1995) that banks have a comparative advantage at originating deals (and less so in funding, hence the growth of loans sales and securitization). Our results show that in the venture capital market banks let others do more of the origination work rather than originate themselves. The base model (i) focuses on the round number as an indicator of how early in the companies' lifecycle banks invest. An alternative measure is the stage of the company. In model (ii) we see that the same result continues to hold for investment stages. In particular, banks shy away from investing in early stage companies.

Tables 1 and 2 also contain some additional results of interest. Banks are relatively more active outside the cluster states of California and Massachusetts.[4] This is intuitive since banks have large branching networks that may allow them to have relatively better access to deals outside the main venture capital clusters.[5] Banks are also found to invest in larger deals. Relative to independent venture firms, banks probably have easier access to a large amount of funds. Banks are also more likely to invest as part of a syndicate.[6] This behavior is in line with the reluctance to originate deals. It confirms again that banks take more of a follower, rather than a leader approach to venture capital investing.

The regression models (i) and (ii) control for individual industry dummies. This is useful to provide a fine-grained control, but it does not allow us to interpret the banks' sector selection. Motivated by our main hypothesis, we ask whether banks focus on high debt industries. We examine the debt level of young public companies, defined as the first three years of data in Compustat. Since Compustat contains SIC codes, we determined for each VE code the two-digit SIC code that is most frequently associated using observations where both VE and SIC codes are reported. We then used this mapping to assign SIC codes (and thus industry debt measures) to those companies that have only their VE codes reported. We consider both an absolute measure (the natural logarithm of the amount of debt) and a relative measure (the debt-to-asset ratio). The absolute measure is relevant in this context, since banks presumably care about the total demand for loans. Columns (iii) and (iv) show that banks invest in industries with more debt, both in absolute and relative terms. This is consistent with the notion that banks strategically invest in those segments of the venture market that is populated by clients with a high demand for debt.[7]

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[4] The venture capital industry is highly concentrated, with California and Massachusetts accounting for 54.87% of all the deals in our sample.

[5] The importance of bank location is also examined in the recent work by Berger et. al. (2003) and Petersen and Rajan (2002).

[6] Lerner (1994) and Brander, Amit and Antweiler (2002) examine the role of syndication in venture capital.

[7] One may wonder if the pattern of bank investment is an SBIC effect as SBICs are governed by certain regulation. Hence we reexamine our sample excluding investments identified by Venture Economics as made under the SBIC program. The results are very similar, suggesting that bank investment behavior is not driven by SBIC constraints.

Overall, Tables 1 and 2 support the notion that banks are a distinct investor from independent venture capital firms. We now follow on the result on high debt industries, and ask whether banks target their investment strategically towards future loan candidates.

3.2 Investing in future loan candidates

Our main hypothesis is that banks are strategic investors that seek complementarities between their venture and lending business. Banks can use their venture investments to strengthen their core lending business. Their banking expertise may also differentiate them in the venture capital market. These complementarities suggest that banks would target their venture investments to establish contact with potential future loan clients. Explaining why banks entered the venture capital industry, Wilson (1985) notes: "By getting in on the ground floor of new companies and industries, they expected to build future customers for the lending side of the bank."

To empirically evaluate this, we ask whether the companies that obtain venture financing from a bank are also more likely to obtain a loan in the future. We use the LPC database, which identifies all large loans from both private and public companies. These large loans play a central role for the banks' core lending businesses. Given our focus is on the leveraging of lending relationships through venture capital, the relevant loans for us are large loans which are well covered in this database. We examine whether bank-backed venture deals have a higher proportion of subsequent loans.

From table 1, we already see that bank deals are more likely to subsequently obtain a loan, the difference being significant at 1%. Table 3 reports results from two probit models, where the independent variable is LOAN. The first model deliberately omits the deal characteristics that are already known at the time of the venture investment. The dependent variables are thus only BANK, the main variable of interest, and IPO, which controls for whether the company also went public.[8] The effect of banks is significant at 1%. The second model then controls for those deal characteristics known

[8] Note that LPC may also record debt of private companies and acquired divisions, so that going public is not necessary to obtain a loan.

at the time of the venture investment, i.e., those we already used in table 2.[9] We still find a statistically significant relationship between obtaining venture financing from a bank and obtaining a loan (significant at 5%). We note that the size of the bank coefficient decreases by more than half between the first and second model. This suggests that observable deal characteristics explain more that half of the correlation between banks' venture financing and obtaining a loan.

In section 3.1 we also noted that banks appear to be somewhat conservative in their investment behavior, perhaps in part due to regulation. We may wonder if this also influences the result that they invest in future loan candidates. Banks might invest in more successful deals, those that are more predictably going public. It might be that the higher loan rates are merely due to banks selecting deals that are closer to exit, in terms of being likely to go public. To examine this alternative explanation, we repeat the analysis of table 3, looking at IPOs instead on loans. Table 4 shows that, unlike with loans, there is no evidence that banks select future IPO candidates. This suggests that the result of banks investing in future loan candidates is not driven by an investment approach of only investing in companies that are more likely to go public.

3.3. Are banks also selecting on unobservable deal characteristics?

So far our evidence is consistent with banks selecting future loan candidates. Table 3 shows the coefficients with and without controlling for deal characteristics. The difference in coefficients shows that part of the correlation between banks and loans is explained by the way that banks select their deals. Naturally, we as econometricians may not capture all the relevant information that banks use for selecting their deals. We may ask whether there is any evidence that banks are also selecting on unobservable characteristics. To test for this, we use an approach similar to Chiappori and Salanié (2000), that is based on the bivariate Probit model. In particular, we estimate the correlation of error terms for the selection and outcome equations. This corresponds to estimating the determinants of LOAN and BANK simultaneously based on observable

[9] From now on, we use model (i) of table 2 as our base specification. All of our results continue to hold

characteristics. A positive correlation of the error terms simply means that there are unobserved characteristics that simultaneously predict banks selecting the deal, and the company subsequently raising a loan. Table 5 reports the results from the bivariate probit model. We find a positive correlation in the error terms of the two equations, with an estimate (ρ) that is significant at 5%. This suggests that, in addition to selecting their deals based on observable characteristics, banks also select their venture investments based on unobservable deal characteristics that are correlated with a higher likelihood of raising loans in the future.

4. Banks' strategic interest in venture capital: evidence from the loan market

The analysis of the previous section suggests that banks invest disproportionately in venture companies that subsequently obtain loans. To fully evaluate the strategic investor hypothesis, we also need to test whether these venture investments strengthen the banks' position in the loan market. Therefore, we investigate whether a prior relationship increases the likelihood that a bank will be selected as a company's lender.

We need a benchmark model of what the likelihood would be without a prior relationship. This requires us to define the sample of companies without relationship loans. Since the loan market is extremely large and heterogeneous, we focus on the smaller segment that is directly relevant for us. In particular we consider the sample of loans obtained by all companies that previously received venture financing from some bank. We exclude companies financed by independent venture capitalists for several reasons. The analysis of the previous section suggests that there is self-selection among companies, so that samples of companies financed by bank versus independent venture capitalists are not directly comparable. And the companies financed by independent venture capitalists cannot obtain a relationship loan, since by definition they do not have

using any of the other models from table 2.

a prior relationship with a lender.[10] However, companies that had a bank venture capitalist can obtain a loan from any bank, not just from the bank with which they have a relationship. And this is the question we address: Are these firms more likely to take a loan from their previous venture investor or from another bank?

We want to examine whether banks are more likely to make loans among the companies it already knows, rather than the market for at large. For our first test, consider a bank that invested in venture capital, and consider all the companies in its portfolio that subsequently obtain a loan.[11] We calculate the percentage of companies to which this bank provides a loan, and call this the PORTFOLIO PARTICIPATION. Intuitively, this measures how well the bank is doing in the microcosm of companies with which it has a prior relationship. We want to compare this to the macrocosm of companies, which adds all the companies with which the bank has no prior relationships. MARKET PARTICIPATION is the percentage of companies that receive a loan from a given bank in our sample.[12] If relationships don't matter, then the microcosm should be representative for the macrocosm, i.e., a bank's PORTFOLIO PARTICIPATION should be equal to its MARKET PARTICIPATION. Table 6 reports that the average MARKET PARTICIPATION of a bank is 7.4%, whereas the average PORTFOLIO PARTICIPATION is 16.5%, the difference being significant at 5%. This suggests that relationships matter, i.e., lending in the microcosm of companies with a prior relationship is different than lending to the market at large. The unconditional probability of lending to a firm more than doubles if the bank has a venture capital funding relationship with the firm.

To further explore the role of relationships, we use data at the level of the individual deal. We estimate a model that predicts the likelihood that a particular bank

[10] Indeed, if we tried to include companies that had an independent venture capitalist, we would immediately notice that in any estimation (such as the logit regressions of table 7 or the propensity regressions for table 8) their observations would simply fall out. This is because there is a one-to-one match between the left-hand side outcome (no relationship loan) and the right-hand side control variable for whether a company obtained venture financing from an independent or bank venture capitalist.

[11] Of the banks that invested in venture capital, 30 funded a company in VE that subsequently raises a loan in LPC. The analysis of table 6 uses these 30 banks. They account for over 95% of venture capital investments for all banks that invest in venture capital.

[12] This is similar to a market share, except that market participations do not sum to 1, since different banks may lend to the same company.

would have a match with a particular company in the loan market. This provides a more fine-grained test of whether a prior relationship affects the probability of a making a loan. A match is defined to occur if a company takes a loan from its VC bank. Our sample consists of all possible pairings of companies that receive bank VC and subsequently raise a loan in LPC with a potential lending bank.[13] There are 279 such companies. Thus, the sample is constructed from the 30 banks that provided venture funding to at least one of these companies and one other bank comprised of all other lenders to these companies.

We estimate two logit models where the independent variable is always LENDER, a dummy variable that indicates whether a particular company obtained a loan from a particular bank. The main dependent variable of interest is whether the company had a prior relationship with the particular bank. We also control for other bank characteristics, namely the percentage of companies to which the bank made loans in this sample (MARKET PARTICIPATION).[14] Our first specification uses a standard logit model. For this model we include company-specific controls, such as industry, time of first venture capital investment or presence in a geographic cluster. Since observations for the same company may be correlated, the specification again allows for clustered standard errors. The second specification uses a conditional logit model. This is a more powerful estimation method in that it controls for all possible company characteristics by using company fixed-effects. This means that all previous company controls (namely CLUSTER, IPO, industry and year controls) drop out of the estimation, since they are replaced by the more fine-grained fixed effects. The only remaining dependent variables are thus the prior venture capital relationship (PRIORVC), and other bank characteristics (MARKET PARTICIPATION). Table 7 reports the results from these two models. We find that the coefficient on a prior venture relationship is large and highly significant in both models. The results support the hypothesis that having a prior venture relationship significantly increases the likelihood of making a loan to the same firm.

[13] As before, if a company raises a loan from more than one bank, we count this as each bank making a loan to that company. But if a bank makes a second loan to the same company, we do not count this as a separate observation.

[14] Market participation for the other bank category is the sum of the market participations for the constituent banks. As a robustness check we also estimate the model without the market participation variable, and for the subsample using only the 30 banks that provided venture funding to one of these companies. The results are similar.

5. The impact of relationships on loan pricing

To provide further evidence for our main hypothesis, we ask whether there is economic impact from these relationships. Firms can potentially benefit from such relationships if they can use these relationships to signal better quality and get better loan pricing. Alternatively, banks may use the private information at their disposal to extract rents from the firm so that there is no benefit to the firm.

We therefore next test whether companies get better terms on relationship-loans than non-relationship-loans. As in section 5 we confine our sample to all companies that received bank venture capital financing. We identify a total of 279 companies that receive venture funding from commercial banks and subsequently raise at least one loan in LPC. We identify 193 relationship loans, which are lending facilities in which the company's venture capitalist is a lender. For non-relationship loans, we consider all non-relationship loans made by banks in Loan Pricing Corporation. We identify 809 non-relationship loans. For the analysis we lose all loans that have no reported yield spread and/or term length. This reduces the sample to 146 relationship loans and 634 non-relationship loans.

Loan pricing is commonly measured by the yield spread, which is the difference between the interest rate on the loan and the safe rate of return, as measured by LIBOR. We use the data item "all-in spread drawn" in LPC, which also incorporates fees paid by the borrowers. These loans are typically syndicated, are typically to public companies, and are reported off of SEC filings. Hence it is unlikely that there are other unreported compensation or costs related to the loan. The pricing data can be considered highly reliable including both interest rates and fees.

To compare relationship loans and non-relationship loans we need to control for differences in the types of loans, such as their size, term length or credit rating. To estimate the difference in yield spreads between relationship and non-relationship loans, we use econometric matching methods developed by Rosenbaum and Rubin (1983), Heckman and Robb (1986), and Heckman, Ichimura and Todd (1997, 1998). In essence, matching methods use the loan characteristics to construct an optimal control sample. There are several variants of the matching model that differ in the way they construct so-called propensity scores. In the appendix we provide an overview of these methods, and how we apply them to our data.

Table 8 reports the results from a number of matching methods. We see that relationship loans consistently have lower yields than non-relationship loans. The estimates range from 18 to 27 basis points. Statistical significance varies across the different methods as well, with P-values ranging from 4.8% to 10.8%. Altogether these results suggest that there is an economically non-negligible pricing difference between relationship and non-relationship loans.

This evidence suggests that the relationships forged at the venture capital stage can have an economic impact, in terms of allowing companies to obtain better loan pricing. Naturally, these calculations are not meant to estimate the net benefit of choosing a bank as a venture capitalist. This would be much more difficult to do, both because it is hard to measure all the benefits, and because of self-selection at the venture capital stage. However, the existence of loan pricing differential does suggest that there is a meaning to the relationships forged between companies and banks, and that these relationships can be economically beneficial not only for banks in terms of better access to loan deals, but also for companies in terms of better loan pricing.

6. Further discussion

This paper examines the role of banks in venture capital. The evidence suggests that banks build relationships in the venture capital market that can be mutually advantageous in the loan market. This highlights the strategic nature of banks' investments in the venture capital market. Naturally, there may be other factors that also influence the venture capital investment of banks. For instance, banks' activities may be influenced by regulation or greater risk-aversion. This is consistent with our finding that banks avoid early stage investments and seek syndication. However, banking regulation and risk-aversion alone cannot explain the evidence on relationship building. Another way of seeing our analysis is thus that within the constraints of banking regulation and risk-aversion, we find evidence that banks tilt their venture capital investments towards strategic goals of relationship building.

Prior research established the importance of value-adding support in venture capital (see e.g., Hellmann and Puri, 2000, 2002; Kaplan and Strömberg, 2004). Some observers argue that banks typically fail to provide such value-adding support. They argue that banks are less skillful investors, and that banks provide insufficient monetary incentives for their venture managers. Again this is consistent with the finding that banks may focus on later-stage investments or syndicated deals, where value-adding support is relatively less critical. But again, it cannot explain the evidence on the building of relationships. Fundamentally, our finding on relationship building actually suggests an explanation for banks' perceived lack of value-adding support. Given that banks have a strategic focus, they endogenously have fewer incentives to expend costly resources on building value added support capabilities. If banks use venture capital mainly to build lending relationships, as our findings suggest, building the infrastructure for providing value-adding support may not be their main priority. For further evidence on this we disaggregated the effect of a prior venture capital relationship into originator versus non-originator relationships. In unreported regressions we found that having an originator relationship does not create stronger loyalty in the loan market. Thus it may not be necessary to fully imitate the independent venture capitalist for banks to achieve complementarities between their venture capital and lending activities. Being present in the venture capital market seems important for the relationship, but exactly when and how the banks invest seems to matter less.

Conclusion

This paper examines the role of banks in the venture industry. The literature on universal banking has typically taken the static view of how banks can cross-sell an array of financial services to a given set of clients. This paper hopes to complement this view with a dynamic perspective of how banks can leverage their relationships across different stages a client's life cycle. Our evidence suggests that banks invest in venture capital for strategic reasons, namely to build relationships early.

Understanding the role of banks in venture capital is important for the development of venture capital markets outside the US. Policy makers in numerous countries have tried to facilitate the development of their own venture capital industry. Some policies focus on the supply of start-ups. Gompers, Lerner and Scharfstein (2002) argue that incumbent corporations may play an important role, especially for spawning off technologies and entrepreneurs. Other policies focus on the supply of venture capital. Black and Gilson (1997) argue that in bank-dominated economies the lack of active stock markets is an obstacle for venture capital. Our paper adds a new perspective to this debate. Our evidence suggests that banks have different incentives than independent venture capitalists. They may focus their venture activities towards building relationships for their lending activities, rather than developing the early stage venture capital market itself. Put differently, banks may play a very useful role in the venture capital industry, in terms of building relationships that are mutually advantageous for companies and banks. But this is a different role than developing the venture capital market by making pioneering investments in early stage ventures.

Appendix: Methodology of matched pricing regressions

The formal econometric methods of matching were developed in Rosenbaum and Rubin (1983), Heckman and Robb (1986), and Heckman, Ichimura and Todd (1997, 1998). We provide an outline of how we apply these methods to our data. Let $D=1$ if the loan is a relationship loan, and let $D=0$ if the loan is a non-relationship loan. In principle, the *i*th of the N loans under study has both a yield spread Y_{1i} that would result with a relationship loan, and another yield spread Y_{0i} that would result with a non-relationship loan. The effect of interest is a mean effect of the difference between Y_1 and Y_0. However, since we only observe Y_1 for our sample of relationship loans, we have a missing data problem that cannot be solved at the level of the individual, so we reformulate the problem at the population level. We focus on the mean effect of the difference between relationship loans and non-relationship loans with characteristics X:

$$E(Y_1 - Y_0 \mid D=1, X) \qquad (1)$$

While the mean $E(Y_1 \mid D=1, X)$ can be identified from data on relationship loans, some assumptions must be made to identify the unobservable counterfactual mean, $E(Y_0 \mid D=1, X)$. The observable outcome of self-selected non-relationship loans $E(Y_0 \mid D=0, X)$ can be used to approximate $E(Y_0 \mid D=1, X)$. The selection bias that arises from this approximation is $E(Y_0 \mid D=1, X) - E(Y_0 \mid D=0, X)$.

We use a method of matching that solves the evaluation problem.[15] Following Heckman and Robb (1986), we assume that the relevant differences between relationship loans and non-relationship loans are captured by their observable characteristics X. Let

$$(Y_0, Y_1) \perp D \mid X \qquad (2)$$

denote the statistical independence of (Y_0, Y_1) and D conditional on X. Rosenbaum and Rubin (1983) establish that when *(2)* and

$$0 < P(D=1 \mid X) < 1 \qquad (3)$$

(which are referred to as the strong ignorability conditions) are satisfied, then $(Y_0, Y_1) \perp D \mid P(D=1 \mid X)$. While it is often difficult to match on high dimension X, this result allows us to match based on the one-dimensional $P(D=1 \mid X)$ alone. $P(D=1 \mid X)$, known as the propensity score, can be estimated using probit or logit models. Heckman, Ichimura, and Todd (1998) extend this result by showing that the strong ignorability conditions are overly restrictive for the estimation of *(1)*. All that is required is the weaker mean independence condition

[15] To determine if econometric matching is a viable method of evaluation, Heckman et. al identify four features of the data and matching techniques that can substantially reduce bias – (i) Participants and controls have the same distributions of unobserved attributes; (ii) They have the same distributions of observed attributes; (iii) Outcomes and characteristics are measured in the same way for both groups; and (iv) Participants and controls are from the same economic environment. Items (iii) and (iv) are met very well for this study because the loan yield spreads and other loan characteristics are measured in the same way for both relationship and non-relationship loans, and the non-relationship loans are from the same time period as the relationship loans. To satisfy condition (ii), we use loan characteristics to match relationship loans to non-relationship loans. Feature (i) cannot be achieved in a non-experimental evaluation. However, Heckman, Ichimura, and Todd (1997) note that feature (i) is only a small part of bias in their experimental study. Thus, the method of matching non-relationship loans to relationship loans can produce a viable estimate of the difference between relationship and non-relationship loan yield spreads.

$$E(Y_0 \mid D=1, P(D=1 \mid X)) = E(Y_0 \mid D=0, P(D=1 \mid X)) \qquad (4)$$

By using the propensity score, we can effectively take into account the fact that the characteristics of relationship loans may differ significantly from non-relationship loans and ensure that such observed characteristics are not driving the results. For each of the relationship and non-relationship loans, we compute a propensity score *P(D=1 | X)* via the following probit model:

$$P(PRIORVC=1 \mid X)=\Phi\begin{pmatrix}\beta_0+\beta_R * RATING+\beta_N * NOTRATED+\beta_F * FACSIZE+\beta_C * CLUSTER \\ +\beta_L * LENGTH+\beta_T * TYPE+\beta_Y * YEARL+\beta_V * VE\end{pmatrix}$$

where *PRIORVC* is a dummy variable that equals one if the lending facility is a relationship loan and zero if the loan is a non-relationship loan, RATING, which provides the Standard & Poor's credit rating of a company at the date of the loan, which we convert as follows: AAA = 1, AA = 2, A = 3, BBB = 4, BB = 5, B = 6, CCC = 7, CC = 8, C = 9, NR=10; NOTRATED, which is 1 if the loan is not rated, 0 otherwise; FACSIZE, which is the notional value of the loan facility between the lender and the borrower, expressed in millions of dollars; CLUSTER, which is 1 if the company is in Massachusetts or California, 0 otherwise; LENGTH, which is the difference between the term facility active date and the term facility expiration date, measured in months; a set dummy variables concerning loan TYPE (LPC classifies loans into term loans, revolving lines of credit, 364 day facilities and other type); a set of dummy variables YEARL based on the year of the lending facility; and set of VE dummy variables based on two-digit primary VE industry code.

There may be loans that have propensity scores that are outside of the common support of relationship loan and non-relationship loan propensity scores. Using loans that fall outside of the common support can substantially bias the results (see e.g. Heckman et. al 1997). As a result, we remove all loans that are outside of the common propensity score support.

As described above, the propensity score is used to match relationship loans to non-relationship loans. We use two classes of propensity score matching methods: (i) nearest neighbor matching, and (ii) kernel based matching.[16] Let Y_{1i} be the yield spread of a relationship loan, Y_{0j} be the yield spread of a non-relationship loan, and let $\overline{Y}^{z}_{0i}$ represent the (weighted) average of yield spreads of the non-relationship loans using estimator *z,* that is matched with Y_{1i}. To match the yield spreads of non-relationship loans to the yield spreads of relationship loans we compute for every *i* the estimated yield difference $Y_{1i} - \overline{Y}^{z}_{0i}$.

For each relationship loan, the nearest neighbor matching estimator chooses the *n* non-relationship loans with closest propensity scores to the relationship loan propensity score. The estimator computes the arithmetic average of the yield spreads of these *n* non-relationship loans. For each Y_{1i}, we match

$$\overline{Y}^{NN}_{0i} = \frac{1}{n}\sum_{j\in N(i)} Y_{0j}$$

where *N(i)* is the set of non-relationship loans that are nearest neighbors to Y_{1i}. We set *n* = 10, 20, 50 and 100.

[16] Both propensity score matching methods are discussed in greater detail in Heckman et. al (1997, 1998).

The kernel estimators construct matches for each relationship loan by using weighted averages of yield spreads of multiple non-relationship loans. If weights from a typical symmetric, non negative, unimodal kernel *K(•)* are used, then the kernel places higher weight on loans close in terms of *P(D=1 | X)* and lower or zero weight on more distant observations. Let

$$K_{ij} = K\left(\frac{P(X_{1i}) - P(X_{0j})}{h}\right)$$

where h is a fixed bandwidth and $P(X) = P(D=1 \mid X)$. For each Y_{1i}, we match a corresponding $\overline{Y}_{0i}^{K}$ where

$$\overline{Y}_{0i}^{K} = \frac{\sum_{j} K_{ij} Y_{0j}}{\sum_{j} K_{ij}}.$$

We use two different kernels to compute $\overline{Y}_{0i}^{K}$. The Gaussian kernel uses all non-relationship loans while the Epanechnikov kernel only uses non-relationship loans with a propensity score $P(X_{0j})$ that falls within the fixed bandwidth h of $P(X_{1i})$. We set h = 0.01. As a robustness check we also set h to different values and obtained similar results.

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Table 1
Descriptive Statistics

The unit of analysis is a deal, which is the unique matching between a company and an investor. BANK is a dummy variable that takes the value 1 if the investor in the deal is a bank; 0 otherwise. ORIGINATION is a dummy variable that takes the value 1 if the deal is the company's first round, 0 otherwise. ROUND 2, ROUND 3 and ROUND 4, which take a value of 1 if the deal is a 2^{nd}, 3^{rd} or 4^{th} round; 0 otherwise. EARLY STAGE is a dummy variable that takes the value of 1 if the company received seed or first stage financing at the time of the round; 0 otherwise. SYNDICATION is a dummy variable that takes the value 1 if the round has more than one investor; 0 otherwise. CLUSTER is a dummy variable which takes the value 1 if the company is located in a geographical core segment of the venture capital industry, namely California or Massachusetts; 0 otherwise. AMOUNT measures the natural logarithm of the amount of financing raised by the company in the particular round. INDUSTRY DEBT is the natural logarithm of the average absolute debt level for young companies in the portfolio company's industry; and INDUSTRY DEBT/ASSET is the average debt to asset ratio for young companies in the portfolio company's industry.

Variable	Number of observations	Mean Full Sample	Mean BANK Sample	Mean INDEPENDENT VC Sample	P-value for Difference in Means
BANK	24659	0.091	1	0	N/A
IPO	24659	0.204	0.201	0.204	0.723
LOAN	24659	0.126	0.157	0.123	0.000
ORIGINATION	24659	0.572	0.461	0.583	0.000
ROUND 2	24659	0.192	0.207	0.191	0.070
ROUND 3	24659	0.099	0.122	0.097	0.000
ROUND 4	24659	0.056	0.094	0.052	0.000
ROUND 5 AND HIGHER	24659	0.081	0.117	0.078	0.000
EARLY STAGE	23650	0.544	0.396	0.559	0.000
SYNDICATION	24659	0.830	0.883	0.825	0.000
CLUSTER	24659	0.549	0.443	0.559	0.000
AMOUNT	24307	9.310	9.447	9.296	0.000
DEBT	24659	4.832	5.061	4.809	0.000
DEBT/ASSET	24659	0.275	0.291	0.274	0.000

Table 2

This table presents the results of two probit regressions. The dependent variable is BANK, which takes the value 1 if the deal investor is a bank; 0 otherwise. The independent variables are ORIGINATION, which takes the value of 1 if the deal is a first round, 0 otherwise; ROUND 2, ROUND 3 and ROUND 4, which take a value of 1 if the deal is a 2nd, 3rd or 4th round; 0 otherwise; SYNDICATION, which is a dummy variable that takes the value 1 if the round is syndicated, 0 otherwise; CLUSTER, which is a dummy variable that takes a value of 1 if the company is in California or Massachusetts, 0 otherwise; AMOUNT, which is the natural logarithm of the amount of financing raised by the company in the particular round; EARLY STAGE, which is a dummy variable that takes the value of 1 if the company received seed or first stage financing at the time of the round, 0 otherwise; DEBT, which is the natural logarithm of the average industry debt level for the portfolio company; DEBT/ASSET, which is the average industry debt to asset ratio for the portfolio company; INDUSTRY, which is a set of unreported dummy variables for the one-digit Venture Economics code; and YEAR, which is a set of unreported dummy variables for the year when the deal occurred. Standard errors are White heteroskedasticity-adjusted and are clustered for the same company (Rogers, 1993). In parenthesis we report z-scores.

Dependent Variable: BANK	**(i)**	**(ii)**	**(iii)**	**(iv)**
Intercept	-0.701 **	-1.162 ***	-1.196 ***	-0.935 ***
	(-2.76)	(-4.89)	(-4.71)	(-3.81)
ORIGINATION	-0. 445 ***		-0. 421 ***	-0. 410 ***
	(-10.12)		(-9.62)	(-9.38)
ROUND 2	-0.280 ***		-0.263 ***	-0.280 ***
	(-6.00)		(-5.64)	(-6.00)
ROUND 3	-0.173 ***		-0.163 ***	-0.173 ***
	(-3.34)		(-3.14)	(-3.34)
ROUND 4	0.036		0.039	0.036
	(0.62)		(0.67)	(0.62)
SYNDICATION	0.178 ***	0.186 ***	0.159 ***	0.135 ***
	(4.62)	(4.66)	(4.19)	(3.59)
CLUSTER	-0.264 ***	-0.220 ***	-0.279 ***	-0.298 ***
	(-10.52)	(-8.49)	(-11.17)	(-11.97)
AMOUNT	0.032 ***	0.060 ***	0.030 ***	0.026 **
	(3.13)	(5.86)	(2.88)	(2.56)
EARLY STAGE		-0.336 ***		
		(-13.09)		
DEBT			0.066 ***	
			(7.97)	
DEBT/ ASSET				0.395 ***
				(5.25)
INDUSTRY controls	Included but not reported			
YEAR controls	Included but not reported		Included but not reported	
	N = 24307 χ^2 (34) = 748.10 Prob > χ^2 = 0.000	N = 23323 χ^2 (34) = 710.12 Prob > χ^2 = 0.000	N = 24307 χ^2 (34) = 669.90 Prob > χ^2 = 0.000	N = 24307 χ^2 (34) = 645.13 Prob > χ^2 = 0.000

*, ** or *** mean the coefficient is significant at 10%, 5% or 1% level respectively

Table 3

This table presents the results of two probit regressions. The dependent variable in each is LOAN, which takes the value 1 if the company obtains a loan, 0 otherwise; The independent variables are BANK, which takes the value 1 if the deal investor is a bank; 0 otherwise; IPO, which takes the value 1 if a company went public; 0 otherwise; ORIGINATION, which takes the value of 1 if the deal is a first round, 0 otherwise; ROUND 2, ROUND 3 and ROUND 4, which take a value of 1 if the deal is a 2^{nd}, 3^{rd} or 4^{th} round; 0 otherwise; SYNDICATION, which is a dummy variable that takes the value 1 if the round is syndicated, 0 otherwise; CLUSTER, which is a dummy variable that takes a value of 1 if the company is in California or Massachusetts, 0 otherwise; AMOUNT, which is the natural logarithm of the amount of financing raised by the company in the particular round; INDUSTRY, which is a set of unreported dummy variables for the one-digit Venture Economics code; and YEAR, which is a set of unreported dummy variables for the year when the deal occurred. Standard errors are White heteroskedasticity-adjusted and are clustered for the same company (Rogers, 1993). In parenthesis we report z-scores.

Dependent Variable: LOAN	**Model I**		**Model II**	
	Marginal Increase in Probability	Coefficient	Marginal Increase in Probability	Coefficient
Intercept	N/A	-1.563 ***	N/A	-3.912 ***
		(-48.70)		(-7.67)
BANK	0.037 ***	0.192 ***	0.013 **	0.093 **
		(4.99)		(2.29)
IPO	0.319 ***	1.241 ***	0.254 ***	1.193 ***
		(23.67)		(20.73)
ORIGINATION			-0.015	-0.113
				(-1.64)
ROUND 2			-0.008	-0.063
				(-0.90)
ROUND 3			-0.007	-0.057
				(-0.76)
ROUND 4			-0.005	-0.041
				(-0.46)
SYNDICATION			-0.031 ***	-0.213 ***
				(-4.93)
CLUSTER			-0.013 *	-0.098 *
				(-1.80)
AMOUNT			0.031 ***	0.233 ***
				(10.62)
INDUSTRY and YEAR controls			Included but not reported	
	N = 24659		N = 24307	
	χ^2 (2) = 590.94		χ^2 (36) = 806.18	
	Prob > χ^2 = 0.000		Prob > χ^2 = 0.000	

*, ** or *** mean the coefficient is significant at 10%, 5% or 1% level respectively

Table 4

This table presents the results of a probit regression. The dependent variable is IPO, which takes the value 1 if the company has an initial public offering, 0 otherwise; The independent variables are BANK, which takes the value 1 if the deal investor is a bank; 0 otherwise; ORIGINATION, which takes the value of 1 if the deal is a first round, 0 otherwise; ROUND 2, ROUND 3 and ROUND 4, which take a value of 1 if the deal is a 2nd, 3rd or 4th round; 0 otherwise; SYNDICATION, which is a dummy variable that takes the value 1 if the round is syndicated, 0 otherwise; CLUSTER, which is a dummy variable that takes a value of 1 if the company is in California or Massachusetts, 0 otherwise; AMOUNT, which is the natural logarithm of the amount of financing raised by the company in the particular round; INDUSTRY, which is a set of unreported dummy variables for the one-digit Venture Economics code; and YEAR, which is a set of unreported dummy variables for the year when the deal occurred. Standard errors are White heteroskedasticity-adjusted and are clustered for the same company (Rogers, 1993). In parenthesis we report z-scores.

Dependent Variable: IPO	Marginal Increase in Probability		Coefficient	
Intercept	N/A		-4.903	***
			(-10.12)	
BANK	-0.007		-0. 028	
			(-0.79)	
ORIGINATION	-0.032	**	-0.123	**
			(-2.25)	
ROUND 2	-0.007		0.027	
			(0.46)	
ROUND 3	-0.020		0.075	
			(1.23)	
ROUND 4	0.029		0.107	
			(1.52)	
SYNDICATION	-0.018	*	-0.066	*
			(-1.88)	
CLUSTER	-0.008		-0.029	
			(-0.70)	
AMOUNT	0.069	***	0.263	***
			(15.94)	
INDUSTRY and YEAR controls	Included but not reported		Included but not reported	
	N = 24307			
	χ^2 (35) = 601.69			
	Prob > χ^2 = 0.000			

*, ** or *** mean the coefficient is significant at 10%, 5% or 1% level respectively

Table 5

This table presents the results of a bivariate probit regression. The dependent variables are LOAN, which takes the value 1 if the company obtains a loan, 0 otherwise; and BANK, which takes the value 1 if the deal investor is a bank; 0 otherwise. The independent variables are IPO, which takes the value 1 if a company went public; 0 otherwise; ORIGINATION, which takes the value of 1 if the deal is a first round, 0 otherwise; ROUND 2, ROUND 3 and ROUND 4, which take a value of 1 if the deal is a 2nd, 3rd or 4th round; 0 otherwise; SYNDICATION, which is a dummy variable that takes the value 1 if the round is syndicated, 0 otherwise; CLUSTER, which is a dummy variable that takes a value of 1 if the company is in California or Massachusetts, 0 otherwise; AMOUNT, which is the natural logarithm of the amount of financing raised by the company in the particular round; INDUSTRY, which is a set of unreported dummy variables for the one-digit Venture Economics code; and YEAR, which is a set of unreported dummy variables for the year when the deal occurred. Standard errors are White heteroskedasticity-adjusted and are clustered for the same company (Rogers, 1993). In parenthesis we report z-scores.

Dependent Variable:	**BANK**		**LOAN**	
	Coefficient		Coefficient	
Intercept	-0.700	***	-3.886	***
	(-2.75)		(-7.60)	
IPO			1. 193	***
			(20.73)	
ORIGINATION	-0.446	***	-0.120	*
	(-10.12)		(-1.75)	
ROUND 2	-0.280	***	-0.068	
	(-6.01)		(-0.97)	
ROUND 3	-0.173	***	-0.060	
	(-3.34)		(-0.80)	
ROUND 4	0.036		-0.039	
	(0.62)		(-0.44)	
SYNDICATION	0.179	***	-0.211	***
	(4.65)		(-4.88)	
CLUSTER	-0.265	***	-0.103	*
	(-10.54)		(-1.87)	
AMOUNT	0.322	***	0.233	***
	(3.11)		(10.65)	
INDUSTRY and YEAR controls	Included but not reported		Included but not reported	
CORRELATION OF ERRORS	$\rho = 0.057$** χ^2 (1) = 6.940 P-value = 0.001 N = 24307 χ^2 (69) = 1574.57 Prob > χ^2 = 0.000			

*, ** or *** mean the coefficient is significant at 10%, 5% or 1% level respectively

Table 6

This table shows the results of a paired-t-test of equality for PORTFOLIO PARTICIPATION and MARKET PARTICIPATION, which are variables that are computed for the 30 banks that made venture investments to companies in our LPC sample. PORTFOLIO PARTICIPATION indicates the number of companies that received a loan from a bank with a prior venture capital relationship, divided by the number of companies funded by the bank that are in our LPC sample. MARKET PARTICIPATION is number of companies that received a loan from a bank divided by the total number companies in our LPC sample.

	Mean	Standard Error	Number of Observations
PORTFOLIO PARTICIPATION	0.165	0.048	30
MARKET PARTICIPATION	0.074	0.017	30
T-value	2.07		
P-value	0.047		

Table 7

This table presents the results from two logit regressions. The data consist of all possible pairs of companies that received bank venture financing and a loan in LPC (there are 279 such companies), with a potential lending bank (there are 30 banks that make venture capital investments to one of these companies and an other category for all other lending banks). The dependent variable is LENDER, which takes a value of 1 if the specified bank in the pair gave a loan to the company in the pair. The independent variables are PRIOR VC, which takes a value of 1 if the bank financed that particular company in the venture market, 0 otherwise and MARKET PARTICIPATION, which is number of companies that received a loan from a bank divided by the total number companies in our LPC sample. The first model uses the following company-specific control variables: IPO, which takes the value 1 if a company went public; 0 otherwise; CLUSTER, which is a dummy variable that takes a value of 1 if the company is in California or Massachusetts, 0 otherwise; INDUSTRY, which is a set of unreported dummy variables for the one-digit Venture Economics code; YEAR1st, which is a set of unreported dummy variables for the year when the first venture capital deal occurred; and LOANYEAR1st, which is a set of unreported dummy variables for the year when the first loan occurred. The first model uses a standard logit model. Standard errors are White heteroskedasticity-adjusted and are clustered for the same company (Rogers, 1993). Models II estimates a conditional logit model, which includes fixed effects for each company. In parenthesis we report z-scores.

Dependent Variable: LENDER	**Model I Standard Logit**	**Model II Conditional Logit**
	Coefficient	Coefficient
Intercept	-2.959 ***	N/A
	(-4.15)	
PRIOR VC	0.554 ***	0.609 ***
	(3.79)	(4.09)
MARKET PARTICIPATION	0.425 ***	0.456 ***
	(19.00)	(19.34)
IPO	0.387 **	N/A
	(2.64)	
CLUSTER	-0.449 ***	N/A
	(-3.39)	
INDUSTRY, YEAR1st, and LOANYEAR1st controls	Included but not reported	N/A
COMPANY FIXED EFFECTS		Included but not reported
	N = 8649	N = 8649
	χ^2 (2) = 517.39	χ^2 (2) = 425.77
	Prob > χ^2 = 0.000	Prob > χ^2 = 0.000

*, ** or *** mean the coefficient is significant at 10%, 5% or 1% level respectively

Table 8

This table provides estimates of the mean difference between the yield spread of relationship loans and non-relationship loans. The yield spread is the rate that the borrower pays the lender, quoted in basis points over LIBOR. Relationship loans are lending facilities in which the firm's venture capitalist is a lender. Non-relationship loans are lending facilities in which the firm's venture capitalist is not a lender, but another commercial bank provides the loan. In the appendix we explain more fully the matching methodology. For the estimation of the propensity scope, we estimate unreported Probit regressions where the dependent variable is PRIOR VC, which takes a value of 1 if the bank financed that particular company in the venture market, 0 otherwise. The independent variables are RATING, which provides the Standard & Poor's credit rating of a firm at the date of the loan, which we convert as follows: AAA = 1, AA = 2, A = 3, BBB = 4, BB = 5, B = 6, CCC = 7, CC = 8, C = 9, NR=10; NOTRATED, which is 1 if the loan is not rated, 0 otherwise; FACSIZE, which is the notional value of the loan facility between the lender and the borrower, expressed in millions of dollars; LENGTH, which is the difference between the term facility active date and the term facility expiration date, measured in months; a set dummy variables concerning loan type (LPC classifies loans into term loans, revolving lines of credit, 364 day facilities and other type); CLUSTER, which is 1 if the company is in Massachusetts or California, 0 otherwise; a set of dummy variables based on the loan origination year of the lending facility; and set of industry dummy variables based on two-digit primary VE code. The estimators, which are described in detail in Heckman, Ichimura, and Todd (1997, 1998), are defined as follows: NEAR NEIGHBOR chooses for each relationship loan, the *n* non-relationship loans with closest propensity scores, and uses the arithmetic average of the *n* non-relationship yield spreads. We use *n* = 10, 20, 50 and 100. GAUSSIAN and EPANECHNIKOV use a weighted average of non-relationship loans, with more weight given to non-relationship loans with propensity score that are closer to the relationship loan propensity score. GAUSSIAN uses all non-relationship loans, while for EPANECHNIKOV, we specify a propensity score bandwidth (*h*) that limits the sample of non-relationship loans. We specify that *h* = 0.01. The number of observations of the matched sample may be lower than the number of firms to be matched because the Probit model may not find a suitable match, such as when the propensity score of a relationship loan falls outside of the support of non-relationship loan propensity scores. Also, the EPANECHNIKOV estimator may reduce the number of matches further because at least one non-relationship loan must be within the bandwidth *h* of the relationship loan for a match to occur. T-ratios are calculated using standard errors that are computed by bootstrapping with 50 replications. We report t-ratios in parenthesis. P-values are in brackets.

Estimator	Differences between relationship and non-relationship yield spreads	Number of Matches
NEAR NEIGHBOR	-22.30**	
(n=10)	(-1.95)	134
	[0.051]	
NEAR NEIGHBOR	-22.47*	
(n=20)	(-1.82)	134
	[0.069]	
NEAR NEIGHBOR	-18.05	
(n=50)	(-1.61)	134
	[0.108]	
NEAR NEIGHBOR	-19.53**	
(n=100)	(-1.98)	134
	[0.048]	
GAUSSIAN	-22.34*	
	(-1.70)	134
	[0.089]	
EPANECHNIKOV	-26.68**	
	(-1.96)	127
	[0.050]	
Number of RELATIONSHIP LOANS	146	
Number of NON- RELATIONSHIP LOANS	634	

*, ** or *** mean the coefficient is significant at 10%, 5% or 1% level respectively