

Building Relationships Early: Banks in Venture Capital

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This paper examines bank behavior in venture capital. It considers the relation between a bank's venture capital investments and its subsequent lending, which can be thought of as intertemporal cross-selling. Theory suggests that unlike independent venture capital firms, banks may be strategic investors who seek complementarities between venture capital and lending activities. We find evidence that banks use venture capital investments to build lending relationships. Having a prior relationship with a company in the venture capital market increases a bank's chance of subsequently granting a loan to that company. Companies can benefit from these relationships through more favorable loan pricing. (*JEL* G21, G24, G32)

The scope of banking activities has always been an important issue to financial economists and policy makers alike. The recent banking literature examines the benefits and costs of expanding the scope of bank activities into different areas, such as underwriting activities (see, e.g., Carow and Kane, 2002; Kroszner and Rajan, 1994; and Puri, 1996). A growing literature suggests that cross-selling across banks' activities might be important (see, e.g., Bharath et al., 2006; and Drucker and Puri, 2005). One area that has received little attention is the bank's foray into venture capital. As a consequence of legislative changes in 1999 (and before that, from exploiting regulatory loopholes), banks regularly make private equity investments in startups. The question arises as to how banks as venture

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capitalists differ from independent venture capitalists and to what extent banks' venture capital investments are related to their core lending activities.

In this paper we examine the relation between a bank's venture capital investments and its subsequent lending to these companies. Although much of the universal banking literature focuses on the cross-selling of different products at a given point in time, this paper investigates a dynamic type of cross-selling relating to the intertemporal expansion of banks' activities. The main hypothesis is that building a relationship at the early venture capital stage increases a bank's likelihood of providing a loan to the company at a later stage. Our central empirical finding is that having made a venture capital investment significantly increases a bank's chances of financing that company in the loan market. We also find that companies may benefit from this relationship through lower loan pricing. Additionally, we contrast banks' venture capital investments with those of independent venture capitalists and find that banks invest in later-stage deals and in companies with potentially greater debt capacity.

Theory suggests that banks may differ from independent venture capitalists because they may act as strategic investors and their venture investments may interact with their other banking activities. Strategic investors target companies in which there are complementarities between the venture capital investments and their other core business (see Hellmann, 2002). They differentiate themselves by virtue of their complementary assets and they reap benefits from exploiting synergies between the venture investments and their core business. For banks, the main complementary asset is their lending expertise, which may be of future interest to the portfolio company. Industry observers seem to believe that banks try to take advantage of such complementarities. Wilson (1985, p. 42), for example, argues, "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 examine the hypothesis that banks are strategic venture capital investors, we provide empirical evidence for such complementarities. Specifically, we show that forging a relationship with a company at the venture capital stage increases the probability that a bank subsequently gets to grant a loan to that company.

For the empirical analysis, 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 a set of facts that suggests that banks invest differently in the venture capital market than independent venture capitalists do. For example, banks invest less in earlier rounds, participate in larger syndicates, and invest in larger deals. Interestingly, banks are also more likely to make investments in high-debt industries (in terms of both the absolute level of debt and the debt-to-asset ratio). And they are more likely to invest in companies that subsequently obtain loans. This evidence is generally consistent with a notion that banks are investors who pursue strategic goals in their venture capital investments.

To test the main hypothesis of strategic complementarities, we ask whether making a venture capital investment in a specific company increases a bank's chance of subsequently granting a loan to that company. For this, we need to go beyond the venture capital market and test whether relationships from venture capital actually affect loan market outcomes. For this purpose, in an approach that is relatively new to the finance literature, we construct all possible company-bank pairs—potential and realized—and track whether a specific bank grants a loan to a specific company. Our empirical model examines whether the likelihood of granting a loan depends on whether the pair has a prior relationship from the venture capital market. We find that a prior relationship significantly increases a bank's chance of becoming a company's lender. This supports the hypothesis that building relationships in the venture capital market complements the banks' lending business. We also submit our results to a large number of robustness checks, including instrumental variables, fixed-effect regressions, and alternative clustering approaches. Indeed, we believe that an additional contribution of this paper is to introduce the analysis of potential and realized pairs for a two-sided market, which is not yet common in the finance literature, and to discuss some of the econometric issues associated with this approach.

Another interesting question is whether companies also benefit from using relationships developed in the venture capital part of 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 raising loans from their relationship bank. Alternatively, banks may engage in rent extraction, so that there are no benefits to companies. We test for this by comparing yields of relationship and nonrelationship loans through the use of matching regressions based on propensity scores (Heckman, Ichimura, and Todd, 1997, 1998). We find that relationship loans have lower yields than nonrelationship loans. This difference suggests that relationships have an economic impact, and using these relationships can benefit companies.

The paper builds on the large literature on relationship banking. James (1987), Lummer and McConnell (1989), Best and Zhang (1993), and 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 (see also the survey in Drucker and Puri, 2007). Petersen and Rajan (1994) and Berger and Udell (1995) examine bank relationships with small private companies. Our examination of the strategic investor hypothesis is related to the literature on corporate venture capital (Block and MacMillan, 1993; Gompers and Lerner, 2000; Dushnitsky and Shaver, 2006). One advantage of examining banks is that the strategic complementarities are more readily identifiable than in the corporate context. The importance of prior relationships has also been examined in the literature on equity offerings (e.g., Gompers and Lerner, 1999; Drucker and Puri, 2005; Li and Masulis, 2005; Ljungqvist, Marston, and Wilhelm, 2006;

Yasuda, 2005). Hamao, Packer, and Ritter (2000) also examine bank-affiliated venture capital in the context of equity underwriting in Japan.

Our analysis suggests a cautionary policy note. 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, and their natural instinct is often to rely on their incumbent banks for this task (Becker and Hellmann, 2005). Our examination of the U.S. evidence suggests that banks may be driven by strategic objectives, making them followers rather than leaders in the venture capital market. Naturally, the lessons from the United States may not necessarily translate directly to other countries, but the evidence highlights banks' strategic incentives when investing in venture capital (see also Mayer, Schoors, and Yafeh, 2005).

The remainder of the paper is organized as follows. Section 1 describes the data and discusses the regulatory environment. Section 2 provides some preliminary evidence on the role of banks in venture capital. Section 3 empirically examines the main hypothesis about the role of prior venture relationships in the loan market. Section 4 examines the impact of relationships on loan pricing. Section 5 concludes with some further discussion.

1. The Data

1.1 Data sources

The data are compiled from several commercially available data sources, including Venture Economics, Loan Pricing Corporation, Compustat, and FDIC, and augmented by hand-collected data from Moody's Manuals. Venture Economics (henceforth VE), a division of Thomson Financial, provides information on venture firms (i.e., the investors),¹ the companies in which they invest, and the details of individual financing rounds.² We collect all data on U.S. investments for the period 1980–2000.³

The VE 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. VE collects data from voluntary

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

² VE is a standard database for venture capital research. It has been used in many recent venture capital studies, including Gompers (1995), Lerner (1995), Kaplan and Schoar (2005), and Gompers, Kovner, Lerner, and Scharfstein (2007). For a detailed discussion of the properties and accuracy of this database, see Lerner (1995), and Kaplan, Sensoy, and Strömberg (2004). Although this database has many strengths, these authors note that the main deficiencies of the VE database are that it does not have complete coverage of financing rounds, that it oversamples larger rounds and California companies, and that it overcounts the number of rounds (where a single round is reported as two separate rounds). Any overcounting of rounds does not affect our analysis, because our unit of analysis does not rely on the counting of rounds. Our analysis also has controls for the size of the round and California companies.

³ VE 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.

disclosures of venture capital firms and limited partners. Because we are interested in venture capital financing of startups or private companies, we exclude all leveraged buyout deals. For each investor the VE database tracks its organizational form and affiliations. With these data we can identify if a venture capital firm is bank-owned, independent, or otherwise. 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.

Although VE identifies bank venture capitalists, its classification is not reliable. Apart from omissions and coding errors, its 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 Manual*. We classify an investor as a bank venture capitalist if it is a commercial bank, a bank holding company, or a subsidiary of a bank. Moreover, the bank must be chartered in the United States. 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 10 years. If necessary, we also went back to the appropriate Moody's issue 10 years prior, to look further for past entries. Classifying venture capitalists with this approach, and also taking into account bank mergers (see discussion below), we identify 50 bank venture capitalists for the entire dataset. For independent venture capitalists, we use all funds that are listed as "Independent Private Partnership" and for which the venture capitalist is listed as "Private Firm Investing Own Capital."

We obtain lending information for bank-financed portfolio companies from the Loan Pricing Corporation's DealScan Database (henceforth LPC).⁴ 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 Moody's Bank and Finance Manual. 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 granted prior to the bank merger.

Because there is no common identifying code between the LPC database and the VE database, we match on company name. We wrote a Perl script that strips organizational form suffixes, spaces, capital letters, and punctuation from the name field in each database in order to match on the "core" of the company

⁴ LPC collects its loan data from SEC filings, and it also receives data from large loan syndicators, from news coverage, and through LPC's relationship with major banks. As such the LPC database covers large loans for companies that have either public equity or public debt, supplemented with voluntary information on other loans. LPC has been used in previous studies for many purposes, including examining the effect of lending on bond yield spreads (see, e.g., Gande et al., 1997) and for differences in lending by banks and finance companies (Cary, Post and Sharpe, 1998).

name.⁵ We also performed this matching on former company names listed in VE.⁶ Furthermore, the results of the program were carefully checked by hand.

VE 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 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.

1.2 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 through financial holding companies. However, during our sample period, banks were yet to take full 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 could make private equity investments that 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 banks 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. At the end of the sample period, the SBA considered a business eligible for the SBIC program if its net worth was \$18 million or less and average annual net after-tax income for the preceding

⁵ The Perl program works by matching on the core of each company name after stripping out non-identifying information such as “Corp.,” “Incorporated,” or “Inc.” Matching without cleaning the name field in such a manner would result in missing matches between “XYZ Co.” and “XYZ Corp.,” for example, strictly because of different naming conventions in the different databases. In addition to organizational form suffixes, we also stripped the name field of spaces, capital letters, and punctuation.

⁶ If a company changes name because of an acquisition, we consider this an exit and do not track lending activity after the acquisition.

2 years was 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).

2. Comparing Bank and Independent Venture Capital Investments

In this section we provide some background analysis on the activities of banks in the venture capital market. We contrast the venture capital investment by banks with independent venture capitalists. This analysis provides a foundation for the main hypothesis, which is examined in Section 3.

In this section, our unit of analysis is a “venture deal,” defined as the unique match of a venture capital investor with a company. This can also be referred to as a realized company-investor pair. It implies that if in a particular round there exists more than one investor, we count each investor as a separate observation. If, for example, one bank and two independent venture capitalists co-invest in the same round, this approach 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 count each of them as one deal.⁷ Our data contain 10,578 companies that generate 24,659 deals.

Our main variables are as follows.

- **BANK** is a dummy variable that takes the value of 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 the bank holding company.
- **EARLY-STAGE** is a dummy variable that takes the value of 1 if the company received seed or first-stage financing in the company’s first round, 0 otherwise.

⁷ 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).

- **ROUND-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 matched investor's first investment, 0 otherwise.
- **ROUND 1,2,3,4** is a set of dummy variables that takes the value of 1 if the first time that the matched investor participated was the company's first, second, third, or fourth round, 0 otherwise.
- **VCCLUSTER** is a dummy variable that takes the value of 1 if the company is in California or Massachusetts, 0 otherwise.
- **AMOUNT** is the natural logarithm of the total amount invested in the company by all venture capital investors across all rounds, as reported by VE.
- **ROUND-AMOUNT** is the natural logarithm of the total amount invested by all investors in the first round that the matched investor participated, as reported by VE.
- **NUMBER-OF-VCS** is the total number of venture capital firms that invested in the company.
- **ROUND-NUMBER-OF-VCS** is the total number of venture capital firms that invested in the first round in which the matched investor participated.
- **INDUSTRY** controls are indicators for the VE 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.
- **IPO** is a dummy variable that takes the value of 1 if the company went public, 0 otherwise.
- **LOAN** is a dummy variable that takes the value of 1 if a company obtained a loan in LPC, 0 otherwise. This variable is obtained from LPC.

Note that the difference between **EARLY-STAGE** and **ROUND-EARLY-STAGE** is that the former is a company-specific variable, whereas the second is specific to an investor-company pair at the time of the investor's first investment round with the company. For all of the above variables, we use the **ROUND** prefix to distinguish those that pertain to an investor-company pair.

Table 1 provides descriptive statistics for venture capital deals by banks versus independent venture capital firms. It includes a test for the statistical significance of the differences in means or, in the case of indicator variables, differences in proportions. It shows that banks are different in a number of dimensions. Consider first the differences in company characteristics at the

Table 1
Descriptive statistics: Realized company and venture-investor pairs

Variable	Number of observations	Mean total sample	Mean BANK sample	Mean INDEPENDENT VC sample	<i>p</i> -value for Difference
BANK	24,659	0.091	1	0	N/A
EARLY-STAGE	23,877	0.725	0.660	0.731	0.000
ROUND-EARLY-STAGE	23,650	0.544	0.396	0.559	0.000
ROUND 1	24,659	0.572	0.461	0.583	0.000
ROUND 2	24,659	0.192	0.207	0.191	0.069
ROUND 3	24,659	0.099	0.122	0.097	0.000
ROUND 4	24,659	0.056	0.094	0.052	0.000
ROUND 5 AND HIGHER	24,659	0.081	0.117	0.078	0.000
VCCLUSTER	24,659	0.548	0.443	0.559	0.000
AMOUNT	24,307	10.477	10.629	10.462	0.000
ROUND-AMOUNT	24,307	9.310	9.447	9.296	0.000
NUMBER-OF-VCS	24,659	6.741	7.720	6.641	0.000
ROUND-NUMBER-OF-VCS	24,659	4.940	6.230	4.810	0.000
DEBT	24,659	4.832	5.061	4.809	0.000
DEBT/ASSET	24,659	0.275	0.291	0.274	0.000
IPO	24,659	0.204	0.201	0.204	0.731
LOAN	24,659	0.126	0.157	0.123	0.000

The unit of analysis is a “venture deal,” which is the unique matching between a company and a venture investor. BANK is a dummy variable that takes the value of 1 if the investor in the deal is a bank, 0 otherwise. EARLY-STAGE is a dummy variable that takes the value of 1 if the company received seed or first-stage financing in the company’s first round, 0 otherwise. ROUND-EARLY-STAGE is a dummy variable that takes the value of 1 if the company received seed or first-stage financing in the first round that the matched investor participated, 0 otherwise. ROUND 1,2,3,4 is a set of dummy variables that take the value of 1 if the first time that the matched investor participated was the company’s first, second, third, or fourth round, 0 otherwise; VCCLUSTER is a dummy variable that takes the value of 1 if the company is in California or Massachusetts, 0 otherwise. AMOUNT is the natural logarithm of the total amount invested in the company by all venture capital investors across all rounds. ROUND-AMOUNT is the natural logarithm of the total amount invested by all investors in the first round in which the matched investor participated. NUMBER-OF-VCS is the total number of venture capital firms that invested in the company. ROUND-NUMBER-OF-VCS is the total number of venture capital firms that invested in the first round that the matched investor participated. DEBT is the natural logarithm of the average industry debt level for each portfolio company. DEBT/ASSET ratio is the average industry debt-to-asset ratio for each portfolio company. IPO is a dummy variable that takes the value of 1 if the company went public, 0 otherwise. LOAN is a dummy variable that takes the value of 1 if a company obtained a loan in LPC, 0 otherwise. Reported *p*-values are based on a *t*-test for differences in means or, in the case of indicator variables, *z*-scores for differences in proportions.

time of making a deal. We note that banks invest less in first rounds and other early rounds.⁸ Banks are relatively more active outside the cluster states of California and Massachusetts.⁹ This is intuitive because banks have large branching networks that may allow them to have relatively better access to deals outside the main venture capital clusters.¹⁰ Banks invest in larger deals. Relative to independent venture firms, banks probably have easier access to a

⁸ Although 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, rather than originating themselves, banks let others do more of the origination work.

⁹ The venture capital industry is highly concentrated, with California and Massachusetts accounting for 54.87% of all deals in our sample.

¹⁰ The importance of bank location is also examined by Berger, Miller, et al. (2005) and Petersen and Rajan (2002).

large amount of funds. Banks are also more likely to invest in companies that have more investors.¹¹ In unreported results, we confirm that these results hold in a multiple regression setting.

Given that banks' core business is lending, we examine whether banks focus on high-debt industries. We examine the debt level of young public companies, defined as the first 3 years of data in Compustat. Because Compustat contains only SIC codes, we determined the two-digit SIC code that is most frequently associated with each VE code using observations for which both VE and SIC codes are reported. We then use 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, because banks presumably care about the total demand for loans. Table 1 shows 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 are populated by clients with a high debt capacity.

In addition to examining company differences at the time of the deal, we can also examine differences in subsequent outcomes. From Table 1 we note that the percentage of deals that go public is very similar for bank versus independent venture capital firms. To the extent that IPO rates are a proxy for success, it appears that banks are neither better nor worse at picking successful companies. However, Table 1 also shows that the proportion of companies that subsequently obtain a large loan (as recorded in LPC) is significantly higher for bank venture capitalists, compared to independent venture capitalists. In unreported results we find that these results continue to hold in a multiple regression framework. It is worth briefly mentioning the economic significance of these numbers. Loans are obtained by 15.7% of bank venture capital deals, as compared to 12.3% of independent venture capital deals. This suggests that in relative terms, bank venture capital deals are 27.6% more likely to obtain a loan.

Overall, this section shows how banks are somewhat distinct investors from independent venture capital firms. The patterns of Table 1 introduce the notion that banks may have some strategic motivations when investing in the venture capital market. Of particular interest is the finding that banks focus their investment on the type of companies that are likely to have a higher debt capacity. This motivates the main question of this paper: whether investing in a company at the venture capital stage has strategic implications. We are now in a position to address our main hypothesis.

¹¹ Lerner (1994) and Brander, Amit, and Antweiler (2002) examine the role of syndication in venture capital.

3. The Effect of Prior Venture Capital Relationships on Loan Market Activity

3.1 Definition of sample

The analysis presented in the previous section suggests that banks invest disproportionately in venture companies that subsequently obtain some funding in the loan market. The central question is whether a bank that invests in a company at the venture capital stage increases its own chance of providing a loan to that company at a later stage. We now provide a formal analysis of the main hypothesis that relationships forged at the venture capital stage increase the likelihood of subsequently becoming a lender.

To evaluate the effect of prior relationships, we need to consider both realized matches in the loan market (where a specific bank does grant a loan to a specific company), and unrealized matches (where a specific bank does not grant a loan to a specific company). This implies that our unit of analysis is the potential pairing between a company and a bank. That is, we need to consider not only the realized pairs of companies and banks, but also those cases in which there is potential to pair even if the pairing does not actually happen.

For “relationship lending” to happen, clearly there needs to be a “relationship,” and there needs to be some “lending.” This means that all companies that experience some relationship lending necessarily satisfy two criteria: they all received some bank venture capital, and they all received some loan. Our sample contains 279 companies that satisfy these two criteria, 259 with complete information. For each of those companies, we consider all possible matches with the 50 banks that invest in venture capital, generating a total of 12,950 possible matches. We use this sample as our base.

Table 2 provides descriptive statistics for the potential deals sample. Our main variables are as follows:

- **LENDER** is a dummy variable that takes the value of 1 if the bank participated in a loan to the company, 0 otherwise.
- **PRIOR-VC** is a dummy variable that takes the value of 1 if the bank made a prior venture investment in the company, 0 otherwise.
- **LOAN-MARKET-SHARE** is a bank-specific variable that consists of a ratio. The numerator counts the number of companies in the sample that received a loan from the specific bank. The denominator counts the total number of companies in the sample.¹²
- **LARGE-BANK** is a bank-specific dummy variable that takes the value of 1 if at the end of the sample period, the bank had assets in excess of \$100 billion, 0 otherwise. Asset information is taken from SDI data available from the FDIC.

¹² Because several lenders may lend to the same company, the sum of our market shares exceeds 1. An equivalent comment also applies to our measures of geographic and temporal venture capital market shares.

Table 2
Descriptive statistics: Company-bank pairs

Variable	Number of observations	Mean	Standard deviation
LENDER	13,950	0.055	0.228
PRIOR-VC	13,950	0.026	0.159
LOAN-MARKET-SHARE	13,950	0.055	0.078
LARGE-BANK	13,950	0.140	0.347
VENTURE-YEAR	13,950	1988	5.711
LOAN-YEAR	13,950	1994	3.940
EARLY-STAGE	13,100	0.615	0.487
VCCLUSTER	13,950	0.473	0.499
AMOUNT	13,800	11.030	1.683
NUMBER-OF-VCS	13,950	8.570	6.623
IPO	13,950	0.570	0.495
GEOGRAPHIC-MARKET-SHARE	13,950	0.005	0.020
TEMPORAL-MARKET-SHARE	13,950	0.003	0.007

The unit of analysis is the company-bank pair. The sample considers all companies that obtain venture capital from a bank, and that obtained a loan. Each company is matched with any of the banks that provide venture capital. There are 50 banks and 279 companies, 259 for which we have complete information. LENDER is a dummy variable that takes the value of 1 if the bank participated in a loan to the company, 0 otherwise. PRIOR-VC is a dummy variable that takes the value of 1 if the bank made a prior venture investment in the company, 0 otherwise. LOAN-MARKET-SHARE is a bank-specific variable that consists of a ratio, where the numerator counts the number of companies that received a loan from the specific bank, and the denominator counts the total number of companies in the sample. LARGE-BANK is a bank-specific dummy variable that takes the value of 1 if at the end of the sample period, the bank had assets in excess of \$100 billion, 0 otherwise. VENTURE-YEAR is a set of dummy variables, one for each calendar year, that takes the value of 1 if the company obtained its first venture capital round in that year, 0 otherwise. LOAN-YEAR is a set of dummy variables, one for each calendar year, that takes the value of 1 if the company obtained its first LPC loan in that year, 0 otherwise. EARLY-STAGE is a dummy variable that takes the value of 1 if the company received seed or first-stage financing in the company's first round, 0 otherwise. VCCLUSTER is a dummy variable that takes the value of 1 if the company is in California or Massachusetts, 0 otherwise. AMOUNT is the natural logarithm of the total amount invested in the company by all venture capital investors across all rounds. NUMBER-OF-VCS is the total number of venture capital firms that invested in the company. IPO is a dummy variable that takes the value of 1 if the company went public, 0 otherwise. GEOGRAPHIC-MARKET-SHARE consists of a ratio, where the numerator counts the number of companies that received venture capital from the specific bank in a company's metropolitan statistical area, and the denominator counts the total number of companies that received venture capital in that metropolitan statistical area. TEMPORAL-MARKET-SHARE consists of a ratio, where the numerator counts the number of companies that received venture capital from the specific bank during the period between a company's first and last venture capital round, and the denominator counts the total number of companies that received venture capital during that same period.

- VENTURE-YEAR is a set of dummy variables, one for each calendar year, that takes the value of 1 if the company obtained its first venture capital round in that year, 0 otherwise.
- LOAN-YEAR is a set of dummy variables, one for each calendar year, that takes the value of 1 if the company obtained its first LPC loan in that year, 0 otherwise.

In addition, we use some company characteristics, as described in Section 2. Note that both the LOAN-MARKET-SHARE and LARGE-BANK variables capture different aspects of bank size. The first measures a bank's presence in this specific loan market, whereas the second captures information about the overall bank size.

3.2 The main model

To test our main hypothesis, we use a Probit regression model. The dependent variable is *LENDER*, which measures whether or not a specific company obtains a loan from a specific bank. The main independent variable of interest is *PRIOR-VC*, which measures whether or not a specific company had previously obtained a venture capital investment from a specific bank. This specification allows us to test the hypothesis that when a bank gives venture capital to a firm, it increases its chances to give a subsequent loan to the same firm.

The regression controls for bank characteristics—namely, the bank's market share in the loan market, and the dummy for large banks. The regression also controls for company characteristics—namely, the year the company entered the venture capital and loan market, the industry and geographic location of the company, whether the company was an early-stage venture company, the total amount raised in the venture capital market, and whether the company went public or not.

Table 3 reports the results from our Probit regressions.¹³ The coefficient for *PRIOR-VC* is positive and statistically significant at the 1% level. This suggests that having established a relationship at the venture capital stage increases a bank's chances of granting a loan to a particular company. In addition to being statistically significant, the effect is economically non-negligible. The base probability of a relationship loan is 2.7% (evaluated at the mean of the independent variables), whereas the estimated coefficient on *PRIOR-VC* translates into a 3.7% increase in the probability of a loan. Subject to the usual caveat of evaluating marginal effects at the mean, this suggests that having a relationship more than doubles the probability of granting a loan. Overall, this result confirms our main hypothesis about the importance of building relationships early.

Table 3 also reports intuitive findings for the main control variables. Banks with higher loan market shares have higher probabilities of granting a loan. Beyond that, being a large bank does not seem to matter. Early-stage companies are less likely to obtain a loan, whereas companies that have gone public are more likely to do so. Companies in the main technology clusters of California and Massachusetts are less likely to obtain loans.

Throughout the analysis we cluster our standard errors by company (Rogers, 1993). This approach is also known as a pooled Probit regression. In Section 3.5 we discuss this technique further, and also discuss the last column of Table 3.

3.3 Instrumental variables

The results from Table 3 establish a correlation between having a prior relationship and granting a loan. Next, we estimate a simultaneous equations model, in which we augment the main Probit equation with an additional equation

¹³ We also reran this model using a pooled Logit model and, unsurprisingly, obtained very similar results.

Table 3
The effect of VC relationships on lending: Base model

Dependent variable: LENDER	Coefficients	Marginal effects	z-score clustered by company	z-score clustered by bank
Intercept	-1.512**	N/A	(-2.78)	[-6.15]
PRIOR-VC	0.407***	0.037	(4.11)	[3.13]
LOAN-MARKET-SHARE	6.401***	0.404	(21.62)	[6.78]
LARGE-BANK	-0.078	-0.005	(-1.02)	[-0.47]
EARLY-STAGE	-0.205**	-0.014	(-2.00)	[-4.74]
VCCLUSTER	-0.273***	-0.017	(-3.28)	[-3.09]
AMOUNT	0.009	0.001	(0.20)	[0.46]
NUMBER-OF-VCS	0.004	0.000	(0.37)	[0.60]
IPO	0.204**	0.013	(2.25)	[5.01]
VENTURE-YEAR		Included but not reported		
LOAN-YEAR		Included but not reported		
INDUSTRY		Included but not reported		
Number of companies		259		
Number of observations		12,950		
		$\chi^2(48) = 1,620.34$		
		Prob > $\chi^2 = 0.000$		

This table presents the results of a Probit regression. The sample considers all companies that obtain venture capital from a bank, and that obtained a loan. Each company is matched with any of the banks that provide venture capital. The dependent variable is LENDER, which is a dummy variable that takes the value of 1 if the bank participated in a loan to the company, 0 otherwise. The independent variables are as follows. PRIOR-VC is a dummy variable that takes the value of 1 if the bank made a prior venture investment in the company, 0 otherwise. LOAN-MARKET-SHARE is a bank-specific variable that consists of a ratio, where the numerator counts the number of companies that received a loan from the specific bank, and the denominator counts the total number of companies in our LPC sample. LARGE-BANK is a bank-specific dummy variable that takes the value of 1 if, at the end of the sample period, the bank had assets in excess of \$100 billion, 0 otherwise. EARLY-STAGE is a dummy variable that takes the value of 1 if the company received seed or first-stage financing in the company's first round, 0 otherwise. VCCLUSTER is a dummy variable that takes the value of 1 if the company is in California or Massachusetts, 0 otherwise. AMOUNT is the natural logarithm of the total amount invested in the company by all venture capital investors across all rounds. NUMBER-OF-VCS is the total number of venture capital firms that invested in the company. IPO is a dummy variable that takes the value of 1 if the company went public, 0 otherwise. VENTURE-YEAR is a set of dummy variables, one for each calendar year, that takes the value of 1 if the company obtained its first venture capital round in that year, 0 otherwise. LOAN-YEAR is a set of dummy variables, one for each calendar year, that takes the value of 1 if the company obtained its first LPC loan in that year, 0 otherwise. INDUSTRY is a set of dummy variables for the one-digit Venture Economics code. Standard errors are White heteroskedasticity-adjusted and are clustered in two possible ways: by company and by bank (see Rogers, 1993). In (), [] we report z-scores. *, **, or *** means the coefficient is significant at the 10%, 5%, or 1% level, respectively, using the specification of clustering by company. *, **, or *** means the coefficient is significant at the 10%, 5%, or 1% level, respectively.

to explain what factors influence PRIOR-VC.¹⁴ Because both LENDER and PRIOR-VC are binary variables, we use a bivariate Probit model. For better identification, we require instrumental variables that predict selection in the venture capital market, but not loan market outcomes.

We propose to use instruments that measure the *availability* of different financial intermediaries (see also Berger et al., 2005). The main idea is that availability affects the likelihood that a company is matched with a certain investor, but should not affect how the specific company and the specific investor interact with each other, once the match is made. We use two measures of

¹⁴ In general it is impossible to say who selects whom in the venture capital market. It could be that certain companies look for certain bank venture capitalists, and/or that certain banks seek out certain types of companies. What matters for the econometric analysis is to account for the resulting self-selection between venture capitalists and companies.

availability: the first is based on an individual bank's venture capital presence in a company's local geographic market; and the second is based on the individual bank's level of venture capital investing during the period that a company was active in the venture capital market.

Our first instrument concerns local geographic market availability—namely, a bank's venture capital market share in the company's local geographic market—and is computed as follows. For each company-bank pair, we calculate the market share of venture capital deals made by the individual bank, in the company's metropolitan statistical area (MSA). We call this variable **GEOGRAPHIC-MARKET-SHARE**. Our second instrument measures the temporal dimension of a bank's market share in the venture capital market. We first define for each company the time window during which it was active in the venture capital market, defined as the time period between its first and last venture capital rounds. For each company-bank pair, we then calculate the bank's market share over that company's time window. We call this variable **TEMPORAL-MARKET-SHARE**.

The choice of these instrumental variables can be justified as follows. In general, the validity of instrumental variables depends on two conditions: first, that they explain selection, and second, that they are unrelated to outcomes. In our context this means, first, that the instrumental variables should be related to the self-selection process in the venture capital market (as captured in the equation for **PRIOR-VC**). The likelihood that a company receives an investment from an investor should naturally depend on the investor's local availability—i.e., his activity level in the company's local market. Our two instruments measure both the geographic and temporal dimensions of these local markets. Second, the instruments should be conceptually unrelated to the outcome variable (as captured in the equation for **LENDER**). The key insight here is that our instruments pertain to the venture capital market, whereas our outcomes pertain to the loan market. These are clearly separate markets. Moreover, through the **LOAN-MARKET-SHARE** variable, our outcome regression already controls for a bank's activity level in the loan market. More formally, our identification assumption is, after controlling for a bank's market share in the loan market, that its probability of granting a loan to a company is unrelated to its past activity level in the company's local venture capital market.

Table 4 reports the results for the bivariate Probit model, again clustering our standard errors by company. The regression for **PRIOR-VC** includes all the observable company characteristics.¹⁵ It includes our two instruments, **GEOGRAPHIC-MARKET-SHARE** and **TEMPORAL-MARKET-SHARE**. In addition, we included **LOAN-MARKET-SHARE** and **LARGE-BANK**, to

¹⁵ In our base specification, we omit IPO as a dependent variable, because the resolution of this variable is not known at the time of the venture investment. Greene (2000) explains why such an omission is econometrically valid for the bivariate Probit. However, as a robustness check, we also reran all of our models, using all exogenous variables, even those pertaining to events that happen after the event (namely the IPO variable, as well as loan year dummies for the base sample). The results are qualitatively similar.

Table 4
The effect of VC relationships on lending: Instrumental variables

Dependent variable: LENDER Dependent variable	Coefficients		Marginal effects	
	PRIOR-VC	LENDER	PRIOR-VC	LENDER
Intercept	−3.265*** (−15.51)	−1.508** (−2.77)	N/A	N/A
PRIOR-VC	N/A	0.540*** (2.84)	N/A	0.055***
LOAN-MARKET-SHARE	−0.480 (−0.96)	6.368*** (21.33)	−0.013	0.403***
LARGE-BANK	0.646*** (6.21)	−0.091 (−1.18)	0.030***	−0.005
EARLY-STAGE	0.036 (0.82)	−0.205** (−2.01)	0.001	−0.014**
VCCLUSTER	−0.074** (−1.90)	−0.272*** (−3.27)	−0.002**	−0.017***
AMOUNT	0.025 (1.63)	0.009 (0.20)	0.001	0.001
NUMBER-OF-VCS	0.018*** (5.17)	0.004 (0.36)	0.000***	0.000
IPO	N/A	0.205** (2.26)	N/A	0.013**
GEOGRAPHIC-MARKET-SHARE	18.089*** (6.97)	N/A	0.471***	N/A
TEMPORAL-MARKET-SHARE	25.159*** (6.89)	N/A	0.655***	N/A
VENTURE-YEAR	Included but not reported			
LOAN-YEAR				
INDUSTRY				
Number of companies	$\rho = -0.74$ ($p = 0.408$)			
Number of observations	259			
	12,950			
	χ^2 (82) = 3,709			
	Prob > χ^2 = 0.000			

This table presents the results of a bivariate Probit regression. The sample considers all companies that obtain venture capital from a bank, and that obtained a loan. Each company is matched with any of the banks that provide venture capital. The variables used are the same as in Table 3, as well as two additional instruments. GEOGRAPHIC-MARKET-SHARE consists of a ratio, where the numerator counts the number of companies that received venture capital from the specific bank in a company's metropolitan statistical area, and the denominator counts the total number of companies that received venture capital in that metropolitan statistical area. TEMPORAL-MARKET-SHARE consists of a ratio, where the numerator counts the number of companies that received venture capital from the specific bank during the period between a company's first and last venture capital round, and the denominator counts the total number of companies that received venture capital during that same period. Standard errors are White heteroskedasticity-adjusted and are clustered for the same company (Rogers, 1993). In parentheses we report z-scores. *, **, or *** means the coefficient is significant at the 10%, 5%, or 1% level, respectively.

account for the possibility that companies might be choosing their bank venture capitalist with an eye on future lending activity. The first column reports these results. We note that both the geographic and the temporal market share variables are statistically highly significant and have considerable explanatory power.¹⁶

¹⁶ Staiger and Stock (1997) propose a test for the strength of instruments that is based on an F-test for the joint significance of the instruments. Our instruments are jointly highly significant, clearly passing the threshold level for this F-test. Bound et al. (1995) suggest that high partial R-square, defined as the difference in R-square between the first-stage regression with and without the instruments, ensures instruments are sufficiently strong. We find that the inclusion of the instruments in a first-stage Probit with all exogenous variables increases the pseudo

The second column of Table 4 reports the main regression for LENDER, now estimated as part of the bivariate Probit. The main finding is that the effect of PRIOR-VC remains positive and statistically significant at the 1% level. The coefficient estimate is in fact slightly higher than in Table 3, but the estimate for ρ , which measures the strength of selection effects, is statistically insignificant. It therefore appears that selection effects do not have a significant effect on the estimated relationship between lending and prior venture capital relationships.

Overall, these findings suggest that self-selection in the venture capital market does not seem to affect our main result that prior venture relationships increase the likelihood of granting a loan.

3.4 Company fixed effects

So far our analysis takes the standard approach of controlling for a number of company characteristics. One of the strengths of working with a sample of company-bank pairs is that we can use a particularly strong set of controls. Specifically, it is possible to account for company fixed effects. This provides a richer set of controls, essentially removing average company effects. It may also help us to control for some of the possible correlations of errors within companies. To see this, note that because we have a binary dependent variable, we can use the conditional logit model (Chamberlain, 1980). This effectively controls for company fixed effects semiparametrically, estimating the likelihood relative to each company. An attractive property of the conditional logit model is that it recognizes the interdependence of choices, estimating the likelihood of a company's choice of a specific bank, conditional on the total number of bank relationships observed for that company.

To implement this model we note that, for a given company, all variables that do not vary across observations (company-bank pairs) are collinear with the fixed effects, and thus fall out of the estimation. This means that we can dispense of all company-specific variables used in Table 3. The only dependent variables left are LOAN-MARKET-SHARE and LARGE-BANK, which are bank specific, as well as PRIORVC, which is company-bank pair specific. Moreover, only companies with variation in the dependent variable contribute to the likelihood, which reduces the number of observations that affect the estimation. The first column of Table 5 reports the base estimates of the conditional logit model. As before, we find that the effect of PRIOR-VC remains positive and significant at the 1% level.

Again we may ask how instrumentation might affect our results. One approach would be to estimate the equation with the dependent variable

R-square from 0.1963 to 0.3176. This highlights the importance of availability of different financial intermediaries, which is at the base of our instrumentation strategy. We also consider the validity of the exclusion restriction for our instruments. We follow the approach of Smith and Blundell (1986), who propose a test for exogeneity in models with limited dependent variables. The test is based on including in the outcome regression residuals from a linear probability model of the selection equation. We find that these residuals are highly insignificant, suggesting that we cannot reject the hypothesis that the instruments are exogenous. We also calculated a standard Hansen-J statistic for the linear probability version of our two equations. Again we were unable to reject the hypothesis that the instruments are exogenous.

Table 5
The effect of VC relationships on lending: Company fixed effects

Dependent variable: LENDER	Conditional logit	Linear probability	Two-stage linear probability
PRIOR-VC	0.836*** (3.76)	0.088*** (3.93)	N/A
IV-PRIOR-VC	N/A	N/A	0.031** (2.22)
LOAN-MARKET-SHARE	12.583*** (17.91)	0.967*** (14.36)	0.951*** (14.00)
LARGE-BANK	0.015 (0.08)	-0.007 (-0.52)	-0.033 (-1.62)
COMPANY-FIXED-EFFECTS	Implied by model	Included but not reported	Included but not reported
Number of companies	259	259	259
Number of observations	12,950	12,950	12,950
Number of observations contributing to likelihood	11,450	N/A	N/A
	$\chi^2(3) = 932.61$ Prob > $\chi^2 = 0.00$	$F(3, 258) = 97.06$ Prob > $F = 0.00$	$F(3, 258) = 91.16$ Prob > $F = 0.00$

This table presents the results of regressions with company fixed effects, implemented by the conditional logit and linear probability models. The sample considers all companies that obtain venture capital from a bank, and that obtained a loan. Each company is matched with any of the banks that provide venture capital. The dependent variable is LENDER, which is a dummy variable that takes the value of 1 if the bank participated in a loan to the company, 0 otherwise. The independent variables are as follows. PRIOR-VC is a dummy variable that takes the value of 1 if the bank made a prior venture investment in the company, 0 otherwise. LOAN-MARKET-SHARE is a bank-specific variable that consists of a ratio, where the numerator counts the number of companies that received a loan from the specific bank, and the denominator counts the total number of companies in our LPC sample. LARGE-BANK is a bank-specific dummy variable that takes the value of 1 if at the end of the sample period, the bank had assets in excess of \$100 billion, 0 otherwise. IV-PRIOR-VC is obtained by regressing PRIOR-VC on all exogenous variables, as well as the two instruments, GEOGRAPHIC-MARKET-SHARE and TEMPORAL-MARKET-SHARE. The first column reports results from a conditional Logit model. The second column reports results from a linear probability model with company fixed effects. The third column reports results from a linear probability model with company fixed effects, in which PRIOR-VC is replaced by its fitted value IV-PRIOR-VC. Standard errors are White heteroskedasticity-adjusted and are clustered for the same company (Rogers, 1993). In parentheses we report *z*-scores for conditional logit and *t*-statistics for the linear probability model. *, **, or *** means the coefficient is significant at the 10%, 5%, or 1% level, respectively.

(PRIOR-VC in our case) as a function of the instruments and all of the exogenous variables, obtain its fitted value, and use it in the main outcome regression. Wooldridge (2001) notes that if the outcome regression is linear, then the fitted value approach generates consistent coefficients and valid standard errors. Even though it includes the approximation of linearizing the probability function, the linear probability model thus has the advantage of always producing consistent estimates. Hence we follow this approach.

We therefore re-estimate the outcome regression for LENDER as a linear probability model, with company fixed effects. To increase our confidence in this model, we first run the outcome regression without instruments. The second column of Table 5 reports the results. It reassuringly shows that the linear model generates comparable significance levels to the nonlinear conditional logit model. We then rerun the model using a fitted value from a first-stage equation including instruments, and report the results in the third column of Table 5. Again, we find that instrumentation does not have a major impact on the results. Although the estimated coefficient is slightly lower than before, it remains significant at the 3% level. The overall message from Table 5 is that

the main result about the effect of PRIORVC on LENDER remains valid even after controlling for company fixed effects.

3.5 Robustness

The evidence from Tables 3, 4, and 5 supports our main hypothesis that having a prior venture capital relationship increases a bank's likelihood of granting a loan to a company. We ran a large number of additional robustness checks on this result. In this subsection we discuss the most important ones.

Our main analysis examines relationship lending within the sample of company-bank pairs that is limited to those companies that can have a relationship loan, in the sense that they all had a venture capital investment from *some* bank, and they all received a loan from *some* bank. The purpose of defining such a tight control group is to limit the amount of unobserved heterogeneity. As a robustness check, we examined whether our results are sensitive to this particular sample choice. We relaxed the restrictions on the set of companies admitted to the sample, first relaxing the restriction that companies need to obtain bank venture capital, then also the condition that they need to obtain a loan. We reran our regressions with these alternative sample definitions, and consistently obtained very similar results.¹⁷ Furthermore, we considered tightening the conditions of our sample. In the main analysis, for every company, we consider all possible matches with the 50 banks that invest in venture capital. However, only 30 of these banks ever grant a loan in LPC to a company financed by venture capital. For the main analysis, we deliberately retained the additional 20 banks, because retaining them presumably makes it harder to find evidence of relationship lending. However, we also reran all of our regressions excluding these additional 20 banks from the analysis. We find that excluding them does not affect any results. Overall, our results appear to be remarkably robust across different sample specifications.

One of the challenges of working with a sample of bank-company pair matches is that there might be correlation in the error term within companies or banks. Before we discuss possible econometric remedies, let us briefly explore the economic meaning of such correlation. Correlation among observations for the same company could arise if a company considers the decisions to borrow from different banks as interdependent decisions. Economically, this appears an important concern because a typical company obtains relatively few loans, and from a handful of banks at most. By contrast, correlation among observations for the same bank would arise if the bank does not make independent lending

¹⁷ We also expanded the sample even further by including companies in VE that obtained venture capital from venture capital investors that were neither independent nor bank owned. The largest single investor type for this group is corporate venture capitalists. We exclude them from our main analysis, because these other types of venture capitalists typically have more complex strategic objectives that may lead to a distinct investment pattern. However, adding them back into the analysis, we found that our results continue to hold.

decisions. Banks are in the business of granting many loans to many companies. As a first-order approximation, the assumption of independent choices thus seems much more reasonable for banks than for companies.

The most important econometric challenge is thus to control for possible correlation among observations for the same company. That is why all of our regressions cluster standard errors by company. This approach relaxes the independence assumption of the traditional Probit model. It allows observations of the same company to have correlated errors by assuming not only an idiosyncratic but also a group-specific (companies in our case) error component for each observation. In addition, note that the model with company fixed effects provides an alternative way of controlling for correlation within companies. Indeed, one of the properties of the conditional logit model is explicitly to take into account interdependencies among observations within the same group. As an additional robustness check, we also examine the possibility that errors may be correlated among observations for the same bank. Again we use two approaches, clustering and fixed effects. We rerun all of our results clustering by banks instead of companies, and find that this does not affect any of our results. The last column of Table 3 reports the results for the base model. In addition, we rerun all of our specifications adding bank fixed effects (and clustering by companies). Again we find that all of our results remain intact. Finally, a recent paper by Thompson (2006) derives a method for two-dimensional clustering. We use this approach and find again that this does not affect the significance of our results. This suggests that concerns about correlation within bank observations are unlikely to affect the main results.

Our measure of geographical and temporal market shares uses the number of venture deals made by a specific bank in a specific market. Whenever a company receives a venture investment from a bank, its own deal is included in this market share measure. One could argue that a company's own deal should be excluded to use market shares as instrumental variables. The idea is that if the market share variable is meant to capture the availability of a specific investor, then we may want to measure availability outside of the company's own realized deal. To address this concern, we run two additional specifications. First, we exclude a company's own deal from the numerator, which essentially amounts to pretending that the specific deal never happened. Second, we exclude a company's own deal from both the numerator and denominator, which essentially amounts to pretending that the company never existed. We estimate our instrumental variable models using these alternative specifications of the market share variables, and find that this does not affect any of our results.

Our analysis focuses on the question of whether a bank grants a loan to a specific company. One may also go a step further and ask what role that bank played in the loan. Of particular interest is whether a bank is a lead lender. Following Drucker (2005), we identify banks as serving a lead role if (1) it is the only bank listed for the loan or (2) it is listed as in LPC as "Lead

Arranger.”¹⁸ We reran our regressions, replacing our dependent variable (LENDER) with a lead lender variable that is based on this definition. Again we find the same pattern of results, suggesting that prior relationships have an effect not only on the likelihood of granting the loan, but also on the likelihood of becoming a lead lender.

Section 1.2 mentioned that banks can invest in private equity through two regulatory loopholes, either through SBIC-registered funds, or through the Bank Holding Act exemption. Although VE does not maintain records of which investments are financed under which loophole, it is possible to track which banks have an SBIC subsidiary. It is thus possible to subdivide banks into two categories, those with and those without SBIC subsidiaries. We reran our base model, dividing the PRIOR-VC coefficient into two: one for SBIC banks and the other for non-SBIC banks. We found that both coefficients were statistically significant, and that the *t*-test for the difference of coefficients was not significant. These results seem to suggest that the choice of regulatory loophole does not matter for our main findings.

4. 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. Companies can potentially benefit from banking 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 companies so that there is no benefit to companies.

In this section we test whether companies get better terms on relationship loans than nonrelationship loans. For this, we naturally confine ourselves to the companies of the restricted sample—namely, the 279 companies that receive venture funding from commercial banks and subsequently obtain 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 nonrelationship loans, we consider all nonrelationship loans granted by banks in LPC. We identify 809 nonrelationship 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 nonrelationship 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. Formally, the variable YIELD SPREAD is the yield of the loan, quoted in basis points over LIBOR. We use the data item “all-in spread drawn” in LPC, which also incorporates all fees paid by the borrowers.

¹⁸ If the Lead Arranger field is blank, we use data from the “Arranger” field. If the Arranger field is blank, we use the “Lead Role” descriptor from the “Lender” field. This procedure is designed to identify true lead banks more accurately. See also Drucker (2005).

These loans are typically syndicated, are typically to public companies, and are reported in SEC filings. Hence it is unlikely that there are other unreported compensation or costs related to the loan. The pricing data can be considered quite reliable including both interest rates and fees.

To compare between relationship loans and nonrelationship 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 nonrelationship 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. For those readers not familiar with this methodology, the Appendix provides a brief explanation of this estimation method.

For each of the relationship and nonrelationship loans, we compute a propensity score via a Probit model, where the dependent variable is PRIOR-VC, and the independent variables are as follows:

- RATING 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 is a dummy variable, which is 1 if the loan is not rated, 0 otherwise;
- FACSIZE is the notional value of the loan facility between the lender and the borrower, expressed in millions of dollars;
- LENGTH is the difference between the term facility active date and the term facility expiration date, measured in months;
- TYPE is a set of dummy variables concerning loan type (LPC classifies loans into term loans, revolving lines of credit, 364-day facilities, and other types);
- YEURL is a set of dummy variables based on the year of the lending facility;
- VE is a set of dummy variables based on two-digit primary VE industry codes;
- VCCLUSTER is a dummy variable that takes the value of 1 if the company is in California or Massachusetts, 0 otherwise.

Our choice of independent variables includes all those characteristics that are economically meaningful, and that are observable for both relationship loans and the control group of nonrelationship loans.

There are several standard approaches for calculating propensity scores, and the Appendix provides a technical overview of their differences. Table 6 reports the results from the various matching methods. We see that relationship loans consistently have lower yields than similar nonrelationship 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%.

Table 6
The effect of VC relationships on loan pricing

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

This table provides estimates of the mean difference between the yield spread of relationship loans and nonrelationship 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 company's venture capitalist is a lender. Nonrelationship loans are lending facilities in which the company'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 score, we estimate unreported Probit regressions in which the dependent variable is PRIOR VC, which takes the 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 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; FACSIZ, 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 of dummy variables concerning loan type (LPC classifies loans into term loans, revolving lines of credit, 364-day facilities, and other types); VCLUSTER, 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 a set of industry dummy variables based on the 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 nonrelationship loans with closest propensity scores, and uses the arithmetic average of the n nonrelationship yield spreads. We use $n = 10, 20, 50$, and 100 . GAUSSIAN and EPANECHNIKOV use a weighted average of nonrelationship loans, with more weight given to nonrelationship loans with propensity scores that are closer to the relationship loan propensity score. GAUSSIAN uses all nonrelationship loans, while for EPANECHNIKOV, we specify a propensity score bandwidth (h) that limits the sample of nonrelationship loans. We specify that $h = 0.01$. The number of observations of the matched sample may be lower than the number of companies 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 nonrelationship loan propensity scores. Also, the EPANECHNIKOV estimator may reduce the number of matches further because at least one nonrelationship 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 parentheses and p -values in brackets. *, **, or *** means the coefficient is significant at the 10%, 5%, or 1% level, respectively.

Together these results suggest that there is an economically non-negligible pricing difference between relationship and nonrelationship 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.

5. Conclusion

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 by banks. For instance, banks' activities may be influenced by regulations or greater risk aversion. This is consistent with our finding that banks avoid early-stage investments. 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 toward 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; and Kaplan and Strömberg, 2004). Some observers argue that banks typically fail to provide such value-adding support, and Bottazzi, Da Rin, and Hellmann (2007) provide some supporting evidence from European venture capital deals. One possible interpretation is 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, for which value-adding support is relatively less critical. However, it is worth noting that this alone 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 to build lending relationships, as our findings suggest, building the infrastructure for providing value-adding support may not be their main priority.

Understanding the role of banks in venture capital is also important for the development of venture capital markets outside the United States. Policy makers in numerous countries have tried to facilitate the development of their own venture capital industry. Some policies focus on the supply of startups. Gompers, Lerner, and Scharfstein (2005) 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 toward 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: Matching Methods

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 nonrelationship loan. In principle, the i th of the N loans under study has both a yield spread Y_{1i} that would result in a relationship loan, and another yield spread Y_{0i} that would result in a nonrelationship loan. The effect of interest is a mean effect of the difference between Y_1 and Y_0 . However, because 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 bank, so we reformulate the problem at the population level. We focus on the mean effect of the difference between relationship loans and nonrelationship loans with characteristic X :

$$E(Y_1 - Y_0 | D = 1, X) \quad (\text{A1})$$

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

We use a method of matching that solves the evaluation problem.¹⁹ Following Heckman and Robb (1986), we assume that the relevant differences between relationship loans and nonrelation-

¹⁹ To determine if econometric matching is a viable method of evaluation, Heckman, Ichimura, and Todd 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.

ship loans are captured by their observable characteristic X . Let

$$(Y_0, Y_1) \perp D \mid X \quad (\text{A2})$$

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

$$0 < P(D = 1 \mid X) < 1 \quad (\text{A3})$$

(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 Equation (1). All that is required is the weaker mean independence condition

$$E(Y_0 \mid D = 1, P(D = 1 \mid X)) = E(Y_0 \mid D = 0, P(D = 1 \mid X)). \quad (\text{A4})$$

By using the propensity score, we can effectively take into account the fact that the characteristics of relationship loans may differ significantly from nonrelationship loans and ensure that such observed characteristics are not driving the results.

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

We use two classes of propensity-score-matching methods: (i) nearest neighbor matching, and (ii) kernel-based matching. Both propensity-score-matching methods are discussed in greater detail in Heckman, Ichimura, and Todd (1997, 1998). Let Y_{1i} be the yield spread of a relationship loan, let Y_{0j} be the yield spread of a nonrelationship loan, and let $\bar{Y}_{0i}^z$ represent the (weighted) average of yield spreads of the nonrelationship loans using estimator z , which is matched with Y_{1i} . To match the yield spreads of nonrelationship loans to the yield spreads of relationship loans, we compute for every i the estimated yield difference $Y_{1i} - \bar{Y}_{0i}^z$.

For each relationship loan, the nearest-neighbor matching estimator chooses the n nonrelationship loans with propensity scores closest to the relationship-loan propensity score. The estimator computes the arithmetic average of the yield spreads of these n nonrelationship loans. For each Y_{1i} , we match $\bar{Y}_{0i}^{NN} = \frac{1}{n} \sum_{j \in N(i)} Y_{0j}$ where $N(i)$ is the set of nonrelationship loans that are nearest neighbors to Y_{1i} . We set $n = 10, 20, 50$, and 100 .

The kernel estimators construct matches for each relationship loan by using weighted averages of yield spreads of multiple nonrelationship 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 $P(\text{PRIOR-VC} = 1 \mid X)$ 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 $P(X) = P(\text{PRIOR-VC} = 1 \mid X)$. For each Y_{1i} , we match a corresponding $\bar{Y}_{0i}^K$ where

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

We use two different kernels to compute $\bar{Y}_{0i}^K$. The Gaussian kernel uses all nonrelationship loans, whereas the Epanechnikov kernel uses only nonrelationship 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 obtain similar results.

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