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A HIGH-TECH START-UP'S DEBT FINANCING STRATEGY: IMPLICATIONS FOR VALUING SOFT INFORMATION

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Cover Page Footnote

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A HIGH-TECH START-UP'S DEBT FINANCING STRATEGY: IMPLICATIONS FOR VALUING SOFT INFORMATION

ABSTRACT

How does entrepreneurial financing differ from traditional financing? This study sheds new light on this central question of entrepreneurial finance literature by exploring the distinctive role of soft information in a high-tech start-up's debt financing. Entrepreneurial investors can obtain soft information from strong relationships with potential investees and use the information to evaluate and select promising investees. Using a dataset on 683 SBA 7(a) loan activities involved with information technology based start-ups, this study provides empirical evidence that high-tech start-ups tend to experience a lower rate of default if they are located close to the lending banks and the lending banks are of considerable size. These conditions allow the lending banks to collect and utilize soft information regarding high-tech start-ups in an efficient manner.

1. Introduction

High-tech start-ups are often unprofitable and lack the necessary resources. As a result, they must gain access to external resources in order to exploit their entrepreneurial opportunities (Colombo and Grilli 2005; Beckman and Burton 2008). Financial capital is especially essential to procure other types of resources. These start-ups, however, often experience a "valley of death" transitional phase where developing technology is deemed promising yet without validated commercial potential (National Research Council 2009) and may fail to access the direct entrepreneurial finance market (e.g., private equity). To overcome these financial constraints in this phase, high-tech start-ups often access the lending market to continue exploiting their entrepreneurial opportunities. Indeed, banks are a critical source of financing for start-ups, providing about 60% of debt financing to small businesses (Federal Reserve Bank of Atlanta 2014). Especially, start-ups have increasingly utilized the SBA 7(a) loan program through commercial banks in recent decades.

While the SBA 7(a) loan program provides a government-backed guarantee on the portion of loans, banks are supposed to select qualified start-ups and take a portion of responsibility associated with a default. This primary role of banks in the entrepreneurial finance is justified because they possess the continuing ability to evaluate, process, disburse, service, and liquidate entrepreneurial loans (Dilger 2013). This unique role of banks raises a natural question about how entrepreneurial debt financing differs from traditional credit financing. Specifically, "what information do banks use to evaluate and select promising start-ups?" A growing body of finance literature suggests that banks are able to overcome the asymmetric information problem by producing information about potential borrowers and using it in the evaluation process. This question, however, remains not fully answered because such information is often unavailable in the entrepreneurial lending market due to the nature of start-ups, which are young and have

insufficient records about their operations. This question should be addressed in a new framework that can be applied in the context of entrepreneurial finance.

A stream of the literature I considered in this study is the literature on soft information, which can be readily applied within the context of entrepreneurial finance (Hodgman 1961; Kane and Malkiel 1965; Fama 1985; Bhattacharya and Thakor 1993; Petersen and Rajan 1994, Berger and Udell 1995; Boot 2000; Ongena and Smith 2000; Brau and Osteryoung 2001; Schenone 2004; Freixas 2005). High-tech start-ups often have private information about the value of their entrepreneurial opportunities. This information is not readily available for external stakeholders, including banks. This asymmetric information between start-ups and banks creates uncertainty about their credit worthiness (Cole 1998), leads to credit rationing equilibria (Stiglitz and Weiss 1981), and invalidates other standard competitive market results (Broecker 1990). By this unique nature of entrepreneurial lending market, theories that have been discussed in the literature of traditional credit market (e.g., perfect capital market, moral hazard, and adverse selection) cannot be applied in the entrepreneurial lending market in the exact same manner.

In the entrepreneurial lending market, banks may obtain private information about high-tech start-ups through a continued relationship. This information can be used to set future contract terms or credit underwriting decisions. Banks necessarily use this “soft” information, which is difficult to quantify and transmit through the official communication channels, as well as “hard” information to provide entrepreneurial finance in an appropriate manner (Brau and Osteryoung 2001; Stein 2002). In contrast, these start-ups are likely to use their superior information position for their own benefits by selectively sharing their soft information with banks. This tendency may become stronger if focal start-ups have a high magnitude of soft information that would negatively affect banks’ decisions about whether the bank lends and what conditions banks offer.

Using a longitudinal dataset on 683 SBA 7(a) loans associated with information technology based start-ups between 1980 and 2005, this study provides empirical evidence that high-tech start-ups tend to experience a lower rate of default if they are located close to the lending banks and the lending banks are of considerable size. These conditions allow the lending banks to more efficiently collect and utilize soft information regarding start-ups. Specifically, high-tech start-ups that are reluctant to share their soft information, such as a perceived risk of default, may want to select banks that have difficulty reaching their soft information. These start-ups come to prefer banks that are distant from them (e.g., distance effect) and inferior to respond to local market competition (e.g., size effect). Furthermore, these distance and size effects interact with each other in determining the defaults. This interaction effect suggests that the distance effect is more salient when high-tech start-ups borrow from smaller banks, and vice versa.

2. Literature and Hypotheses Development

2.1. SBA 7(a) loan

The goal of SBA 7(a) loan is to help start-ups resolve their financial constraints by providing loan guarantee programs designed to encourage banks to provide entrepreneurial finance. Proceeds from SBA 7(a) loans may be used to establish a new business or to assist in the operation, acquisition, or expansion of an existing business. To be eligible for the loan, a start-up must be located in the United States, be a for-profit-operating business, qualify as small under the SBA's size requirements, demonstrate a need for the desired credit, and be certified by a banker designated by the SBA. The maximum loan amount is up to \$5 million (up to \$3.75 million maximum guarantee). The average loan amount was \$34,000 in 2012. The maximum loan term is typically 10 years, and can be extended up to 25 years with extensions. Banks are allowed to charge start-ups a reasonable fixed interest rate or a variable interest rate. The maximum allowable fixed interest rate in 2013 was 9.42%. The interest rates vary by the loan amount and are determined by a multi-step formula published in the Federal Register.

When a start-up submits an application for the SBA 7(a) loan, a bank reviews the application and decides whether it merits a loan on its own or not. The SBA guarantee assures the bank that, if the start-up does not repay the loan and the bank adhered to all applicable regulations concerning the loan, the SBA will reimburse the bank for its loss, up to the percentage of the SBA's guarantee. If the bank determines that it is willing to provide the loan, but only with the SBA guarantee, it submits the application for approval to the Standard 7(a) Loan Guaranty Processing Center. These centers eventually decide whether or not to approve the applications. The SBA charges banks upfront a one-time guarantee fee and an annual ongoing servicing fee, which cannot exceed 5.55% per year of the outstanding balance of the SBA's share of the loans. The bank may charge a start-up reasonable fees customary for similar banks in the geographic area where the loan is being made for packaging and other services.

There is a debate that the SBA should be provided additional resources to assist start-ups that would create more jobs (Stiglitz and Weiss 1981; Evans and Jovanovic 1989; Evans and Leighton 1989). Others worry about the long-term adverse economic effects of spending programs that increase the federal deficit and that many of the small businesses are not Schumpeterian innovators – they do not attempt to introduce new ideas, nor do they seek to enter a new or underserved market (Hurst and Pugsley 2011; Neumark et al. 2011; Haltiwanger et al. 2013). This debate is still ongoing in the literature. Some studies report that a small but positive and statistically significant relationship exists between guaranteed loans and regional economics (Riding and Haines Jr. 2001; Craig et al. 2007; Lee 2013). Young et al. (2014) find that the SBA lending activity has a negative effect on per capita income growth; and De Andrade and Lucas (2009) find that the SBA loan borrowers are charged rates that are no lower than on comparable uninsured securities.

It is surprising that little is known about what information banks do use to evaluate and select promising high-tech start-ups, which would facilitate long-term economic developments. It is important

to understand these issues because it helps us understand what strategy a start-up does use to obtain necessary entrepreneurial debt financing and how the entrepreneurial lending resource is allocated in an effective and efficient manner. In a broad sense, these issues explore what external contingencies shape the entrepreneurial finance market. By filling this gap in the literature, we are able to better understand how start-ups respond to overcome their financial constraints.

2.2. Information asymmetry and soft information in the entrepreneurial lending market

Start-ups want to acquire necessary capital to exploit their entrepreneurial opportunities, and banks need investment opportunities that match up deposits and borrows for reasonable rates of return. These two parties exchange their resources with each other in the entrepreneurial lending market. However, they may have difficulties when purchasing and exchanging resources, particularly due to limited information about each other (Duhaime and Schwenk 1985; Haspeslagh and Jemison 1991; Coff 1999; Reuer and Koza 2000; Barkema and Schijven 2008; Slepsov and Anand 2008; Agarwal et al. 2012). The conventional wisdom on the role of banks provides dichotomous perspectives. On one hand, banks constitute an important source of specialized information and expertise for entrepreneurial lending. On the other hand, the appropriate information flow from start-ups may not occur for a variety of reasons, including lack of recording, inadequate incentives, and conflicts of interests.

Start-ups are typically much more informationally opaque than larger corporations because they often do not have certified audited financial statements to yield credible financial information on a regular basis (Berger, Frame, and Miller 2005). Due to this opacity, start-ups take superior positions in terms of the use of information, when compared with banks, and thus determine the ability and willingness of providing their private information (Hansen 1999). This information asymmetry is more salient within the context of high-tech based industries because high-tech start-ups often pursue technologies that would be the most important resources and difficult to understand without the expertise in the field. Banks, in contrast, should seek a number of lending technologies to cope with the information asymmetry. They necessarily use *hard information* and combine it with relatively limited data about start-ups using statistical methods to predict future credit performance. The hard information includes credit history, identifiable assets, and business data involved with the stock holders of start-ups. Hard information is useful because it is available in the secondary market with lower cost and yields significant growth in the credit availability of start-ups.

For an alternative information source, banks use *soft information* gathered through contacts over time with start-ups, including the owners, managers, and other members of local communities. Soft information refers to any kind of data other than the relatively transparent and public information about the start-up such as financial statements or the availability of collateral. Soft information is essentially qualitative in nature, so it cannot be easily or verifiably recorded in written form (Garcia-Appendini

2011). It takes a significant amount of time to accumulate soft information about start-ups. Banks may interchangeably use soft and hard information to allocate their credits among start-ups.

2.3. Hypotheses development

Soft information may travel within a specific range of local community because such information is difficult to communicate and quantify. Banks often should have a local presence to maintain direct and indirect contacts with start-ups to collect soft information (Petersen and Rajan 1994; Berger and Udell 1995). Typically, this would increase the cost of having large scale, geographically spread-out lending operations, implying strong diseconomies of scale in the entrepreneurial lending (Petersen and Rajan 2002). Beyond the range of community, start-ups are more likely to exert their efforts, if necessary, to conceal the soft information that would negatively affect the likelihood of loan approvals and contract terms.

As such, if the physical distance between start-ups and banks increases, the contacts between two parties may become more impersonal and dependent on hard information. The nature of this relationship gives start-ups the incentive to release hard information that is prepared by their loan professionals, such as brokers, accountants, and lawyers, in favor of them. Start-ups are also able to provide selected soft information in this regime. Thus, the distance between the two parties creates a greater information asymmetry. Especially, start-ups that perceive a high chance of default or predict the unpromising future of business are more likely to access banks at a distance. These banks may be unable to access the soft information. If this conjecture is true, we will see:

Hypothesis 1. High-tech start-ups are likely to experience a lower rate of default when they are close to the lending banks.

Large banks may be able to serve start-ups well by using a greater volume of hard information, such as credit scoring and lending against fixed asset collateral with values (Frame, Srinivasan, and Woosley 2001; Frame, Padhi, and Woosley 2004; Berger, Frame, and Miller 2005; Berger and Udell 2006). Large banks have also recently come to maintain decentralized decision making structures and are able to respond more to local market competition (Canales and Nanda 2011), allowing them to have better access to soft information. Combining both types of information, large banks may outcompete in the entrepreneurial lending market. In other words, large banks can reduce information asymmetry by using their rich resources and better organizational structures that smaller banks would not emulate. As a result, start-ups that want to conceal the negative soft information are less likely to access large banks.

Notice that contrary to my prediction, it can be argued that small banks are better able to form strong relationships with start-ups, while large banks tend to serve more transparent firms (Berger and Udell 2002; Stein 2002). This approach seems reasonable in the traditional lending market in which banks are able to prefer a specific group of applicants, but less so in the context of entrepreneurial lending

market. As long as large banks compete in the entrepreneurial lending market, their applicants cannot be transparent. If they maintain decentralized structure, the structure is likely to be advantageous for them in terms of accessing both soft and hard information. If this conjecture is true, we will see:

Hypothesis 2. High-tech start-ups are likely to experience a lower rate of default when they borrow from the large banks.

3. Data and Empirical Strategy

3.1. Data

For the purpose of this study, I utilized two data sources, including a dataset on SBA 7(a) loan activity involved with information technology based start-ups from the SBA via a Freedom of Information Act request, and the Bank Regulatory database available from Wharton Research Data Services. The SBA has several loan programs. Their main effort is the 7(a) loan program that facilitates loans to existing small businesses by guaranteeing varying percentages of loans. The maximum guarantee is typically 75% of the loan amount. I limited my sample within 7(a) loan program because this program is over 90% of loans approved by the SBA and intended to encourage long-term entrepreneurial financing for start-ups.

The SBA provided a number of variables, including the identities of lending banks and start-ups, loan amounts, and interest rates associated with each individual loan. Furthermore, I was able to obtain data on loan failure (i.e., default) amounts on each loan. This data allows me to estimate the actual default rates of individual loans, which are, on average, 8% according to my sample. This actual default rate is considerably lower than the probability of SBA loan failures (i.e., 17%) estimated by prior studies (Treacy and Carey 1998; Glennon and Nigro 2005), and higher than the average loan failure rates of the U.S. commercial banks (i.e., 3.5%) (<http://www.federalreserve.gov/releases/chargeoff/delallsa.htm>).

The Bank Regulatory database provides financial accounting data for regulated depository financial institutions, including bank holding companies, commercial banks, saving banks, and saving and loans institutions. The source of the data comes from the required regulatory forms filed for supervising purposes. Specifically, I use the Commercial Bank database from the Federal Reserve Bank of Chicago. It contains data from all banks filing the Report of Condition and Income that are regulated by the Federal Reserve System, Federal Deposit Insurance Corporation, and the Comptroller of the Currency. From these data sources, I was able to obtain the total amounts of assets and the net income of sample banks. My dataset is composed of 683 individual SBA 7(a) loans borrowed by information technology based start-ups.

3.2. Dependent variable: default

I define an outcome variable (i.e., *default*) as the log amount of default at the end of individual loan term. All dollar values are converted into 2005 constant dollars using the GDP deflator. Ideally, one

would measure the amount of default by observing at the time of loan approval to alleviate time-varying unobserved heterogeneity that may lead me to mistakenly estimate the effects of independent variables on *default*.¹ However, such a measure is hardly available at the level of individual loan, except for a perceptual measure that also may lead to a bias in parameter estimation (Ketokivi and Schroeder 2004). For a sensitivity analysis, I use the rank variable of *default* (i.e., *default rank*). The greater rank denotes a greater value of *default*. This approach alleviates my concerns about the abnormal effects of outliers.

3.3. Independent variables

3.3.1. Distance

Distance measures the linear distance between the zip codes of a start-up and a bank. All the longitude/latitude data came from the 2000 U.S. Census. I use a simple distance calculation method that calculates the distance in miles by passing the latitude and longitude coordinates. For a robust check and to refine the effect of *distance*, I also examine the effects of city and state boarder lines. I create a set of dummy variables, including *same city* and *same state*, and replace these variables with *distance* in some models. *Same city* equals one if a start-up borrows from a bank located within the borderline of same city, and zero otherwise. Similarly, *same state* equals one if a start-up does from a bank located within the borderline of same state, and zero otherwise.

3.3.2. Bank size

Bank size is measured by the log of total assets of a bank (Berger, Goulding, and Rice 2014). I believe this measure may capture the effect of bank size on what technologies will be used to evaluate loan applications by the bank. However, I also use *national bank (16)* and *national bank (41)* to elaborate the effect of *bank size* in some models for a sensitivity analysis. *National bank (16)* equals one if a bank has branches spanning 16 states (i.e., the mean of the number of states in which banks have branches in the sample), and zero otherwise. Similarly, *national bank (41)* equals one if a bank has branches in over 41 states (i.e., the 90th percentile of the number of states in which banks have branches in the sample). These two variables will help examine the spatial size as well as the monetary size of bank.

3.4. Control variables

3.4.1. Loan characteristics

The loan characteristics, including *loan amount* and *loan interest rate*, can impact the likelihood of the defaults of start-ups (Glennon and Nigro 2005; Riding and Haines 2001). The former is measured by the log of the amount of individual loans, and the latter is the interest rates approved with the loans. As the dollar amount of loan increases, banks are likely to utilize a more rigorous asset protection in the event that borrowers do not repay the bank credits, impacting the variation of *default*. Interest rates on

¹ Variables names are in *italic*.

individual loans inversely reflect how start-ups have capacities to repay bank credits, and represent the financial burdens imposed on them.

3.4.2. Bank net income

Bank net income is measured by the log of a bank's net income. *Bank net income* is a measure of banks' financial performances and has been found to affect the likelihood of effective monitoring and controlling of the banks' loan processes (Cole 1998). As such, banks that already have strong financial performances are more likely to select start-ups that are more likely to repay the bank credits.

3.4.3. Fixed effects: Ownership, state, year fixed effects.

I use several fixed effects in the following analyses. First, *ownership fixed effects* control for the ownership structure of start-ups. This variable is categorized into three groups, including sole proprietorships, limited partnerships, and corporations. The ownership structure can determine how much soft information banks will use. For example, a bank may need more soft information for a start-up that has a single owner because this start-up does not produce sufficient hard information. Second, *state fixed effects* control for states in which start-ups operate. These fixed effects control for institutional factors that are different among states, such as tax conditions and entrepreneurial policies. Finally, *year fixed effects* control for time varying conditions. The risk of default is not constant, but varies significantly over time according to the current economic conditions (Glennon and Nigro 2005).

3.5. Empirical specification

I use two econometric approaches to estimate the effects of *distance* and *bank size* on *default*, including ordinary least squares (OLS) and negative binomial (NB) regressions. The OLS regression approach, which has been popular due to its simplicity, performs a one-tailed t-test on one variable of interest and all observable exogenous variables in the regression of other variables of interest (Lokshin et al. 2007). In the OLS specification, I estimate the following models: $C_i = \alpha + \beta X_i + \gamma Z_i + \varepsilon_i$, where C_i denotes my dependent variable, *default*; X_i are independent variables of interest, including *distance* and *bank size*; and Z_i are control variables. Control variables include loan characteristics, bank characteristics, and several fixed effects. As a corollary analysis, I test interaction effects between *distance* and *bank size* using a production function approach that performs a simple one-tailed t-test on the interaction term of the two variables (e.g., *distance* and *bank size*).

For a sensitivity analysis, I use *default rank*, the rank variable of *default*, with negative binomial regression models. This specification uses the negative binomial distribution that is a discrete probability distribution of the number of successes in a sequence of independent and identically distributed Bernoulli trials before a specified number of failures occur. As discussed, this approach reduces my concerns about the abnormal effects of outliers.

To refine the effects of *distance* and *bank size* on *default*, I use two approaches: segmented regression with seemingly unrelated (SU) post-estimation, and replacing new variables, including *same city*, *same state*, *national bank (16)*, and *national bank (41)*, with the existing variables of interest, respectively. The segmented regression approach is used to find the optimal range of independent variables to differentiate the effects of variables on the dependent variable. When analyzing a relationship between a dependent and an independent variable, it may be apparent that for different ranges of independent variables, different linear relationships occur. In these cases, a single linear model may not provide an adequate description and a nonlinear model may not be appropriate. Segmented regression is a form of regression that allows multiple linear models to be fit to the data for different ranges of independent variables. Breakpoints are the values of independent variables where the slope of the linear function drastically changes. I use SU post-estimation whether the resulting two regression coefficients of independent variable are statistically different or not. SU post-estimation consists of several regression equations (e.g., two regressions in my analysis), and each equation is a valid linear regression on its own. These equations are estimated separately and allow me to compare the resulting regression coefficients of independent variables that are included in both equations.

As discussed, to examine more specific effects of city and state boarder lines on *default*, I replace *distance* with *same city* and *same state* in some specifications. Moreover, I replace *bank size* with *national bank (16)* and *national bank (41)* in some specification to examine the effects of the range of locations covered by a bank on *default*.

4. Empirical Results

4.1. Descriptive statistics

The descriptive statistics are presented in Table 1. In Panel A, Group 1 (i.e., all samples) has 683 observations and is categorized into two groups: Group 2 (i.e., default) and Group 3 (i.e., paid in full). Columns report the distribution of samples and the summary statistics categorized by my independent variables, including *distance* and *bank size*. The first column reports the distribution of all samples. Group 2 has 56 observations and accounts for 8% of samples; and Group 3 has 627 observations and accounts for 92% of samples. The proportion of each group is overall consistent with the statistics provided by prior studies (e.g., De Andrade and Lucas 2009).

In the second column, I observe that Group 2 has, on average, a considerably greater *distance* (i.e., 250.32) than Group 3 does (i.e., 205.76). These differences are statistically significant at the 1% level and consistent with my prediction made in Hypothesis 1. I also observe, in the third column, that Group 3 indicates, on average, greater *bank size* (i.e., 13.20) than Group 2 does (i.e., 13.07). These statistics are supportive of my prediction made in Hypothesis 2. However, these statistics need to be

interpreted with caution because they are simply univariate results and may be biased due to unobserved heterogeneity.

Panel B reports summary statistics for the five groups of variables used in the following analyses. These groups include dependent variables, variables of interest, loan characteristics, bank characteristics, and environmental characteristics. Start-ups borrow, on average, \$274 thousand with a 9.97% interest rate. Banks have, on average, \$8.50 billion of total assets; and \$107 million of net incomes.²

Table 1. Summary statistics

Panel A: Dependent variable						
	Sample distribution		Distance		Bank size	
	N	%	Mean	S.D.	Mean	S.D.
1. All samples	683	100.00	209.421	539.822	13.084	2.533
2. Default	56	8.00	250.321	606.849	13.074	2.598
3. Paid in full	627	92.00	205.768	533.814	13.195	2.528

Panel B: Variables						
	All samples					
	N	Mean	S.D.	Min	Max	
1. Dependent variables						
Default	683	0.883	2.986	0.000	13.195	
Default rank	683	342.000	197.164	1.000	683.000	
2. Variables of interest						
Distance	683	209.422	539.823	0.000	2491.000	
Bank size	683	13.084	2.533	8.863	18.993	
3. Loan characteristics						
Loan amount	683	11.767	1.405	8.577	14.568	
Loan interest rate	683	9.970	2.657	4.250	23.250	
4. Bank characteristics						
Bank net income	683	8.511	2.796	0.693	14.525	
5. Environmental characteristics						
Ownership fixed effects	683	N/A	N/A	0.00	1.00	
State fixed effects	683	N/A	N/A	0.00	1.00	
Year fixed effects	683	N/A	N/A	0.00	1.00	

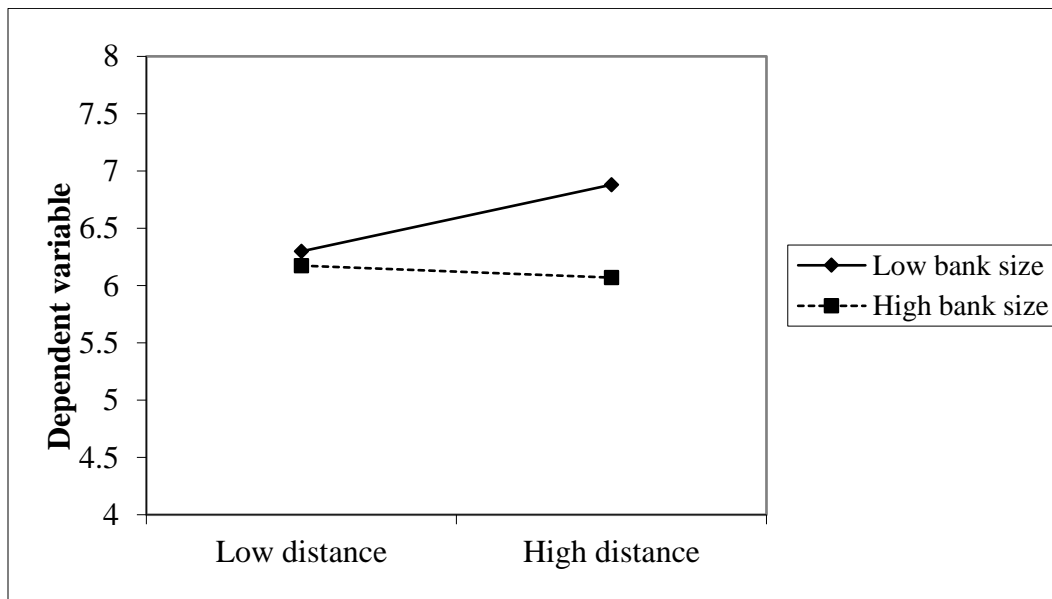
4.2. Effects of distance and bank size on default

To understand the effects of *distance* and *bank size* on *default*, I obtain benchmark results by using several OLS and NB regression models presented in Table 2. Model 1 uses the OLS specification to estimate the effect of *distance* on *default*. *Distance* indicates a positive and significant regression

² These numbers are calculated by converting logarithms back to natural numbers.

coefficient on *default* at the 1% level. More specifically, and by converting logarithms back to natural numbers, as the distance between a start-up and a bank increases beyond 1 mile, the amount of default increases, on average, \$4.45. These statistics support my first hypothesis. Model 2 includes *bank size* as an independent variable and shows that *bank size* decreases *default*, with the effect statistically significant at the 1% level. This result supports my second hypothesis. For a corollary analysis, I include the interaction term of two independent variables (i.e., *distance*×*bank size*) to consider the interaction effects of two variables in Model 3. *Distance*×*bank size* indicates a negative and significant regression coefficient at the 1% level. These statistics suggest that the effect of *distance* on *default* is more salient when start-ups borrow loans from smaller banks. These interaction effects are illustrated in Figure 1.

Figure 1. Interaction effects of distance and bank size



To control for the abnormal effects of outliers, I use the NB specification using the rank variable of *default*, *default rank*, in Model 4. Consistent with the result in Model 1, *distance* indicates a positive and significant regression coefficient at the 1% level. These results suggest that my finding in Model 1 is robust against the effects of outliers. In Model 5, I replace *distance* with *bank size*. The results show that *bank size* has a negative and significant effect at the 1% level, supporting my finding in Model 2. I include all the independent variables of interest in Model 6 and find that these results are consistent with my findings in Model 3. As a result, I conclude that two hypotheses are supported.

Table 2. Effects of distance and bank size on default

	OLS	OLS	OLS	NB	NB	NB
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Default	Default	Default	Default rank	Default rank	Default rank
Distance	0.253*** (0.015)		1.290*** (0.085)	0.021*** (0.001)		1.182*** (0.006)
Bank size		-0.073*** (0.011)	-0.082*** (0.012)		-0.811*** (0.112)	-0.911*** (0.011)
Distance×Bank size			-0.075*** (0.005)			-0.711*** (0.023)
Loan amount	-0.455*** (0.093)	-0.464*** (0.093)	-0.415*** (0.095)	-0.040*** (0.007)	-0.041*** (0.007)	-0.361*** (0.078)
Loan interest rate	-0.430*** (0.119)	-0.425*** (0.118)	-0.441*** (0.120)	-0.033*** (0.008)	-0.032*** (0.008)	-0.034*** (0.008)
Bank net income	0.067 (0.061)	-0.016 (0.147)	0.007 (0.152)	0.005 (0.004)	0.000 (0.011)	0.003 (0.011)
Constant	10.615*** (2.746)	10.101*** (2.830)	6.153*** (2.122)	12.142*** (0.134)	12.131*** (0.152)	12.032*** (0.154)
Ownership fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	683	683	683	683	683	683
F (Log likelihood)	-1.6e+03	-1.6e+03	-1.6e+03	-7.7e+03	-7.7e+03	-7.7e+03
Prob>F (Chi ²)	0.000	0.000	0.000	0.0000	0.000	0.000
R ² (Pseudo R ²)	0.194	0.194	0.198	0.131	0.142	0.189

Note. Robust standard errors are presented in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01. *Distance* is divided by 1000 to adjust its unit in the results.

4.3. Refining the effects of distance and bank size on default

I further explore to refine the effects of *distance* and *bank size* on *default* in Table 3. In Models 1 and 2, I carry out a segmented regression approach and optimize a break point (*distance*=20) where the slope of the linear function changes to better fit to the data for different ranges of *distance*. Specifically, in Model 1 I run an OLS regression model with the group of samples that report *distance*≤20. In Model 2, I run an OLS regression model with the group of samples that report *distance*>20. I find the regression coefficient of *distance* is 7.484 in Model 1. This slope significantly decreases to 0.186 in Model 2. SU post-estimation tests the regression coefficients of *distance* across Models 1 and 2, and shows two regression coefficients are significantly different at the 5% level ($\chi^2=6.73$ and Prob> $\chi^2=0.018$). These results suggest that I find robust empirical evidence that start-ups that borrow from non-local banks tend to experience greater rates of default. Moreover, this effect of *distance* is significantly greater within the range of 20 miles.

To examine more specific effects of border lines, I include *same city* and *same state* in Models 3 and 4. While *same city* indicates -0.158 of regression coefficients with the effect statistically significant at

the 1% level in Model 3, *same state* indicates -0.060 of regression coefficient at the 1% level in Model 4. These contrasting regression coefficients can be interpreted in a way that if start-ups borrow 7(a) loans from banks located within the same city, their default risks considerably decrease. However, these boundary effects significantly decrease when start-ups borrow the loans from banks located within the same state. Conclusively, the effects of *distance* are greater when start-ups are located within the radius of 20 miles from lending banks or within same city border lines. These results suggest that the role of soft information is salient within these spatial ranges; and it is not necessarily much greater as the distance increases.

In Models 5 and 6, I use similar steps from Models 1 and 2 to better fit the data for different ranges of *bank size*. I optimize a break point ($bank\ size=11.69$) and split the sample into two groups: $bank\ size \leq 11.69$ and $bank\ size > 11.69$. While the regression coefficient of *bank size* in Model 5 is -0.012, *bank size* in Model 6 is 0.071. These results suggest that the negative effects of *bank size* on *default* are more salient in the range of $bank\ size \leq 11.69$. This finding is interpreted in a way that the size of banks decreases the likelihood of start-ups' defaults when lending banks are small and medium size banks. However, these effects are not necessarily consistent for very large banks.

Given the positive effects of large banks on start-ups' defaults, I redefine large banks as banks that operate in several states and use two independent variables, *national bank (16)* and *national bank (41)*, in Models 7 and 8. In Model 7, *national bank (16)* indicates a negative and significant regression coefficient, suggesting that national banks that operate in at least 16 states have decreased defaults. In Model 8, the regression coefficient of *national bank (41)* is considerably greater than that of *national bank (16)* in Model 7, suggesting that national banks that operate over 41 states have significantly increased the defaults. Combined together, I conclude that start-ups' defaults tend to decrease as the size of lending bank increases up to a point, but when the bank is too large, the defaults begin to increase. Arguably, this is because a large bank, when compared with its competitors, has difficulty maintaining a decentralized decision making structure that allows it to respond more to local market competition (Canales and Nanda 2011).

Table 3. Refining the effects of distance and bank size on default

	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable	Default	Default	Default	Default	Default	Default	Default	Default
Distance	7.484** (1.853)	0.186** (0.013)			0.433*** (0.038)	0.053*** (0.018)	0.238*** (0.016)	0.064*** (0.020)
Bank size	0.078 (0.021)	-0.174*** (0.018)	-0.072*** (0.017)	-0.070*** (0.018)	-0.012 (0.032)	0.071*** (0.018)		
Same city			-0.158*** (0.011)					
Same state				-0.060*** (0.020)				
National bank (16)							-0.045** (0.019)	
National bank (41)								1.199* (0.689)
Loan amount	-0.315** (0.158)	-0.538*** (0.124)	-0.474*** (0.094)	-0.455*** (0.092)	-0.362* (0.205)	-0.565*** (0.132)	-0.417*** (0.091)	-0.418*** (0.099)
Loan interest rate	-0.375*** (0.141)	-0.661*** (0.235)	-0.431*** (0.119)	-0.433*** (0.120)	-0.385* (0.221)	-0.563*** (0.151)	-0.430*** (0.117)	-0.441*** (0.120)
Bank net income	0.170 (0.347)	0.014 (0.184)	-0.011 (0.149)	-0.009 (0.148)	-0.413 (0.318)	-0.002 (0.233)	-0.002 (0.064)	0.058 (0.059)
Constant	7.120* (3.996)	3.963 (7.073)	10.678*** (2.883)	10.506*** (3.024)	-1.039 (6.185)	9.328** (3.691)	9.920*** (2.693)	10.380*** (2.772)
SME structure fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	380	303	683	683	261	422	683	683
F (Log likelihood)	-915.283	-669.711	-1.6e+03	-1.6e+03	-628.716	-965.414	-1.6e+03	-1.6e+03
Prob>F (Chi ²)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
R ² (Pseudo R ²)	0.263	0.370	0.196	0.194	0.274	0.309	0.209	0.199

Note. Robust standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. *Distance* is divided by 1000 to adjust its unit in the results. SU post-estimation tests the regression coefficients of *distance* across Models 1 and 2, and shows two regression coefficients are significantly different at the 5% level ($\chi^2=5.73$ and $\text{Prob}>\chi^2=0.0167$). Similarly, regression coefficients of *bank size* are significantly different at the 1% level across Models 5 and 6 ($\chi^2=43.97$ and $\text{Prob}>\chi^2=0.000$).

5. Discussion and Conclusion

This paper examines what information is used to evaluate and select promising high-tech start-ups in the entrepreneurial lending market. Based on SBA 7(a) loan activities involved with information technology based start-ups, this study finds that these start-ups tend to experience a lower rate of default if they are close to the lending banks and the lending banks are of considerable size. These conditions facilitate the lending banks to collect and utilize soft information regarding the focal start-ups.

These findings clarify the contributions of this study. First, the prior literature has not fully examined the nature of information used in the entrepreneurial lending market. This study attempts to fulfill this gap in the entrepreneurial finance literature by analyzing the defaults of high-tech start-ups. This analysis highlights the relational configuration between high-tech start-ups and lending banks. By

doing so, this study contributes to the ongoing debate about the optimal mechanism for nurturing high technology based entrepreneurs by the SBA.

Secondly, my findings expand our understanding about the entrepreneurial lending market by examining how a lending bank's location and size serve to access soft information regarding high-tech start-ups. This study suggests that a bank's capacity to access soft information reduces information asymmetry between the bank and high-tech start-ups, thereby enhancing effective selections on promising high-tech start-ups.

Finally, this study expands the information asymmetry theory within the context of entrepreneurial lending market. This theoretical application is particularly suitable to analyze how high-tech start-ups are willing to reveal soft information and what information lending banks use to reduce information asymmetry that is common in the entrepreneurial lending market.

Limitations from this study provide avenues for future research. This study did not fully consider the characteristics of start-ups mainly due to the lack of available data. To alleviate this concern, at least in part, this study used several fixed effects, including ownership, state, and year fixed effects. These fixed effects, however, cannot perfectly control for the several characteristics of high-tech start-ups, including firm specific technology and operation factors. Future studies need to examine how a start-up's specific characteristics interact with its entrepreneurial debt financing strategy to enhance the start-up's consequent performance.

Furthermore, future studies could probe more deeply into what financing sources a start-up tried to access, how it behaved with the financing sources, and whether the access was successful, prior to obtaining SBA loans. For example, it is possible that a start-up searched lending opportunities at larger or local banks but was rejected prior to applying for SBA loans at a distant bank. This possibility may provide alternative explanations for the empirical results of this study. Future studies need to more fully explore the dynamics of a start-up's debt financing activities.

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