How Much does Credit Matter for Small Business Success in the United States?

Cesare Fracassi
UT Austin

Mark J. Garmaise
UCLA Anderson

Shimon Kogan
UT Austin

Gabriel Natividad
NYU Stern

Abstract

A lot. Using data on startup loan applicants from a U.S. lender that employed an automated algorithm in its application review, we implement a regression discontinuity design assessing the causal impact of receiving a loan on entrepreneurial success. Obtaining a relatively small loan has a strong effect on the long-term financial position of startups. Startups receiving funding are dramatically more likely to survive, enjoy higher revenues and create more jobs. Loans are more consequential for survival among entrepreneurs with more education and less managerial experience. Access to credit creates a skewed firm size distribution by enabling quite small firms to succeed.

JEL codes: G32, L26, M13

We would like to thank Catherine Meyrat, Nelly Rojas-Moreno, and Duangkamol Phuengpanyalert for their guidance about Accion's institutional details. We are grateful to Manuel Adelino, Nishant Dass, Joan Farre-Mensa, Thomas Hellmann, David Robinson, and audiences at Berkeley, Instituto de Empresa, NYU Stern, Rutgers, UCLA, Wharton, the ASU Finance Conference, the Napa Conference on Financial Markets, the SFS Finance Cavalcade, the Texas Finance Festival, the UBC Winter Finance Conference, and the UNC-Duke Corporate Finance Conference for useful comments. We also thank Rosy Manzanarez, Alejandra Garcia, and Siddharth Subramanian for their research support. Garmaise gratefully acknowledges support from the Harold and Pauline Price Center. Contact information: `cesare.fracassi@mccombs.utexas.edu`, `mark.garmaise@anderson.ucla.edu`, `shimon.kogan@austin.utexas.edu`, `gnativid@stern.nyu.edu`.

After decades spent studying whether access to credit matters for economic development around the world (King and Levine 1993, Rajan and Zingales 1998), attention is now turning back to the United States. In particular, the funding of small businesses has become a pressing policy concern. For example, President Obama's Affordable Care Act provides substantial exemptions for firms with fewer than 50 employees, which account for 5.8 million out of 6 million total firms, in the interest of saving money for small business growth.[1] But what is the economic impact of small business access to credit in the United States? The answer to this basic question has implications for different areas of economics such as macroeconomics, public finance, industrial organization, and corporate finance. From a policy implementation standpoint, moreover, an inherently related question is what kinds of business owners make the best use of small business financing. As loan supply is limited, the adequate targeting of credit to the most promising prospects may help magnify the impact of credit on small business success.

On the first issue of the importance of credit, consider a potential loan to a small firm from a given lender. It may be argued that this funding will have a large impact on the firm's success, as loans typically represent a major source of small business financing (e.g., Bates (1990), Black and Strahan (2002), Robb and Robinson (2012)), and early-stage credit may enable entrepreneurial ventures to invest in value-creating opportunities and achieve necessary scale. On the other hand, there are reasons to suggest that the effect of the loan will be minimal. Specifically, there is evidence that entrepreneurs who cannot obtain bank financing are of relatively low quality (Kerr and Nanda (2009), Cetorelli (2009) and Andersen and Nielsen (2012)). In that case, good firms that are rejected by one lender will find financing elsewhere, while poor firms that do receive a loan will be unlikely to succeed in any event. Moreover, there are indications that liquidity constraints do not matter much for entrepreneurial firm creation (Hurst and Lusardi (2004)) and some surveys suggest that

[1] See examples at `http://www.whitehouse.gov/healthreform/small-business/tax-credit/cases`.

small firms are unlikely to be financially constrained (Angelini and Generale (2008)). Further, there has been considerable debate on whether financial constraints matter for small firm growth trajectories in developed economies, as financial capital may be substituted for by other available factors (e.g., Carpenter and Petersen (2002), Beck, Demirguc-Kunt, and Maksimovic (2005)) and entrepreneurs may be able to self-fund using retained earnings (i.e., bootstrap) or by having recourse to family wealth. In short, there is no firm consensus on whether or how much credit matters for small businesses' economic success.

On the second issue of what kinds of small business owners make the best use of early-stage financing, an answer would be of particular relevance for business and public policy implementation. Given the limited availability of capital for the large mass of small businesses, suppliers of early-stage financing such as government agencies, banks, and angels would prefer to place funds with entrepreneurs who receive the greatest benefit from capital. However, while different weights have been found for entrepreneurs' wealth (Bitler, Moskowitz and Vissing-Jørgensen (2005)), education (Parker and van Praag (2006)), managerial experience (Kaplan, Sensoy and Strömberg (2009)), or credit scoring (Berger, Frame and Miller (2005)) as direct drivers of venture success, it is not clear whether these attributes also serve as multipliers of the effect of credit on new small business performance.

This paper provides new evidence on the importance of access to credit for small business success and on the differential effects of access to credit across business owner characteristics. In particular, we study each and every startup loan application received by Accion Texas, a financial institution providing loans to U.S.-based startups in a wide range of business activities in the period 2006–2011. (Startups are defined as new businesses with six or fewer months of operation.) Importantly, Accion Texas does not target high-tech growth companies likely to emerge as high-profile IPOs. The applicant firms in our sample are typically in the business services, small retail, and restaurant industries. As emphasized by Hurst and Pugsley (2011), firms in these types of sectors constitute the large mass of small businesses in the U.S. Hurst and Pugsley (2011) also make the point that small employers with fewer than 20 workers account for almost 20% of U.S. private employment and that most of these firms do not engage in innovation or intend to grow very big in size. According to the U.S. Census, in addition to these employers, there were in 2008 over 21 million nonemployer firms (i.e., sole proprietorships with no other workers) with close to $1 trillion in total sales. It is also the case that the applicants we study are more likely to belong to minority groups than typical entrepreneurs. As we discuss in more detail below, minority small business owners constitute a growing proportion of all entrepreneurs, especially in certain regions of the U.S. such as Texas. In this sense, our application-level database offers a rare window into a growing sector of the American economy that has received very little scholarly attention.[2]

Our empirical approach complements existing studies in four ways. First, the institutional features of Accion Texas, the Lender, enable a sharper research design. The Lender employed a proprietary computer algorithm in its review process for startups applying for a loan. For each applicant, the Lender's algorithm calculated a function of the income and expenses that was defined to be the applicant's borrowing capacity score. Applicants with a capacity score below a fixed threshold set in advance by the Lender were recommended for automatic rejection; those above the threshold were further reviewed towards receiving a loan. We exploit this formula and threshold, which were not known by the applicants, as the basis for a regression discontinuity design assessing the causal impact of access to credit on a startup's economic success going forward. The sharply discontinuous rule of this Lender allows us to obtain more precise estimates of the effect of access to credit than survey studies in which the endogeneity of loan making processes cannot be addressed. Second, our data focus exclusively on "entrepreneurs," that is, "owners of small business startups with six or fewer months of operation," thus providing a clearer definition to a literature that has often

[2]See Einav, Jenkins, and Levin (2012) for a study of consumer finance analyzing loan application-level data from a single firm serving the subprime market in the United States.

raised interpretation concerns about what entrepreneurship or small businesses really mean (Cagetti and De Nardi (2006), Neumark, Wall, and Zhang (2011), Haltiwanger, Jarmin, and Miranda (2013)). Third, the presumed unattractiveness of this applicant pool to the eyes of mainstream banks makes our Lender almost a last resort for credit. While this lack of substitution (which we also test) may be more common in some U.S. banking markets than others, we view it as advantageous to help isolate the economic impact of receiving a loan from the competitive effects that would be expected in an integrated financial market. Fourth, the multi-year structure of our data allows us to estimate the effects of access to credit on future economic outcomes such as business survival, employment and revenue growth for both accepted and rejected loan applicants. The magnitude of these effects is an important yet understudied question in a literature mostly focused on the determinants of access to credit rather than on its impact on subsequent small business success.

We use a regression discontinuity design to estimate the effect of access to credit on subsequent outcomes, essentially contrasting a startup that just meets the capacity threshold to be further reviewed for a loan with another startup that falls just below the capacity threshold. We first show that crossing the capacity threshold in the automatic review process led to a discontinuous increase in the probability that a nascent firm was granted a loan by the Lender. We check that observable characteristics of applicants above and below threshold did not vary discontinuously at the time of application, thus confirming that above and below threshold applicants are quite similar in every respect, except that above threshold applicants were substantially more likely to receive a loan. We also find no evidence of differences in the density of capacity scores around the threshold, concluding that this flat density both below and above the threshold is not consistent with systematic manipulation. We therefore use whether a startup was above threshold in the automatic review process as an instrument for loan provision. In essence, the Lender's algorithm allows us to employ observational data in a quasi-experimental design to assess the causal impact of early-stage credit on small business future success.

Using our instrumenting strategy, we find that receiving a loan has a large positive effect on the subsequent financial position of an applicant across its lending relationships; the total future secured debt of applicants granted a loan significantly increases compared to that of rejected applicants. This suggests that rejected applicants do not easily substitute other financing for the rejected loan.

We then examine the causal impact of receiving a loan on entrepreneurial success. Applicants belong to a segment of the economy for which survival is a first-order measure of success, especially in our sample period (2006–2011). Defining survival as being active in business in May 2012 with the same owner as that of the time of application, only 30% of the startup applicants in the sample survived. Using our instrumenting strategy, we find that receiving a loan increases survival probability by 51 percentage points, suggesting that the impact of early-stage financing on success is enormous, despite the relatively small size of these loans (with a median amount of about $11,000, not much different from the typical startup capital of U.S. small businesses). We also find that receiving a loan has a positive and significant effect on startups' revenue growth rate, revenue levels, and number of employees. Our results thus indicate that providing early-stage loans substantially enhances small businesses' future economic performance across several important dimensions.

The large magnitude of the impact of financing that we find raises the question of whether this result may almost be mechanically linked with entry, as if those applicants who receive loans can start their businesses while those who do not must close down. We emphasize that for the bulk of the firms in the sample we are measuring survival 3-5 years after the loan application is made. In other words, we are not considering simply if the firm continues until the next year, but rather whether it is able to maintain itself as a going entity for a significant period of time. What is most striking about our finding is that relatively small loans can have a tremendous influence on the medium-term survival of these startups.

Having found a large effect of early-stage financing on small business success, we next analyze what kinds of entrepreneurial characteristics may enhance this impact. Using our instrumenting approach across split samples, we find that the effect of receiving a loan on startup survival is significantly larger for more educated entrepreneurs. We show that a loan from our Lender helps increase the probability of future secured debt financing for entrepreneurs of both high and low education, but it is apparently only the former that have the ability to use the credit to increase their survival probability.

More surprisingly, we find that receiving a loan has a significantly larger impact on survival for entrepreneurs *without* prior senior managerial experience. We show that a loan has a large effect on the future financings of these entrepreneurs, while entrepreneurs who have previous senior management experience appear to be able to obtain debt from other sources. Other entrepreneurial characteristics such as credit score or industry experience have no observable effect on the relative benefit of a loan.

We also analyze the impact of variation in the intended size and use of the requested loan. We find that the loan amount requested is unrelated to whether receiving the loan influences entrepreneurial survival. By contrast, receiving a loan has a larger effect on survival when the application is made for purposes different from funding working capital (i.e., equipment purchase, advertising). Taken together, our findings suggest that financing does not have an indiscriminate effect. Entrepreneurs with high education, no prior senior management experience, or a plan to invest in something other than working capital will make for the most attractive recipients of funds, from the point of view of either an early-stage investor or a policy maker.

A natural extension of our analysis focuses on the impact of financial constraints on the size distribution of firms. We find that access to finance creates a skewness in the distribution of small firms, by providing essential support that keeps some quite small businesses in operation. This is in contrast to the findings of Cabral and Mata (2003) and Angelini and Generale (2008), who analyze survey-based data on European firms larger than ours and show that it is financial constraints that generate skewness in the firm size distribution by limiting the growth rate of firms that lack capital. Our results thus help provide a nuanced picture of the impact of financing on the firm size distribution, with contrasting effects for small and medium-sized firms that could be more broadly useful when assessing the product-market ramifications of access to credit.

Our findings shed new light on a growing policy debate on the real consequences of small business funding in the United States that has received very little academic attention. The small business environment in the U.S. significantly differs from that in developing countries in which randomized grant allocations and microloans have been recently analyzed (e.g., de Mel, McKenzie and Woodruff (2008), Karlan and Zinman (2010)), often without a consensus on their benefits. Individuals in the U.S., unlike those in many emerging markets, typically choose to be entrepreneurs, growing their ventures if they succeed, or closing their firms to seek outside employment if they fail. Our work provides direct evidence on the impact of early financing on these outcomes. Our study also complements Kerr, Lerner, and Schoar's (2012) emphasis on large angel funding for firms seeking to go public; we analyze a large sample of small firms in a relatively understudied sector of the economy for which loans are a primary source of capital. Finally, our study is one of the very few benefiting from full access to the internal loan making processes of an American financial institution to assess its broader impact on U.S.-based business clients; in the context of a vast literature on bank-firm relationships in the United States, our methodology offers a new path to a deeper understanding of the role of financial institutions in economic activity.

1 Data

To assess the impact of receiving early-stage credit on entrepreneurial success, we assembled a data repository merging three data sets obtained from different sources. The main data set used in this paper is proprietary and comes from Accion Texas Inc., a U.S.-based financial institution whose sole purpose is to provide loans to small businesses. In this paper we analyze the complete set of startup loan applications received by Accion Texas between 2006 and 2011; the Lender defines startups as businesses in existence for six or fewer months. The applicants requesting funding operated in a wide range of businesses in a geographic footprint including mainly Texas and Louisiana. As described in Table I, loan amounts granted to these nascent firms were small, an average loan size of $15,552. Loans were payable over 36 months on average, and the mean annual interest rate was 11.5%; these terms exhibited relatively little variation across borrowers. The stated purpose of the loans consisted mainly of working capital, equipment purchase, and advertising. The personal self-stated background of the entrepreneurs indicates that they had an average twelve years of education and almost ten years of industry experience. Moreover, around 10% of applicants had prior senior management experience. The businesses reported an average annualized revenue of $30,028 per year at the time of application. The data also include application information and loan decisions, as described in greater detail in Section 1.2 below. In total, we observe a 18.2% loan approval rate.

The second source of information is Dun and Bradstreet (D&B), which provides a regularly updated registry of existing businesses. In particular, we use D&B's matching procedures to determine the status as of May 2012 of all startup businesses that applied for loans. Firms that are successfully matched to D&B's database are considered to have survived. Overall, the survival rate was between 28% and 32%, depending on the criteria used for matching. We also use D&B's information on business revenues and number of employees to measure the growth of surviving firms.

Finally, we use identifiers provided by the Lender to match the *entrepreneurs* with their public records using Lexis Nexis Person Locator. Lexis Nexis provides a panel data set of these records for individuals over time. Specifically, we obtain data indicating business activity such as Uniform Commercial Code (UCC) secured loans[3] before and after the application date and proxies for personal financial distress such as bankruptcy filings and tax liens. On average, around 8% of the entrepreneurs in our sample had UCC secured loans at some point prior to applying to Accion Texas and 16% obtained new UCC secured loans in the period after the application date.

1.1 Individual Owner Demographics and Business Characteristics

Our research design exploits rich data on a large sample of startup loan applicants in Texas and Louisiana, but it is also useful to clarify to what extent these applicants resemble the typical U.S. small firm owner. To this purpose, we compare our sample with the U.S. Census statistics from the 2007 Survey of Business Owners (SBO). The Census SBO reports demographic information about business owners both nationwide and by state for established and newly formed businesses (i.e., less than 1 year). Business owners in our sample appear to be quite representative of the median business owner in Texas and nationwide in terms of gender, age, and education. In our sample, 42% of business owners are women, compared to 38% nationwide, 39% in Texas, 43% for newly formed US businesses, and 42% for newly formed Texan businesses. The median business owner age in our sample is 39 years, compared to 50 nationwide and in Texas, and 40 for new business owners in US and Texas. The median business owner education in our sample is 13 years, compared to 14 for US and Texan business owners.

[3] UCC is a state-level filing registry that records loans secured by fixed assets.

Ethnicity is a demographic characteristic in our sample that is skewed relative to the U.S. and Texas. Sixty three percent of Accion's borrowers are Hispanic. This contrasts with the Census SBO where only 9% and 22% of business owners are Hispanic in the U.S. and in Texas, respectively, suggesting that Accion Texas's serves an applicant pool with a larger Hispanic share. Ethnicity in our sample also differs from Hurst and Lusardi's (2004) description of entrepreneurs who are very largely white, a difference that may be explained by timing and geography, as Hurst and Lusardi describe entrepreneurs nationwide during a period ranging from the late 1980s to the mid-1990s. With this caveat in mind, the oversampling of minority applicants in our pool may serve as a window into the future given demographic current trends. According to the Small Business Administration, in Texas in 2011, minorities accounted for 41% of self-employed individuals. Moreover, over the period 2000-2011 minority self-employment in Texas grew by 76%, compared to 17% growth in overall self-employment. Nationally, minorities accounted for 22% of self-employment in 2011, and over the period 2000-2011, minority self-employment grew by 30%, while overall self-employment grew by only 6%. In other words, minority small business ownership has grown dramatically in the recent period.[4]

A list of the most common business lines for the applicants is given in Table II. A comparison with the U.S. Census statistics on small businesses cited by Hurst and Pugsley (2011) is informative of the industry representativeness of our sample. In common with their description, our applicants are focused in the areas of business services, restaurants and small retail; by contrast, one major category in the census data that is largely missing from our sample is skilled professionals (e.g. doctors and lawyers). Overall, while the industry focus of the firms in our sample is not likely to generate tremendous growth or technical innovation as discussed by Hurst and Pugsley (2011), in this respect these applicants are

[4]Source: Small Business Administration data available at http://www.census.gov/econ/sbo/pums.html and http://www.sba.gov/sites/default/files/us12.pdf.

broadly representative of U.S. small businesses.

Given the scale and scope of small business in the United States, it is also useful to assess what is the typical amount of startup capital small businesses require. In this respect, Accion's applicants are also quite representative of U.S. small businesses, with the median loan amount requested of $11,344 compared with the SBO's median startup capital of $7,500.

Overall, our sample appears to be representative of a large segment of U.S. small businesses in terms of owner demographics (except for ethnicity), industry focus, and scale. One last relevant characteristic of our sample is the focus of the financial institution providing capital. Accion Texas is a private non-profit financial institution and, as such, it mission is to target its loans at small businesses that are likely to not have access to commercial bank financing. Thus, for many of the applicants of interest, Accion is likely to be the lender of last resort. This feature, which we address more fully in our empirical tests, may constitute an advantage to help isolate the causal impact of receiving a loan from this Lender on future economic outcomes.

1.2 Automatic Review of Loan Applications

To lower the processing costs of loan application reviews, Accion Texas developed a proprietary algorithm designed to help screen loan requests at the initial stage. The algorithm used information from the application to automatically review all startup loan applications. One of the criteria for denial depended on the applicant's "borrowing capacity," defined by the Lender as a score using a proprietary formula based on personal income and expenses, business rent and pro forma loan payments. Applications with capacity below zero were automatically recommended for denial. Applicants were not aware of the formula used to calculate the capacity score, nor were they informed of the threshold level. Other information (such as an active bankruptcy) would also trigger an automatic denial. As we discuss below, the automatic review process had a material impact on the probability of the granting of a loan. Of course, applicants whose capacity exceeded zero were not guaranteed loans; they were subject to further review that may or may not have led to the granting of credit.

Our data set includes these capacity scores, final decisions on the loans (whether a loan was issued and at what terms), and the threshold.[5] It is important to note that the data set does not suffer from a survivorship bias, as it includes all applications submitted during the sample period, irrespective of the final decision. Figure 1 shows that there is a thick mass of applicants both below and above the capacity threshold of zero, suggesting that a comparison of these applicants is meaningful.

2 Empirical Specification

We study the impact of the provision of financing on the success of entrepreneurial ventures. We are interested in whether the granting of a loan to a small business has a causal impact on the firm's future fate. Specifically, we estimate equations of the following form:

$$Firm\ characteristic_{i,t'} = \alpha + \beta * Loan_{i,t} + \gamma * controls_{i,t} + \lambda_t + \epsilon_{i,t}, \tag{1}$$

where $Firm\ characteristic_{i,t'}$ is an attribute of entrepreneurial firm i in future period t', $Loan_{i,t}$ is an indicator for whether firm i was granted a loan in period $t < t'$, $controls_{i,t}$ is a vector of controls, λ_t is a year fixed effect and $\epsilon_{i,t}$ is an error term. Each firm is observed at two points in time: initially at time t of the loan application (where t lies between 2006 and 2011) and later at time $t' = 2012$ at the end of the sample period.

[5] The analysis excludes 51 of the 5,455 observations for which data about the capacity score is missing.

Equation (1) may clearly not be estimated directly using ordinary least squares (OLS) because the provision of financing is endogenous; better firms are more likely to receive loans, and any observed correlation between entrepreneurial success and the provision of credit may be attributed to a Lender's ability to direct loans to firms that are superior. There will always be firm attributes that are not observable by an econometrician, so it is not possible to control for all potentially omitted variables.

To address this problem, we make use of a regression discontinuity design that exploits the nature of the Lender's automatic review process. We define an indicator variable I_C that denotes applicants with capacity above the threshold:

$$I_C = \begin{cases} 1 & \text{if capacity} \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

We test whether there is a discontinuity in loan provision at the automatic review threshold by estimating the following model:

$$Loan_{i,t} = \zeta + \delta I_{Ci,t} + \sum_{j=1}^{n} \omega_j^C C_{i,t}^j + \sum_{j=1}^{n} \xi_j^C I_{Ci,t} C_{i,t}^j + \kappa * controls_{i,t} + \eta_t + \sigma_{i,t}, \tag{3}$$

where $C_{i,t}$ is the capacity of the applicant, $I_{Ci,t}$ is an indicator for whether this capacity is above zero, η_t is a year fixed effect and $\sigma_{i,t}$ is an error term. We consider polynomials in capacity of varying degree n.

The coefficient of interest in (3) is δ, which measures the discontinuity (if any) in the probability of loan provision at the capacity threshold. If δ is non-zero, then there is a jump at zero capacity in the probability of whether credit is granted. Entrepreneurs with capacity just below and just above zero are likely very similar, so the above-threshold indicator $I_{Ci,t}$

can essentially serve as an instrument for loan provision. We jointly estimate (3) and

$$Firm\ characteristic_{i,t'} = \alpha + \beta * Loan_{i,t} + \sum_{j=1}^{n} \mu_j^C C_{i,t}^j + \sum_{j=1}^{n} \pi_j^C I_{Ci,t} C_{i,t}^j \tag{4}$$

$$+\gamma * controls_{i,t} + \lambda_t + \epsilon_{i,t},$$

using 2SLS (two-stage least squares). We estimate (3) using a linear model despite the binary value for the *Loan* variable, because in our main specification we make use of a number of fixed effects, which generates the nuisance parameter problem in non-linear maximum likelihood estimation (Abrevaya (1997)). Linear models are not subject to this issue. Our approach makes use of the main elements of the regression discontinuity designs presented by Card, Dobkin, and Maestas (2004), and Matsudaira (2008).

In essence, we compare subsequent outcomes for entrepreneurs that are just above and below the capacity threshold. Because the Lender bases its decisions on the capacity score threshold, these entrepreneurs are very similar at the time of application, but they differ specifically in one respect: above threshold entrepreneurs are more likely to receive loans. Our set-up therefore allows for a quasi-experimental design in which credit is basically allocated randomly. We can then interpret any differences we observe in firm success to the causal impact of loan provision. We would like to make clear that this specification does not assume that capacity itself has no impact on loan provision. Indeed, we include in (3) terms allowing for a non-linear effect of capacity on whether a loan is granted. The identifying assumption in our regression discontinuity analysis is that a jump in loan provision specifically at the automatic cutoff threshold is driven by the Lender's policy and not by a discontinuity in some unobservable borrower characteristic.

For some tests we consider whether the provision of loans has a greater impact on the success of different types of applicants by estimating (3) and (4) in disjoint subsamples.

3 Results

3.1 Automatic Review and Loan Provision

We begin by analyzing the impact of the automatic review process and the applicant capacity threshold on the provision of credit. As we discuss above, applicants with capacity below zero were slated for a denial recommendation. There were other criteria, however, that triggered denial (e.g., if the applicant was in the midst of an active bankruptcy). Did the capacity threshold have a significant effect on the probability of an auto-denial?

To consider this question, we regress a dummy for an auto-denial on an indicator for above-threshold capacity and third degree polynomials in capacity on both sides of the threshold. As we show in the first column of Table III, there is a jump of -47.0 percentage points (t-statistic=-28.91) in the probability of an auto-denial precisely at the threshold of zero. The overall likelihood of an auto-denial is 49.8%. In other words, falling just below the capacity threshold more than doubles a applicant's probability of an auto-denial, relative to the mean. A graphical representation of this jump is displayed in Figure 2. Clearly the capacity threshold has a very large impact on whether the applicant receives an auto-denial.

The central question, however, is whether the capacity threshold has a significant impact on the provision of a loan. That is, does the regression discontinuity design provide an instrument for the granting of credit? Summary statistics provide some initial information: applicants who receive an auto-denial are given a loan with probability of 6.1% and those who do not receive an auto-denial are provided financing with a probability of 30.4%. This suggests that the auto-denial is sometimes overridden by the Lender but that it may nonetheless have an important effect on the final credit decision.

To determine the specific nature of this effect, we consider whether there is a discontinuity in the probability of loan provision at the capacity threshold of zero. Formally, we estimate equation (3) by regressing a dummy for loan provision on an indicator for above-threshold capacity and third degree polynomials in capacity. We find, as we display in the second column of Table III, that there is an jump of 11.3 percentage points (t-statistic=8.78) in the probability of a loan for applicants with capacity just above zero. This is a large effect: applicants with capacity just below the zero threshold experience a reduction in their likelihood of receiving credit of over sixty percent, relative to the overall mean loan probability of 18.2%. A graphical representation of this analysis is displayed in Figure 3.

It is evident that loan provision increases discontinuously at the threshold, but the increase in probability is not from zero to one; in other words, this is a "fuzzy" regression discontinuity design. Other unobserved variables likely affect the Lender's decision about whether to grant a loan, but that does not invalidate the identification. Identification arises essentially from a comparison of above and below threshold applicants, and we use this comparison as an instrument for loan provision, thereby enabling us to uncover the causal effect of receiving a loan, independent of any unobserved variables. All that is required for identification in this "fuzzy" design setting is a discontinuous jump in the probability of loan provision at the threshold (Hahn, Todd and Van der Klaauw, 2001) and that is clearly present here.

The basic loan provision finding is robust to other specifications. Reducing the polynomial order to two yields an estimate of 12.9 percentage points (t-statistic=10.99) and increasing it to four generates an estimated coefficient of 9.2 percentage points (t-statistic=6.11), as shown in the third and fourth columns of Table III.

The above specifications do not include controls other than the polynomials in capacity.

These tests rely on the identifying assumption that above- and below-threshold capacity applicants are relatively similar (or at least not discontinuously dissimilar). We also estimate the loan provision regression (3) with controls for the applicant's credit score, an indicator for a past bankruptcy, year of application fixed effects and fixed effects for the applicant's line of business. Standard errors are clustered by line of business. As we display in the last column of Table III, this specification yields an estimate of 11.3 percentage points (t-statistic=7.07) for the impact of above-threshold capacity on loan provision. The magnitude of this coefficient is very similar to the estimate without controls in the second column of Table III.

3.2 Capacity Threshold and Applicant Characteristics

3.2.1 Assessing Discontinuities in Observables

We showed in Table III that loan provision jumps at the capacity threshold of zero. Our empirical specification relies on the assumption that applicants do not vary discontinuously around the threshold. While we cannot test this assumption for all variables, we can provide evidence on observable applicant characteristics around the zero threshold. First we assess the impact of the threshold on the probability that an applicant has a prior bankruptcy filing. We regress a dummy for a prior bankruptcy on the indicator for above-threshold capacity and the third degree polynomials in capacity. As shown in the first column of Table IV, the above-threshold indicator has an insignificant coefficient of -0.0115 (t-statistic=-0.83).

We also find, as detailed in the second and third columns of Table IV, that both the probability that the applicant previously had a tax lien placed against his property and applicant credit scores are not significantly different between above- and below-capacity borrowers. Thus, the threshold does not appear to be linked to systematically different credit histories for applicants.

Other applicant qualities also appear unrelated to the capacity threshold of zero. A Uniform Commercial Code (UCC) filing documents a lender's security interest in the property of an individual or firm and is often associated with small business financing. UCC filings typically describe security interests in collateral such as general office equipment or machinery. The major categories of secured debt not covered by UCC filings are loans against real estate or motor vehicles, which are usually documented in other forms (e.g. mortgages and vehicle liens). Prior UCC filings provide evidence of previous entrepreneurial financing. We find, as documented in column four of Table IV, that there is no significant jump in prior UCC filings at the capacity threshold. The applications also provide information on the applicant's years of formal education and industry experience. Neither the log of years of education nor the log of years of industry experience is significantly different between above- and below-threshold applicants, as displayed in columns five and six of Table IV.

The regression results detailed in Table IV are described graphically in Figure 4. Overall, we find no evidence that applicant characteristics are significantly different for those just above and just below the threshold of zero.

3.2.2 Assessing Threshold Manipulation

Did applicants or loan officers manipulate capacity scores so as to allow certain types of applications to pass the automatic review? To analyze this question it is first important to note that applicants did not know the capacity formula or cutoff. The data used to calculate the formula were verified by the Lender. Though document falsification is certainly not impossible, without a knowledge of the capacity formula and cutoff, applicants could not target their scores to exceed the threshold, and applications just above and below the threshold should not differ in their potential susceptibility to fraud. This suggests that any manipulations by applicants alone should not have any effect on our regression discontinuity analysis.

Loan officers, on the other hand, may have had some knowledge of the formula and/or threshold. Did they manipulate scores? There are several pieces of evidence to suggest that in general they did not. First, as described in Table IV, there do not appear to be any systematic differences in the observable characteristics of above and below threshold borrowers. Loan officers did not sort borrowers into the above threshold category based on any of these characteristics. Second, Figure 1 uses McCrary's (2008) estimator to depict the density of capacity scores from the 10th to 90th percentiles. As is evident from the figure, there is no meaningful drop in the density of applicants with capacity scores just below the threshold. McCrary's formal test estimates the log difference in kernel heights as -0.009 (*t*-statistic= -0.11). (The bin size of 0.09 and bandwidth of 1.23 are selected using McCrary's automatic algorithm.) That is, the density is quite flat both at and below the threshold. Any systematic effort by loan officers to manipulate scores would have led to a sharp drop in the density of below threshold applicants, as these applicants would have been shifted into the above threshold category. There is no evidence of that phenomenon in the data.

3.3 Incremental Financing

We now turn to the question of the impact of our Lender's financing on entrepreneurial firms. The evidence in Tables III and IV establishes that the capacity threshold generates a quasi-experimental allocation of loans to applicants who are very similar to those who do not receive credit. In this section we consider the incremental effect of the Lender's loan on the overall financial status of an applicant. Presumably rejected applicants could seek financing from other sources. In a well-functioning loan market every worthy entrepreneur should be funded and a rejection by one lender should not have an effect on an entrepreneur's ability to raise capital from other credit providers. Are rejected applicants able to secure replacement funding?

While we do not have access to the full balance sheets of these entrepreneurial firms, we do have a listing of all UCC filings for 98% of the entrepreneurs. We define $Any\,Subsequent\,UCC?$ to be a dummy indicating whether the applicant is listed as a debtor on any UCC filing subsequent to the application date. To assess the effect of the Lender's loan on the overall financing of the applicant, we estimate (3) and (4) via 2SLS, where the firm characteristic is $Any\,Subsequent\,UCC?$. That is, we use above-threshold capacity as an instrument for loan provision and study the causal impact of the Lender's granting credit on the subsequent financing of the applicant. For this specification we include all the standard controls and cluster by line of business.

The results, displayed in the first column of Table V, show that loan provision (instrumented) increases the probability of a subsequent UCC filing by 53.9 percentage points (t-statistic=4.79). This is a large effect compared to the overall mean of 15.7 percent for $AnySubsequentUCC?$. In other words, the loan from the Lender has a substantial impact on the total borrowing of an applicant. This suggests that rejected applicants cannot fully substitute other financing for the lost loan. Is there evidence of any degree of substitution? It might be argued that without some form of substitution, the effect of a loan should be to increase the probability of a later UCC filing by 100 percent. The fact that the coefficient on loan provision is different from one, however, should not be over-interpreted, as not all financing from the Lender are associated with a UCC filing (e.g., it may involve an unsecured loan).

To provide more evidence on substitution, we define a new dummy variable indicating whether the borrower is a debtor on any subsequent UCC filing in which the creditor is different from our Lender. We regress this indicator on the instrumented loan provision and find, as displayed in the second column of Table V, an insignificant effect (coefficient=-0.038 and t-statistic=-0.44). There is thus no evidence that rejected applicants are more likely than accepted applicants to secure financing from other sources. We view this as an indication that rejected applicants are unable to substitute new loans in place of the financing they did not receive from our Lender. While this lack of substitution may be a more common feature of some U.S. banking markets rather than others, we view it as advantageous here to help isolate the impact of receiving a loan from this Lender on future outcomes.

3.4 Entrepreneurial Survival

The results in Table V suggest that a loan from our Lender grants significant incremental funding to accepted applicants and that rejected applicants do not replace the lost credit with other financing. We now focus on the central issue of the paper: what are the causal real effects of financing on entrepreneurial firms?

The most basic measure of firm success is survival. To assess survival rates, we match each applicant firm to firms in the Dun and Bradstreet (D&B) private company database in May 2012 using their Optimizer matching program. We identify a firm as surviving if it meets all the following criteria:

- The applicant's firm is matched to a D&B company by the Optimizer program.
- The D&B company is listed as an active business with employees.
- The owner of the applicant's firm is the same as the owner of the D&B company.

For the third criterion, we count two last names as the same if they have 80% of their letters in common (Braun and Schwind 1976). Below we show that our results are robust to insisting on a 100% match rate.

Using this procedure, we find that 30.1% of all applicant firms have survived into May 2012. Given the low general survival rate of young firms (Headd 2003) and the difficult economic conditions during the sample period, this rate appears reasonable.

We regress an indicator for survival in May 2012 on instrumented loan provision, third degree polynomials in capacity and year fixed effects. (Survival rates will of course differ across applications made in different years, but the year fixed effects account for that.) The result, detailed in the first column of Table VI, shows that the coefficient on loan provision is 54.6% (t-statistic=3.44). Applicants who received loans were far more likely to survive. This is strong evidence that receiving a formal loan is crucial for entrepreneurial success. Alternative strategies for starting a business without formal credit are often proposed to constrained entrepreneurs. These may include bootstrapping (self-financing), vendor financing, borrowing from family and friends or simply growing slowly. For our sample of entrepreneurs, however, it is clear that receiving a loan from a financial institution yields tremendous benefits. Despite the relatively small size of the loans (the mean amount is $15,552), formal credit has a first-order effect on entrepreneurial survival.

Including business line fixed effects and the full set of standard controls, the estimated effect of loan provision remains strong, as displayed in the second column of Table VI (coefficient=51.0 percentage points and t-statistic=2.58). Requiring that the owner names in the application and D&B record exhibit a 100% match reduces our estimated survival rate to 28.2%. Using this exact match to define survival generates a coefficient on instrumented loan provision of 48.2 percentage points (t-statistic=2.32), as detailed in Table VI, column 3.

In the fourth column of Table VI we show the result from the reduced form regression of survival on capacity above threshold including the polynomial controls. As expected, the estimated effect is positive and significant (coefficient=6.22 percentage points and t-

statistic=3.34). A graphical representation of this regression is displayed in Figure 5. Given the 11.3 percentage point increase in loan provision associated with having a capacity above threshold (as described in the fifth column of III), the 6.22 percentage point increase in survival in the reduced form regression is broadly consistent with the 51.0 percentage point estimate from the 2SLS regression in the second column of VI (as $6.22/11.3 = 0.55 \approx 0.51$).

One hypothesis is that the Lender provides follow-up financing to its borrowers, thereby keeping them essentially on life-support and mechanistically boosting their survival rate. While this would still arguably be a form a survival, it is not a significant phenomenon in our data. Only 4.3% of the borrowers receive follow-up loans. We find in untabulated results that excluding these borrowers has little effect on the estimated impact of loan provision.

3.5 Narrow Windows

To complement our standard polynomial regression discontinuity analysis using the full data set, we also consider a comparison of outcomes for above and below threshold applicants in varying narrow windows around the threshold. In Panel A of Table VII we display the results from regressing a dummy for auto-denial on an indicator for above threshold capacity and year and business line fixed effects in capacity windows varying from $[-2, +2]$ to $[-0.5, +0.5]$. The estimates are similar, and are in the range of the 0.47 coefficient estimated in the first column of Table III. Although, as expected, statistical significance declines as the sample narrows, all the estimates are highly significant. Table VII, Panel B details the analogous regressions for loan provision, and the estimates are again all significant and similar to one another and to the coefficients in the range of 0.09-0.13 estimated using the polynomial approach, as described in Table III, columns two through five. In Table VII, Panel C we describe the results for survival. These estimates exhibit somewhat greater variability across the windows, but all are significant at least at the 10% level and are reasonably close to the coefficient 0.062 described in the fourth column of Table VI. Taken together, these results suggest that our basic findings are all quite robust and consistent results emerge using different discontinuity estimatation approaches.

3.6 Revenues and Employees

Success for an entrepreneurial firm can be measured in more than simply its survival — growing firms may also be expected to increase revenues and employees. To determine the impact of credit provision on revenues, we calculate the sales growth for each applicant firm by subtracting the log of one plus revenue at the time of application from the log of one plus the 2012 revenue. We follow the method recommended by Angrist and Pischke (2009) and include failed firms with revenue zero to avoid the selection problems inherent in the "conditional on positive" approach.[6] We regress sales growth on instrumented loan provision and the usual controls via 2SLS and find, as displayed in the first column of Table VIII, that the supply of credit leads to sales growth that is 77.4 percentage points higher (t-statistic=2.60). The fact that sales growth is measured over different periods for firms applying in varying years is accounted for by the year fixed effects. The mean sales growth is 41 percentage points, so the granting of a loan leads to almost a doubling of growth relative to the mean.

We also regress the log of one plus the current (2012) revenues on instrumented loan provision, the log of one plus revenue at the time of application and the standard controls. As shown in the second column of Table VIII, we find that entrepreneurial firms that receive

[6] The basic issue is that loan provision may enable some very small firms to survive that would not have survived absent the loan. These marginal firms may exhibit low sales and employee growth, but this is not due to the causal impact of loan provision; it is due to the fact that without loan provision these firms would have exited the data set. A "conditional on positive" regression could thus substantially understate the positive impact of loan provision on sales or employee growth, through the inclusion of only those marginal firms that did receive loans. In fact, as we discuss in Section 3.8, there is indeed evidence that the Lender's financing did keep some quite marginal firms in business.

a loan have significantly higher revenues in 2012. This specification provides further evidence that a loan from a financial institution helps a company achieve higher revenues several years later.

In the third column of Table VIII we detail the results from regressing the log of one plus the number of current employees on loan provision and the controls. Firms that are allocated loans have significantly higher (t-statistic=2.59) workforces in 2012. For a firm with mean employment in 2012, a loan at the time of application would have led to a workforce that was more than twice its current size. We do not have employment data from all firms at the time of application, so that variable cannot be included as a control. In the fourth column of Table VIII, however, we show that including the log of revenue at the time of application as a control yields very similar results.

Taken together, the findings in Table VIII provide evidence that credit helps generate increased revenues and employment. Given the positive effects of the Lender's loans on its clients, from a general equilibrium standpoint it is important to ask whether these gains may only be interpreted as transfers. For example, de Mel, McKenzie and Woodruff (2008) find a strong causal impact on profits of grants given to micro-enterprises in Sri Lanka, but grants are not meant to be returned to their providers. In our case, however, Accion Texas makes business loans that are recovered in order to sustain the Lender's ongoing operation in funding small businesses. While we do not have full access to the Lender's operating costs, in an untabulated analysis we find that Accion Texas's internal rate of return (IRR) before operating costs was slightly positive even during this period of weak macroeconomic performance, suggesting that the impact of startup loans is a net gain.

3.7 Which Entrepreneurs Most Benefit from Financing?

The findings described in Tables VI and VIII document the strong positive effect of credit on firm survival and growth. We now consider whether the benefits of financing differ across sub-groups of applicants. Were some entrepreneurs better equipped to make the best use of credit? From another perspective, did a loan from our Lender matter less to some applicants because they had access to alternative sources of financing? Our basic strategy is to contrast the estimated effect of loan provision on firm survival for disjoint groups of applicants. Applicants for whom credit has a larger impact on ultimate survival will be said to experience a more substantial benefit from the loan. We also contrast the effects of a loan from our Lender on the future secured financings of different groups of entrepreneurs.

3.7.1 Entrepreneurial Survival – Education and Credit Background

The first entrepreneur characteristic we study is years of formal education. We divide the sample into those who have the median number of years of education (thirteen) or more and those who have less. In essence this splits the applicants into a group with some post-secondary education and a group with none. We then estimate (3) and (4) via 2SLS in these two samples separately. The results are documented in the first two columns of Table X, Panel A. As the table makes clear, applicants with more education experienced a large benefit from the loan (coefficient=1.03 and t-statistic=2.62), while those with less education experienced no significant benefit (coefficient=-0.03 and t-statistic=-0.07). The difference between these coefficients is significant at the 10% level. The fact that the coefficient in the high education sample exceeds one is a product of the linear probability model we use, but it is clear that those applicants with some post-secondary education receive much greater benefit from the loan.

This finding does not necessarily indicate that education causes entrepreneurs to make better use of capital. Education could be proxying for intelligence, diligence, family access to resources, etc. As in Parker and van Praag (2006) and De Mel, McKenzie and Woodruff (2008), though, we do find that better educated entrepreneurs are more constrained by restricted access to credit. In Table X, Panel B we report the results from regressing the probability of any subsequent UCC secured loans on instrumented loan provision in the two samples separately. The estimated coefficients are not statistically different; that is, the loan appears to have the same influence on the financing of both the more and less-educated entrepreneurs (both types use it to the same extent to acquire secured financing), but it has a much greater impact on the survival rate of better educated applicants.

Our second characteristic of interest is the entrepreneur's credit score. There are two competing hypotheses for the effect of credit score on the benefit from the loan. It may be argued that higher credit score applicants are more reliable and more likely to make sensible use of any funding. Indeed, credit scoring of small business loan applications has become standard in the U.S. (Berger, Frame and Miller (2005)) because it is regarded as a very reliable indicator of repayment. The counter-argument is that high credit score borrowers are less financially constrained, and so may benefit less from a loan from our specific Lender.

To test these hypotheses, we estimate the impact of (instrumented) loan provision on survival for high and low credit score applicants (dividing the sample using the 605 median score) and display the results in the third and fourth columns of Table IX, Panel A. The difference between the estimated coefficients is statistically insignificant, with a p-value of 0.77. In Table IX, Panel B we find no significant difference between the two groups in the effect of the loan on overall UCC financing. It does not appear that higher credit score entrepreneurs find it significantly easier to obtain alternate financing. (Had this been the case, we would have expected to find that the loan had a smaller impact on total UCC financing for high credit score applicants).

Higher credit scores are unconditionally associated with higher overall survival rates, though the mean survival rates for the two types are not that different: 31.5% for the high credit score applicants and 29.4% for those with low credit scores. As we showed in Table III, however, entrepreneurs with higher credit scores are also more likely to receive a loan. Controlling for loan provision, though, higher credit scores are actually associated with weakly lower survival rates, as we showed in Table VI. The weight of this evidence appears to offer broad support for neither of the two hypotheses discussed above. High credit score applicants do not experience greater benefits from loan provision. They are also no more likely to access outside sources of funding. These results do raise some questions about the widespread practice of credit scoring small business loan applications. It is not clear from these data that, controlling for loan provision, high credit score entrepreneurs make for more successful borrowers.

A related argument is that homeowners are more likely to be wealthy and to have access to other forms of capital and that they may therefore be in less need of outside financing (e.g., Di, Belsky and Liu 2007). In unreported results, we find no evidence of differences between homeowners and renters in the effects of loan provision on either survival or subsequent UCC financing.

3.7.2 Entrepreneurial Survival – Experience and Loan Purpose

It is not clear whether the benefits of a loan from our Lender should be expected to be greater for experienced or inexperienced entrepreneurs. As we argued for high credit score applicants, it may be that experienced entrepreneurs make more successful use of credit or, conversely, that they are less in need of financing from this particular source. We divide the sample into entrepreneurs who had senior management experience (e.g., president, vice president or chief financial officer) at a different firm prior to establishing the entrepreneurial venture that is applying for a loan and those who did not. We regress firm survival on loan provision and the standard controls via 2SLS and provide details on the results in the first two columns of Table X, Panel A. Loan provision has an insignificant effect on survival in the sample of former senior managers (coefficient=-1.19 and t-statistic=-1.12) and a positive and significant effect in the sample of entrepreneurs without any prior senior managerial experience (coefficient=0.59 and t-statistic=2.78). The difference between the coefficients is significant at the 10% level.

Overall survival rates are higher for entrepreneurs with senior managerial experience (34.2% versus 29.6% for those without this experience), but they are not so high that financing could not possibly provide any additional assistance. In columns one and two of Table X, Panel B, we show that loan provision has an insignificant impact on total subsequent UCC secured financing for former senior managers (coefficient=-1.13 and t-statistic=-0.75) and has a positive and significant impact on other entrepreneurs (coefficient=0.67 and t-statistic=5.93). The difference is large in magnitude, though it is not statistically significant, perhaps due to the small sample of former senior managers. The results do suggest, though, that loans from our Lender to former senior executives do little to benefit them, and it appears that this is because they can access credit from other financial institutions. Fewer than 0.5% of the entrepreneurs in the sample are described as having been owners of other firms, so we cannot make inferences about the effects of financing on serial entrepreneurs.

Our results suggest that external finance is hard to substitute for when entrepreneurs lack experience running a business. While prior work has argued that finance may be substitutable by other factors in developed economies (e.g., Angelini and Generale (2008)), little is known about what those other factors may be. We find that startups owners without senior managerial experience find it hard to do without financing.

We also characterize loans by the applicant's proposed use of the funds. Approximately

21.5% of applicants state that the loan will be used to supply working or operating capital. In the third and fourth columns of Table X, Panel A we show that granting a loan to these applicants has no effect on firm survival, in contrast to the positive and significant impact for other applicants. The difference in coefficients is significant at the 10% level. This finding is consistent with the hypothesis that working capital loans are less helpful to young businesses, perhaps because they simply support the on-going operations of a firm rather than promoting large-scale expansion. As detailed in the last two columns of Table X, Panel B, the effect of loan provision on subsequent UCC financing is broadly the same irrespective of the loan purpose.

In unreported tests we find that differences across entrepreneurs in their level of industry experience and loan size requested do not impact the effectiveness of loan provision in promoting firm survival.

3.7.3 Synthesis: Heterogeneity in the Effects of Capital

Suppliers of early stage capital such as banks and angels often negotiate with entrepreneurs on the terms of financing. Early stage investors presumably receive a larger share of the firm when the marginal value of the capital they supply is higher. The results described in Tables IX-X thus highlight specific characteristics that should make entrepreneurs attractive to investors; financing is most useful to entrepreneurs who have the ability to use it (i.e., those that are highly educated), who cannot find it elsewhere (i.e., those who have not worked as senior managers) and who deploy it to expand the firm (i.e., not for working capital). Other characteristics commonly thought to be important such as the entrepreneur's credit score or industry experience appear not to matter.

3.8 Firm Size Distribution and Financial Constraints

The results described in Tables V-VIII show that loans from our Lender lead to more overall financing, improve firm survival rates and generate greater revenue and a larger workforce. In addition to these direct firm-level outcomes, we now consider the impact of the loans on the distribution of firm sizes in 2012.

A recent literature (Cabral and Mata (2003) and Angelini and Generale (2008)) has argued that the density of firm sizes is generally lognormal, as broadly suggested by Gibrat's Law, but that for young firms the density of the log of firm sizes exhibits a pronounced positive skewness. While there is some debate about the underlying cause of this skewness, evidence from survey responses and proxies for financial constraints appears to indicate that persistently financially constrained firms do have a positively skewed firm size distribution. This may be due to the restricted growth of constrained firms which leaves them stunted in size compared to their unconstrained counterparts.

We explore the impact of financial constraints on firm size using the quasi-random allocation of loans to entrepreneurs in our data. Specifically, we consider the subsample of entrepreneurs with capacity in the range of $[-2, +2]$, and we label those firms with capacity of zero or above as "financially unconstrained" and the firms with negative capacity as "financially constrained." Essentially, we are arguing that in this relatively narrow band around the cutoff, the firms are all quite similar, except that above-threshold firms are more likely to receive a loan.

For each firm that survives to 2012, we calculate the log of the number of its employees. The previous literature has emphasized the importance of comparing firms within the same age cohort, so we normalize this firm size measure by subtracting the mean of the log of employees for all firms that were founded in the same year. In Figure 6 we present the densities of the age-adjusted firm sizes for both constrained and unconstrained firms.

The first point evident from the graph is that the unconstrained firm size distribution, with its larger peaks on the left side of the graph, is actually more skewed than the constrained firm size distribution. (The skewness for the unconstrained firms is 1.25 and for the constrained firms it is 0.95.) A Kolmogorov–Smirnov test rejects at the 5% level the null hypothesis that the two distributions are equal. That is, in contrast with earlier results, we find that the distribution of unconstrained firms exhibits greater skewness, with a relatively large mass of quite small firms.

Consistent with the results we found on the impact of financing on survival (Table VI), the firm size distributions indicate that access to credit has a first-order effect in maintaining small firms as on-going businesses. The "additional" small firms observed in the unconstrained distribution are likely firms that would have exited without the financing they received from the Lender. That is, access to credit shifts the firm size distribution by enabling some quite small businesses to remain active.

The distinction between our result and those in the previous literature is therefore likely driven by differences in firm sizes. Our firms are quite small (over 90% have fewer than 5 employees), while the median firm in the main Angelini and Generale (2008) sample has over 30 employees. In other words, the stunted growth of constrained firms that is found in previous studies is likely an important effect for medium-sized young firms and does lead to skewness in the distribution of constrained firms. We are uncovering a separate effect at the left end of the distribution, namely the crucial role that financial access plays in keeping small firms in the marketplace. Together these results present a somewhat nuanced picture of the impact of financial constraints on the firm size distribution, with contrasting impacts for small and medium-sized companies.

Our findings complement research on banking deregulation (e.g., Cetorelli and Strahan (2006) and Kerr and Nanda (2009)) that shows that more competitive banking markets can bring particular benefits to small firms. Previous work has emphasized the market-level effects of deregulation in encouraging new firm entry and churning. Our study makes use of quasi-random credit provision to existing firms to demonstrate that access to financing is critical to the survival of small companies.

4 Conclusion

In this paper, we provide direct evidence on the impact of early-stage business loans on entrepreneurial success by analyzing a large sample of startup loan applicants in the United States. Loans can enhance entrepreneurs' pursuit of value creation opportunities, but the analysis of this influence is complicated by the interacting forces of selection and treatment involved in loan-making and by the lack of credible counterfactuals for external funding. We exploit proprietary information on a financial institution's automated loan application review process, which allows us to undertake a regression discontinuity design assessing the causal impact of access to entrepreneurial credit. We find that obtaining a loan has a strong effect on the overall future secured financings of a startup. Startups receiving funding are dramatically more likely to survive, enjoy higher revenues and create more jobs. We also assess whether the personal characteristics of the entrepreneur enhance the impact of credit on firm success. We find that loans are more consequential for firm survival among entrepreneurs with more education and less senior managerial experience. Last, we show that access to credit leads to a more skewed distribution of firm sizes, as financing enables some quite small firms to survive.

Access to credit has a profound impact on young companies, changing the contours of opportunity in quite different ways for entrepreneurs of varying skills and backgrounds. Financing for new ventures has effects that extend beyond the founders themselves, potentially altering the local competitive landscape in the industries in which they participate and offering employment to those who may prefer to work in smaller organizations.

Taken together, our findings suggest that there is significant unmet demand for early-stage funding that is crucial for the success of a broad segment of businesses much talked about but largely understudied. A deeper understanding of whether this capital can be supplied on terms that are attractive to investors is likely to have significant implications for policy and practice.

References

Abrevaya, J., 1997, The equivalence of two estimators of the fixed-effects logit model, *Economics Letters* 55, 41–43.

Acs, Z. and D. Audretsch, 1990, *Innovation and small firms*, MIT Press.

Andersen, S. and K. Nielsen, 2012, Ability or finances as constraints on entrepreneurship? Evidence from survival rates in a natural experiment. *Review of Financial Studies*, forthcoming.

Angelini, P. and A. Generale, 2008, On the evolution of firm size distributions, *American Economic Review* 98, 426–438.

Angrist, J.D. and J.S. Pischke, 2009, *Mostly harmless econometrics: An empiricist's companion*, Princeton University Press.

Bates, T., 1990, Entrepreneur human capital inputs and small business longevity, *Review of Economics and Statistics* 72, 551–559.

Beck, T., A. Demirguc-Kunt, and V. Maksimovic, 2005, Financial and legal constraints to growth: Does firm size matter? *Journal of Finance* 60, 137–177.

Berger, A. , W. Frame, and N. Miller, 2005, Credit scoring and the availability, price, and risk of small business credit, *Journal of Money, Credit and Banking* 37, 191–222.

Bertrand, M., A. Schoar, and D. Thesmar, 2007, Banking deregulation and industry structure: Evidence from the French banking reforms of 1985. *Journal of Finance* 62, 597–628.

Bitler, M., T. Moskowitz and A. Vissing-Jørgensen, 2005, Testing agency theory with entrepreneur effort and wealth. *Journal of Finance* 60, 539– 576.

Black, S. E. and P. E. Strahan, 2002, Entrepreneurship and bank credit availability. *Journal of Finance* 57, 2807–2833.

Braun, S., and C. Schwind, 1976, Automatic, semantics-based indexing of natural language texts for information retrieval systems. *Information Processing & Management* 12: 147–153.

Cabral, L. and J. Mata, 2003, On the evolution of the firm size distribution: Facts and theory, *American Economic Review* 93: 1075–1090.

Cagetti, M. and M. De Nardi, 2006, Entrepreneurship, frictions, and wealth, *Journal of Political Economy* 114: 835–870.

Card, D., C. Dobkin, and N. Maestas, 2004, The impact of nearly universal insurance coverage on health care utilization and health: Evidence from Medicare, NBER working paper.

Carpenter, R. and B. Petersen, 2002, Is the growth of small firms constrained by internal finance? *Review of Economics and Statistics* 84, 298–309.

Cetorelli, N., 2009, Surviving credit market competition. *Economic Inquiry*, forthcoming.

Ceterolli, N., and P. Strahan, 2006, Finance as a barrier to entry: bank competition and industry structure in local U.S. markets. *Journal of Finance* 61, 437–461.

De Mel, S., D. McKenzie, and C. Woodruff, 2008, Returns to capital in microenterprises: Evidence from a field experiment, *Quarterly Journal of Economics* 123, 1329–1372.

Di, Z., E. Belsky, and X. Liu, 2007, Do homeowners achieve more household wealth in the long run? *Journal of Housing Economics* 16: 274–290.

Einav, L., M. Jenkins, and J. Levin, 2012, Contract pricing in consumer credit markets, *Econometrica* 80: 1387–1432.

Hahn, J., P. Todd and W. Van der Klaauw, 2001, Identification and estimation of treatment effects with a regression-discontinuity design. *Econometrica* 69, 201–209.

Haltiwanger, J., R. Jarmin, and J. Miranda, 2013, Who creates jobs? Small vs. large vs. young. *Review of Economics and Statistics* 95: 347–361.

Headd, B., 2003, Redefining business success: Distinguishing between closure and failure. *Small Business Economics* 21: 51–61.

Hurst, E. and A. Lusardi, 2004, Liquidity constraints, household wealth, and entrepreneurship, *Journal of Political Economy* 112(2), 319–347.

Hurst, E. and B. Pugsley, 2011, What do small businesses do?, Brookings Papers on Economic Activity, Economic Studies Program, The Brookings Institution, vol. 43(2 (Fall)), 73–142.

Kaplan, S., B. Sensoy, and P. Strömberg, 2009, Should investors bet on the jockey or the horse? Evidence from the evolution of firms from early business plans to public companies, *Journal of Finance* 64, 75–115.

Karlan, D., and J. Zinman, 2010, Microcredit in theory and practice: Using randomized credit scoring for impact evaluation, *Science* 332, 1278–1284.

Kerr, W., J. Lerner, and A. Schoar, 2011, The consequences of entrepreneurial finance: Evidence from angel financings, *Review of Financial Studies*, forthcoming.

Kerr, W. and R. Nanda, 2009, Democratizing entry: Banking deregulations, financing constraints, and entrepreneurship, *Journal of Financial Economics* 94, 124–149.

King, R. and R. Levine, 1993, Finance and growth: Schumpeter might be right, *Quarterly Journal of Economics* 108, 717–737.

Matsudaira, J. 2008, Mandatory summer school and student achievement, *Journal of Econometrics* 142, 829–850.

McCrary, J. 2008, Manipulation of the running variable in the regression discontinuity design: a density test. *Journal of Econometrics* 142:698–714.

Neumark, D., B. Wall, and J. Zhang, 2011, Do small businesses create more jobs? New evidence for the United States from the National Establishment Time Series. *Review of Economics and Statistics* 93(1): 16–29.

Parker, S. and C. M. van Praag, 2006, Schooling, capital constraints, and entrepreneurial performance, *Journal of Business & Economic Statistics* 24: 416–431.

Rajan, R. and L. Zingales, 1998, Financial dependence and growth, *American Economic Review* 88, 559–586.

Robb, A., and D. Robinson, 2012, The capital structure decisions of new firms. *Review of Financial Studies*, forthcoming.

Roberts, M., and T. Whited, 2011, Endogeneity in Empirical Corporate Finance. University of Rochester Working Paper.

Smith, S. W, 2012, New firm financing and performance. Chapter 4 in *The Oxford Handbook of Entrepreneurial Finance*, Douglas Cumming (Editor). Oxford University Press.

Sutton, J., 1997, Gibrat's legacy, *Journal of Economic Literature* 35, 40–59.

Table I: Summary Statistics

Observations are at the application level. Auto-deny is a dummy for whether the application was rejected by the Lender's automatic review process. The capacity score is a proprietary formula based on the applicants personal income and expenses, business rent and pro forma payment. Loan provided is an indicator for whether a loan was granted, and statistics on the loan amount are given only for loans that were provided. Survives is an indicator for whether the firm was an active business in May 2012. Prior revenues describes the annualized revenues of the applicant firm. Years of education and industry experience are supplied by the applicant. Prior bankruptcy and tax lien are dummies indicating whether the applicant had any history of bankruptcy or tax liens prior to the application date. Prior UCC is an indicator for whether the applicant had ever had a secured debt Uniform Commercial Code filing prior to application, and Post UCC is an indicator for the same event in the period between the application date and May 2012. Senior management experience is an indicator for whether the applicant had ever held a senior position (e.g., CEO, CFO, President or Vice President) in a different firm prior to the application date. Homeowner is a dummy for whether the applicant owned a home at the time of application, and credit score is the applicant's FICO score. Gender is a dummy variable that is equal to 1 if the applicant is a woman. Age is the age of the applicant in years at the time of the application

	Mean	Median	Standard Deviation	1^{st}%	99^{th}%
Auto-deny	0.50	0.00	0.50	0.00	1.00
Capacity score	3.18	0.92	14.38	-5.06	28.72
Loan provided	0.18	0.00	0.39	0.00	1.00
Loan amount	15552.20	11344.37	13926.41	925.00	56255.23
Survives	0.30	0.00	0.46	0.00	1.00
Prior revenues	30028.45	9153.88	421057.45	0.00	257603.00
Years of education	12.62	13.00	4.54	0.00	20.00
Years of industry experience	9.76	7.00	8.73	0.00	38.00
Prior bankruptcy	0.15	0.00	0.36	0.00	1.00
Prior tax lien	0.05	0.00	0.22	0.00	1.00
Prior UCC	0.08	0.00	0.28	0.00	1.00
Post UCC	0.16	0.00	0.36	0.00	1.00
Senior manager	0.10	0.00	0.30	0.00	1.00
Homeowner	0.55	1.00	0.50	0.00	1.00
Credit score	606.35	605.00	80.98	460.00	785.00
Gender (Women=1)	0.42	0.00	0.49	0.00	1.00
Age	40.56	39.03	10.80	23.08	69.41

Table II: Lines of Business (partial list)

Business line	Count
Business services	536
Eateries	369
Beauty shops	158
Local trucking	122
Transportation services	81
Child care services	70
Repair Services	59
Women's clothing stores	56
Single-family house construction	51
Business consulting	44
Building maintenance	36

Table III: Automatic Review and Loan Provision

Results from the regressions of an indicator for auto-denial (column 1) and loan provision (columns 2-5) on applicant characteristics. The regressors with reported coefficients are a dummy for whether the capacity of the applicant is zero or above, the applicant's credit score (column 5) and a dummy for whether the applicant had ever declared bankruptcy prior to the application (column 5). The regressions also include as controls a third degree polynomial in capacity estimated separately on both sides of zero (columns 1,2 and 5), a second degree polynomial in capacity (column 3), a fourth degree polynomial in capacity (column 4), year fixed effects (column 5) and business line fixed effects (column 5). Reported t-statistics are heteroskedasticity-robust and clustered by business line (column 5).

	Auto-deny?	Loan?	Loan?	Loan?	Loan?
Capacity Above Threshold	-0.470**	0.113**	0.129**	0.0923**	0.113**
	(-28.91)	(8.78)	(10.99)	(6.11)	(7.07)
Credit Score					0.00104**
					(11.70)
Prior Bankr.					0.00616
					(0.41)
Year F.E.	No	No	No	No	Yes
Bus. Line F.E.	No	No	No	No	Yes
Polynomial Order	3	3	2	4	3
Sample	Full	Full	Full	Full	Bus. Line Avail.
Est. Method	OLS	OLS	OLS	OLS	OLS
Observations	5404	5404	5404	5404	4693
Adjusted R^2	0.261	0.036	0.035	0.037	0.087

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$

Table IV: Capacity Threshold and Applicant Characteristics

Results from the regressions of applicant characteristics on the capacity threshold of zero. The dependent variables are an indicator for a prior bankruptcy (column 1), an indicator for a prior tax lien (column 2), the applicant's credit score (column 3), an indicator for a prior UCC secured debt filing (column 4), the log of the years of education of the applicant (column 5) and the log of the years of industry experience of the applicant (column 6). The regressor with a reported coefficient is a dummy for whether the capacity of the applicant is zero or above. The regressions also include as controls a third degree polynomial in capacity. Reported t-statistics are heteroskedasticity-robust.

	Prior Bankruptcy?	Prior Tax Lien?	Credit Score	Prior UCC	Educ.	Ind. Exp.
Capacity Above Threshold	-0.0115	0.00354	2.809	0.00195	0.0132	-0.0290
	(-0.83)	(0.39)	(0.86)	(0.18)	(0.67)	(-0.76)
Polynomial Order	3	3	3	3	3	3
Est. Method	OLS	OLS	OLS	OLS	OLS	OLS
Observations	5307	5307	5073	5307	4902	4950
Adjusted R^2	-0.001	0.001	0.013	0.000	-0.000	0.001

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$

Table V: Incremental Funding

Results from the 2SLS regressions of an indicator for whether the applicant had any secured debt UCC filing after the application date (column 1) and an indicator for whether the applicant had any secured debt UCC filing from a non-Accion Texas lender after the application date (column 2) on loan provision and applicant characteristics. The regressors with reported coefficients are an instrumented dummy for loan provision, the applicant's credit score and a dummy for whether the applicant had ever declared bankruptcy prior to the application. The regressions also include as controls a third degree polynomial in capacity estimated separately on both sides of zero, year fixed effects and business line fixed effects. Reported t-statistics are heteroskedasticity-robust and clustered by business line.

	Any Subsequent UCC Secured Loans?	Any Subsequent Other-Lender UCC Secured Loans?
Loan Provided (instr.)	0.539**	-0.0383
	(4.79)	(-0.44)
Credit Score	0.000164	0.000208**
	(1.25)	(1.97)
Prior Bankr.	0.0186	0.00238
	(1.46)	(0.21)
Year F.E.	Yes	Yes
Bus. Line F.E.	Yes	Yes
Est. Method	2SLS	2SLS
Observations	4482	4482

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$

Table VI: Entrepreneurial Survival

Results from the 2SLS regressions (columns 1-3) and OLS regression (column 4) of an indicator for whether the applicant's firm survives as an active business until May 2012 on loan provision and applicant characteristics. Survival is defined using an 80% name match requirement in columns 1,2 and 4 and using a 100% name match requirement in column 3. The regressors with reported coefficients are an instrumented dummy for loan provision (columns 1-3), the applicant's credit score (columns 2-3), a dummy for whether the applicant had ever declared bankruptcy prior to the application (columns 2-3) and a dummy for whether the applicant's capacity score was zero or above (column 4). The regressions also include as controls a third degree polynomial in capacity estimated separately on both sides of zero, year fixed effects and business line fixed effects. Reported t-statistics are heteroskedasticity-robust and clustered by business line.

	Survives?	Survives?	Survives?	Survives?
Loan Provided (instr.)	0.546**	0.510**	0.482**	
	(3.44)	(2.58)	(2.32)	
Credit Score		-0.000419*	-0.000345	
		(-1.93)	(-1.53)	
Prior Bankr.		0.0274*	0.0133	
		(1.70)	(0.79)	
Capacity Above Threshold				0.0622**
				(3.34)
Year F.E.	Yes	Yes	Yes	Yes
Bus. Line F.E.	No	Yes	Yes	Yes
Est. Method	2SLS	2SLS	2SLS	OLS
Match Type	Approx.	Approx.	Exact	Approx.
Observations	5404	4482	4482	4991

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$

Table VII: Narrow Windows

Results from regressions of an indicator for auto-denial (Panel A), loan provision (Panel B) and whether the applicant's firm survives as an active business until May 2012 (Panel C) on applicant characteristics in varying capacity windows. Only observations in a capacity window of $[-2, 2]$, $[-1.5, 1.5]$, $[-1, 1]$ and $[-0.5, 0.5]$ are considered in the first through fourth columns, respectively. The regressor with a reported coefficient is a dummy for whether the applicant's capacity score was zero or above. The regressions also include as controls year fixed effects and business line fixed effects. Reported t-statistics are heteroskedasticity-robust.

Panel A:	Auto-deny?	Auto-deny?	Auto-deny?	Auto-deny?
Capacity Above Threshold	-0.526**	-0.536**	-0.519**	-0.409**
	(-29.68)	(-28.08)	(-22.52)	(-10.76)
Sample	Capac. $\in$ $[-2, +2]$	Capac. $\in$ $[-1.5, +1.5]$	Capac. $\in$ $[-1, +1]$	Capac. $\in$ $[-0.5, +0.5]$
Observations	2940	2629	2006	1052

Panel B:	Loan?	Loan?	Loan?	Loan?
Capacity Above Threshold	0.140**	0.135**	0.113**	0.0778**
	(9.08)	(8.07)	(5.65)	(2.59)
Sample	Capac. $\in$ $[-2, +2]$	Capac. $\in$ $[-1.5, +1.5]$	Capac. $\in$ $[-1, +1]$	Capac. $\in$ $[-0.5, +0.5]$
Observations	2940	2629	2006	1052

Panel C:	Survives?	Survives?	Survives?	Survives?
Capacity Above Threshold	0.0383**	0.0459**	0.0573**	0.0555*
	(2.20)	(2.48)	(2.66)	(1.72)
Sample	Capac. $\in$ $[-2, +2]$	Capac. $\in$ $[-1.5, +1.5]$	Capac. $\in$ $[-1, +1]$	Capac. $\in$ $[-0.5, +0.5]$
Observations	2940	2629	2006	1052

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$

Table VIII: Revenues and Employees

Results from the 2SLS regressions of revenue growth from the application date to 2012 (column 1), the log of one plus the 2012 revenues (column 2) and the log of one plus the 2012 number of employees (columns 3-4) on loan provision and applicant characteristics. The regressors with reported coefficients are an instrumented dummy for loan provision, the applicant's credit score, a dummy for whether the applicant had ever declared bankruptcy prior to the application and the log of one plus the annualized revenues at the time of application (columns 2 and 4). The regressions also include as controls a third degree polynomial in capacity estimated separately on both sides of zero, year fixed effects and business line fixed effects. Reported t-statistics are heteroskedasticity-robust and clustered by business line.

	Revenue Growth	Log of Curr. Rev.	Log of Curr. Empl.	Log of Curr. Empl.
Loan Provided (instr.)	0.774**	6.022**	0.544**	0.598**
	(2.60)	(2.73)	(2.59)	(2.78)
Credit Score	-0.000779**	-0.00512**	-0.000415*	-0.000530**
	(-2.31)	(-2.08)	(-1.80)	(-2.19)
Prior Bankr.	0.0373*	0.308	0.0246	0.0246
	(1.72)	(1.64)	(1.25)	(1.27)
Log(Prior Rev.)		0.143**		0.0207**
		(3.17)		(3.95)
Year F.E.	Yes	Yes	Yes	Yes
Bus. Line F.E.	Yes	Yes	Yes	Yes
Observations	4411	4482	4482	4482

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$

Table IX: Entrepreneurial Survival - Education and Credit Background

Results from the 2SLS regressions of an indicator for whether the applicant's firm survives as an active business until May 2012 (Panel A) and an indicator for whether the application had any secured debt UCC filing after the time of application (Panel B) on loan provision and applicant characteristics. Results in columns one and two split the sample into high and low education subsamples using the median years of applicant education (13) as the dividing line. Results in columns three and four split the sample into high and low credit score subsamples using the median credit score (605) as the dividing line. The regressors with reported coefficients are an instrumented dummy for loan provision, the applicant's credit score and a dummy for whether the applicant had ever declared bankruptcy prior to the application. The regressions also include as controls a third degree polynomial in capacity estimated separately on both sides of zero, year fixed effects and business line fixed effects. Reported t-statistics are heteroskedasticity-robust and clustered by business line.

Panel A:	Survives?	Survives?	Survives?	Survives?
Loan Provided (instr.)	1.030**	-0.0281	0.558**	0.742
	(2.62)	(-0.07)	(2.01)	(1.28)
Credit Score	-0.00125**	0.000198	0.0000289	-0.00107
	(-2.60)	(0.55)	(0.14)	(-1.09)
Prior Bankr.	0.0356	0.0532*	0.00484	0.0475*
	(1.27)	(1.79)	(0.18)	(1.67)
Year F.E.	Yes	Yes	Yes	Yes
Bus. Line F.E.	Yes	Yes	Yes	Yes
Sample	High Educ.	Low Educ.	High Cred. Sc.	Low Cred. Sc.
Observations	2255	1828	2195	2137

Panel B:	Subsequent UCC Loans?	Subsequent UCC Loans?	Subsequent UCC Loans?	Subsequent UCC Loans?
Loan Provided (instr.)	0.437**	0.0457	0.518**	0.382
	(2.26)	(0.14)	(2.84)	(1.06)
Credit Score	0.000237	0.000679**	-0.000119	0.000645
	(0.97)	(2.27)	(-0.85)	(1.09)
Prior Bankr.	0.0249	0.0327	0.0445**	-0.00419
	(1.40)	(1.40)	(2.04)	(-0.28)
Year F.E.	Yes	Yes	Yes	Yes
Bus. Line F.E.	Yes	Yes	Yes	Yes
Sample	High Educ.	Low Educ.	High Cred. Sc.	Low Cred. Sc.
Observations	2255	1828	2195	2137

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$

Table X: Entrepreneurial Survival - Experience and Loan Purpose

Results from the 2SLS regressions of an indicator for whether the applicant's firm survives as an active business until May 2012 (Panel A) and an indicator for whether the application had any secured debt UCC filing after the time of application (Panel B) on loan provision and applicant characteristics. Results in columns one and two split the sample into subsamples in which the applicant either had prior senior management experience or did not. Results in columns three and four split the sample into subsamples in which the stated purpose of the loan was either for working capital or for other purposes. The regressors with reported coefficients are an instrumented dummy for loan provision, the applicant's credit score and a dummy for whether the applicant had ever declared bankruptcy prior to the application. The regressions also include as controls a third degree polynomial in capacity estimated separately on both sides of zero, year fixed effects and business line fixed effects. Reported t-statistics are heteroskedasticity-robust and clustered by business line.

Panel A:	Survives?	Survives?	Survives?	Survives?
Loan Provided (instr.)	-1.193	0.588**	0.135	0.958**
	(-1.12)	(2.78)	(0.47)	(2.42)
Credit Score	0.00135	-0.000471**	-0.000145	-0.000526**
	(1.43)	(-1.99)	(-0.34)	(-2.12)
Prior Bankr.	0.0585	0.0283	0.0380	0.0376**
	(0.72)	(1.51)	(0.92)	(1.97)
Year F.E.	Yes	Yes	Yes	Yes
Bus. Line F.E.	Yes	Yes	Yes	Yes
Sample	Sr. Mgmt. Exper.	No Sr. Mgmt. Exper.	For Working Capital	For Other Purposes
Observations	445	3857	909	3432

Panel B:	Subsequent UCC Loans?	Subsequent UCC Loans?	Subsequent UCC Loans?	Subsequent UCC Loans?
Loan Provided (instr.)	-1.128	0.666**	0.355	0.602**
	(-0.75)	(5.93)	(1.62)	(2.45)
Credit Score	0.00166	0.0000350	0.000281	0.000130
	(1.16)	(0.25)	(0.92)	(0.80)
Prior Bankr.	0.00668	0.0161	0.0806**	0.00252
	(0.07)	(1.17)	(2.24)	(0.18)
Year F.E.	Yes	Yes	Yes	Yes
Bus. Line F.E.	Yes	Yes	Yes	Yes
Sample	Sr. Mgmt. Exper.	No Sr. Mgmt. Exper.	For Working Capital	For Other Purposes
Observations	445	3857	909	3432

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$

Figure 1: Borrower Capacity Density

This figure depicts the estimated kernel densities on both sides of zero of capacity scores for the sample of applicants with scores between the 10th-percentile and 90th-percentile. Zero is the threshold for automatic review denial recommendation. The 95% confidence bands are portrayed in thin lines. The circles describe scaled frequencies analogous to histograms. Estimation is via the McCrary (2008) method.

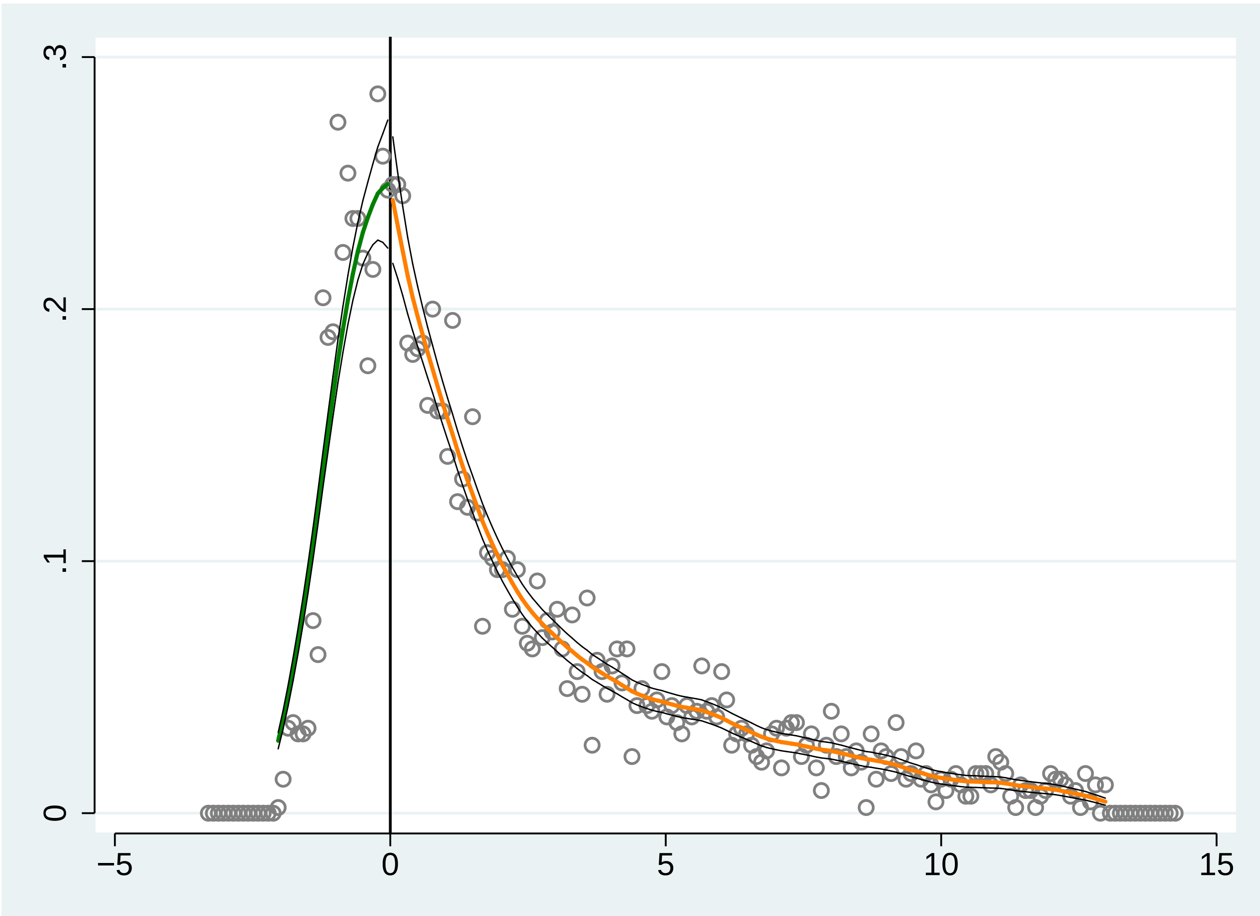

Figure 2: Borrower Capacity and Automatic Denial

This figure displays regression discontinuity results characterizing the impact of borrower capacity scores on automatic denial recommendation. The results are displayed for all applicants between the 10th-percentile and 90th-percentile of applicant capacity scores, in which zero is the threshold for automatic review denial recommendation. The thick curved lines represent the predicted probability of automatic denial from an OLS regression of an indicator for automatic denial on a third degree polynomial in borrower capacity. The 95% confidence interval is portrayed in thin lines, and the connected points describe the average automatic denial probability for each of the buckets of 0.5 units of capacity.

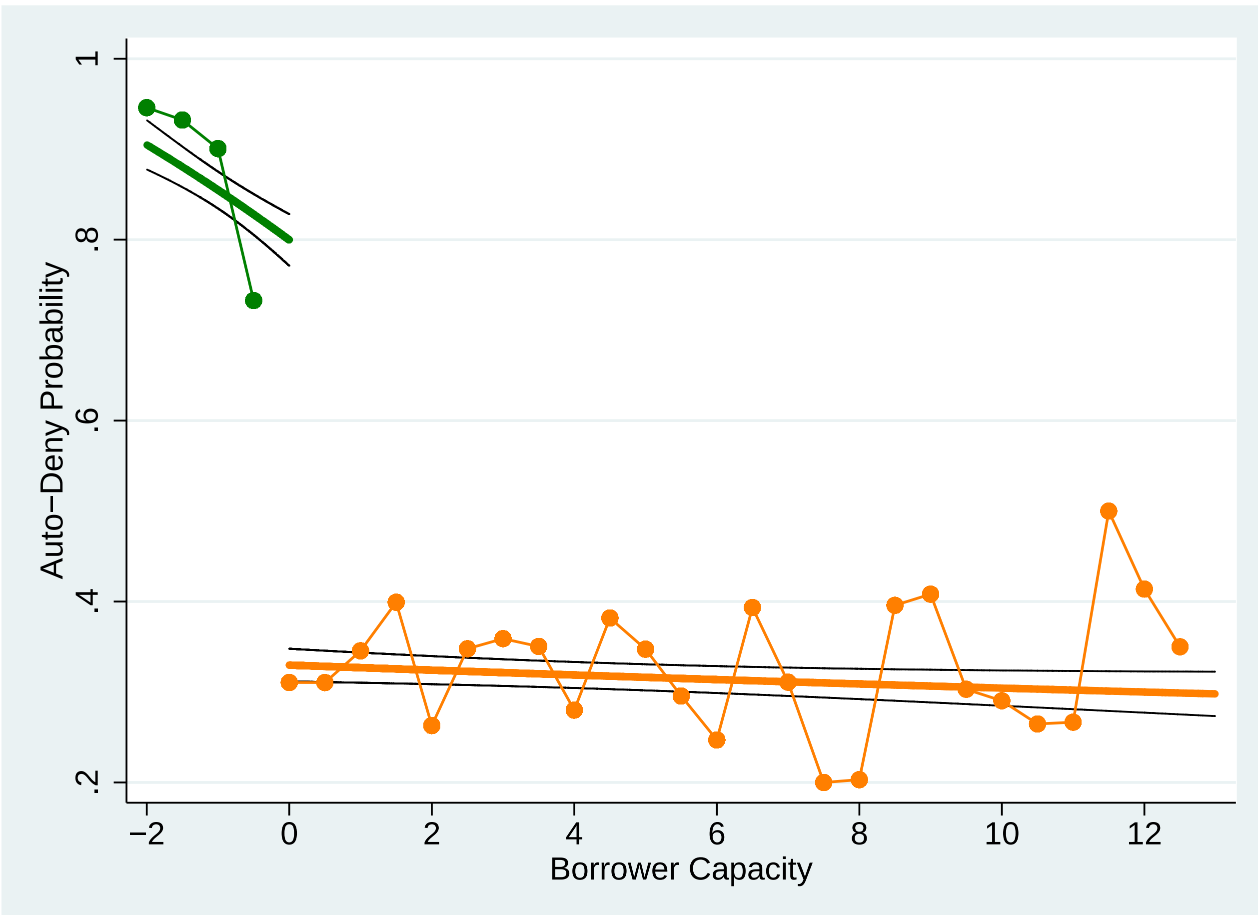

Figure 3: Borrower Capacity and Loan Provision

This figure displays regression discontinuity results characterizing the impact of borrower capacity scores on the probability of receiving a loan. The results are displayed for all applicants between the 10th-percentile and 90th-percentile of applicant capacity scores, in which zero is the threshold for automatic review denial recommendation. The thick curved lines represent the predicted probability of loan provision from an OLS regression of an indicator for loan provision on a third degree polynomial in borrower capacity. The 95% confidence interval is portrayed in thin lines, and the connected points describe the average loan provision probability for each of the buckets of 0.5 units of capacity.

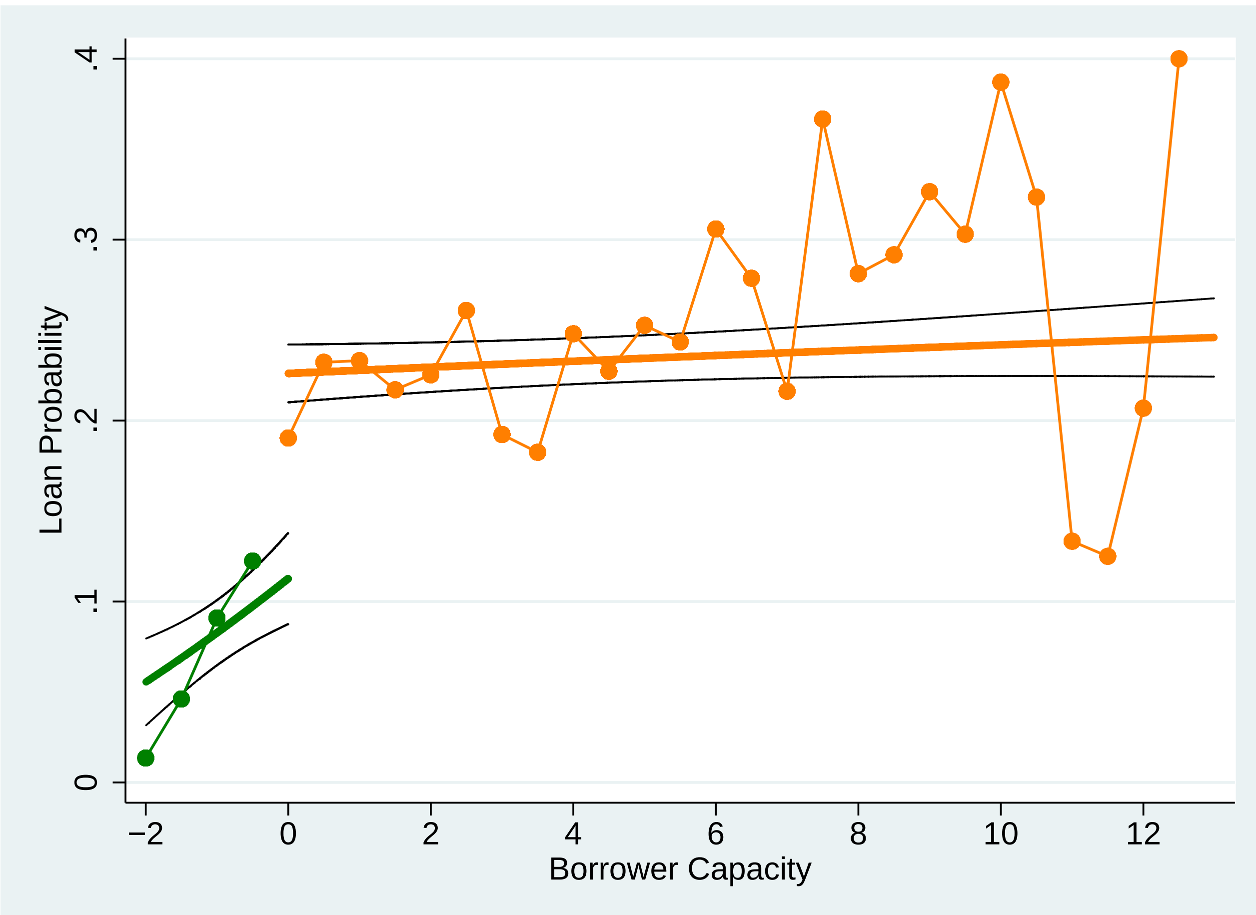

Figure 4: Borrower Capacity and Observable Characteristics

This figure displays regression discontinuity results characterizing the impact of borrower capacity scores on the probability the applicant had a prior bankruptcy filing, the probability the applicant had a prior tax lien, applicant credit score, the probability the applicant had a prior UCC filing, years of education, and the applicant log of years of industry experience. The results are displayed for all applicants between the 10th-percentile and 90th-percentile of applicant capacity scores, in which zero is the threshold for automatic review denial recommendation. The thick curved lines represent the predicted probability of loan provision from an OLS regression of an indicator for loan provision on a third degree polynomial in borrower capacity. The 95% confidence interval is portrayed in thin lines, and the connected points describe the average loan provision probability for each of the buckets of 0.5 units of capacity.

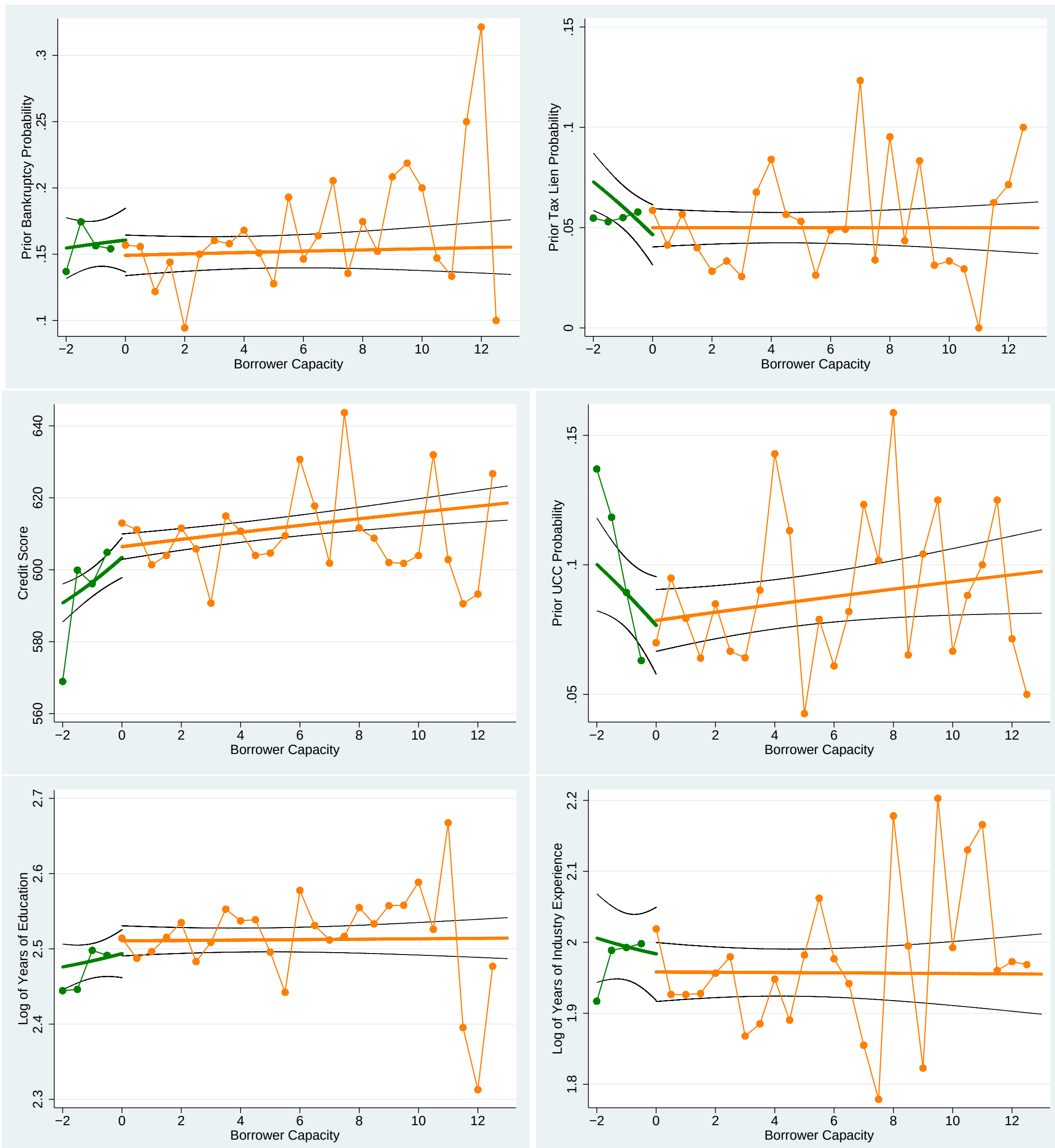

Figure 5: Borrower Capacity and Firm Survival

This figure displays regression discontinuity results characterizing the impact of borrower capacity scores on the probability of firm survival as of May 2012. The results are displayed for all applicants between the 10th-percentile and 90th-percentile of applicant capacity scores, in which zero is the threshold for automatic review denial recommendation. The thick curved lines represent the predicted probability of survival from an OLS regression of an indicator for firm survival on a third degree polynomial in borrower capacity. The 95% confidence interval is portrayed in thin lines, and the connected points describe the average survival probability for each of the buckets of 0.5 units of capacity.

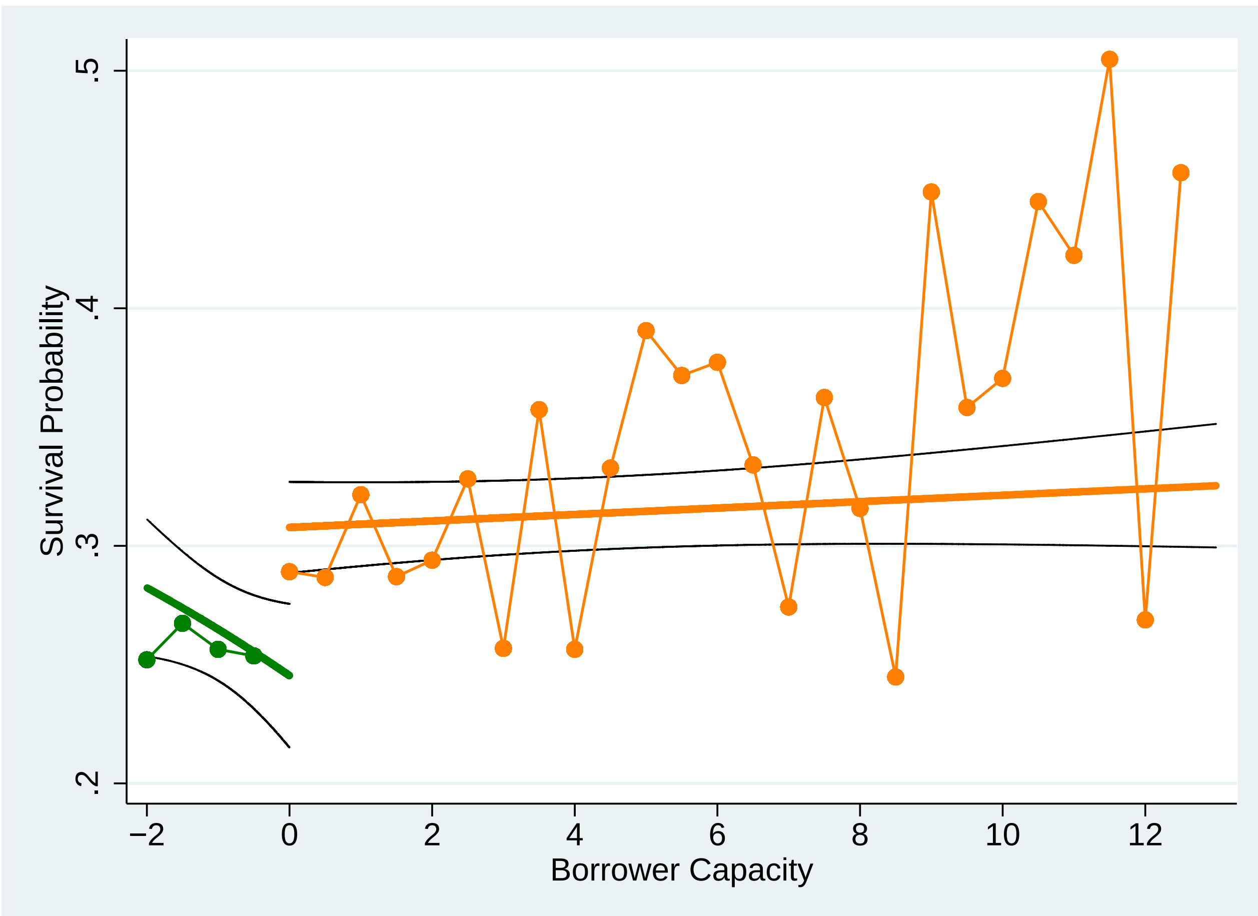

Figure 6: Firm Size Distribution and Financial Constraints

This figure displays the density of the age-adjusted log of employees per firm in 2012 for both financially constrained and unconstrained entrepreneurs. The sample is restricted to entrepreneurs with capacity scores in the range $[-2, +2]$. All entrepreneurs with scores of zero or above are labeled unconstrained and those with below zero scores are labeled constrained.