

Business Microloans for U.S. Subprime Borrowers

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Abstract

We show that business microloans to U.S. subprime borrowers have a very large impact on subsequent firm success. Using data on startup loan applicants from a 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 firms. Startups receiving funding are dramatically more likely to survive, enjoy higher revenues and create more jobs. Loans are more consequential for survival among subprime business owners with more education and less managerial experience.

JEL codes: G32, L26, M13

I Introduction

Small businesses represent a strikingly large portion of the American economy. Basic indicators such as GDP growth, job creation, the innovation rate and wealth accumulation all depend to a great extent on the success of newly founded small firms in constantly revitalizing U.S. markets. The role of financial institutions in funding nascent firms has become a central area of research and debate. The growing policy debate on the real consequences of small business funding in the United States, however, has received relatively little academic attention. Policymakers in the U.S. have started to view the funding of small, often marginal, businesses as a key to growth and prosperity, but this interest has not always been informed by empirical work.

A dynamic and important feature of small business creation in the U.S. is the newly prominent role played by non-traditional entrepreneurs. Standard studies of small business owners (e.g., Hurst and Lusardi (2004)) have traditionally portrayed a group that was almost exclusively white in ethnicity. This has changed, and recent data show that minorities accounted for 22% of U.S. self-employment in 2011, and, further, 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.¹ Many of these minority small business owners may well be classified as subprime borrowers who are granted only limited access to formal sources of financing.² This suggests the possibility that financial constraints may be limiting the growth of an important and growing component of the small firm sector of the economy.

¹Source: Small Business Administration data available at <http://www.census.gov/econ/sbo/pums.html> and <http://www.sba.gov/sites/default/files/us12.pdf>.

²Fairlie (1999) finds that low wealth is a particularly serious problem for minorities considering small business ownership, and Calem, Gillen and Wachter (2004) document that subprime lending is especially common in minority neighborhoods.

How much of an impact does a small amount of external financing have on the performance of firms owned by subprime borrowers? In this paper we address this question by analyzing outcomes for businesses owned by U.S. borrowers who applied for a loan from a non-profit subprime lender. Overall, it is not clear whether loans to subprime business owners might be expected to be helpful for their firms. Our data extend from 2006–2011, and a business expansion funded by a new loan during this difficult economic period had the potential to force a firm into bankruptcy, much like the negative effect that mortgages had on subprime borrowers (Mian and Sufi (2009) and Demyanyk and Van Hemert (2011)). There is also evidence that access to payday loans leads to increased hardship for marginal borrowers (Melzer (2011), Skiba and Tobacman (2011) and Carrell and Zinman (2008)), though others have found net benefits (Morse (2011), Morgan and Strain (2008) and Zinman (2010)). Further, some researchers have found that firm owners 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. On the other hand, 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) and Black and Strahan (2002)), and early-stage credit may enable new ventures to invest in value-creating opportunities and achieve necessary scale. In short, there is no firm consensus on whether or how much credit matters for subprime businesses’ economic success. It is especially unclear how much a relatively small loan might matter for the medium-term (3–5 year) outcomes.

Randomized controlled trial (RCT) studies of grant allocations and microloans in developing countries (e.g., de Mel, McKenzie and Woodruff (2008), Karlan and Morduch (2009), Banerji and Duflo (2010) and Karlan and Zinman (2010)) have also not drawn unambiguous conclusions as to their benefits. It is worth emphasizing, however, that the

small business environment in the U.S. significantly differs from that in most emerging markets. Individuals in the U.S., even those with low credit scores, typically choose to be small business owners, growing their ventures if they succeed, or closing their firms to seek outside employment if they fail. In many emerging markets, by contrast, small firm ownership is the only available work option for a broad segment of society. Funding is also generally more widely available for small businesses in the U.S. than in developing countries. Our work thus provides direct evidence on the impact of a marginal loan on small businesses specifically in the U.S. context.

A second issue is to consider what kinds of subprime small business owners make the best use of early-stage financing. Given the limited availability of capital for financially restricted small businesses, suppliers of early-stage financing such as government agencies and banks would prefer to place funds with small business owners who receive the greatest benefit from capital. However, while different weights have been found for business owners' 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 the small business success of subprime business owners and on the differential effects of access to credit across business owner characteristics. Specifically, we study every startup loan application received by Accion Texas, a non-profit financial institution providing loans to U.S.-based existing startups in a wide range of business activities in the period 2006–2011. The applicant firms in our sample are typically low-credit-score borrowers from minority backgrounds. In addition to their increasing national prominence, minority small business owners have become especially important in certain relatively thriving regions of the U.S. such as Texas. In this sense, our application-level database on existing startups offers a rare window into a growing

sector of the American economy that has received very little scholarly attention.³

Our empirical approach complements existing studies in three 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 offer some of the first causal evidence on the real effects of access to credit in a small business setting. Second, we are able to provide some evidence on whether rejected applicants were able to secure outside sources of financing. Third, 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

³See 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.

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 firm 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 of comparable size). We also find that receiving a loan has a positive and significant effect on startups’ revenue growth rate, revenue levels, and number of employees. While the large magnitude of the effects we document likely reflects

the severe financial constraints affecting the specific population that applies to this lender for financing, the results do indicate that providing early-stage loans substantially enhances the future economic performance of small businesses led by subprime owners.

In a robustness analysis, we consider specifications that include only those applicants with capacity scores in narrow windows around the auto-denial threshold. We confirm all our main findings in these tests, thereby showing that our results are driven by differences between firms just above and just below the threshold for automatic denial.

Two aspects of our findings are worth emphasizing. First, they indicate not only that external funding is beneficial for these firms, as financial economists may perhaps expect, but that the absence of financing actually explains a large bulk of the seventy percent failure rate that we observe. That is, we find that access to a relatively small amount of funding is the first-order cause of survival for subprime businesses. While these firms are likely subject to more severe financial constraints than others, our results do raise questions about the links between small business failure and restricted access to capital in broader sectors of the economy. Second, for most of the firms in our sample we measure survival 3-5 years after the loan application is made. We are therefore not merely assessing the impact of a loan on the short-term viability of a business. It may well be that certain start-ups immediately collapse without outside credit, while those that receive a loan are able to at least start operations. What is striking about our result, however, is that \$11,000 loans have a tremendous influence on firm survival a number of years later.

Having found a large effect of early-stage financing on subprime small business success, we next analyze what kinds of firm and owner 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 owners. We show that a loan from our Lender helps increase the probability of future secured debt financing for owners

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 owner *without* prior senior managerial experience. We show that a loan has a large effect on the future financings of these owners, while owners who have previous senior management experience appear to be able to obtain debt from other sources. Other owner characteristics such as industry experience have no observable effect on the relative benefit of a loan.

Our results on the nuanced interaction of financial capital and human talent in driving business outcomes also speak to recent RCT work focused on developing economies that has found mixed results. RCT studies exposing entrepreneurs to training programs have often found insignificant results on real business outcomes (e.g., Karlan and Valdivia (2011)), or short-lived, relatively small business productivity gains (e.g., Bruhn, Karlan and Schoar (2013)) or instead have found enhanced knowledge outcomes without focusing on business outcomes (e.g., Bjorvatn and Tungodden (2010)). Our U.S.-based study, while not relying on a field experiment, allows us to offer evidence on the differential role of education and senior management experience in shaping how access to finance matters for firm performance. Education appears to be a complement to financial capital, while senior management experience is a substitute. Heterogeneity not only in the amount but also in the type of human capital available at firms is thus an important dimension that could inform future research in both developed and developing economies.

Our findings shed new light on the real consequences of subprime small business funding in the United States. Our study is one of the very few benefiting from privileged 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 promoting economic activity.

II Data

To assess the impact of receiving early-stage credit on small business 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 non-profit 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, with mean and median loan sizes of \$15,552 and \$11,344, respectively. 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 owners 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 B 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 *owners* 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 before and after the application date and proxies for personal financial distress such as bankruptcy filings and tax liens.⁴

A 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.⁵

Ethnicity and credit score are two demographic characteristics in our sample that

⁴UCC is a state-level filing registry that records loans secured by fixed assets. On average, around 8% of the owners 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.

⁵In 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.

are 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 current demographic trends.⁶ The mean credit score of applicants is 606.35, and 65.0% of the applicants have scores below 640. It is clear that our Lender is serving a largely subprime market of borrowers. While for some entrepreneurs the home equity in their houses might be used as collateral to finance their small business (see Adelino, Schoar and Severino (2014)), the subprime borrowers in our sample are unlikely to have had a significant amount of home equity against which to borrow.

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

⁶According 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. Texas thus experienced an accentuated version of the national trends we discussed in the introduction.

broadly representative of U.S. small businesses.

It is also instructive to compare our sample companies to the start-up firms included in the Kauffman Firm Survey (KFS) described by Robb and Robinson (2014). The firms in our sample are somewhat smaller (for example, the fraction of firms with prior revenues exceeding \$25,000 is 35.4% in the KFS and only 20.9% in our sample) and, consistent with the analysis above, the entrepreneurs' demographics are somewhat different: Hispanics represent 5.5% of the owners in the KFS compared to 63% of the owners in our sample and 13.9% of the owners are high-school graduates or less in the KFS compared with 45.9% in our sample. Entrepreneurs in both samples, however, have similar levels of industry experience (29.5% of entrepreneurs in the KFS had 1-5 years of experience compared with 24.9% of entrepreneurs in our sample, and 60.7% of entrepreneurs in the KFS had more than 5 years of experience compared with 68.8% of entrepreneurs in our sample).

How large are the loans granted by our Lender relative to the typical amount of startup capital that small businesses require? While the KFS firms are larger, we can nonetheless use that sample to contrast the relative magnitude of the loans provided by our Lender with the outside financing secured by KFS firms. Specifically, we compare the loan amount to revenues in our sample and in the KFS sample. Lowrey (2009) reports that the average revenues of firms in the KFS sample is \$121,358 and Robb and Robinson (2014) report that these firms had on average \$50,130 of outside debt, leading to a mean debt-to-mean revenues ratio of 41%. This ratio is comparable to what we find in our sample: our firms have mean revenues of \$30,028 and received a mean of \$15,552 in debt from our Lender, leading to a mean debt-to-mean revenues ratio of 52%. A second comparison may be made with the median startup capital of \$7,500 for firms in the SBO sample, relative to the median loan of \$11,344 granted by our lender.

Broadly speaking, the loans provided by our Lender are likely to represent a substantial

portion of the initial financing required by the sample firms. Though the Lender’s average loan size is smaller than in the KFS, the firms in our sample are also smaller, and the Lender’s funding appears to be large enough, in general, to provide start-up financing.

Overall, our sample appears to be representative of a large segment of U.S. small businesses in terms of industry focus and scale, though it differs in terms of owner ethnicity and credit score. One last relevant characteristic of our sample is the focus of the Lender. Accion Texas is a private non-profit financial institution and, as such, its mission is to target its loans at small businesses that are likely to not have access to commercial bank financing.

B 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 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. 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.⁷ Importantly, the data set does not suffer

⁷The analysis excludes 51 of the 5,455 observations for which data about the capacity score is missing.

from survivorship bias, as it includes all applications submitted during the sample period. 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.

III Empirical Specification

We study the impact of the provision of financing on the success of small business 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:

$$(1) \quad \textit{Firm characteristic}_{i,t'} = \alpha + \beta * \textit{Loan}_{i,t} + \gamma * \textit{controls}_{i,t} + \lambda_t + \epsilon_{i,t},$$

where $\textit{Firm characteristic}_{i,t'}$ is an attribute of firm i in future period t' , $\textit{Loan}_{i,t}$ is an indicator for whether firm i was granted a loan in period $t < t'$, $\textit{controls}_{i,t}$ 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.

Estimating equation (1) directly using ordinary least squares (OLS) is inadvisable because the provision of financing is endogenous; better firms are more likely to receive loans, and any observed correlation between firm 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 is equal one if the applicant’s capacity is above the threshold, and zero otherwise.

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

$$(2) \quad Loan_{i,t} = \zeta + \delta I_{C_{i,t}} + \sum_{j=1}^n \omega_j^C C_{i,t}^j + \sum_{j=1}^n \xi_j^C I_{C_{i,t}} C_{i,t}^j + \kappa * controls_{i,t} + \eta_t + \sigma_{i,t},$$

where $C_{i,t}$ is the capacity of the applicant, $I_{C_{i,t}}$ 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 (2) 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. Owners with capacity just below and just above zero are likely very similar, so the above-threshold indicator $I_{C_{i,t}}$ can essentially serve as an instrument for loan provision. We jointly estimate (2) and

$$(3) \quad Firmcharact_{i,t} = \alpha + \beta * Loan_{i,t} + \sum_{j=1}^n \mu_j^C C_{i,t}^j + \sum_{j=1}^n \pi_j^C I_{C_{i,t}} C_{i,t}^j + \gamma * controls_{i,t} + \lambda_t + \epsilon_{i,t},$$

using 2SLS (two-stage least squares). We estimate (2) 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 small business owners that are just above and below the capacity threshold. Because the Lender bases its decisions on the capacity score threshold, these business owners are very similar at the time of application, but they differ specifically in one respect: above threshold owners 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 (2) 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 (2) and (3) in disjoint subsamples.

IV Results

A 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. The overall likelihood of an auto-denial is 49.8%. Thus, 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 the top panel of 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 (2) 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 the bottom panel of Figure 2.

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 (2) with controls for the applicant’s credit score, an indicator for a past bankruptcy, and fixed effects for the applicant’s line of business and year of application. 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.

B Capacity Threshold and Applicant Characteristics

B.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 small business 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 3. Overall, we find no evidence that applicant characteristics are significantly different for those just above and just below the threshold of zero.

B.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, 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 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 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.⁸ 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.

⁸McCrary’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.

C Incremental Financing

We now turn to the question of the impact of our Lender’s financing on small 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 owner should be funded and a rejection by one lender should not have an effect on an owner’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 firms, we do have a listing of all UCC filings for 98% of the owners. 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 (2) and (3) 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 *Any Subsequent UCC?*. 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, which makes sense for our sample of largely minority and subprime borrowers.

To investigate substitution further, we define an indicator variable for whether the borrower is a debtor on any subsequent UCC filing in which the creditor is different from our Lender. We regress this dummy 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 other financing. This suggests that rejected applicants are unable to substitute new loans in place of the financing they did not receive from our Lender.

D Firm 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 small firms?

The most basic measure of firm success is survival. To assess survival rates, we match applicant firms 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: (1) The applicant firm is matched to a D&B company by the Optimizer program; (2) the D&B company is listed as an active business with employees; (3) the owner of the applicant 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)). 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 0.546 (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 small business success for our sample of applicants. Alternative strategies for starting a business without formal credit are often proposed to constrained firm owners. These may include bootstrapping (self-financing), vendor financing, borrowing from family and friends or simply growing slowly. For our group of owners, 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 firm survival.

Not only do we find that firms benefit from external funding, as financial economists may perhaps expect, but the magnitude of the estimated impact suggests that that lack of financing explains the major portion of the seventy percent failure rate for the subprime businesses in our data. This result raises questions about the potential effects of restricted access to capital on small business failures more broadly. Importantly, we are not simply measuring a mechanical effect whereby owners who receive loans continue their businesses for a short period, while though who do not immediately close up. For the bulk of the firms in the sample we are measuring survival 3-5 years after the loan application is made. A relatively small loan thus has an enormous effect on medium-term survival.

Splitting the sample into applications made during or before the median year 2009 and those made afterwards, columns two and three of Table VI show that the estimated effect of loan provision on survival is quite similar and not statistically different. The samples differ both in the age of the firms in 2012 and in the economic conditions during the founding year, so it is difficult to directly compare firms across groups, but the results do make clear that

the overall findings are not driven simply by applications from one specific time period.

Including business line fixed effects and the full set of standard controls, the estimated effect of loan provision remains strong, as displayed in the fourth column of Table VI (coefficient=0.51 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 0.482 (t -statistic=2.32), as detailed in Table VI, column 5.

In the sixth 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 4. Given the 11.3 percentage point increase in loan provision associated with having a capacity above threshold (as described in the sixth 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 conjecture is that the Lender provides follow-up financing to its borrowers, thereby keeping them essentially on life-support and 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.

E Revenues and Employees

Success for a small business 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.⁹ We regress sales growth on instrumented loan provision and the usual controls via 2SLS and find, as displayed in the first column of Table VII, 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 VII, we find that small businesses that receive a loan have significantly higher revenues in 2012. This specification provides further evidence that a loan helps a company achieve higher revenues several years later.

As a purely descriptive exercise, we regress the log of current revenues on instrumented loan provision and the usual controls in the restricted sample of firms that did survive. The coefficient on instrumented loan provision, displayed in the third column of Table VII, is much smaller and statistically insignificant in this specification. As argued above, this could have various interpretations. Loans may increase revenues for all firms but also help some

⁹The 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.

marginal slow growing firms to survive, which depresses the overall estimated effect in the selected sample of surviving firms. It may also be the main effect of loan provision is to enable survival and that it has little impact on revenue growth for successful firms. As Angrist and Pischke (2009) make clear, only the full sample regressions in columns one and two allow for a causal interpretation, and they show that loan provision leads to higher revenue.

In the fourth column of Table VII 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 fifth column of Table VII, however, we show that including the log of revenue at the time of application as a control yields very similar results. The sixth column of Table VII reports the descriptive results from the regression in the restricted sample of surviving firms. As for revenues, this specification does not allow for a causal interpretation. Taken together, the findings in Table VII provide evidence that credit helps generate increased revenues and employment.

F Which Owners Most Benefit from Financing?

The findings described in Tables VI and VII 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 owners 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 owners.

F.1 Firm Survival – Education and Credit Background

The first owner 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 (2) and (3) via 2SLS in these two samples separately. The results are documented in the first two columns of Table VIII, Panel A. We find that applicants with more education experienced a large benefit from the loan (coeff.=1.03 and t -statistic=2.62), while those with less education experienced no significant benefit (coeff.=-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 small business owners to make better use of capital. Education could be a proxy 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 owners are more constrained by restricted access to credit. In Table VIII, 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 owners (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 owner’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 VIII, Panel A. The difference between the estimated coefficients is statistically insignificant, with a p -value of 0.77. In Table VIII, 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 owners 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, small business owners 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. This evidence offers 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, at least within the range of the relatively low credit scores of the borrowers in our sample. 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, relatively high credit score owners 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)) or may be able to use home equity loans to fund their businesses (Adelino, Schoar and Severino (2014)). In unreported models, we find no evidence of differences between homeowners and renters in the effects of loan provision on either survival or subsequent UCC financing. This is consistent with the argument that the subprime borrowers in our sample likely did not have substantial home equity values against which to borrow.

F.2 Firm 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 small business owners. As we argued for high credit score applicants, it may be that experienced owners 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 owners who had senior management experience (e.g., president, vice president or chief financial officer) at a different firm prior to establishing the new 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 IX, 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 owners 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 owners 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 IX, 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 owners (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 small business owners in the sample are described as having been owners of other firms, so we cannot make inferences about the effects of financing on serial firm founders.

Our results suggest that external finance is hard to substitute for when small firm owners 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 IX, 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 IX, Panel B, the effect of loan provision on subsequent UCC financing is broadly the same irrespective of the loan purpose.

G Robustness Tests: Samples Close to the Discontinuity

To complement our standard polynomial spline regression discontinuity analysis using the full data set, we also undertake a comparison of outcomes for above and below threshold applicants in varying narrow windows around the threshold. In this robustness analysis, we consider all the main outcome variables in the paper. Our full sample consists of 4,693 observations- in the tests below, we consider results for various smaller subsamples of observations close to the auto-denial cutoff.

In the first row of Table X 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. The second row of Table X 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 the third row of Table X 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 sixth column of Table VI.

The fourth row of Table X shows that firms just above the threshold experienced subsequent revenue growth of 0.06-0.08 greater than firms just below the threshold. Firms above the threshold also end up with higher 2012 revenues and employees than those just below, as shown in rows 5 and 6 of Table X, respectively.

In these narrow window tests, outliers far from the discontinuity have no influence on the estimated coefficients- the results are driven by applicants close to the auto-denial

threshold. Taken together, these tests suggest that our basic findings are robust as consistent results emerge using different discontinuity estimation approaches.

V Conclusion

In this paper, we provide direct evidence on the impact of early-stage business loans on the success of small firms led by subprime owners by analyzing a large sample of startup loan applicants in the United States. Loans can enhance owners' 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 non-profit financial institution's automated loan application review process, which allows us to undertake a regression discontinuity design assessing the causal impact of access to small business credit. We find that obtaining a loan has a strong effect on the future of a young firm—startups receiving funding are dramatically more likely to experience medium-term survival, enjoy higher revenues and create more jobs. The magnitude of the estimated effect of financing on survival suggests that the absence of external credit explains a large bulk of the overall failure rate we observe. We also find that loans are more consequential for firm survival among subprime owners with more education and less senior managerial experience.

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.

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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	15,552	11,344	13,926	925	56,255
Survives	0.30	0.00	0.46	0.00	1.00
Prior revenues	30,028	9,153	421,057	0	257,603
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 line	Count
Business services	536	Child care services	70
Eateries	369	Repair Services	59
Beauty shops	158	Women's clothing stores	56
Local trucking	122	Single-family house construction	51
Transportation services	81	Business consulting	44

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** (-28.91)	0.113** (8.78)	0.129** (10.99)	0.0923** (6.11)	0.113** (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 (-0.83)	0.00354 (0.39)	2.809 (0.86)	0.00195 (0.18)	0.0132 (0.67)	-0.0290 (-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** (4.79)	-0.0383 (-0.44)
Credit Score	0.000164 (1.25)	0.000208** (1.97)
Prior Bankr.	0.0186 (1.46)	0.00238 (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: Firm Survival

Results from the 2SLS regressions (columns 1-5) and OLS regression (column 6) 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 1-4 and 6 and using a 100% name match requirement in column 5. The regressors with reported coefficients are an instrumented dummy for loan provision (columns 1-5), the applicant's credit score (columns 4-5), a dummy for whether the applicant had ever declared bankruptcy prior to the application (columns 4-5) and a dummy for whether the applicant's capacity score was zero or above (column 6). The sample in column 2 consists of loans made in 2009 or earlier and the sample in column 3 consists of loans made in 2010 or later. 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?	Survives?	Survives?
Loan Provided (instr.)	0.546** (3.44)	0.671** (2.67)	0.473 (1.25)	0.510** (2.58)	0.482** (2.32)	
Credit Score				-0.000419* (-1.93)	-0.000345 (-1.53)	
Prior Bankr.				0.0274* (1.70)	0.0133 (0.79)	
Capacity Above Threshold						0.0622** (3.34)
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Bus. Line F.E.	No	No	No	Yes	Yes	Yes
Sample	Full	Full: 2006–2009	Full: 2010–2011	Bus. Line Avail.	Bus. Line Avail.	Bus. Line Avail.
Est. Method	2SLS	2SLS	2SLS	2SLS	2SLS	OLS
Match Type	Approx.	Approx.	Approx.	Approx.	Exact	Approx.
Observations	5404	3178	2226	4482	4482	4991

t statistics in parentheses, * $p < 0.10$, ** $p < 0.05$

Table VII: 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), the log of the 2012 revenues (column 3), the log of one plus the 2012 number of employees (columns 4-5) and the log of the 2012 number of employees (column 6) 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 2-3 and 5-6). The sample in columns 3 and 6 only includes those firms that survived until 2012. 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. Rev.	Log of Curr. Empl.	Log of Curr. Empl.	Log of Curr. Empl.
Loan Provided (instr.)	0.774** (2.60)	6.022** (2.73)	0.377 (0.53)	0.544** (2.59)	0.598** (2.78)	0.472 (0.77)
Credit Score	-0.000779** (-2.31)	-0.00512** (-2.08)	-0.0000879 (-0.09)	-0.000415* (-1.80)	-0.000530** (-2.19)	-0.000415 (-0.51)
Prior Bankr.	0.0373* (1.72)	0.308 (1.64)	-0.00360 (-0.06)	0.0246 (1.25)	0.0246 (1.27)	-0.0420 (-0.88)
Log(Prior Rev.)		0.143** (3.17)	0.0501** (4.19)		0.0207** (3.95)	0.0324** (2.99)
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Bus. Line F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Bus. Line Avail.	Bus. Line Avail.	Bus. Line Avail. & Survives	Bus. Line Avail.	Bus. Line Avail.	Bus. Line Avail. & Survives
Observations	4411	4482	1370	4482	4482	1377

t statistics in parentheses, * $p < 0.10$, ** $p < 0.05$

Table VIII: Firm 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** (2.62)	-0.0281 (-0.07)	0.558** (2.01)	0.742 (1.28)
Credit Score	-0.00125** (-2.60)	0.000198 (0.55)	0.0000289 (0.14)	-0.00107 (-1.09)
Prior Bankr.	0.0356 (1.27)	0.0532* (1.79)	0.00484 (0.18)	0.0475* (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** (2.26)	0.0457 (0.14)	0.518** (2.84)	0.382 (1.06)
Credit Score	0.000237 (0.97)	0.000679** (2.27)	-0.000119 (-0.85)	0.000645 (1.09)
Prior Bankr.	0.0249 (1.40)	0.0327 (1.40)	0.0445** (2.04)	-0.00419 (-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 IX: Firm 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 (-1.12)	0.588** (2.78)	0.135 (0.47)	0.958** (2.42)
Credit Score	0.00135 (1.43)	-0.000471** (-1.99)	-0.000145 (-0.34)	-0.000526** (-2.12)
Prior Bankr.	0.0585 (0.72)	0.0283 (1.51)	0.0380 (0.92)	0.0376** (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 (-0.75)	0.666** (5.93)	0.355 (1.62)	0.602** (2.45)
Credit Score	0.00166 (1.16)	0.0000350 (0.25)	0.000281 (0.92)	0.000130 (0.80)
Prior Bankr.	0.00668 (0.07)	0.0161 (1.17)	0.0806** (2.24)	0.00252 (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, * $p < 0.10$, ** $p < 0.05$

Table X: Robustness Tests: Samples Close to the Discontinuity

Results from regressions of an indicator for auto-denial (Row 1), an indicator for loan provision (Row 2), an indicator for whether the applicant's firm survives as an active business until May 2012 (Row 3), revenue growth from the application date to 2012 (Row 4), the log of one plus the 2012 revenues (Row 5), and the log of one plus the 2012 number of employees (Row 6) on applicant characteristics in varying capacity windows. The full sample consists of 4,693 observations; only observations in smaller subsamples drawn from capacity windows 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.

Sample	Capac. \in $[-2, +2]$	Capac. \in $[-1.5, +1.5]$	Capac. \in $[-1, +1]$	Capac. \in $[-0.5, +0.5]$
Capacity Above Threshold for Auto-deny	-0.526** (-29.68)	-0.536** (-28.08)	-0.519** (-22.52)	-0.409** (-10.76)
Capacity Above Threshold for Loan Provision	0.140** (9.08)	0.135** (8.07)	0.113** (5.65)	0.0778** (2.59)
Capacity Above Threshold for Survival Dummy	0.0383** (2.20)	0.0459** (2.48)	0.0573** (2.66)	0.0555* (1.72)
Capacity Above Threshold for Revenue Growth	0.0556** (2.49)	0.0657** (2.78)	0.0753** (2.77)	0.0798* (1.95)
Capacity Above Threshold for Log of Curr. Rev.	0.409** (2.07)	0.503** (2.39)	0.651** (2.67)	0.644* (1.76)
Capacity Above Threshold for Log of Curr. Empl.	0.0380* (1.73)	0.0480** (2.06)	0.0780** (2.85)	0.0799* (1.93)
Observations	2940	2629	2006	1052

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.

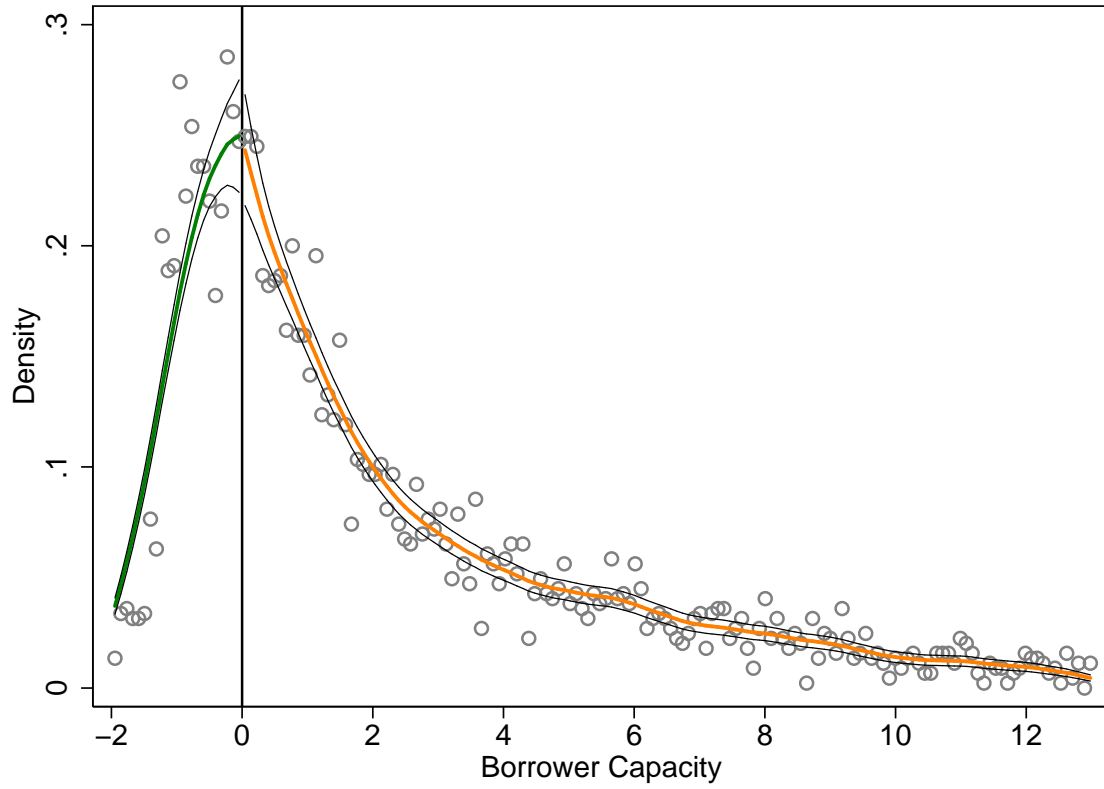
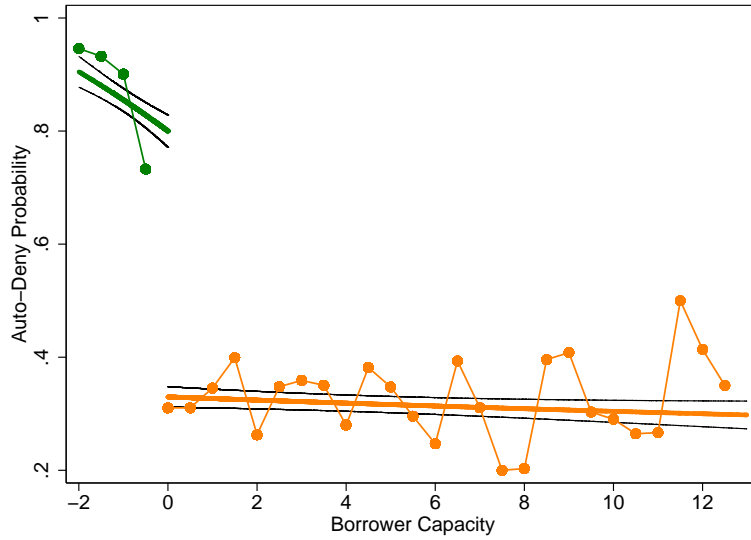


Figure 2: Borrower Capacity, Automatic Denial, and Loan Provision

This figure displays regression discontinuity results characterizing the impact of borrower capacity scores on automatic denial recommendation (Graph A) and on the probability of receiving a loan (Graph B). 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.

Graph A. Auto-Deny Probability



Graph B. Loan Probability

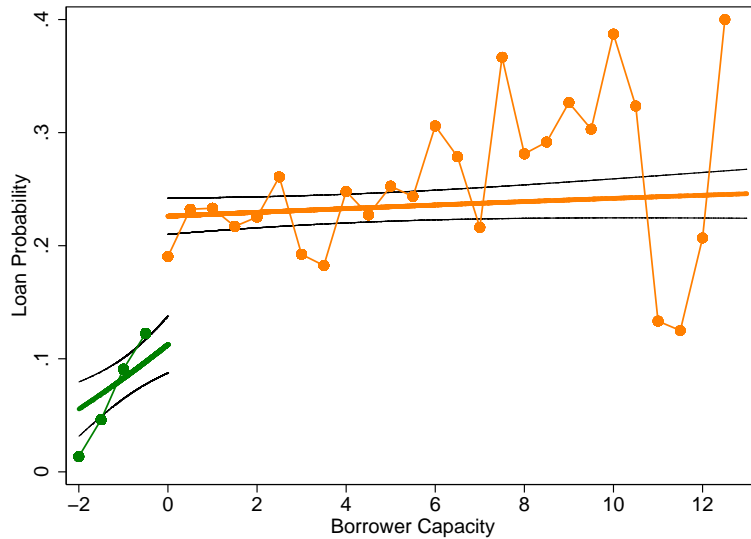


Figure 3: Borrower Capacity and Observable Characteristics

This figure displays regression discontinuity results characterizing the impact of borrower capacity scores on the probability the applicant had a prior bankruptcy filing (Graph A), the probability the applicant had a prior tax lien (Graph B), applicant credit score (Graph C), the probability the applicant had a prior UCC filing (Graph D), years of education (Graph E), and the applicant log of years of industry experience (Graph F). 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.

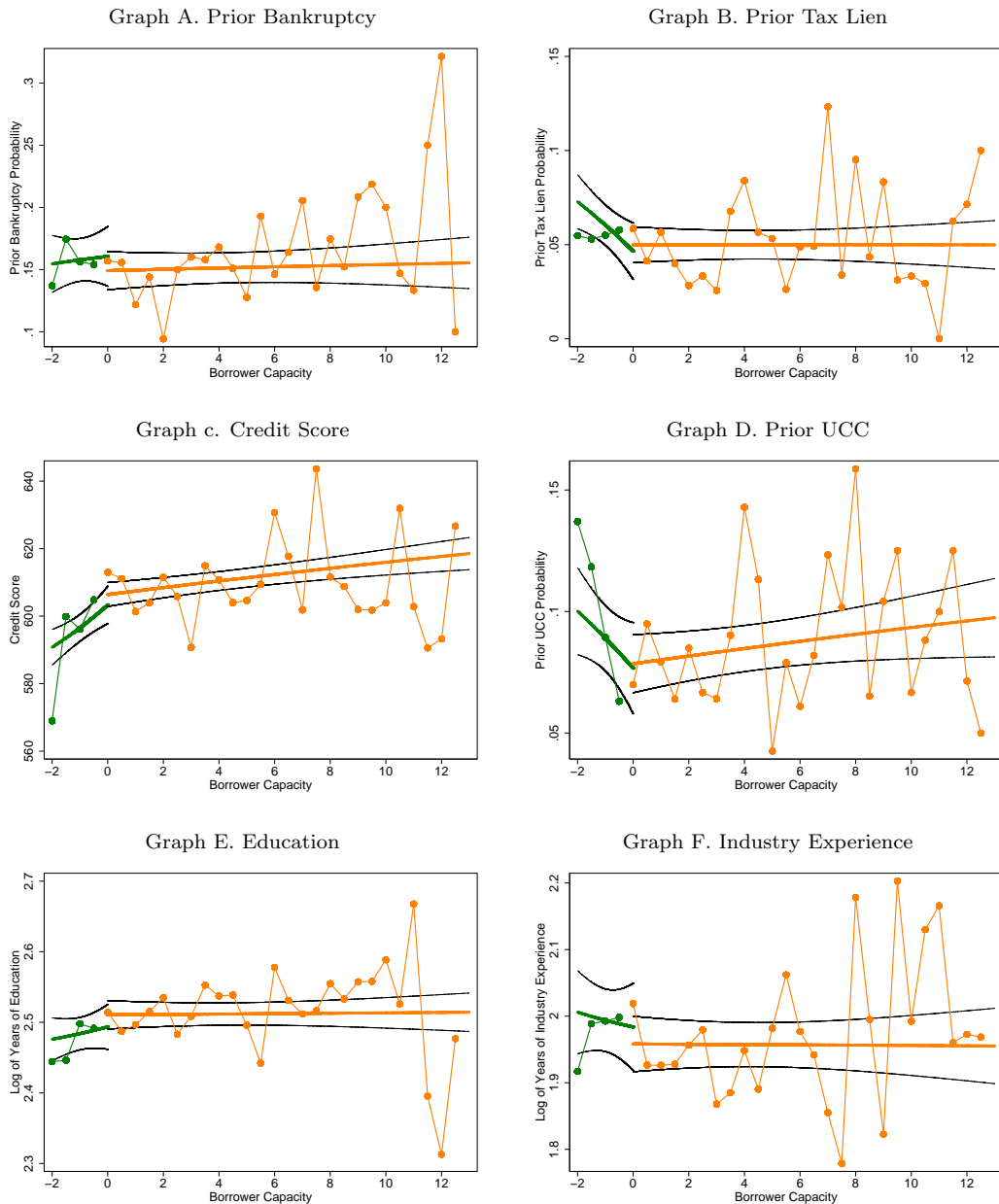


Figure 4: Borrower Capacity and Firm Survival

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.

