The Financial Consequences of Customer Satisfaction: Evidence from Yelp Ratings and SBA Loans

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ABSTRACT

This paper demonstrates the financial and real consequences of customer satisfaction using a novel and comprehensive Yelp dataset. I show that Yelp ratings are significant indicators of business outcomes in a regression discontinuity design setting. A one-half star increase in Yelp ratings leads to a higher probability of receiving SBA loans, better loan terms, and better loan performance. The results are more pronounced when banks have less information about the borrowers. Yelp ratings become less effective when using repeated loan transactions. Lastly, higher Yelp ratings lead to increases in consumer demand and the likelihood of subsequent business opening.

Keywords: Social Media, Customer Satisfaction, Credit Rating, Small Business Loan, Bank Lending

JEL Classifications: G21, G30, H81, L15

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I. Introduction

Businesses, large or small, have devoted numerous resources to maintaining their customer satisfaction. Customer satisfaction has been widely recognized as a valuable intangible asset to businesses in fiercely competitive markets. The question arises, then, whether customer satisfaction brings those businesses any direct financial consequences. In this paper, I focus on Yelp ratings and use Small Business Administration (SBA) loans as the outcome. I show that customer satisfaction aspects of crowd-sourced ratings have a real impact on the small businesses.

Small businesses are the backbone of the U.S. economy. They represent more than 95% of all firms and employ more than 50% of the private sector workforce. Additionally, small businesses create roughly 65% of new employment opportunities. Due to limited access to public equity and debt markets, small businesses mainly rely on bank credit, especially term loans, to finance their growth. One major obstacle in small business lending is that banks have scarce reliable information about borrowers because small businesses are not subject to strict regulatory filing requirements. The usual toolbox lenders possess might offer little to no benefit. That being said, lenders have access to alternative and less traditional methods for measuring customer satisfaction and public perception about potential borrowers thanks to the proliferation of review websites like Yelp.com. Yelp ratings are generated by individuals and aggregated by the Yelp web platform. To some extent, these ratings represent businesses' customer satisfaction, reputations, popularity, and prospects. The Yelp platform enables such soft information to quickly reach consumers as well as lenders. More importantly, Yelp ratings affect the outcome of the small businesses in two ways.

Social learning helps reduce uncertainties regarding the quality of goods and services. For example, consumers choose to buy books with higher customer ratings (Chevalier and Mayzlin, 2006), update their beliefs about a movie's quality based on peer feedback (Moretti, 2011), and order a restaurant's most popular dishes once they become aware of them (Cai et al., 2009). Because customers learn from peer reviews posted on social media platforms and make consumption choices accordingly, businesses with higher ratings are more likely to attract larger numbers of consumers. That is, businesses with five-star Yelp ratings will attract more customers than those with one-star ratings.

In turn, the noticeable differences in consumer receptions between businesses with different ratings could translate to higher revenue and cash flow streams. Those characteristics shown by businesses with higher ratings make them attractive candidates in the eyes of rational lenders. In other words, rational lenders, exploiting the good prospects of highly-rated businesses that are generated by consumer demand, make sensible lending decisions that coincide with Yelp ratings. Since mechanisms to resolve information asymmetry problems are imperfect, banks ration borrowers (Stiglitz and Weiss, 1981). Lenders believe borrowers with a track record are more likely to repay their loans and have better outcomes (Diamond, 1991). In the modern era of bank lending, customer satisfaction reported from social media platforms could indicate businesses' prospects and in turn serve as salient signals to complement lenders' existing evidence. Indeed, successful and high-quality businesses usually command higher premiums to compensate for business owners' investments, which translates into enhanced revenue and profitability (Allen, 1984). Borrowers with higher ratings, as indicated by information aggregated on social media platforms, would therefore have more financial slack with which to fulfill their loan commitments.[1]

Anecdotally, the SBA and Yelp have formed a partnership to help small businesses succeed with online reviews.[2] Similarly, many other major financial institutions, such as

[1]One might argue that each review written on Yelp by itself is considered noisy at best and may not provide insightful information. However, the true information is revealed when aggregating each individual piece (Diamond and Verrecchia, 1981; Verrecchia, 1982; Ellison and Fudenberg, 1995).

[2]For more information regarding the partnership, see https://www.sba.gov/about-sba/sba-

J.P. Morgan Chase, offer advice on their websites to educate small business owners about social media.[3] Last but not least, mainstream news outlets, like Forbes and the BBC, have published articles about social media and the ability to qualify for bank loans.[4] Overall, Yelp's business ratings could provide lenders with reliable information regarding borrowers' business prospects.

In this paper, I examine the impact of Yelp ratings on SBA loan outcomes, specifically the probability of receiving loans, loan terms, and loan performance. To do so, I collect a novel and comprehensive Yelp review dataset that begins at Yelp's inception in 2004. The final sample has over 80 million distinct reviews covering more than 1 million businesses across the United States. I obtain the SBA loan data from the SBA through a Freedom of Information Act (FOIA) request. In the baseline results, I find that aggregated Yelp ratings have a positive and significant relationship with the probability of receiving SBA loans. I further show that the loans have better terms, such as lower interest rates and lower collateral requirements, and perform better, with lower default probability and a lower amount of write-offs upon default. However, many confounding factors might coexist with the Yelp ratings and hence may cause an endogeneity problem. More specifically, some unobservable or observable elements may be correlated with Yelp ratings, which could affect my findings.

To address this identification issue, I exploit a unique feature of the Yelp platform. Though each individual review has its own unique rating assigned by the user who writes it, Yelp aggregates those ratings and presents an overall rating of the business. The overall rating is only shown as a number of stars. Because of the institutional design, Yelp ratings range on a scale of 1 to 5 stars in one-half star increments, which means each

initiatives/sba-and-yelp-present-success-online-reviews (last retrieved: July 15, 2017).

[3]For more details, see https://www.chase.com/news/111416-social-media (last retrieved: July 15, 2017).

[4]For more details, see http://www.bbc.com/news/business-37224847 and https://www.forbes.com/sites/chynes/2017/04/25/how-data-will-help-drive-universal-financial-access/#1466f1eb57e6 (last retrieved: July 15, 2017).

overall rating is rounded to the nearest one-half star by using predetermined rounding thresholds. For example, a business with an overall rating of 3.75 is rounded up to 4 stars, while a business with an overall rating of 3.74 is rounded down to 3.5 stars. I implement a regression discontinuity design (RDD) around the rounding thresholds. I assume that the closer a rating is to the rounding thresholds, the more similar predetermined business characteristics that affect loan outcomes become. My key identifying assumption is that, in the absence of a discontinuous jump in overall ratings near the rounding thresholds, there are no other discontinuous changes in business characteristics that directly affect loan outcomes.

Using the RDD tool, I document a causal relationship between Yelp ratings and loan outcomes. I first examine the probability of receiving SBA loans. I find that a one-half star increase in Yelp rating leads to a significant increase in the probability of receiving loans. This effect is also economically significant, representing a 40% increase in the probability of receiving SBA loans. This is direct evidence that businesses' customer satisfaction ratings have significant effects in small business lending. To provide further support to the argument, I next explore loan terms, more specifically loan spreads and collateral. Again, utilizing the RDD design, I document that a one-half star increase in Yelp rating leads to significantly lower financing costs. The average business 'just above' the rounding thresholds enjoys a 36 basis points lower loan spread and 4% less collateral requirements than the average business 'just below' the threshold. The effect is also economically substantial, corresponding to 12% cheaper loan pricing and lower required collateral, which is a tremendous benefit for small businesses. Lastly, I examine loan performance in terms of default probability and the amount of write-off upon default given that businesses with higher ratings are attracting more customers, which means higher revenue and a better position to repay loans. I find that a one-half star increase in Yelp rating leads to two-times better loan performance, that is both statistically and economically significant. I interpret the loan outcome results as consistent with the notion that aggregated Yelp ratings represent the borrowers' prospects.

I then use cross-sectional comparisons and show that the role of Yelp ratings is more pronounced when retrieving information about the borrower is more costly to provide support that lenders refer to such ratings as salient signals. Specifically, I focus on the local business environment and bank monitoring effectiveness. My findings show that a one-half star increase in Yelp rating has a stronger impact on businesses in sectors with fewer competitors and on those located far away from the lending banks. For businesses with fewer competitors, the available information is quite opaque. Yelp ratings serve as good indicators of future revenue potential for those types of businesses. Similarly, banks need to devote extra effort to obtaining the creditworthiness of and monitoring borrowers, especially those that reside far from them. Social media therefore helps to alleviate this problem, since Yelp ratings are readily available to lenders.

Next, I focus on situations in which other sources of information could potentially dilute the effects of the Yelp ratings. I focus on small businesses that take out subsequent loans from the SBA. In those cases, the lenders have already had prior experience with the borrowers. I find evidence that the lenders rely less on Yelp ratings in subsequent lending decisions compared to the first decisions. In addition, I identify whether the first and second loans are originated by the same lender. I document that, when a second loan is taken out with the same bank, businesses' Yelp ratings become less revealing, because the banks have had direct interactions with the borrowers. However, the overall effects of Yelp ratings are not completely canceled out, indicating that Yelp remains a good predictor of loan outcomes even for subsequent loans.

Lastly, I turn to two alternative outcomes, one from a consumer and one from a business perspective, to test whether Yelp ratings could be effective determinants. I first study the changes in consumer demand due to increases in Yelp ratings. I proxy consumer demand using new reviews received by businesses and find that higher Yelp ratings lead to higher probability of receiving more reviews. Then I measure subsequent location openings for companies already on Yelp to develop an understanding of small businesses' investment decisions. I find that a one-half star increase in Yelp rating leads to a 23% increase in the likelihood of opening a new location.

Considered together, my results shed light on the effects of social media on small businesses' financial consequences. My work makes a critical contribution into several strands of inquiry. First, I contribute to a large body of literature on the financial and real consequences of credit ratings. Unlike credit ratings, which take effects through regulatory certification (Bongaerts et al., 2012), I show that Yelp ratings have a direct effect on bank lending. I also show that other types of ratings, i.e., crowd-sourced Yelp ratings, play important roles in economic outcomes, similar to the unexpected effects of sovereign ratings (Almeida et al., 2017). In terms of ratings' discreteness, I find evidence consistent with the fact that creditors favor firms with ratings above a pre-determined cutoff (Chernenko and Sunderam, 2011).

This research also enriches the results of studies that have examined the role of social media and reputation capital. My work identifies important and effective information contents from consumer opinion, which is an integral part of business reputation. Existing studies, e.g., Da et al. (2011) and Huang (2017), show that Internet popularity influences asset prices in a way that cannot be explained by existing risk factors. I study small businesses where there is extremely scarce public knowledge about their financial health. The amount of information provided by the crowd appears to be even more significant in these cases.[5] To the best of my knowledge, this paper marks the first attempt to utilize a comprehensive Yelp dataset that provides valuable information coverage on more than

[5]The paper is also related to valuating intangibles in light of Edmans (2011) where customer satisfaction ratings can be regarded as firms' intangible capital.

1 million businesses.[6]

My paper is also related to the literature on bank lending. Earlier studies, both empirical and theoretical, have focused on relationship lending through repeated transactions between the borrowers and lenders (e.g., Diamond, 1991; Petersen and Rajan, 1994; Berger and Udell, 1995). More recent studies have explored the relationship between additional dimensions between lenders and borrowers and loan outcomes, such as the loan syndicate structure (Sufi, 2007), asymmetric information in loan syndicates (Ivashina, 2009), and corporate ownership structure (Lin et al., 2012). I study loan decisions in the realm of social media, i.e., reviews by separate individuals averaged by a web platform. With over 80 million reviews to support my analysis, I show that customer satisfaction is critical in determining loan outcomes. Furthermore, it is difficult to establish a causal relationship between banking relationships and bank lending. As such, I utilize an RDD identification strategy that exploits Yelp rating rounding thresholds to address this endogeneity concern.

This study also adds to the literature about small business financing and entrepreneurship in general. First, my paper introduces a new data source to the literature that provides excellent coverage on entrepreneurial firms. Second, existing studies mainly document the impact of small business loans on, for example, employment growth (Brown and Earle, 2017), business growth (Hackney, 2016), and local economic performance (Craig et al., 2005). My paper focuses on the determinants of those loans and provides additional ways to understand the lending process, especially in the small business setting.

The remainder of the paper is organized as follows. Section 2 provides the details of the identification strategy and the data. Section 3 focuses on loan-level analysis. Section 4

[6]Scholars in other fields have used Yelp data to answer different research questions (e.g., Anderson and Magruder, 2012; Luca, 2016; Elder et al., 2017). However, they tend to focus on one single city or industry, which could potentially introduce city- or industry-specific biases that make it nearly impossible to generalize the results.

presents the additional findings, and Section 5 examines other business outcomes. Section 6 concludes.

II. Empirical Design and Data

A. Empirical strategy

First, it's important to establish the relationship between Yelp ratings and loan outcomes. I carry out a standard ordinary least squares (OLS) approach as shown in Equation (1). In the regression equation, $outcome_{it}$ takes on different measures of loan outcomes, $actual\ rating_{it}$ is the unrounded actual Yelp rating, X_{it} is a vector of business and loan level controls, κ_i is firm fixed effects, τ_t represents year fixed effects, η_i is Yelp industry fixed effects, and θ_i is county fixed effects. This relationship should be understood as a correlation.

$$Outcome_{it} = \beta_0 + \beta_1 \cdot actual\ rating_{it} + \beta_6 \cdot X_{it} + \kappa_i + \tau_t + \eta_i + \theta_i + \epsilon_{it} \tag{1}$$

Identifying the effects of Yelp ratings on loan outcomes in general is challenging because lenders possess additional information about the borrowers. Those elements, together with unobservable factors, might be correlated with Yelp ratings. The regression in Equation (1) is subject to potential endogeneity problems. Furthermore, whether the small businesses receive SBA loans and what the loan terms would be are inherent selection issues arising from the loan granting institutions.

[Place Figure 1 about here]

To overcome this identification problem, I exploit a design feature of the Yelp platform. When one looks up businesses on Yelp.com, the website prominently displays the overall ratings of businesses on the top left corner under the business names. Figure 1 shows two examples of Yelp ratings. The overall ratings are presented in the form of stars. The stars range from one to five, and they increase in one-half star increments, which yields nine possible rating categories. More specifically, businesses on Yelp receive overall ratings of 1 star, 1.5 stars, 2 stars, 2.5 stars, 3 stars, 3.5 stars, 4 stars, 4.5 stars, and 5 stars. In the example shown in Figure 1, the business at the top of the figure has a Yelp rating of 4 stars, whereas the business at the bottom has a Yelp rating of 4.5 stars. However, those star ratings are not the exact ratings of those businesses. They are, instead, average ratings calculated from all the individual reviews left by users. When Yelp aggregates those reviews, the platform uses a predetermined rule to round the average ratings to display them in one of the aforementioned nine possible overall star ratings. Due to Yelp's institutional design, the rounding thresholds are set exactly at the mid-point of two neighboring star ratings. For example, in determining whether a business belongs to the 4-star group or the 4.5-star group, Yelp compares the business's average star rating calculated from all user reviews to the mid-point of 4 and 4.5, which is 4.25. If the business has an average review below 4.25, then the overall rating is rounded down to 4 stars and shown as such on Yelp. Otherwise the business's overall star rating is rounded up to 4.5 stars and displayed accordingly.[7]

I implement an RDD strategy around the rounding thresholds to study their effects on loan outcomes. Since Yelp provides nine possible star ratings, there are eight rounding thresholds. I recenter the average ratings to their cutoff points and assign the businesses with average ratings 'just above' the rounding thresholds to the treatment group and the businesses with average ratings just below the rounding thresholds to the control group. The idea is that assignment to the treatment is determined by whether the Yelp ratings are

[7] In Appendix A, I show the Yelp ratings as shown in Google search results of the sample businesses. Google extracts the Yelp ratings and displays them directly in the search results. First, the lenders do not need to find the specific Yelp pages to get businesses' Yelp ratings. Second, Google preserves the format of Yelp ratings so my identification strategy is still valid even if loan decisions are based on the Google search results.

rounded up or down given the fixed rounding thresholds. Businesses with average ratings 'just above' the rounding thresholds are similar in many relevant respects to businesses with average ratings 'just below'. The average ratings may themselves be associated with loan outcomes, but this association is assumed to be smooth. As a result, I can interpret any discontinuity of the conditional distribution of loan outcomes as a function of Yelp ratings at the rounding thresholds as causal. My key identifying assumption is that, in the absence of a discontinuous jump in overall ratings around the rounding thresholds, there are no other discontinuous changes in business characteristics that directly affect the loan outcomes.[8]

To empirically carry out my identification strategy, I adopt the parametric approach as suggested by Lee and Lemieux (2010) and utilize the full sample with higher order polynomials. I estimate a regression of the following form:

$$\begin{aligned} Outcome_{it} = {} & \beta_0 + \beta_1 \cdot I_{round\ up_{it}} + \beta_2 \cdot recentered\ actual\ rating_{it} + \beta_3 \cdot recentered \\ & actual\ rating_{it}^2 + \beta_4 \cdot I_{round\ up_{it}} \times recentered\ actual\ rating_{it} + \\ & \beta_5 \cdot I_{round\ up_{it}} \times recentered\ actual\ rating_{it}^2 + \beta_6 \cdot X_i t + \\ & \phi_i + \kappa_i + \tau_t + \eta_i + \theta_i + \epsilon_{it} \end{aligned} \tag{2}$$

where $outcome_{it}$ takes on different measures of loan outcomes, $I_{round\ up_{it}}$ is an indicator variable that equals one if the Yelp rating is rounded up and equals zero if rounded down, $recentered\ actual\ rating_{it}$ is the unrounded average rating recentered around each cutoff, X_{it} is a vector of business and loan level controls, ϕ_i is cutoff fixed effects, κ_i is firm fixed

[8]For the RDD framework to be valid, the treatment must satisfy the ignorability assumption, i.e., it must be randomly assigned conditional on observables. This means that all factors are accounted for and no omitted variable bias exists to be correlated with the treatment. In the RDD setting at hand, this is satisfied trivially. More specifically, when the actual rating is above the cutoff, the treatment takes the value of 1. When the actual rating is below the cutoff, the treatment takes the value of 0. Conditional on the actual rating, there's no variation left in the treatment dummy, making it impossible to be correlated with any other factor. Nevertheless, I plot the number of reviews and price range in Appendix B and show that they are indeed continuous around the cutoffs.

effects, τ_t represents year fixed effects, η_i is Yelp industry fixed effects, and θ_i is county fixed effects.[9]

One potential concern arises with using the Yelp data. The rounding thresholds are also known to the business owners. They have an incentive to manipulate their ratings so they appear to be one-half star higher in ratings. The reasons behind the manipulation could be to attract more customers and to window-dress their ratings before applying for financing. Anecdotally, Yelp has always maintained that they employ a team of engineers to combat fake reviews with complex and advanced computer algorithms.[10] Additionally, federal judges have dismissed lawsuits against allegations of Yelp review manipulation.[11] Both counts afford me some confidence in ruling out manipulation by business owners. Formally, I carry out a McCrary (2008) density test to rule out the manipulation concern, and present the findings in Appendix C.

B. Yelp data

Founded in 2004, Yelp is a crowd-sourced website where people post their reviews of businesses. Yelp attracts 26 million unique visitors on average through the mobile application and 73 million unique visitors on average through the web each month. It contains over 127 million reviews as of the first quarter 2017.[12] Everyone can sign up

[9]In robustness tests shown in the appendices, I also adopt the nonparametric approach by estimating the effects of Yelp ratings on loan outcomes with data right around the cutoffs in the spirit of Hahn et al. (2001). The purpose is to carry out a local linear randomization experiment. I test three bandwidths around the cutoffs: 0.05, 0.1, and 0.15 points.

[10]Yelp claims that their sophisticated software constantly sifts through the reviews and removes the potentially fake ones in a short period of time. For example, see a WSJ interview with Yelp founder Jeremy Stoppelman: https://www.wsj.com/articles/yelp-looks-beyond-reviews-1494986641 (last retrieved: July 15, 2017).

[11]For details, see class action lawsuit against potential Yelp review manipulation https://www.wsj.com/articles/SB10001424052970204505304577002170423750412 and its appeal after the initial dismissal http://sanfrancisco.cbslocal.com/2014/09/04/court-sides-with-san-francisco-based-yelp-in-lawsuit-from-small-business-owners-9th-circuit-court-of-appeals-online-reviews (last retrieved: July 15, 2017).

[12]For details, see http://www.yelp.com.

for a Yelp.com account free of charge to rate businesses and write reviews. The reviews consist of reviewer names, review dates, one- to five- star ratings, and comments from the reviewers. Everyone can access Yelp through mobile devices and computers by directly searching the business names in search engines or on Yelp.com. Users also have the ability to look up businesses by a specific star rating, a particular location, a Yelp industry, or a price range, among many other criteria.

[**Place Figure 2 about here**]

I search and download relevant business information and reviews from Yelp. Figure 2 provides a sample business listed on Yelp and the data extraction procedure. For each business, I collect the business name (i.e., Bacaro), Yelp business category (i.e., American, Italian, Lounges), address (i.e., 113 N Walnut St., Champaign, IL 61820), price range (i.e., $$$ and $31-60), each reviewer rating and review date (i.e., 5 stars, 1/2/2017), along with other identifying information embedded in the source HTML code. I collect data on businesses located in the United States only. The data includes Yelp reviews starting in October 2004 (Yelp inception date) through the end of 2016. I require businesses to have more than five reviews in order to be included in the sample for the empirical analysis.[13]

[**Place Figure 3 and Table 1 about here**]

Figure 3 plots the Yelp data coverage at the county level on a map. For each business, I assign a census-defined county code based on the address. I count the number of businesses in each county. The counties with higher numbers of businesses represented on Yelp are presented in darker colors and counties with lower numbers of businesses on Yelp are in lighter colors. The map shows that my data provides comprehensive coverage of most parts of the United States. Table 1, Panel A breaks down the Yelp data by year. Over the years, Yelp has increasingly gained popularity and continues to add an increasing number

[13]It is crucial to ensure that the ratings I calculated from my data match with the actual ratings displayed on Yelp.com. Comparing the imputed Yelp ratings as of the end of 2016 with actual Yelp ratings posted on Yelp.com, my data could match over 99% of the actual Yelp ratings posted.

of businesses and reviews. The average number of reviews per business has increased from less than two in 2004 to almost 13 in 2016. Table 1, Panel B divides the Yelp data into 22 Yelp-defined categories. This panel shows the average Yelp rating, average number of reviews, and category weight. Of the 22 categories, restaurants account for around 20% and shopping accounts for about 10%. The average rating ranges from 3.49 to 4.49, and the average number of reviews ranges from 5 to over 120.

C. SBA loan data

Traditional data sources that provide details about loans, such as Thomson Reuters DealScan and S&P Cap IQ, mostly focus on syndicated loans that are taken out by multinational corporations. Regarding small business loans, only certain banks are required to report their activity according to the Community Reinvestment Act of 1977; in fact, the federal government increased reporting thresholds to $1 billion in 2005. Those businesses are mostly rated by rating agencies, have to follow strict regulatory requirements, are thoroughly researched by the lenders, and are closely covered by the media compared to true small businesses.

The SBA 7(a) loan program caters to small businesses with a maximum loan amount of $5 million.[14] These loans provide the ideal environment in which to study the role of social media and customer satisfaction because the covered businesses tend to have a single location and be family owned and operated. They are not subject to strict government filing requirements and do not have much publicly available information. I

[14]The SBA 7(a) loans are made to small businesses who are not able to able to obtain credit on reasonable terms. The SBA also requires the borrowers to have good prospects to repay those loans and be small, among other things. The normal procedure is that the borrowers apply to the lenders directly then the local SBA office makes a final deicision. The SBA has rolled our Certified Lender Program, Preferred Lender Program, and Express Loan Program to expedite the process. SBA 7(a) loans are no more pricer than conventional non-guaranteed small business loans. For more details about the SBA 7(a) loan program, please see: https://www.sba.gov/partners/lenders/7a-loan-program (last retrieved: July 15, 2017)

obtain the SBA loan data from the SBA through a FOIA request. The data provides detailed information on each SBA loan, including business name, business address, bank name, bank address, loan granting date, loan amount, interest rate, collateral, default status, write-off amount, etc.

[Place Figure 4 about here]

Figure 4 plots SBA loan coverage at the county level on a map. For each business that participates in the SBA loan program, I assign a census-defined county code based on the address. I count the number of businesses in each county. Similar to the Yelp coverage map, the counties with higher numbers of businesses in the SBA loan program are presented in darker colors, and counties with lower numbers of businesses in the SBA loan program are in lighter colors. The map shows that businesses in most of the United States take part in the SBA lending program.

D. Summary statistics

I make an extensive effort to match businesses in the Yelp data to the SBA loan data by name and address. I then construct my variables of interest. The key outcome variables are loan probability, loan spread, collateral, default probability, and write-off amount. Loan probability is a dummy variable that equals one if the business receives an SBA loan and equals zero otherwise. Loan spread is the interest rate charged on the loan that is determined by the lending institution, minus the prime rate at the beginning of that month. Collateral is the amount required as collateral divided by total loan amount. Default is a dummy variable that equals one if the business defaults on the loan and equals zero otherwise. Write-off amount is the amount written off by the lender divided by total loan amount. I also define a host of control variables to control for business and loan characteristics. Average rating is the average unrounded monthly Yelp rating. Number of reviews is the cumulative number of reviews at the end of each month. Price ranges are dummy variables that are based on the four Yelp price range categories displayed in the business profiles. For example, price range ($) is a dummy variable that equals one if the business is in the one dollar-sign price range category on Yelp and equals zero otherwise. I also include loan amount and loan maturity as control variables. For the regressions regarding the probability of receiving SBA loans, I construct a business-month level panel and match the loan probability dummy to the most recent month.

[Place Table 2 about here]

I present the summary statistics in Table 2. Businesses on Yelp have an average actual rating of 3.66 stars. Thirty-eight percent of the businesses are in the one dollar-sign price range and 55% are in the two dollar-sign price range. The average loan granted by the SBA is about $371,000 with a maturity of 10 years. The loans on average require 34% of the loan amount in assets as collateral, command a 289-basis-point spread over the prime rate, and experience a 1.3% default rate.

III. Loan-level Analysis

In this section, I examine the relationships between Yelp ratings and loan outcomes. I demonstrate that increases in Yelp ratings lead to a higher probability in getting SBA loans. The loans for businesses with higher ratings enjoy more favorable terms compared to those with lower ratings. I also show that positive Yelp ratings lead to better loan performance.

A. Loan probability

Yelp ratings complement existing information lenders already possess because consumers choose to frequent businesses with higher ratings, i.e., higher customer satisfaction. Diamond (1991) shows that lenders are more willing to grant loans to borrowers with a track record and a sound business practice because they are more likely to repay the loans. To assess whether lenders refer to Yelp ratings in their lending decisions, the most appropriate way is to examine the probability of receiving approval for loans.

Yelp ratings are posted by users at any given time and Yelp updates the overall ratings after receiving each new rating. To strike a balance between keeping valuable information and maintaining a reasonable data analysis process, I calculate an average rating for each business at the end of every month. More specifically, I average the ratings that the businesses have received since their appearance on Yelp at each month end. This way, I obtain a snapshot of every business's average rating for each month, effectively constructing a business-month level panel. Since I have SBA loan data showing the exact approval date, I assign the loan probability indicator to the nearest past month end.[15]

[Place Figure 5 and Table 3 about here]

I begin by reporting the reduced-form result between having higher Yelp ratings and receiving SBA loans in Table 3 Column (1). I regress the loan probability indicator on average actual Yelp rating and control for the number of reviews, firm fixed effects, and year fixed effects. Overall, this evidence suggests a positive relationship between Yelp ratings and getting loans. I then focus on the RDD framework. First, I graphically show the results in Figure 5. For each one of the eight pre-determined rounding cutoffs,

[15]The ideal way to carry out the test is to compare firms applied for SBA loans and were approved to firms applied to SBA loans but were rejected. One caveat is that only approved SBA loans are made available to me. As a compromise, in the loan probability test, I compare firms with SBA loans to the rest of the firms on the Yelp platform. For tests studying loan terms and loan performance, I restrict the sample to all firms with SBA loans.

I plot the average loan probabilities relative to the rounding thresholds on each side of the cutoffs. The graphs show clear discontinuities in loan probabilities between the businesses that fall 'just above' the cutoffs and the businesses that fall 'just below' the cutoffs.[16] Businesses with Yelp ratings above the rounding thresholds are more likely to receive SBA loans compared to businesses with ratings below the rounding thresholds. Taking a closer look at the graphs at each cutoff point, I observe that the effects of Yelp ratings increase from the lower cutoffs to the higher cutoffs, with the 3.75 and 4.25 cutoffs being the most prominent.[17]

To formally test this relationship, I run an OLS regression following Equation (2).[18] In Table 3, Column (2), I implement the parametric approach to utilize all the available data (Hahn et al., 1999). I control for the number of reviews. I include second-order polynomials in the regression and interact them with the Yelp rating indicator variable.[19] Doing so, I address potential nonlinearity in the relationship between loan probability and Yelp ratings. I also include cutoff fixed effects to rule out the possibility that I am comparing businesses at different cutoffs. I also include firm and year fixed effects in the regression. The coefficient of interest is highly statistically significant and positive at the 1% level, meaning that a one-half star increase in Yelp rating leads to a significant increase in the probability of receiving loans. This effect is also economically significant, representing a 40% increase in the probability of getting SBA loans.[20]

[16] I follow the guidance of Lee and Lemieux (2010) to formally test bin width choice. The same applies to graphs presented throughout this paper.

[17] The graphs show similar behavior to consumers when one's making consumption choices. For firms in the lower range of the rating spectrum, consumers are less likely to choose them. For firms in the higher range of the spectrum, consumers become indifferent between them given only a one-half star difference in Yelp ratings. This is also the reason why we observe little effects when the ratings are low and smaller effects when the ratings are very high (i.e., at the 4.75 cutoff).

[18] The results are robust to a logit specification. The same applies to loan probability analysis in later sections.

[19] Again, I follow Lee and Lemieux (2010) to find the optimal functional form to estimate in terms of higher order polynomials. The same applies to the tables presented throughout this paper.

[20] In Appendix D, I implement a non-parametric approach by using data right around the cutoffs and vary the bin width around the rounding thresholds. More specifically, I regress loan probability on the treatment dummy and control for the number of reviews, cutoff fixed effects, firm fixed effects, and year fixed effects. I show that the results using loan probability as the dependent variables are not sensitive

Columns (3) and (4) focuses on the businesses that fall just around the 3.75 and 4.25 cutoffs, respectively. Those two cutoffs are the ones that matter the most in determining loan probabilities as shown in the figures. For businesses belonging to the 3.75 cutoff, the ones rounded up to 4 stars are much more likely to receive SBA loans compared to the ones rounded down to 3.5 stars. The regression coefficient represents a 60% increase in the likelihood of receiving loans. For the 4.25 cutoff, the effects are smaller, i.e., 40% increase in the likelihood of obtaining loans for the businesses rounded up to 4.5 stars compared to the ones rounded down to 4 stars, but it is still significant, both statistically and economically

Taken together, I have shown that Yelp ratings play a significant role in the loan decision process. This is direct evidence that customer satisfaction presented on social media platforms affects loan decisions in the small business lending setting.

B. Loan terms

After establishing the fact that Yelp ratings have causal effects on the probability of receiving small business loans, I next study whether such ratings also affect loan terms. Ratings on social media platforms represent borrowers' customer satisfaction rating, which in turn could provide complementary information regarding borrowers' ability to repay loans due to the effect on potential future revenue streams. Such business conditions are reflected in the loan terms.

I follow a similar approach as before. However, I restrict the sample to businesses that have received SBA loans only because businesses without SBA loans, by definition, do not have loan terms for me to analyze. I consider two measures for loan terms following the banking literature. First, I calculate the loan spread as the difference between the reported

to the choice of the estimation window and method.

interest and the beginning of month prime rate. I use collateral as the second measure for loan terms. I define collateral as the collateral required for each loan divided by their respective total loan amount. Second, I run OLS regressions in the form of Equations (1) and (2).[21] I report the results in Table 4 where Panel A focuses on loan spread as the dependent variable and Panel B focuses on collateral as the dependent variable.

[**Place Figures 6 and 7 and Table 4 about here**]

I first report the simple OLS regression estimates in Column (1) and show that Yelp ratings are negatively and significantly correlated with loan terms, i.e., loan spread and collateral. This evidence suggests that higher Yelp ratings mean lower financing costs and less assets are required as collateral. Again, these results demonstrate a correlation. I next turn to the RDD setting. I plot the average loan spreads and collateral requirements by rounding cutoffs in Figures 6 and 7, respectively. The graphs show discontinuous jumps in loan terms near the rounding thresholds. Taking the 3.75 cutoffs as an example (i.e., Panel F), for the average firm in the first bin to the left of the cutoff (just below), it requires about 310 basis points in loan spread. However, the average firm in the first bin to the right of the cutoff (just above) pays around 270 basis points in loan spread. Similarly, in terms of collateral, the average firm in the bin 'just above' the cutoff pledges about 5% less in assets compared to the average firm in the bin 'just below' the cutoff.

To test the observations empirically, I carry out the full sample regression approach by adding second-order polynomials and interaction terms, and I report the results in Column (2). When using loan spread as the dependent variable, the Yelp rating indicator has a statistically significant regression coefficient of about -0.36. This means that a one-half star increase in Yelp rating translates to a 36-basis-point reduction in loan spread.

[21] I make a slight modification to the empirical specifications in the loan probability tests by removing firm fixed effects because not many firms in the sample borrow more than once from the SBA. Including firm fixed effects would greatly reduced the sample size. Instead, I add industry and county fixed effects, loan characteristics controls (i.e., loan amount and maturity), and price range controls. The same specification applies to the loan performance tests as well.

Given that loan spread averages about 2.90% (290 basis points), the finding is also economically significant, representing close to 12% cost savings in business borrowing. Using collateral as the dependent variable, I also document a negative and statistically significant result. More specifically, the businesses falling 'just above' the rounding thresholds pledge 12% fewer assets as collateral compared to businesses falling 'just below' the rounding thresholds.[22] In Columns (3) and (4), I again restrict the sample to businesses belong to the 3.75 and 4.25 cutoffs, respectively. I find similar results in both loan spread and collateral. Taking these results as a whole, aggregated Yelp ratings clearly influence lenders in their decision-making process.

C. Loan performance

Allen (1984) shows that business owners are compensated with higher premiums when they have higher quality products and services. Such additional premiums translate to extra cash flow streams and financial slacks that can be used towards fulfilling the loan commitments, i.e., paying back debts on time and in full. In this subsection, I examine loan performance.

I follow a similar approach as that in the previous subsection. I use two measures for loan performance. First, I look at the default probability. Default probability is an indicator variable that equals one if the borrower defaults on the loan and equals zero otherwise. Second, I use the outstanding loan amount that is written off by the lending institutions as the other measure for loan performance. I calculate the write-off amount as the percent of the loan amount that is written off divided by the respective total loan

[22]In Appendix E, I implement a non-parametric approach by using data right around the cutoffs and vary the bin width around the rounding thresholds. More specifically, I regress loan terms on the treatment dummy and control for the number of reviews, price range, loan characteristics (i.e., loan amount and maturity), cutoff fixed effects, year fixed effects, industry fixed effects, and county fixed effects. I show that the results using loan spread and collateral as the dependent variables are not sensitive to the choice of the estimation window and method.

amount. The results are reported in Table 5. I use default probability as the dependent variable in Panel A and the write-off amount as the dependent variable in Panel B.[23]

[Place Figures 8 and 9 and Table 5 about here]

I again start with regressing loan performance on overall actual Yelp ratings to gauge the relationship between them and report the results in Column (1). I find significant correlations between loan performance and Yelp ratings. Specifically, higher Yelp ratings correspond to lower default probability and write-off amounts. This evidence suggests that Yelp ratings help to address costly information acquisition problems when available information on the borrowers is scarce. Subsequently, I focus on the RDD strategy. In Figures 8 and 9, I plot the average SBA loan default probabilities and write-off amounts on each side of the eight pre-determined Yelp cutoffs separately. Businesses that are rounded up to the next Yelp rating categories exhibit lower default probabilities and write-off amounts compared to the businesses that are rounded down.

I next formally test this observation. In Column (2), I implement the specification in the previous section to conduct the full sample parametric approach. I find the regression coefficients on Yelp ratings, i.e., $I_{round\ up}$, are negative and statistically significant when using both default probability and write-off amount as the dependent variables, indicating that Yelp ratings have a causal relationship with loan performance, i.e., higher Yelp ratings imply a greater likelihood of borrowers repaying the loans. These results are also economically large, compared to businesses that fall below the rounding thresholds, and businesses that are above the rounding thresholds are two times less likely to default on SBA loans. When studying write-off amount as the outcome variable, I find results with similar economic magnitude.[24]

[23]In a robustness test, I also exclude loans originated in the last five years of the sample to account for the fact that those loans might not have reached their point of default yet. I choose five years because it takes an average of 4.7 years for SBA loans to default.

[24]In Appendix F, I implement a non-parametric approach by using data right around the cutoffs and vary the bin width around the rounding thresholds. More specifically, I regress loan terms on the

In Column (3), I focus on a sample where the businesses are in the 3.75 cutoff window. I find not only a statistically significant relationship between loan performance and Yelp ratings, but also a bigger economic meaning compared to the full sample. Businesses that are rounded up to 4 stars are three times less likely to default and the write-off amounts are three times lower compared to businesses that are rounded down to 3.5 stars. In Column (4), I study businesses that belong to the 4.25 cutoff window. I find the effects in this instance to be even larger. Overall, I show that a one-half star higher Yelp rating leads to better SBA loan performance. One reason is that businesses with higher ratings have better prospects, and the other reason is that with the help of SBA loans, businesses have more resources to grow and be profitable.

Taking the loan-level analysis together, I interpret the loan outcome results as consistent with the notion that aggregated Yelp ratings provide reliable information about the borrowers' future earnings potentials and, as a result, such ratings are significant factors in the SBA lending process.[25]

IV. Additional Findings

So far, I have shown how customer satisfaction through Yelp ratings informs loan outcomes in terms of loan probability, loan terms, and loan performance. In this section, I first illustrate how the effectiveness of Yelp ratings is greatly enhanced in situations where

treatment dummy and control for the number of reviews, price range, loan characteristics (i.e., loan amount and maturity), cutoff fixed effects, year fixed effects, industry fixed effects, and county fixed effects. I show that the results using loan default probability and write-off amount as the dependent variables are not sensitive to the choice of the estimation window and method.

[25] In Appendix G, I show my robustness tests by adding employment and credit score as control variables using data from Reference USA. It is prohibitively costly to collect Reference USA data on all businesses. Therefore, I choose to focus on businesses with SBA loans and examine loan terms and performance as the outcome variables. Further, I am only able to match about half of the sample businesses to Reference USA. In the same results, I also include the portion of SBA guarantee in the control variables because the amount of SBA guarantee might affect the loan terms and performance. When studying loan outcome, I include the loan terms, i.e., loan spread and collateral, in the control variables as well. This helps me to control for the effects of better financing terms on loan outcomes.

banks have less information about the businesses. More specifically, I study cases when businesses have fewer competitors in their local environments and when banks' monitoring abilities are weak. I then examine situations where other sources of information could potentially complicate the Yelp ratings to see whether they remain effective in loan decisions. Specifically, I study small businesses that take out a subsequent loan from the SBA.

A. Cross-sectional Analysis

To better understand the role of customer satisfaction on bank lending decisions, I investigate characteristics of businesses and banks that could amplify my results. Specifically, I focus on scenarios when banks have less information about the borrowers. I look into the local business environments to identify businesses that have more competitors versus fewer competitors. I also analyze the distances between businesses and banks to find the differences between effective and ineffective bank monitoring efforts.

For businesses that operate in sectors with fewer competitors, it would be harder for lenders to make informed lending decisions (Rothschild and Stiglitz, 1976). In turn, lending institutions have to exert additional effort to acquire creditworthiness and operation information about those businesses with fewer competitors compared to those with more competitors. Yelp ratings help mitigate these problems as Yelp ratings could potentially supplement the existing information and provide additional knowledge about a business' prospects. Consequently, I expect my results on the effectiveness of Yelp ratings in determining loan outcomes to be particularly pronounced for businesses in segments with fewer competitors. Similarly, for businesses that are located farther away from the banks, banks incur extra communication, transportation, and monitoring costs to obtain the information they need to approve the loans and to oversee the loans (Degryse and Ongena, 2005). As a result, Yelp ratings may play an important role in helping lenders obtain better knowledge about borrowers located farther away.

[Place Table 6 about here]

I carry out the empirical tests following the main results and focus on the full sample with all cutoffs. I again use loan probability, loan spread, collateral, default, and write-off amount as the measures for loan outcomes. The results are presented in Table 6. In Panel A, I report results on the business environment competitiveness. More specifically, I define the 'fewer competitors indicator', which is a dummy variable that equals one if the Yelp business is in a below the median number of competitors environment based on Yelp price range, Yelp industry, and county of location, and equals zero otherwise. In Panel B, I examine the distance between banks and borrowers. I calculate straight-line distances using businesses' physical addresses. I create what I call the 'far-from-lender' indicator, which is a dummy variable that equals one if the distance between the Yelp business and the lender is above the sample median, and equals zero otherwise. I also construct interaction terms between these two indicator variables and the Yelp rating dummy, i.e., $I_{round\ up}$, to capture the effects of competition and distance.

Using the RDD setting, my findings show that a one-half star increase in Yelp rating has a stronger impact on businesses in sectors with fewer competitors as well as on the ones located farther from banks. For businesses that are rounded a one-half star rating up, they are more likely to get SBA loans, enjoy lower loan spread and collateral requirement, are less likely to default, and write off a less amount when they have less competition in the same segments and are located farther from the banks, compared to otherwise similar businesses that are rounded down.[26]

Yelp ratings serve the purpose well when banks are less informed about the businesses. For businesses in sectors with less competition, their business prospects are considerably

[26]Note that the 'distance-to-bank' test requires that the businesses have already received loans. Otherwise, it would be impossible to find the distances between the businesses and the banks. Consequently, the loan probability test is infeasible here and intentionally left blank in the table.

more difficult to obtain. Yelp ratings serve as good indicators of future revenue potential of those types of businesses. Similarly, banks need to spend extra effort to obtain creditworthiness about and monitor borrowers located farther from them. Yelp ratings help to alleviate this problem since they are readily available to the lenders. The results provide suggestive evidence that banks refer to Yelp ratings when making lending decisions.

B. Repeated borrowers

In this subsection, I study small businesses that are repeat participants in the SBA loan program. Banks already have credit history information for these businesses, not to mention other borrower-specific information. Additionally, long-term borrowing relationships are beneficial for all parties, which one can see in the loan terms (Boot and Thakor, 1994). Consequently, I expect Yelp ratings to be less effective in this setting.

[Place Table 7 about here]

For the empirical analysis, I utilize the RDD environment and focus on loan terms as suggested by Boot and Thakor (1994). More specifically, I analyze loan spread and collateral and report the results in Table 7, again following the specifications in Table 4. In Columns (1) and (2), I use the same data as in Table 4. However, I create the second loan indicator variable as a dummy variable that equals one if the underlying loan is the second loan between the business and the SBA, and it equals zero otherwise. I interact this second loan indicator variable with the Yelp rating dummy, i.e., $I_{round\ up}$, effectively capturing the effect of subsequent borrowing. The results show positive and significant coefficients on the interaction terms, suggesting that the lenders rely less on Yelp ratings in subsequent lending decisions compared to the first borrowing encounters. In Columns (3) and (4), I push the results further by studying only the businesses with more than one loan with the SBA, using the lending bank information. I define the same bank indicator variable, which is a dummy variable that equals one if the second loan is taken out with the same bank, and equals zero otherwise. I also include the interaction term of the same bank indicator and $I_{round\ up}$ to capture the effect of a same-bank lending relationship. The coefficients on the interaction terms are, again, positive and significant. This indicates that when the second loan is taken out with the same bank, Yelp ratings become less significant because the banks have had direct interactions with the borrowers already. However, if we examine the overall effects of Yelp ratings in the presence of existing banking relationships, Yelp ratings are still good indicators of loan outcomes as the additional sources of information do not counteract the Yelp effects entirely.

Taking the cross sectional analysis and the repeated loan transactions results together, I am able to exploit situations where available information regarding the borrowers varies greatly among the banks. I show that Yelp ratings become more effective when information is scarce and remain effective when additional soft information is present.

V. Other Business Outcomes

In the previous sections, I have shown that Yelp ratings are effective determinants of SBA loan outcomes and the effects of Yelp ratings in the cross section and in repeated loan transactions. In this section, I examine the effects of Yelp ratings from both consumer and business perspectives. I first study the changes in consumer demand due to Yelp ratings by examining the probability of receiving more reviews. I then focus on the effects of Yelp ratings on small businesses' investment decisions. More specifically, I study subsequent business openings.

A. Changes in consumer demand

In this subsection, I study the effects of Yelp ratings from a consumer perspective. The mechanism that Yelp ratings take effect through which is that customers learn from peer feedbacks about the businesses and make their subsequent consumption choices accordingly. Naturally, businesses with higher Yelp ratings will attract a larger number of customers. I empirically test this here. In an ideal situation, I would like to observe the number of customers who visit the businesses. However, such data is not available. To circumvent this problem, I use the number of Yelp reviews for the businesses by assuming that the number of reviews the businesses receive is proportional to the number of total customers. Using the number of reviews the businesses receive each month, I am able to examine whether higher Yelp ratings lead to a higher probability of receiving more reviews, i.e., higher consumer demand.

To perform the empirical test, I construct a business-month panel that is similar to the one for the loan probability test. I calculate the number of reviews each business receives in a given month. I create the change in consumer demand variable as an indicator variable that equals one if a business receives a higher number of reviews in the next month compared to the current month and equals zero otherwise. I follow a similar format as the main analysis and report the results in Table 8.

[Place Table 8 about here]

In Column (1), I start by regressing the changes in consumer demand indicator on average actual Yelp ratings in the simple OLS estimation, where I also control for the number of reviews, firm fixed effects, and year fixed effects. I find a positive and significant relationship between receiving more reviews and Yelp ratings, which suggests that higher Yelp ratings lead to a higher customer demand. To make a causal claim, I again utilize the Yelp rating rounding thresholds RDD setting and report the results in Columns (2) to (4). I add second-order polynomial controls and the interaction terms between those polynomials and the Yelp rating dummy to address potential nonlinearity problems. I report a statistically and economically significant relationship between consumer demand and Yelp ratings. Comparing businesses falling 'just above' the cutoff to businesses falling 'just below' the cutoff, the former has a higher probability of receiving more reviews than the latter, indicating a higher customer demand due to higher Yelp ratings.[27]

B. Subsequent business opening

In this subsection, I turn my focus to the relationship between investment decisions by small businesses and Yelp ratings. More specifically, I examine given a high Yelp rating, whether the businesses open a second location. The purpose of this test is twofold. First, subsequent openings serve as an alternative way to test whether Yelp ratings could be effective determinants and convey business prospects. Second, and more importantly, nobody knows more about a particular business than the owner. They only open subsequent stores when they believe their current operations are profitable and full of potential. Consequently, the prediction of Yelp ratings will coincide with the businesses' actual behavior, as measured by opening subsequent stores.

To carry out the test, I follow a similar approach as the previous subsection and construct a business-year panel. I identify businesses' subsequent locations if they share the same business name, Yelp industry, and are located within the same county. I create the subsequent business opening variable as an indicator variable that equals one if an existing business opens another location and equals zero otherwise. I use the first review date of those subsequent locations on Yelp as the subsequent opening date. I assign the subsequent business opening indicator to its nearest past year end.

[27] In robustness tests, I include a control for whether the businesses have received any SBA loans, cluster the standard errors at the business-year level, and implement logit regressions. I also carry out the same tests for the results presented in the next subsection.

[Place Table 9 about here]

I follow a similar format as the main analysis and report the results in Table 9. In Column (1), I regress the subsequent business opening dummy on the actual Yelp rating and control for the number of reviews, firm fixed effects, and year fixed effects. I find a positive and significant relationship between Yelp ratings and subsequent business openings, meaning higher Yelp ratings are associated with a higher likelihood of opening another location.

In Columns (2) to (4), I carry out the RDD approach as depicted in Equation (2). More specifically, I regress the subsequent business opening dummy on the treatment dummy and control for the number of reviews, higher order polynomials, firm fixed effects, and year fixed effects. I use the full sample and include cutoff bin fixed effects in Column (2). I document that a one-half star increase in Yelp rating leads to statistically significant higher probability of subsequent business openings. This result is also economically significant. The average business falling 'just above' the rounding thresholds is 23% more likely to open a subsequent store compared to the average business falling 'just below' the thresholds. In Columns (3) and (4), I again focus on the two rounding cutoffs that matter the most, namely 3.75 and 4.25, respectively. For businesses that are rounded up to 4 stars, they are close to 60% more likely to open a new location compared to businesses that are rounded down to 3.5 stars. Though not as big of an effect, comparing to businesses rounded down to 4 stars, businesses rounded up to 4.5 stars have a 30% higher probability to start another location.

Taking the changes in consumer demand and subsequent business opening results together, I document that Yelp ratings are significant indicators in businesses' future performance and investment decisions. Furthermore, Yelp ratings matter non-trivially from both consumer and business perspectives. In sum, though not perfect, the results provide further support to my main argument.

VI. Concluding Remarks

In this paper, I investigate the role of customer satisfaction measured by Yelp ratings in the small business lending process. Higher Yelp ratings are important indicators of businesses' future revenue and cash flow streams due to consumers' social learning behavior. Borrowers with higher ratings have more financial resources to satisfy the loan commitments. Lenders, knowing the differences in business prospects, approve SBA loans corresponding to borrowers' Yelp ratings.

Using an RDD empirical setting that exploits the Yelp rating rounding thresholds, I show that Yelp ratings are good indicators of loan outcomes and document that a one-half star increase in Yelp rating leads to a 40% higher probability of receiving SBA loans, 12% reductions in collateral and loan pricing, and significantly better loan performance. In the cross section, my findings show that a one-half star increase in Yelp rating has a more significant impact on businesses with fewer competitors and those located farther from the banks. I test situations in which Yelp ratings become less effective using repeated loan transactions and show the overall effects of Yelp ratings remain powerful. I also document that higher Yelp ratings lead to a higher probability of receiving more reviews and an increase in the likelihood of opening new locations.

Overall, my results shed light on the importance of crowd-sourced information and customer satisfaction in the determination of business outcomes. As technology advances rapidly, such resources only become more critical, because it has never been easier to access this type of knowledge about a business. Exceptional customer satisfaction can bring firms a higher chance of financing and larger savings in financing costs. In practice, businesses should emphasize the importance of the online presence in their customer satisfaction management. Future research could extend this analysis to other situations and incorporate other useful contents generated by Internet users.

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Figure 1.
Examples of Yelp rating

The figures show examples of Yelp ratings for two sample businesses. Yelp displays ratings in the form of stars with half-star increments. The top business has a Yelp rating of 4 stars and the bottom business has a Yelp rating of 4.5 stars.

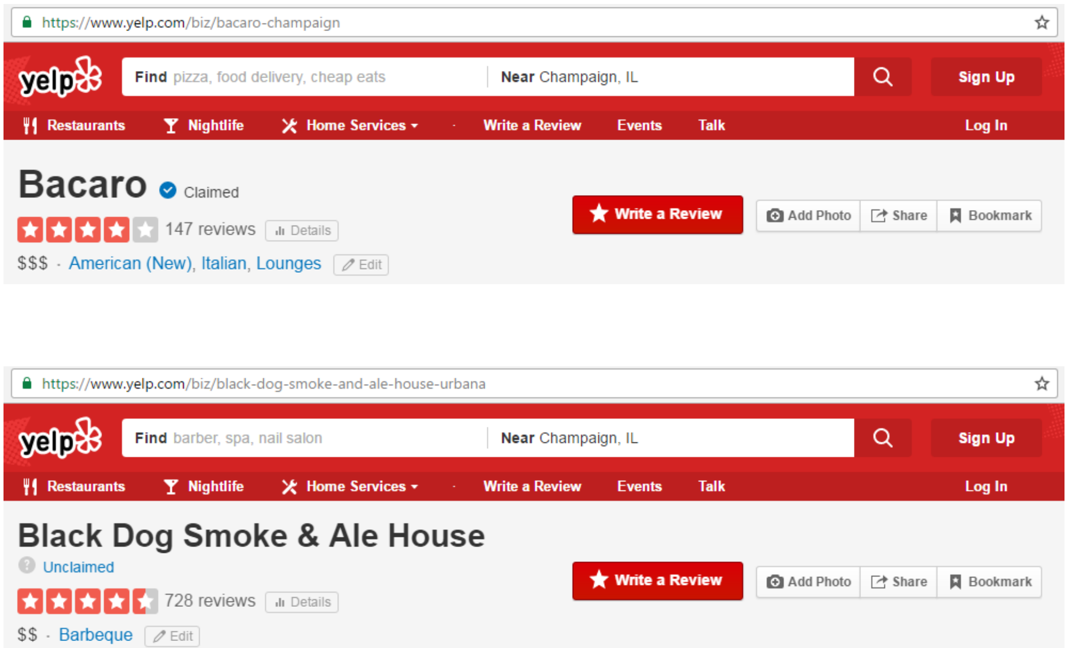


Figure 2.
Yelp data collection

This figure shows a sample business listed on Yelp and the data collection process. For each business, I collect the business name (i.e., Bacaro), Yelp business category (i.e., American, Italian, Lounges), address (i.e., 113 N Walnut St., Champaign, IL 61820), price range (i.e., $$$ and $31-60), each reviewer rating and review date (i.e., for example, 5 stars, 1/2/2017), along with other identifying information embedded in the source HTML code.

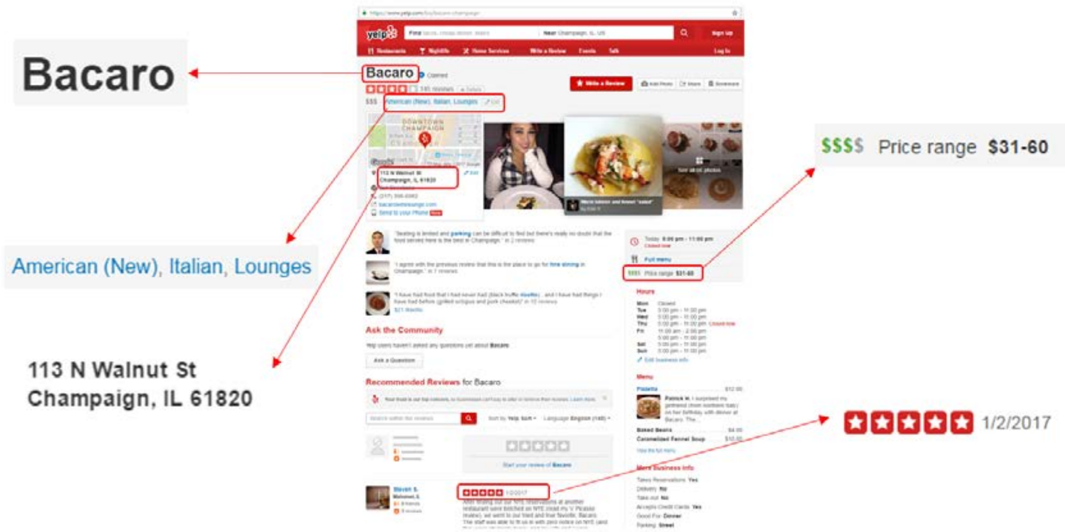


Figure 3.
Yelp data coverage

This map plots Yelp data coverage at the county level. Yelp data is available from 2004 to 2016. I count the number of businesses in each county. I require the businesses to have more than five reviews to be included in the sample for the empirical analysis. Regions range from darker (counties with higher numbers of businesses on Yelp) to lighter (counties with lower numbers of businesses on Yelp).

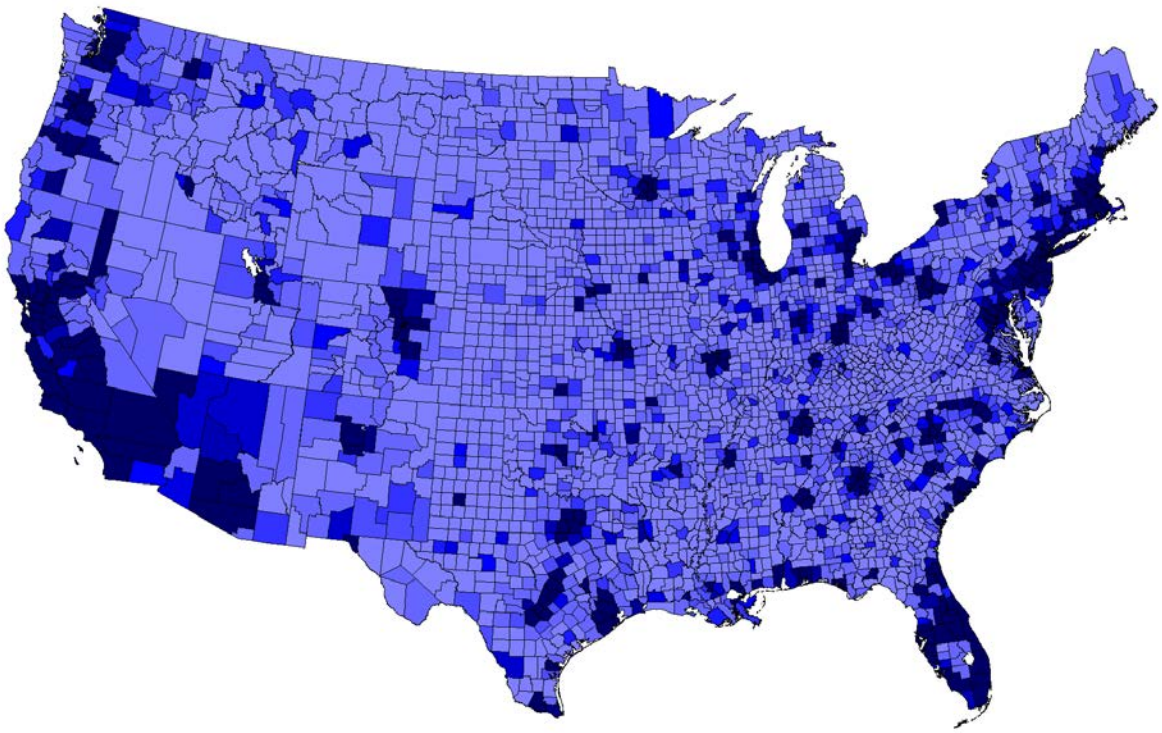


Figure 4.
SBA loan data coverage

This map plots SBA loan data coverage at the county level. SBA loan data is available from 2004 to 2016. I count the number of SBA 7(a) loans in each county. Regions range from darker (counties with higher numbers of SBA loans) to lighter (counties with lower numbers of SBA loans).

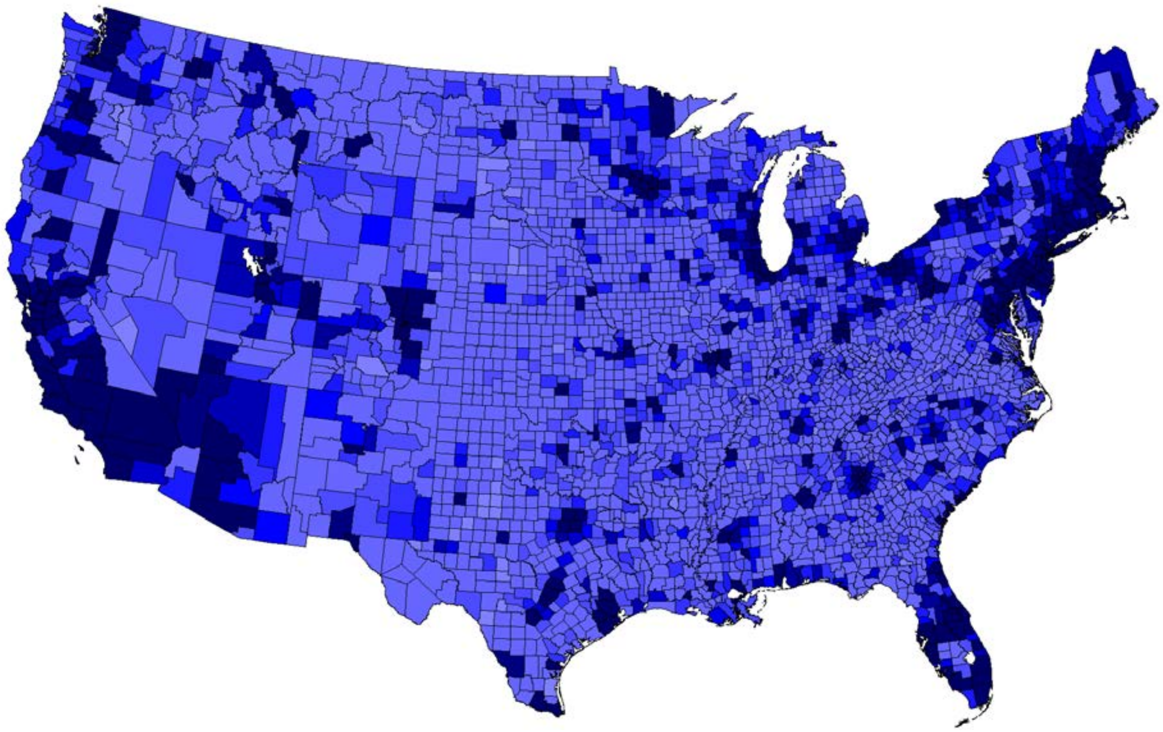


Figure 5.
Loan probability

The figures plot the probability of receiving an SBA loan as a function of Yelp ratings around each cutoff. Yelp roundsthe average ratings of the businesses up and down to the nearest half point based on predetermined cutoffs. On a scale from 1 to 5, the ratings 1.25, 1.75, 2.25, 2.75, 3.25, 3.75, 4.25, and 4.75 are the cutoff points, and the graphs are displayed accordingly. Businesses with average ratings above the cutoff points are assigned Yelp ratings that are rounded up, and businesses with average ratings below the cutoff points are assigned Yelp ratings that are rounded down to the nearest half points. Throughout the analysis, I recenter Yelp ratings around their respective cutoffs to 0. For every Yelp rating bin, the dots represent the probability of receiving an average SBA loan in that bin, which is calculated as the number of businesses receiving a loan over the total number of businesses within the bin. The lines are first- or second-order polynomials fitted through the probabilities of receiving the loans on each side of the cutoff.

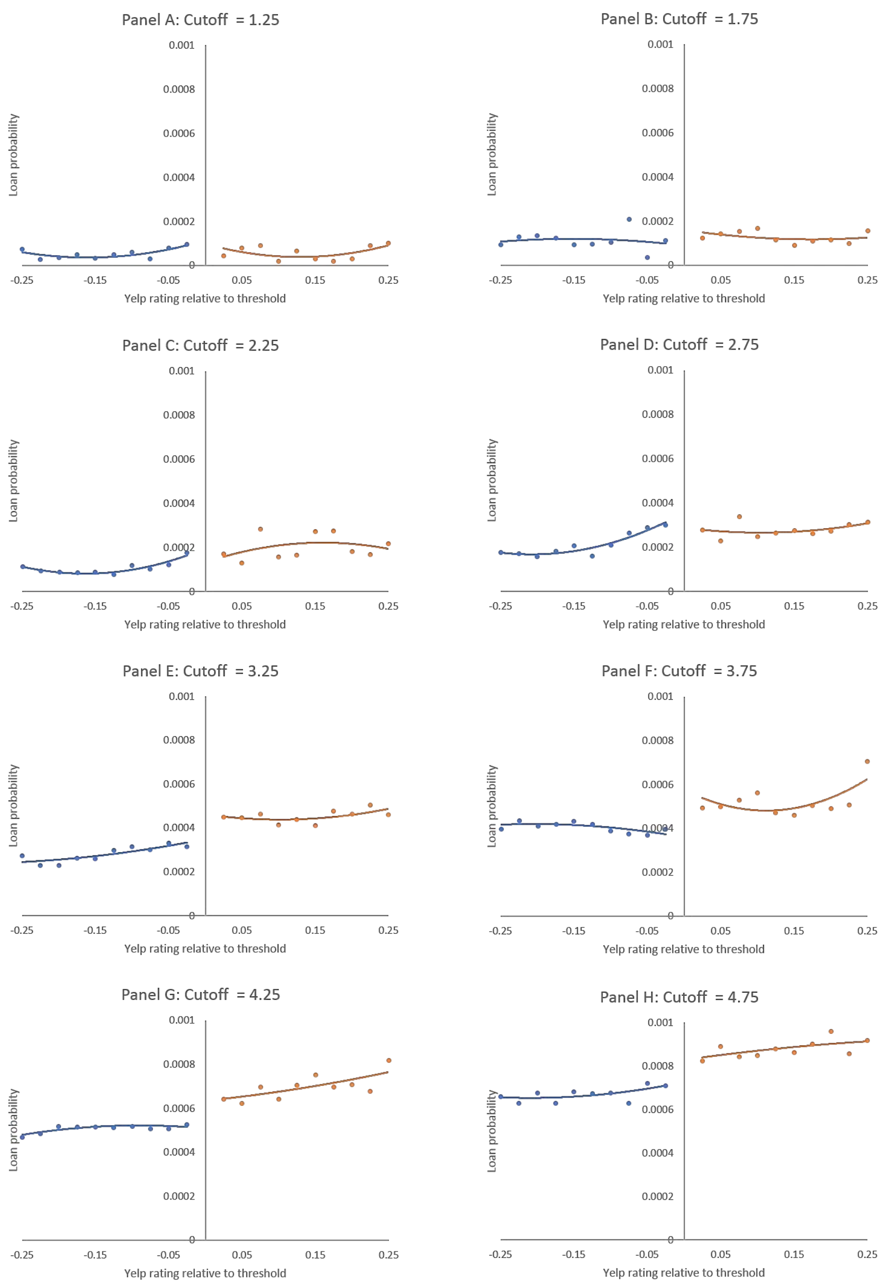


Figure 6.
Loan Spread

The figures plot the SBA loan spread as a function of Yelp ratings around each cutoff. Yelp rounds the average ratings of the businesses up and down to the nearest half point based on predetermined cutoffs. On a scale from 1 to 5, the ratings 1.25, 1.75, 2.25, 2.75, 3.25, 3.75, 4.25, and 4.75 are the cutoff points, and the graphs are displayed accordingly. Businesses with average ratings above the cutoff points are assigned Yelp ratings that are rounded up, and businesses with average ratings below the cutoff points are assigned Yelp ratings that are rounded down to the nearest half points. Throughout the analysis, I recenter Yelp ratings around their respective cutoffs to 0. For every Yelp rating bin, the dots represent the average SBA loan spread in that bin, which is calculated as the average loan spread across all loans within the bin. The lines are first- or second-order polynomials fitted through the loan spreads on each side of the cutoff.

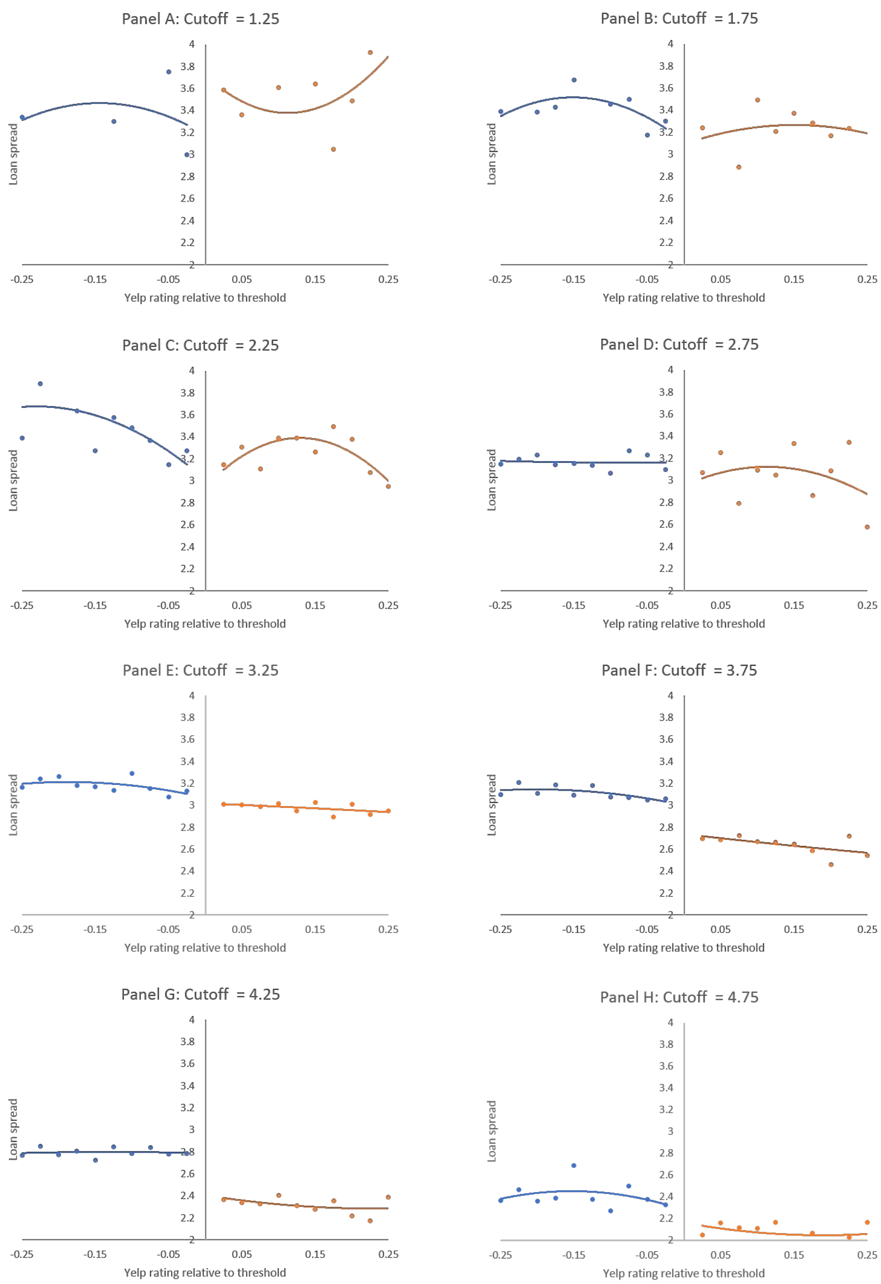


Figure 7.
Loan Collateral

The figures plot the collateral required for SBA loans as a function of Yelp ratings around each cutoff. Yelp roundsup and down the average ratings of the businesses up and down to the nearest half point based on predetermined cutoffs. On a scale from 1 to 5, the ratings 1.25, 1.75, 2.25, 2.75, 3.25, 3.75, 4.25, and 4.75 are the cutoff points, and the graphs are displayed accordingly. Businesses with average ratings above the cutoff points are assigned Yelp ratings that are rounded up, and businesses with average ratings below the cutoff points are assigned Yelp ratings that are rounded down to the nearest half points. Throughout the analysis, I recenter Yelp ratings around their respective cutoffs to 0. For every Yelp rating bin, the dots represent the collateral required for an average SBA loan in that bin, which is calculated as the collateral for each loan divided by the respective total loan amount averaged across all loans within the bin. The lines are first- or second-order polynomials fitted through the required loan collaterals on each side of the cutoff.

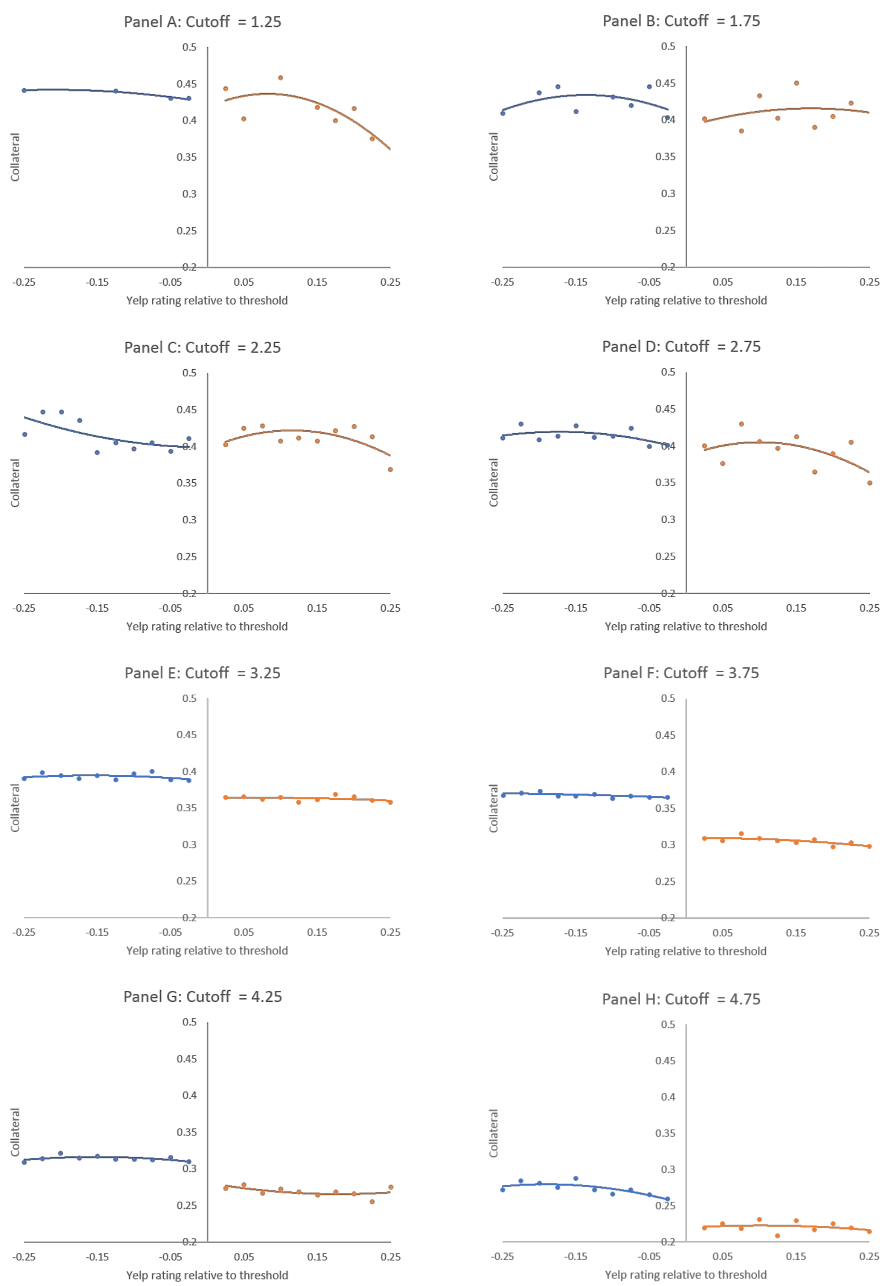


Figure 8.
Loan Default Probability

The figures plot default probability of SBA loans as a function of Yelp ratings around each cutoff. Yelp rounds the average ratings of the businesses up and down to the nearest half point based on predetermined cutoffs. On a scale from 1 to 5, the ratings 1.25, 1.75, 2.25, 2.75, 3.25, 3.75, 4.25, and 4.75 are the cutoff points, and the graphs are displayed accordingly. Businesses with average ratings above the cutoff points are assigned Yelp ratings that are rounded up, and businesses with average ratings below the cutoff points are assigned Yelp ratings that are rounded down to the nearest half points. Throughout the analysis, I recenter Yelp ratings around their respective cutoffs to 0. For every Yelp rating bin, the dots represent the probability of default for an average SBA loan in that bin, which is calculated as the number of loans default over the total number of loans within the bin. The lines are first- or second-order polynomials fitted through the probabilities of default on each side of the cutoff.

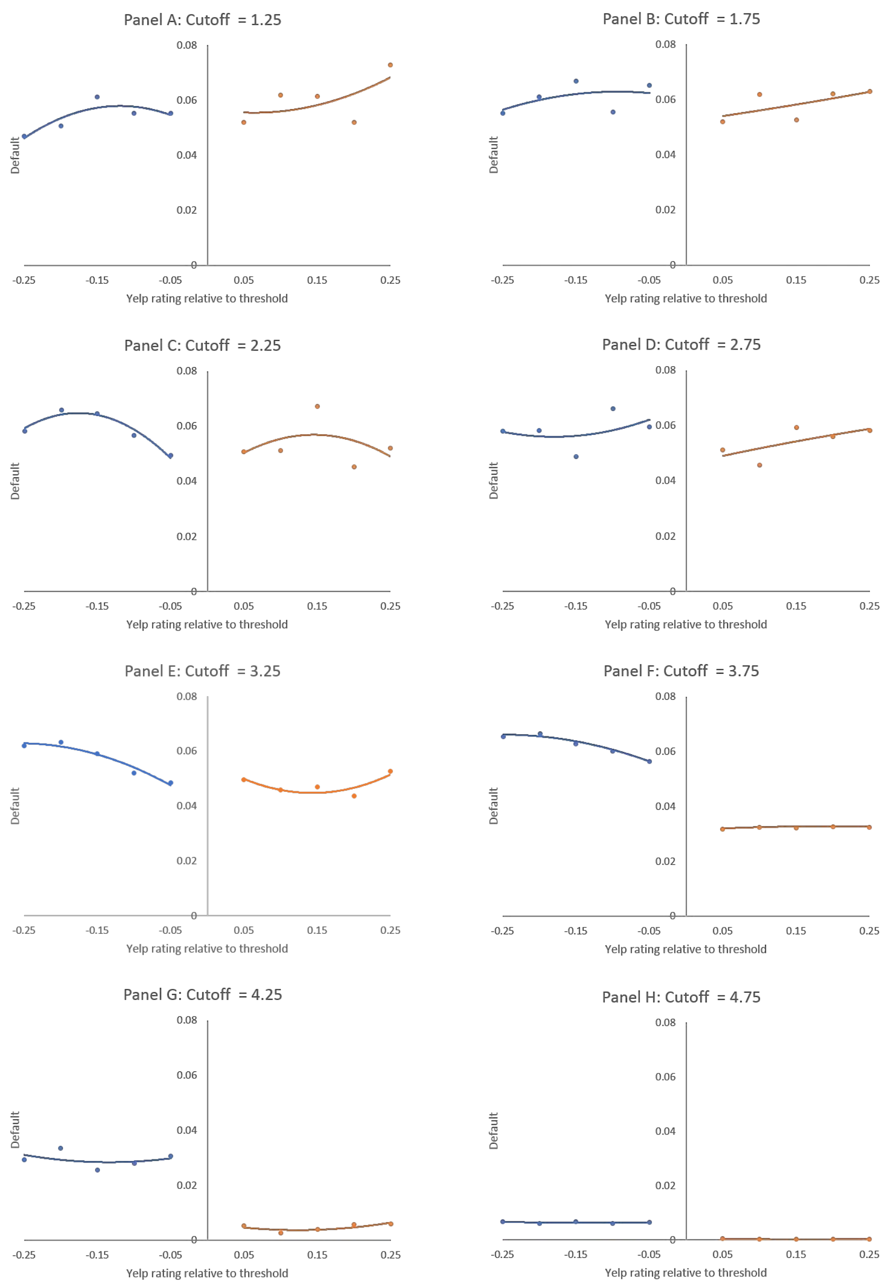


Figure 9.
Loan Charge-off Amount

The figures plot the SBA loan write-off amount upon default as a function of Yelp ratings around each cutoff. Yelp rounds the average ratings of the businesses up and down to the nearest half point based on predetermined cutoffs. On a scale from 1 to 5, the ratings 1.25, 1.75, 2.25, 2.75, 3.25, 3.75, 4.25, and 4.75 are the cutoff points, and the graphs are displayed accordingly. Businesses with average ratings above the cutoff points are assigned Yelp ratings that are rounded up, and businesses with average ratings below the cutoff points are assigned Yelp ratings that are rounded down to the nearest half points. Throughout the analysis, I recenter Yelp ratings around their respective cutoffs to 0. For every Yelp rating bin, the dots represent the write-off amount for an average SBA loan in that bin, which is calculated as the write-off amount for each loan divided by the respective total loan amount averaged across all loans within the bin. The lines are first- or second-order polynomials fitted through the write-off amounts on each side of the cutoff.

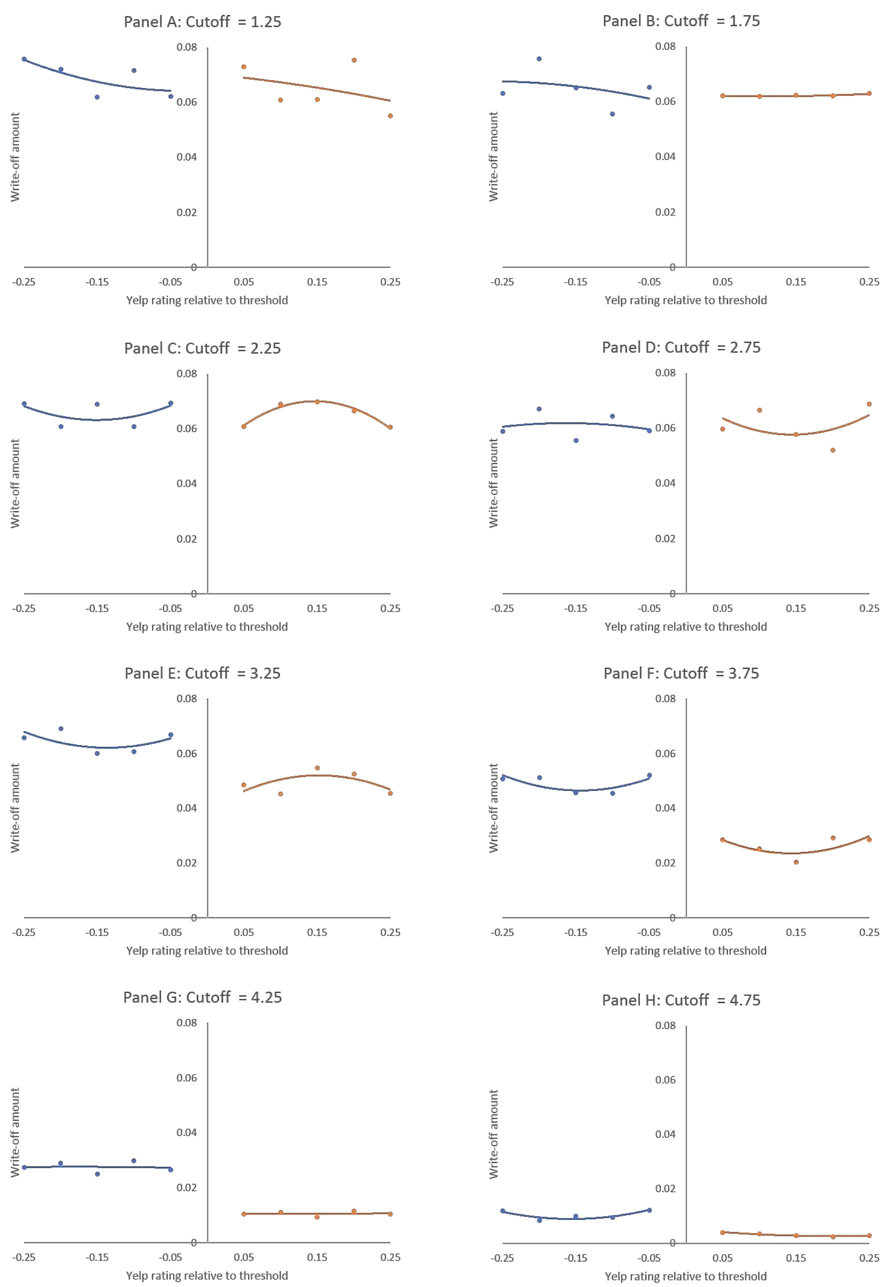


Table 1.
Yelp Data Summary

This table presents a summary of the Yelp data collected. In Panel A, I show the number of businesses, number of reviews, and the average number of reviews per business covered by Yelp in each year. In Panel B, I breakdown the Yelp sample by 22 Yelp business categories. I present the average rating, average number of reviews, and the category weight out of total Yelp businesses for each category. Yelp data is available from 2004 to 2016. I require the businesses to have more than five reviews to be included in the sample for the empirical analysis.

Panel A: Yelp data by year

Year	Number of businesses	Number of reviews	Number of reviews per business
2004	577	879	1.52
2005	17,729	48,764	2.75
2006	56,861	232,144	4.08
2007	124,862	681,431	5.46
2008	207,286	1,329,585	6.41
2009	286,580	2,053,547	7.17
2010	410,747	3,191,291	7.77
2011	561,496	4,841,449	8.62
2012	684,470	5,719,592	8.36
2013	847,984	7,694,181	9.07
2014	1,032,939	11,376,074	11.01
2015	1,239,229	15,425,396	12.45
2016	1,395,928	17,994,708	12.89

Panel B: Yelp data by category

Yelp Category	Average rating	Average number of reviews	Category Weight
Restaurants	3.49	96.13	20.17 %
Shopping	3.77	15.91	10.30 %
Home Services	3.91	11.72	8.77 %
Food	3.76	55.00	8.19 %
Health & Medical	4.09	11.92	6.95 %
Beauty & Spas	4.12	25.03	6.45 %
Local Services	3.90	14.14	6.30 %
Automotive	3.72	19.12	5.78 %
Active Life	4.23	20.71	4.07 %
Event Planning & Services	4.18	26.96	3.63 %
Nightlife	3.60	119.61	3.48 %
Professional Services	4.15	8.26	2.93 %
Education	4.16	9.51	2.05 %
Hotels & Travel	3.39	33.67	2.01 %
Financial Services	3.54	6.65	1.99 %
Arts & Entertainment	4.10	37.28	1.83 %
Pets	4.18	22.13	1.68 %
Real Estate	3.63	8.42	1.59 %
Public Services & Government	3.53	19.01	0.77 %
Religious Organizations	4.49	4.98	0.65 %
Local Flavor	4.18	17.49	0.22 %
Mass Media	3.53	8.78	0.17 %

Table 2.
Summary Statistics

This table presents summary statistics for the sample. Average rating is the unrounded average monthly Yelp rating. $I_{round\ up}$ is an indicator variable that equals one if the Yelp rating is rounded up and equals zero if rounded down. Number of reviews is the cumulative number of reviews at the end of each month. Price ranges are dummy variables that based on the four Yelp price range categories displayed in the business profile. For example, price range ($) is a dummy variable that equals one if the business is in the $ price range category on Yelp and equals zero otherwise. Loan probability is a dummy variable that equals one if the business receives an SBA loan and equals zero otherwise. Collateral is the amount required as collateral divided by total loan amount. Loan spread is the interest rate charged on the loan that is determined by the lending institution minus the beginning of month prime rate. Default is a dummy variable that equals one if the business defaults on the loan and equals zero otherwise. Write-off amount is the amount that is written off by the lender divided by total loan amount.

Variable	Mean	Standard deviation	N
Actual rating	3.6577	0.8697	49,518,899
$I_{round\ up}$	0.4402	0.4964	49,518,899
Number of reviews	41.7856	84.0932	49,518,899
Price range ($)	0.3768	0.4846	49,518,899
Price range ($$)	0.5488	0.4976	49,518,899
Price range ($$$)	0.0641	0.2449	49,518,899
Price range ($$$$)	0.0104	0.1014	49,518,899
Loan probability	0.0003	0.0184	49,518,899
Collateral	0.3428	0.1516	16,058
Loan spread (%)	2.8960	1.3656	16,058
Default	0.0125	0.1112	16,058
Write-off amount	0.0101	0.0924	16,058
Loan amount ('000)	371.9049	641.4089	16,058
Maturity (months)	122.1028	78.5376	16,058

Table 3.
Loan Probability

This table reports OLS regression results for SBA loan probability and Yelp ratings. The dependent variable is a dummy variable that equals one if the business receives an SBA loan and equals zero otherwise. In Column (1), I show the results of a simple OLS regression of loan probability and actual Yelp rating. In Columns (2) to (4), $I_{round\ up}$ is an indicator variable that equals one if the Yelp rating is rounded up and equals zero if rounded down. I carry out the RDD analysis, introducing a polynomial in the Yelp rating of order two on each side of the cutoff, interacted with $I_{round\ up}$. Column (2) utilizes the full sample with all cutoffs. Column (3) examines cases where the cutoff equals 3.75, and Column (4) examines cases where the cutoff equals 4.25. The cutoffs are defined in Figure 5. The control variables are defined in Table 2. All the right-hand-side variables are scaled up by a factor of 1,000. Robust standard errors clustered by Yelp businesses are in parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Variables	Simple OLS (1)	Full model (2)	Cutoff=3.75 (3)	Cutoff=4.25 (4)
Actual rating	0.0681***			
	(0.0007)			
$I_{round\ up}$		0.1393***	0.1808***	0.1388**
		(0.0211)	(0.0448)	(0.0509)
Log(number of reviews)	0.0001	0.0005	0.0278	0.0255
	(0.0007)	(0.0007)	(0.0234)	(0.0174)
Higher order polynomial		✓	✓	✓
Cutoff fixed effects		✓		
Firm fixed effects	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓
Observations	49,518,616	49,518,616	10,662,939	11,909,948
R-squared	0.0067	0.0067	0.0087	0.0078

Table 4.
Loan Terms

This table reports OLS regression results for SBA loan terms and Yelp ratings. In Panel A, the dependent variable is the loan spread, calculated as the interest rate charged on the loan that is determined by the lending institution minus the beginning of month prime rate. In Panel B, the dependent variable is the amount required as collateral divided by total loan amount. In Column (1), I show the results of simple OLS regressions of loan terms and actual Yelp rating. In Columns (2) to (4), $I_{round\ up}$ is an indicator variable that equals one if the Yelp rating is rounded up and equals zero if rounded down. I carry out the RDD analysis, introducing a polynomial in the Yelp rating of order two on each side of the cutoff, interacted with $I_{round\ up}$. Column (2) utilizes the full sample with all cutoffs. Column (3) examines cases where the cutoff equals 3.75, and Column (4) examines cases where the cutoff equals 4.25. The cutoffs are defined in Figures 6 and 7. Loan characteristics control includes loan amount and maturity. The control variables are defined in Table 2. Robust standard errors clustered by Yelp businesses are in parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Variables	Simple OLS (1)	Full model (2)	Cutoff=3.75 (3)	Cutoff=4.25 (4)
		Panel A: Loan spread		
Actual rating	-0.0454***			
	(0.0139)			
$I_{round\ up}$		-0.3580***	-0.3660***	-0.3893***
		(0.0693)	(0.1342)	(0.1420)
Log(number of reviews)	0.0168*	0.0185*	0.0192	0.0292
	(0.0093)	(0.0109)	(0.0243)	(0.0220)
Price range ($)	-0.0615	0.0634	0.0540	0.3072
	(0.1016)	(0.1083)	(0.3305)	(0.2404)
Price range ($$)	-0.0407	0.0396	0.0625	0.1577
	(0.0989)	(0.1056)	(0.3268)	(0.2338)
Price range ($$$)	-0.0581	0.0200	0.0716	0.1081
	(0.1038)	(0.1099)	(0.3332)	(0.2391)
Higher order polynomial		✓	✓	✓
Loan characteristics control	✓	✓	✓	✓
Cutoff fixed effects		✓		
Year fixed effects	✓	✓	✓	✓
Yelp industry fixed effects	✓	✓	✓	✓
County fixed effects	✓	✓	✓	✓
Observations	15,777	15,777	3,652	4,001
R-squared	0.4173	0.3201	0.3692	0.3900
		Panel B: Collateral		
Actual rating	-0.0041***			
	(0.0016)			
$I_{round\ up}$		-0.0418***	-0.0399***	-0.0373***
		(0.0071)	(0.0149)	(0.0139)
Log(number of reviews)	0.0003	0.0018	0.0007	0.0012
	(0.0010)	(0.0011)	(0.0026)	(0.0022)
Price range ($)	-0.0079	-0.0106	0.0112	0.0336
	(0.0094)	(0.0104)	(0.0275)	(0.0235)
Price range ($$)	-0.0088	-0.0119	0.0168	0.0202
	(0.0091)	(0.0102)	(0.0269)	(0.0229)
Price range ($$$)	-0.0177*	-0.0169	0.0067	0.0299
	(0.0100)	(0.0108)	(0.0281)	(0.0239)
Higher order polynomial		✓	✓	✓
Loan characteristics control	✓	✓	✓	✓
Cutoff fixed effects		✓		
Year fixed effects	✓	✓	✓	✓
Yelp industry fixed effects	✓	✓	✓	✓
County fixed effects	✓	✓	✓	✓
Observations	15,777	15,777	3,652	4,001
R-squared	0.4670	0.3747	0.4287	0.4445

Table 5.
Loan Performance

This table reports OLS regression results for SBA loan performance and Yelp ratings. In Panel A, the dependent variable is a dummy variable that equals one if the business defaults on the loan and equals zero otherwise. In Panel B, the dependent variable is the write-off amount by the lender divided by total loan amount. In Column (1), I show the results of simple OLS regressions of loan performance and actual Yelp rating. In Columns (2) to (4), $I_{round\ up}$ is an indicator variable that equals one if the Yelp rating is rounded up and equals zero if rounded down. I carry out the RDD analysis, introducing a polynomial in the Yelp rating of order two on each side of the cutoff, interacted with $I_{round\ up}$. Column (2) utilizes the full sample with all cutoffs. Column (3) examines cases where the cutoff equals 3.75, and Column (4) examines cases where the cutoff equals 4.25. The cutoffs are defined in Figures 8 and 9. Loan characteristics control includes loan amount and maturity. The control variables are defined in Table 2. Robust standard errors clustered by Yelp businesses are in parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Variables	Simple OLS (1)	Full model (2)	Cutoff=3.75 (3)	Cutoff=4.25 (4)
		Panel A: Default		
Actual rating	-0.0032**			
	(0.0015)			
$I_{round\ up}$		-0.0259***	-0.0354**	-0.0446**
		(0.0091)	(0.0167)	(0.0225)
Log(number of reviews)	0.0005	0.0018	-0.0039	-0.0005
	(0.0008)	(0.0013)	(0.0026)	(0.0028)
Price range ($)	-0.0013	-0.0215	-0.0080	-0.0838
	(0.0101)	(0.0153)	(0.0239)	(0.0549)
Price range ($$)	-0.0021	-0.0253*	-0.0109	-0.0931*
	(0.0099)	(0.0150)	(0.0230)	(0.0544)
Price range ($$$)	-0.0023	-0.0280*	-0.0137	-0.0792
	(0.0105)	(0.0151)	(0.0247)	(0.0533)
Higher order polynomial		✓	✓	✓
Loan characteristics control	✓	✓	✓	✓
Cutoff fixed effects		✓		
Year fixed effects	✓	✓	✓	✓
Yelp industry fixed effects	✓	✓	✓	✓
County fixed effects	✓	✓	✓	✓
Observations	15,777	15,777	3,652	4,001
R-squared	0.0986	0.0835	0.1267	0.1545
		Panel B: Write-off amount		
Actual rating	-0.0028**			
	(0.0013)			
$I_{round\ up}$		-0.0217***	-0.0291**	-0.0322**
		(0.0075)	(0.0139)	(0.0162)
Log(number of reviews)	0.0006	0.0017*	-0.0035	-0.0001
	(0.0006)	(0.0010)	(0.0022)	(0.0022)
Price range ($)	-0.0045	-0.0158	-0.0119	-0.0532
	(0.0097)	(0.0129)	(0.0241)	(0.0443)
Price range ($$)	-0.0049	-0.0196	-0.0145	-0.0635
	(0.0096)	(0.0126)	(0.0234)	(0.0437)
Price range ($$$)	-0.0050	-0.0209	-0.0151	-0.0502
	(0.0099)	(0.0127)	(0.0249)	(0.0422)
Higher order polynomial		✓	✓	✓
Loan characteristics control	✓	✓	✓	✓
Cutoff fixed effects		✓		
Year fixed effects	✓	✓	✓	✓
Yelp industry fixed effects	✓	✓	✓	✓
County fixed effects	✓	✓	✓	✓
Observations	15,777	15,777	3,652	4,001
R-squared	0.0928	0.0826	0.1180	0.1592

Table 6.
Cross-sectional Analysis

This table reports OLS regression results for SBA loan information and Yelp ratings in the cross-section. $I_{round\ up}$ is an indicator variable that equals one if the Yelp rating is rounded up and equals zero if rounded down. In Panel A, I include the 'non-competitive' indicator, which is a dummy variable that equals one if the Yelp business is in a below the median competitiveness environment based on Yelp price range, Yelp industry, and county of location and equals zero otherwise. I interact $I_{round\ up}$ with this 'non-competitive' indicator variable. In Panel B, I include the 'far-from-lender' indicator, which is a dummy variable that equals one if the distance between the Yelp business and the lender is above the sample median and equals zero otherwise. I interact $I_{round\ up}$ with this 'far-from-lender' indicator variable. I introduce a polynomial in the Yelp rating of order two on each side of the cutoff, interacted with $I_{round\ up}$, and uses the full sample. The cutoffs are defined in Figure 5. Business characteristics control includes different price ranges. Loan characteristics control includes loan amount and maturity. The control variables are defined in Table 2. In Column (1), all the right-hand-side variables are scaled up by a factor of 1,000. Robust standard errors clustered by Yelp businesses are in parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Variables	Loan probability (1)	Loan spread (2)	Collateral (3)	Default (4)	Write-off amount (5)
		Panel A: Competition			
$I_{round\ up}$	0.0877***	-0.3204***	-0.0320***	-0.0208**	-0.0172**
	(0.0219)	(0.0715)	(0.0073)	(0.0094)	(0.0076)
Non-competitive indicator	0.0128	0.0520	0.0071*	0.0117**	0.0110**
	(0.0193)	(0.0390)	(0.0041)	(0.0054)	(0.0045)
$I_{round\ up}$ × non-competitive indicator	0.1110***	-0.0829*	-0.0215***	-0.0112**	-0.0099**
	(0.0142)	(0.0432)	(0.0046)	(0.0051)	(0.0042)
Control for number of reviews	✓	✓	✓	✓	✓
Business characteristics control		✓	✓	✓	✓
Higher order polynomial	✓	✓	✓	✓	✓
Loan characteristics control		✓	✓	✓	✓
Cutoff fixed effects	✓	✓	✓	✓	✓
Firm fixed effects	✓				
Year fixed effects	✓	✓	✓	✓	✓
Yelp industry fixed effects		✓	✓	✓	✓
County fixed effects		✓	✓	✓	✓
Observations	49,518,616	15,777	15,777	15,777	15,777
R-squared	0.0067	0.3203	0.3758	0.0840	0.0832
		Panel B: Distance to bank			
$I_{round\ up}$		-0.2322***	-0.0402***	-0.0220**	-0.0175**
		(0.0695)	(0.0073)	(0.0092)	(0.0076)
Far from lender indicator		0.5240***	0.0410***	0.0026	0.0047
		(0.0342)	(0.0036)	(0.0049)	(0.0041)
$I_{round\ up}$ × far from lender indicator		-0.3750***	-0.0122***	-0.0086*	-0.0097**
		(0.0440)	(0.0046)	(0.0049)	(0.0041)
Control for number of reviews		✓	✓	✓	✓
Business characteristics control		✓	✓	✓	✓
Higher order polynomial		✓	✓	✓	✓
Loan characteristics control		✓	✓	✓	✓
Cutoff fixed effects		✓	✓	✓	✓
Year fixed effects		✓	✓	✓	✓
Yelp industry fixed effects		✓	✓	✓	✓
County fixed effects		✓	✓	✓	✓
Observations		15,777	15,777	15,777	15,777
R-squared		0.3345	0.3836	0.0837	0.0829

Table 7.
Repeated Borrowing

This table reports OLS regression results for repeated borrowing and Yelp ratings. $I_{round\ up}$ is an indicator variable that equals one if the Yelp rating is rounded up and equals zero if rounded down. In Columns (1) and (2), I include the second loan indicator, which is a dummy variable that equals one if the underlying loan is the second one through the SBA loan program and equals zero otherwise. I interact $I_{round\ up}$ with this second loan indicator variable. In Columns (3) and (4), I restrict the sample to businesses with two loans and include the same bank indicator, which is a dummy variable that equals one if the second loan is taken out with the same bank and equals zero otherwise. I interact $I_{round\ up}$ with this same bank indicator variable. I introduce a polynomial in the Yelp rating of order two on each side of the cutoff, interacted with $I_{round\ up}$, and uses the full sample. The cutoffs are defined in Figure 5. Business characteristics control includes number of reviews and different price ranges. Loan characteristics control includes loan amount and maturity. The control variables are defined in Table 2. Robust standard errors clustered by Yelp businesses are in parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% level, respectively.

	Loan spread (1)	Collateral (2)	Loan spread (3)	Collateral (4)
$I_{round\ up}$	-0.2009***	-0.0151*	-0.2977**	-0.0276**
	(0.0778)	(0.0077)	(0.1454)	(0.0139)
Second loan indicator	-0.2057***	-0.0013		
	(0.0313)	(0.0033)		
$I_{round\ up}$ ×	0.0816*	0.0083*		
second loan indicator	(0.0458)	(0.0049)		
Same bank indicator			-0.0488*	-0.0029
			(0.0275)	(0.0031)
$I_{round\ up}$ ×			0.0907**	0.0094**
same bank indicator			(0.0439)	(0.0047)
Business characteristics control	✓	✓	✓	✓
Higher order polynomial	✓	✓	✓	✓
Loan characteristics control	✓	✓	✓	✓
Cutoff fixed effects	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓
Yelp industry fixed effects	✓	✓	✓	✓
County fixed effects	✓	✓	✓	✓
Observations	15,777	15,777	5,264	5,264
R-squared	0.4208	0.4683	0.4136	0.5310

Table 8.
Changes in Consumer Demand

This table reports OLS regression results for changes in consumer demand and Yelp ratings. The dependent variable is a dummy variable that equals one if a business receives a higher number of reviews in the next month compared to the current month and equal zero otherwise. In Column (1), I show the results of a simple OLS regression of changes in consumer demand and actual Yelp rating. In Columns (2) to (4), $I_{round\ up}$ is an indicator variable that equals one if the Yelp rating is rounded up and equals zero if rounded down. I carry out the RDD analysis, introducing a polynomial in the Yelp rating of order two on each side of the cutoff, interacted with $I_{round\ up}$. Column (2) utilizes the full sample with all cutoffs. Column (3) examines cases where the cutoff equals 3.75, and Column (4) examines cases where the cutoff equals 4.25. The cutoffs are defined in Figure 5. The control variables are defined in Table 2. Robust standard errors clustered by Yelp businesses are in parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Variables	Simple OLS (1)	Full model (2)	Cutoff=3.75 (3)	Cutoff=4.25 (4)
Actual rating	0.0047*** (0.0002)			
$I_{round\ up}$		0.0011*** (0.0004)	0.0058*** (0.0008)	0.0048*** (0.0009)
Log(number of reviews)	-0.0275*** (0.0002)	-0.0305*** (0.0002)	-0.0660*** (0.0007)	-0.0479*** (0.0005)
Higher order polynomial		✓	✓	✓
Cutoff fixed effects		✓		
Firm fixed effects	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓
Observations	48,223,996	48,223,996	10,508,060	11,578,801
R-squared	0.0794	0.0796	0.0560	0.0849

Table 9.
Subsequent Business Opening

This table reports OLS regression results for subsequent business openings and Yelp ratings. The dependent variable is is a dummy variable that equals one if an existing business on Yelp opens another location under the same name in the same county and Yelp industry and equal zero otherwise. In Column (1), I show the results of a simple OLS regression of subsequent business opening and actual Yelp rating. In Columns (2) to (4), $I_{round\ up}$ is an indicator variable that equals one if the Yelp rating is rounded up and equals zero if rounded down. I carry out the RDD analysis, introducing a polynomial in the Yelp rating of order two on each side of the cutoff, interacted with $I_{round\ up}$. Column (2) utilizes the full sample with all cutoffs. Column (3) examines cases where the cutoff equals 3.75, and Column (4) examines cases where the cutoff equals 4.25. The cutoffs are defined in Figure 5. The control variables are defined in Table 2. Robust standard errors clustered by Yelp businesses are in parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% level, respectively.

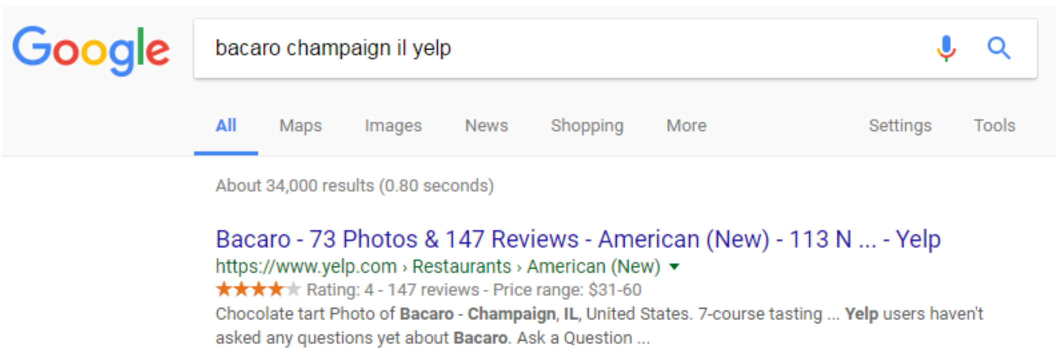
Variables	Simple OLS (1)	Full model (2)	Cutoff=3.75 (3)	Cutoff=4.25 (4)
Actual rating	0.0149***			
	(0.0003)			
$I_{round\ up}$		0.0087***	0.0224***	0.0131***
		(0.0009)	(0.0020)	(0.0019)
Log(number of reviews)	0.0041***	0.0052***	0.0082***	0.0023***
	(0.0003)	(0.0003)	(0.0011)	(0.0007)
Higher order polynomial		✓	✓	✓
Cutoff fixed effects		✓		
Firm fixed effects	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓
Observations	2,335,710	2,335,710	449,765	528,149
R-squared	0.1659	0.1670	0.1521	0.1869

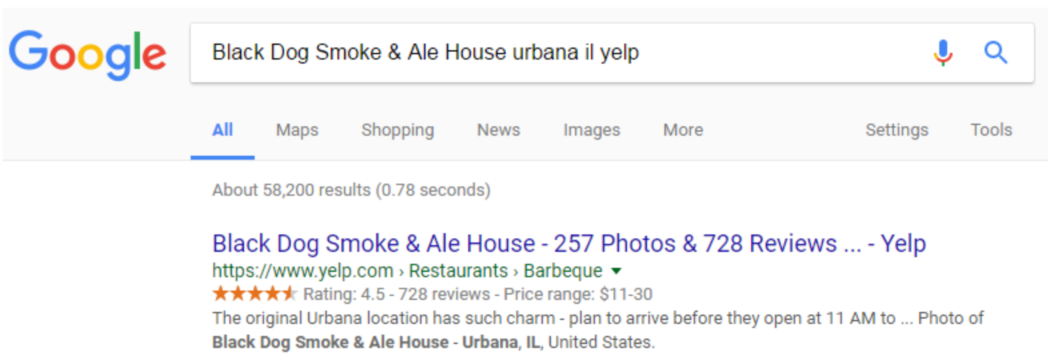
The Financial Consequences of Customer Satisfaction: Evidence from Yelp Ratings and SBA Loans

Appendix

A. Examples of Yelp Ratings Shown in Google Search

The figures present the corresponding Google search results of Yelp ratings for the two sample businesses shown in Figure 1. Yelp displays ratings in the form of stars with half-star increments. The top business has a Yelp rating of 4 stars and the bottom business has a Yelp rating of 4.5 starts. Google displays the same Yelp ratings as shown on the businesses' Yelp page.





B. Control Variables around the Cutoffs

The figures plot the control variables as a function of Yelp ratings around the cutoffs. Yelp rounds up and down the average ratings of the businesses to the nearest half point based on predetermined cutoffs. On a scale from 1 to 5, 1.25, 1.75, 2.25, 2.75, 3.25, 3.75, 4.25, and 4.75 are the cutoff points. Businesses with average ratings above the cutoff points are assigned Yelp ratings that are rounded up, and businesses with average ratings below the cutoff points are assigned Yelp ratings that are rounded down to the nearest half points. Throughout the analysis, I re-center Yelp ratings around their respective cutoffs to 0. Figure A1 plots the number of reviews and for every Yelp rating bin, the dots represent the average number of reviews in that bin. Figure A2 plots the price range and for every Yelp rating bin, the dots represent the average price range in that bin. The lines are second-order polynomials fitted through the averages on each side of the cutoff.

Figure A1. Number of Reviews

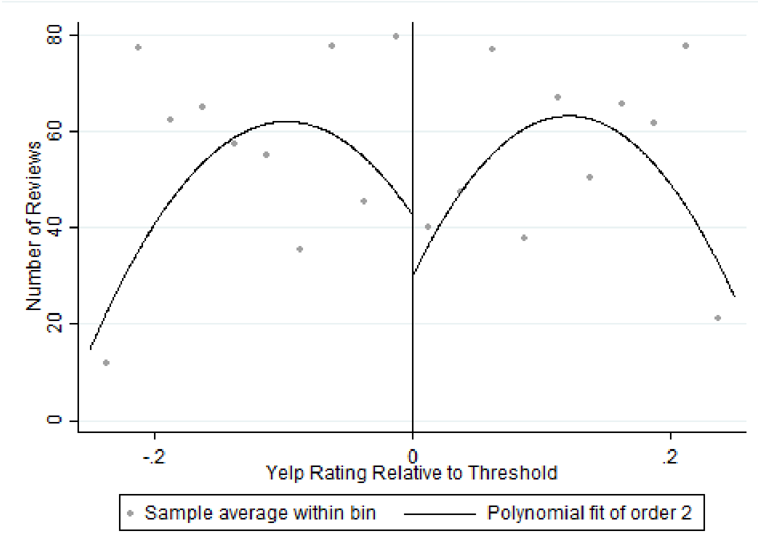
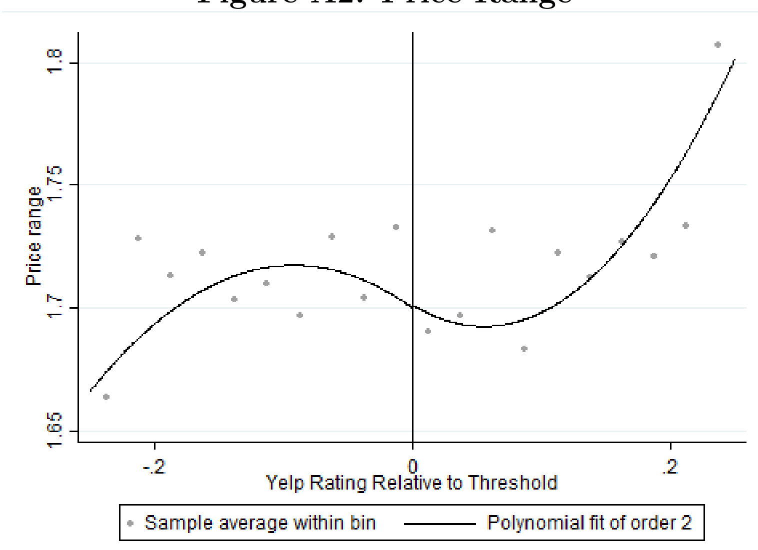


Figure A2. Price Range



C. Yelp Manipulation Test

To formally rule out the possibility that business owners manipulate their Yelp ratings, I carry out a test in the spirit of McCrary (2008). The concern is that business owners may post fake ratings to boost their overall Yelp ratings to the next one-half star level because they are aware of the rounding thresholds. If this is the case in practice, one should observe ratings clustering just above the rounding thresholds. I start with all the raw Yelp ratings and their corresponding dates at each business. I calculate a moving average of the Yelp ratings for each business. I then assign those averages to bins and test whether clustering exists in the bins right above the rounding thresholds.

In the table below, I present the results. In Column (1), I assign average ratings into bins in the increment of 0.01 point. The dependent variable is the weight of each bin related to the total number of reviews. I define the independent variable, potential manipulation, as an indicator variable that equals one if the bin is right above the rounding thresholds and equals zero otherwise. I find that the regression coefficient is not statistically different from zero and the magnitude is close to zero. The evidence suggests that business owners do not manipulate Yelp ratings on average. Similarly, in Column (2), I conduct the same test using a wider bin, i.e., in the increment of 0.05 point. I find qualitatively similar result.

	Rating bin weight	
	[0.01 bin]	[0.05 bin]
	(1)	(2)
Potential manipulation	0.0008	-0.0008
	(0.0015)	(0.0049)
Observations	401	80
R-squared	0.0007	0.0003

D. Loan Probability

This table reports OLS regression results for SBA loan probability and Yelp ratings. The dependent variable is a dummy variable that equals one if the business receives an SBA loan and equals zero otherwise. $I_{round\ up}$ is an indicator variable that equals one if the Yelp rating is rounded up and equals zero if rounded down. Columns (1), (2), and (3) restricts the sample to observations with Yelp ratings within 0.05, 0.10, and 0.15 points of the cutoffs, respectively. The cutoffs are defined in Figure 5. The control variables are defined in Table 2. All the right-hand-side variables are scaled up by a factor of 1,000. Robust standard errors clustered by Yelp businesses are in parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Variables	[-0.05, +0.05] (1)	[-0.10, +0.10] (2)	[-0.15, +0.15] (3)
$I_{round\ up}$	0.1475***	0.1392***	0.1282***
	(0.0196)	(0.0130)	(0.0103)
Log(number of reviews)	0.0050	0.0164	0.0293**
	(0.0295)	(0.0166)	(0.0136)
Cutoff fixed effects	✓	✓	✓
Firm fixed effects	✓	✓	✓
Year fixed effects	✓	✓	✓
Observations	8,132,329	16,319,910	23,706,125
R-squared	0.0194	0.0108	0.0003

E. Loan Terms

This table reports OLS regression results for SBA loan terms and Yelp ratings. In Panel A, the dependent variable is the loan spread, calculated as the interest rate charged on the loan that is determined by the lending institution minus the beginning of month prime rate. In Panel B, the dependent variable is the amount required as collateral divided by total loan amount. $I_{round\ up}$ is an indicator variable that equals one if the Yelp rating is rounded up and equals zero if rounded down. Columns (1), (2), and (3) restricts the sample to observations with Yelp ratings within 0.05, 0.10, and 0.15 points of the cutoffs, respectively. The cutoffs are defined in Figures 6 and 7. Loan characteristics control includes loan amount and maturity. The control variables are defined in Table 2. Robust standard errors clustered by Yelp businesses are in parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Variables	[-0.05, +0.05] (1)	[-0.10, +0.10] (2)	[-0.15, +0.15] (3)
	Panel A: Loan spread		
$I_{round\ up}$	-0.4581***	-0.4786***	-0.5067***
	(0.0670)	(0.0447)	(0.0363)
Log(number of reviews)	0.0214	-0.0289	-0.0160
	(0.0316)	(0.0213)	(0.0179)
Price range ($)	0.0286	0.1457	0.2146
	(0.3665)	(0.2268)	(0.1760)
Price range ($$)	0.0908	0.1388	0.2057
	(0.3627)	(0.2232)	(0.1716)
Price range ($$$)	0.0134	0.0860	0.1591
	(0.3626)	(0.2272)	(0.1776)
Loan characteristics control	✓	✓	✓
Cutoff fixed effects	✓	✓	✓
Year fixed effects	✓	✓	✓
Yelp industry fixed effects	✓	✓	✓
County fixed effects	✓	✓	✓
Observations	2,588	5,159	7,720
R-squared	0.2474	0.1979	0.1589
	Panel B: Collateral		
$I_{round\ up}$	-0.0524***	-0.0500***	-0.0538***
	(0.0069)	(0.0047)	(0.0038)
Log(number of reviews)	-0.0031	-0.0013	-0.0012
	(0.0032)	(0.0022)	(0.0019)
Price range ($)	0.0069	-0.0224	-0.0339*
	(0.0388)	(0.0258)	(0.0202)
Price range ($$)	0.0046	-0.0242	-0.0355*
	(0.0381)	(0.0254)	(0.0198)
Price range ($$$)	-0.0173	-0.0500*	-0.0475**
	(0.0390)	(0.0262)	(0.0206)
Loan characteristics control	✓	✓	✓
Cutoff fixed effects	✓	✓	✓
Year fixed effects	✓	✓	✓
Yelp industry fixed effects	✓	✓	✓
County fixed effects	✓	✓	✓
Observations	2,588	5,159	7,720
R-squared	0.2897	0.2601	0.2291

F. Loan Performance

This table reports OLS regression results for SBA loan performance and Yelp ratings. In Panel A, the dependent variable is a dummy variable that equals one if the business defaults on the loan and equals zero otherwise. In Panel B, the dependent variable is the write-off amount by the lender divided by total loan amount. $I_{round\ up}$ is an indicator variable that equals one if the Yelp rating is rounded up and equals zero if rounded down. Columns (1), (2), and (3) restricts the sample to observations with Yelp ratings within 0.05, 0.10, and 0.15 points of the cutoffs, respectively. The cutoffs are defined in Figures 8 and 9. Loan characteristics control includes loan amount and maturity. The control variables are defined in Table 2. Robust standard errors clustered by Yelp businesses are in parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Variables	[-0.05, +0.05] (1)	[-0.10, +0.10] (2)	[-0.15, +0.15] (3)
		Panel A: Default	
$I_{round\ up}$	-0.0281***	-0.0281***	-0.0311***
	(0.0067)	(0.0043)	(0.0037)
Log(number of reviews)	0.0065**	0.0029	0.0006
	(0.0031)	(0.0021)	(0.0017)
Price range ($)	0.0183	-0.0063	-0.0061
	(0.0240)	(0.0234)	(0.0200)
Price range ($$)	0.0258	-0.0067	-0.0077
	(0.0241)	(0.0233)	(0.0197)
Price range ($$$)	0.0491*	0.0019	-0.0106
	(0.0264)	(0.0255)	(0.0208)
Loan characteristics control	✓	✓	✓
Cutoff fixed effects	✓	✓	✓
Year fixed effects	✓	✓	✓
Yelp industry fixed effects	✓	✓	✓
County fixed effects	✓	✓	✓
Observations	2,588	5,159	7,720
R-squared	0.2126	0.1344	0.1001
		Panel B: Write-off amount	
$I_{round\ up}$	-0.0226***	-0.0233***	-0.0253***
	(0.0056)	(0.0036)	(0.0031)
Log(number of reviews)	0.0058**	0.0028	0.0005
	(0.0025)	(0.0017)	(0.0014)
Price range ($)	0.0131	-0.0105	-0.0070
	(0.0212)	(0.0246)	(0.0174)
Price range ($$)	0.0184	-0.0114	-0.0080
	(0.0214)	(0.0246)	(0.0172)
Price range ($$$)	0.0385*	-0.0053	-0.0109
	(0.0232)	(0.0263)	(0.0183)
Loan characteristics control	✓	✓	✓
Cutoff fixed effects	✓	✓	✓
Year fixed effects	✓	✓	✓
Yelp industry fixed effects	✓	✓	✓
County fixed effects	✓	✓	✓
Observations	2,588	5,159	7,720
R-squared	0.2044	0.1342	0.1000

G. Additional Control Variables

This table reports OLS regression results for SBA loan terms and Yelp ratings. The dependent variables are the loan terms used in the main analysis. $I_{round\ up}$ is an indicator variable that equals one if the Yelp rating is rounded up and equals zero if rounded down. I carry out the RDD analysis, introducing a polynomial in the Yelp rating of order two on each side of the cutoff, interacted with $I_{round\ up}$. The cutoffs are defined in Figure 5. Loan characteristics control includes loan amount, maturity, and the portion of loan guarantee. Columns (3) and (4) includes additional loan characteristics controls of loan spread and collateral. The control variables are defined in Table 2. Robust standard errors clustered by Yelp businesses are in parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Variables	Loan spread (1)	Collateral (2)	Default (3)	Write-off amount (4)
$I_{round\ up}$	-0.2000**	-0.0285***	-0.0423***	-0.0342***
	(0.0955)	(0.0057)	(0.0156)	(0.0128)
Log(number of reviews)	0.0253	0.0010	-0.0019	-0.0014
	(0.0156)	(0.0009)	(0.0018)	(0.0015)
Price range ($)	0.0211	-0.0062	-0.0072	-0.0023
	(0.1424)	(0.0071)	(0.0212)	(0.0172)
Price range ($$)	-0.0305	-0.0049	-0.0072	-0.0028
	(0.1400)	(0.0069)	(0.0208)	(0.0169)
Price range ($$$)	-0.1015	-0.0080	-0.0133	-0.0068
	(0.1462)	(0.0074)	(0.0213)	(0.0176)
Log(number of employees)	0.0072	-0.0001	0.0037	0.0029
	(0.0195)	(0.0013)	(0.0028)	(0.0024)
Credit score control	-0.1098	-0.0050	0.0068	0.0042
	(0.1553)	(0.0097)	(0.0185)	(0.0157)
Higher order polynomial	✓	✓	✓	✓
Loan characteristics control	✓	✓	✓	✓
Cutoff fixed effects	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓
Yelp industry fixed effects	✓	✓	✓	✓
County fixed effects	✓	✓	✓	✓
Observations	7,800	7,800	7,800	7,800
R-squared	0.3687	0.4254	0.1579	0.1447

H. Placebo Test

This table reports OLS regression results for SBA loan terms and Yelp ratings using placebo cutoffs. The dependent variables are the loan terms used in the main analysis. $I_{round\ up}$ is an indicator variable that equals one if the Yelp rating is rounded up and equals zero if rounded down. I carry out the RDD analysis, introducing a polynomial in the Yelp rating of order two on each side of the cutoff, interacted with $I_{round\ up}$. The placebo cutoffs are the midpoints between each actual cutoff and rating, i.e., 1.13, 1.38, 1.63, 1.88, 2.13, 2.38, 2.63, 2.88, 3.13, 3.38, 3.63, 3.88, 4.13, 4.38, 4.63, and 4.88. I focus on observations with Yelp ratings within 0.05 points of the cutoffs. Business characteristics control includes different price ranges. Loan characteristics control includes loan amount and maturity. The control variables are defined in Table 2. In Column (1), all the right-hand-side variables are scaled up by a factor of 1,000. Robust standard errors clustered by Yelp businesses are in parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Variables	Loan probability (1)	Loan spread (2)	Collateral (3)	Default (4)	Write-off amount (5)
$I_{round\ up}$	-0.0249	-0.1498	-0.0188	0.0209	0.0126
	(0.0411)	(0.1299)	(0.0155)	(0.0155)	(0.0131)
Log(number of reviews)	0.0381**	0.0050	0.0014	-0.0034	-0.0032
	(0.0166)	(0.0213)	(0.0022)	(0.0022)	(0.0019)
Business characteristics control		✓	✓	✓	✓
Higher order polynomial	✓	✓	✓	✓	✓
Loan characteristics control		✓	✓	✓	✓
Cutoff fixed effects	✓	✓	✓	✓	✓
Firm fixed effects	✓				
Year fixed effects	✓	✓	✓	✓	✓
Yelp industry fixed effects		✓	✓	✓	✓
County fixed effects		✓	✓	✓	✓
Observations	15,286,339	4,852	4,852	4,852	4,852
R-squared	0.0110	0.2696	0.3551	0.0129	0.0060