Does FinTech Compete With or Complement Bank Finance? *

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Abstract

We consider comprehensive data on crowdfunding in the U.S., including debt (marketplace lending), rewards, donations, and equity crowdfunding, to formally test for the first time if banks are complements or substitutes to crowdfunding. The data indicate that bank failures in a county are associated with a reduction in debt and rewards crowdfunding, and total crowdfunding (including donations and rewards as well, however, bank failures are statistically unrelated to those types of crowdfunding in our empirical setting). The data are consistent with bank failures being associated with a reduction in the aggregate number of entrepreneurs in a county, while the remaining entrepreneurs seeking crowdfunding are less reliant on external debt finance in their county. Overall, the data indicate crowdfunding and traditional bank finance are complements.

Keywords: Banks, Bank Loans, Bank Failure, Crowdfunding, FinTech

JEL Codes: G21, G23, G24, G28, G33, G38

"Fintech has unsettled just about every corner of global finance. Traditional bankers at first scoffed when the arrivistes promised to reinvent their business. Then services such as Venmo, the person-to-person money-transfer app owned by PayPal Holdings Inc., started displacing established bank products…

"Fintech companies are getting a lot of attention, but they're not about to replace Wall Street's stalwarts."

Source: Bloomberg, 2018.[1]

1. Introduction

It is often repeated in popular media, as illustrated by the quotes above, that fintech has the potential to substitute for, or even replace, traditional bank finance. Managerial and discussion articles echo this sentiment (e.g., Mackenzie, 2015). One of the more common and popular forms of fintech is crowdfunding. Crowdfunding involves sourcing funds, typically through online portals, from a large number of people in the form of donations, rewards, loans, or equity (Schwienbacher and Larralde, 2012; Belleflamme and Schwienbacher, 2014). Crowdfunding competes with traditional sources of capital by offering easier access to finance at a lower cost, and without potential biases that favor either race, gender, age, location, or ethnicity (Belleflamme and Schwienbacher, 2014; Cumming, Meoli, and Vismara, 2018).

In this paper, we address the question as to whether or not crowdfunding and bank finance are complements or substitutes. We address this question by examining bank failures in the U.S. Banks fail for a number of reasons[2], including high concentrations of real estate construction and development loans, commercial mortgages, and multi-family mortgages (Cole and White, 2012). When regulators decide to close a bank, this decision imposes an exogenous shock to the supply of credit in the lending markets in which that bank operated. Our evidence and examination of the data point to a causal link from bank failures to crowdfunding.

Our empirical exercise is made possible by exploring new data and matching different sources of data. We examine data from the fourth quarter of 2006 to the fourth quarter of 2014 in the U.S. from multiple sources on information on banks and rewards-based crowdfunding and crowdlending. We create a panel dataset of quarterly observations at the county level. We use county level data to better capture the impact local banks have on local

[1] https://www.washingtonpost.com/business/fintech/2018/11/26/d4a50c6a-f1ba-11e8-99c2-cfca6fcf610c_story.html?noredirect=on&utm_term=.46a3d70ceb45

[2] Demyanyk and Hasan (2009) contain extensive reviews of the causes of bank failure

entrepreneurs, which is further motivated by Guenther, Johan and Schweizer (2018). Their paper documents the influence of geographic distance among retail, accredited and overseas investors and venture location on equity crowdfunding. We also explore data at the entrepreneurial project level. We examine crowdfunding investment amounts and the number of crowdfunding projects in a county. We separate out reward-based projects from debt-based projects.

Our analysis strongly indicates that the closure of a bank in a county leads to fewer crowdfunded projects. Said differently, we show that bank finance complements crowdfunding. More specifically regarding the different types of crowdfunding, we find complementarity between bank finance and both rewards and debt crowdfunding.

The literature on bank finance spans many decades. The literature on crowdfunding is much more recent. Most crowdfunding papers have addressed issues pertaining to success factors in crowdfunding campaigns; for example, see Schwienbacher and Larralde (2012) for rewards crowdfunding; Lin et al. (2013) and Ding et al., 2018 for crowdlending; Ahlers et al. (2015), Vismara (2017), Signori and Vismara (2018) for equity crowdfunding. As described in Cumming, Johan and Zhang (2018), prior scholars have examined links between crowdfunding and venture capital, venture capital to IPOs, incubators and venture capital, universities and venture capital, and across different types of crowdfunding, but there is a comparative dearth of papers that examine whether or not traditional bank finance and fintech innovations such as crowdfunding are complements or substitutes.[3]

Tang (2019) analyzes data from a single platform (Lending Club) over the years 2009-2012 and finds mixed evidence that banks serve as complements versus substitutes for P2P lending, depending on loan size (complements for small loans, substitutes otherwise). De Roure, Pelizzon and Thakor (2019) develops and tests a model of bank and P2P lending using state-level German P2P data from one platform (Auxmoney). They provide evidence that P2P lenders compete with bank lenders when there is some sort of shock to the banks. Cornaggia, Wolfe, and Yoo (2018) use peer-to-peer lending data from two U.S platforms (Lending Club and Prosper Marketplace) over the years 2009-2015 aggregated as the state level to test how peer-to-peer lending affects the dollar amount of U.S. bank loans. Their evidence suggests that peer-to-peer lenders and banks are substitutes as they find that banks reduce the amount of outstanding consumer loans as the dollar volume of state-level peer-to-peer lending increases. Maskara

[3] Thakor (2019) provides a review of this literature.

and Kuvvet (2018) find evidence that rural P2P lending is more likely in regions with fewer alternative lenders. De Roure, Pelizzon and Tasca (2016) examine state-level German P2P data from one platform (Auxmoney) and data from small, geographically restricted German banks over the years 2010-2014 and provide evidence that P2P loans are made to high-risk consumers that banks are unable or unwilling to serve. Blaseg and Koetter (2015) examine 2011-2014 data from a sample of 357 German startup firms that had relationships with 82 German banks and find that a venture having a relationship with a stressed bank is significantly more likely to use crowdfunding.

Our approach differs from these papers by examining entrepreneurial projects (not merely personal loans), examining different types of crowdfunding (rewards and loans) and very samples from numerous crowdfunding and crowdlending platforms, and examining all different types of crowdlending (small business loans, credit card loans, medical loans, secured assets such as car loans, and personal loans). We examine a long horizon from 2007-2014. Further, we examine county level versus project level effects and show notable differences depending on the unit of analysis. We identify causality by examining the effect of bank failures in a county and consider robustness to numerous measures of bank failure drawing from insights in banking and when failure is identified, among other robustness checks.

This paper is organized as follows. The next section describes related literature and introduces the main hypotheses. Section 3 introduces the data. Section 4 presents the empirical results. A discussion of other robustness checks, limitations and alternative explanations is provided in section 5. The last section concludes.

2. Related Literature and Hypotheses

In theory, it is possible that traditional bank finance and crowdfunding are either complements or substitutes; or they could be completely unrelated. In this section, we present arguments each way leading to three alternative hypotheses. These hypotheses are then tested in later sections of the manuscript.

There are at least two main reasons why crowdfunding and bank finance are independent. First, crowdfunding operates in a different market than banks. Entrepreneurs are differentiated by the types of finance that they seek. Entrepreneurs that are in the market for bank loans are completely distinct from entrepreneurs that are in the market for crowdfunding. Entrepreneurs seeking bank finance normally have a superior credit history, which enables them to seek bank finance at a lower interest rate. In a sense, there is a separating equilibrium where the highest quality entrepreneurs seeking external finance use bank finance, followed by crowdlending, and thereafter followed by equity finance (Stiglitz and Weiss, 1981; DeMeza and Webb, 1988). In a similar way, other work in entrepreneurial finance has shown large selection differences between banks and venture capitalists such that they attract different types of entrepreneurs that are interested in different types of finance (Cosh et al., 2009; Robb and Robinson, 2014; Tykvova, 2018; Winton and Yerramilli, 2008; Cole and Sokolyk, 2018; Wilson et al., 2018). Similarly, other work on crowdfunding has shown that rewards and equity and rewards crowdfunding do not compete with each other and operate independently of one another (Cholakova and Clarysse, 2015). Second, covenants in bank loans may render the use of other forms of finance such as crowdfunding impossible (Demiroglu and James, 2010). Such covenants mean that entrepreneurs are less likely to hold both crowdfunded capital and bank finance.

Hypothesis 1: *Traditional bank finance and crowdfunding are independent of one another.*

There are at least five reasons why crowdfunding and bank lending may be considered to be substitutes. First, banks and crowdfunding markets offer the ability to raise very similar amounts of funds. Second, different crowdfunding platforms offer an array of fee arrangements with more variety (Cumming, Johan and Zhang, 2017), and with such a menu of alternatives entrepreneurs may find a fee arrangement which is more attractive than the fee arrangements offered by banks. Third, crowdfunding markets may be subject to comparatively less investor bias, at least in respect of age and location (Cumming, Meoli and Vismara, 2018) and potentially gender and ethnicity. Traditional forms of finance have been criticized for gender discrimination (Bellucci, Borisov and Zazzaro, 2010) in offers of financing arrangements. Fourth, there is evidence that entrepreneurs who need credit become discouraged and do not even apply for traditional bank finance (van Stel, Storey and Thurik, 2007; Cole and Dietrich, 2013; Cole and Sokolyk, 2016). The mechanisms that lead to discouraged borrowers seem to be less pertinent to crowdlending and other forms of crowdfunding, albeit further work is warranted. Fifth, there may be competing interests in bank lending versus crowdfunding markets. That is, banks may advise against the use of crowdfunding; and crowdfunding intermediaries (platforms) may similarly discourage entrepreneurs from seeking bank finance. Similar conflicts of interest have been seen in respect of technology parks and venture capital leading them to be substitutes and not complements (Cumming, Werth and Zhang, 2017). Likewise, similar evidence has been seen in respect of angel investors and venture capitalists as being substitutes and not complements (Cumming and Zhang, 2018; Capizzi et al., 2018a,b; Goldfarb et al., 2013).

Hypothesis 2: *Traditional bank finance and crowdfunding are substitutes.*

There are at least five reasons why crowdfunding and bank finance are complements. First, a bank loan and/or credit card debt is typically needed for nascent entrepreneurs (Gartner, Frid and Alexander, 2012; Robb and Robinson, 2014; Cole and Sokolyk, 2018). Bank debt would be needed to get a project ready for crowdfunding. A crowdfunded project typically involves a video, extended text description of the intended use of capital, a prototype of the product that forms the basis of the entrepreneurial opportunity, pre-crowdfunding promotion and marketing efforts, and possibly put together a team of advisors and/or directors. While these things are going on to develop the crowdfunding campaign, the entrepreneur will have living costs, have to pay employee salaries (if any), and pay office rent (if applicable), among other expenses. In effect, crowdfunding can be used to scale up from bank debt. Similar evidence is seen in crowdfunding markets enabling entrepreneurs to scale up to subsequent venture capital (Colombo and Shafi, 2016; Kaminski et al., 2016; Sorensen et al., 2016); the mechanism is similar here, albeit for a much earlier stage of finance and whether or not bank finance can facilitate subsequent crowdfunding.

Second, bank loans may enable external certification that you have support of reputable intermediary to get money online. Cole and Sokolyk (2018) find that start-up firms obtaining a bank loan in the name of the firm rather than in the name of the owner grow faster and are more likely to survive their first few years of operations. In other contexts, earlier forms of finance enable larger subsequent forms of finance through signaling quality by obtaining finance at that earlier stage. For example, government grants can facilitate subsequent venture capital (Howell, 2017), and venture capital can facilitate a subsequent IPO (Nahata, 2008; Nahata et al., 2014; Barry and Mihov, 2015; Jeppsson, 2018).

Third, multiple sources of capital can mitigate hold-up problems for entrepreneurs. Hold-up problems arise in the context of investors threatening to renegotiate contract terms in staged financing arrangements. These problems are evident in venture capital markets (Gompers, 1995). Entrepreneurs are therefore more likely to want to start businesses if they have access to multiple sources of finance (Cumming and Johan, 2013).

Fourth, there can be positive spillover effects insofar as more entrepreneurial financing in an area by banks creates incentives and opportunities for other entrepreneurs to engage entrepreneurship. That is, even if entrepreneurs are differentiated whereby one type seeks bank finance and another type seeks crowdfunding, the presence of more entrepreneurs in a region creates market opportunities that positively benefit everyone and open up new economic opportunities for another. This type of regional agglomeration effect in turn leads to more entrepreneurs overall (Avnimelech and Teubal, 2006; Audretsch, 2007) and, of course, to more entrepreneurs seeking financing.

Fifth, entrepreneurs often apply for multiple sources of finance, even after they are turned down from other sources. Both Robb and Robinson (2014) and Cole and Sokolyk (2018) document the various sources of capital used by entrepreneurs during their startup year, which included not only bank loans but also loans from family and friends as well as from outsiders. Cosh et al. (2009) document the fact that entrepreneurs typically end up getting the amount of capital that they want, albeit not necessarily in the form that they would like. Cole (2013) documents that leverage at small businesses is higher at firm with more bank and nonbank relationships. Hence, having more sources of capital enables more entrepreneurs to seek capital.

Hypothesis 3: *Traditional bank finance and crowdfunding are complements.*

3. Data

Our data come from several different sources. Our bank branch data comes from the Federal Deposit Insurance Corporation (FDIC) Summary of Deposits (SOD) file, which is an annual survey of the dollar amount of deposits at each branch office of a bank as of June 30th for all FDIC-insured institutions. The SOD file also provides the Federal Information Processing Standards (FIPS) code by state and county for each branch location. We use county-level data to better capture the effect a bank closure has on the community in which it serves. Most of the commercial bank closures during our sample period were community and regional banks, which necessarily has impacts on the local markets it serves rather than the broader state or geographic region in which it is located. We use the 2005 SOD file to determine third and fourth quarter summary data for 2005 and first and second quarter

2006 bank-branch data. Similarly, the 2006 SOD file is used to create third and fourth quarter summary data for 2006 and first and second quarter 2007 bank-branch data. This procedure is repeated for the full time period of our study.

Our database of US-based crowdfunding projects comes from TAB Marketplace Finance Intelligence and includes 1,116,422 individual projects from September, 2001 to November, 2017. There are 338 different crowdfunding platforms represented. Of the 1.1 million projects in the initial sample, 689,729 projects report a city name and 781,536 report a state name. Of those projects, 654,249 report a city name and state name. From this dataset, we extract the rewards-based projects on the Kickstarter and Indiegogo crowdfunding platforms. We supplement the TAB Marketplace Finance Intelligence database with crowdlending data directly from Lending Club and Prosper.

In order to determine the county location of a crowdfunding project, we match the provided city and state to a database of zip codes which contain the associated city and state using a matching program developed in Python[4]. In our database, many zip codes include common abbreviations and other affiliated names of locations within a zip code. For instance, a project may list their city as "Manhattan" which would not match to "New York City" without human intervention. This allows for a much richer matching profile.

The crowdfunding projects are then matched to the U.S. Department of Housing and Urban Development (HUD) USPS-ZIP crosswalk file. Wilson and Din (2018) provide a thorough description of how HUD developed the cross-walk file and how to decide what county a zip code should be assigned to. We choose the first approach offered by Wilson and Din (2018), which is to assign a zip code to the county with the highest proportion of addresses. Their analysis shows that "73.8% of zip codes have no county overlap, and for the 26.2% of residential addresses that are in multiple counties, 16% of residences are 90-99% in one area, 4% are 80-89% in one area, and 6% of residences are between 30-79% in one area." As a result of their research we have high confidence in the matching procedure. This matching procedure provides us with the basis for the rest of the data, the 5-digit FIPS code.

[TABLE 1 ABOUT HERE]

Next, we gather county-level data from the US Census Bureau, US Bureau of Labor Statistics, the Federal Reserve Bank of New York and Equifax (using the FRED API from the Federal Reserve Bank of St. Louis), and the US

[4] Python Software Foundation - www.python.org

Bureau of Economic Analysis. These data are described in Table 1. We match data based on the 5-digit FIPS code and the year-quarter of the data.

[FIGURE 1 ABOUT HERE]

[FIGURE 2 ABOUT HERE]

[FIGURE 3 ABOUT HERE]

We require that every project assigned to a county have no missing demographic data and that every county included in the county panel regressions have no missing demographic data. This final matching step at the project level leaves us with 122,690 rewards-based projects and 665,138 debt-based projects that begin in June, 2007 and we end the sample as of December, 2014. We have data on 3,216 counties to include in our panel regressions over the same time period. Figure 1 shows a county choropleth with county-level aggregate crowdfunding dollars raised over the sample period for rewards-based projects. Counties with deeper shades of red raise more money. Figure 2 shows a county choropleth with county-level aggregate crowdfunding dollars raised over the sample period for all types of debt-based projects. Figure 3 shows a county choropleth with county-level aggregate crowdfunding dollars raised over the sample period for debt-based small business projects. The data for these choropleths were winsorized at the 95% level to aid in visualization; New York City and Los Angeles dominate the map in such a way that the regional diversity of crowdfunding would be hard to see otherwise.

[FIGURE 4 ABOUT HERE]

Figure 4 shows a county choropleth of counties that experience bank failure in our sample period. We matched the FDIC Bank Failure list to the bank's branches to determine the specific counties that experience bank failure. The choropleth shows that the bank failures are concentrated in areas dissimilar to the crowdfunding choropleths. Thus, the analysis of bank failures and crowdfunding is a non-trivial task.

[TABLE 2 ABOUT HERE]

Table 2 Panels A and B provide summary statistics for our panel regression variables which are aggregated at the county level by quarter year for rewards-based and debt-based crowdfunding projects, respectively. Our data does not include every county in the US because some counties have so few residents that it makes anonymizing certain data impossible. As such, our panel is not a perfect representation of all counties but figures 1-3 shows how well our data encompass a majority of the US. Bank Failures are rare events; on average, 1% of counties experience failure in our sample period. In total, 441 banks actually fail during this sample period.

Because not all troubled banks actually fail during our sample period or fail in a timely manner due to regulatory forbearance (Cole and White, 2017), we cannot accurately measure the impact of a failing bank on crowdfunding projects without expanding our definition of failure. As such, we utilize the measure of a technical failure following Cole and White (2012, 2017).

$$NACR0\ Fail = 1\ when: (Equity + Reserves - 0.5\ x\ NPA) < 0, \tag{1}$$

where NPA (nonperforming assets) equals the sum of loans past due 30-89 days and still accruing interest, loans past due 90+ days and still accruing interest, nonaccrual loans, and foreclosed real estate. Equity is total equity capital and Reserves are Allowances for Loan and Lease Losses. All are deflated by total assets. Table 2 shows that 4.3% of our county-quarter observations experience technical failure. Thus, the importance of including troubled banks is now readily apparent.

We also include two additional measures of failure following the work of Cole and White (2017).

$$NACR1\ Fail = 1\ when:$$

$$(Equity + Reserves - 0.2\ x\ PD30 - 0.5\ x\ PD90 - Nonaccrual - OREO) \div Assets < 2\%, \tag{2}$$

Where NPA is divided into its component parts; loans past due 30-89 days and still accruing interest (PD30); loans past due 90 or more days and still accruing interest (PD90); nonaccrual loans (Nonaccrual); and foreclosed real estate (OREO). These are weighted by what the supervisory loan-loss provisioning requirements that are used by U.S. and other nations' banking regulators as the provisioning thresholds for these categories (see formula above). When NACR is less than 2%, we classify that bank as a failing bank in that quarter.

We also use a measure of nonperforming assets that is used by the International Monetary Fund in assessing banks in countries where prudential data is sparse. This measure is:

$$NACR2\ Fail = 1\ when:$$

$$(Equity + Reserves - 0.5\ x\ NPA) \div Assets < 2\% \tag{3}$$

The calculation of NPA follows (2) above but lacks the detailed weighting method.

Table 2 Panels A and B show that the first method of calculating NACR indicates that 4.3% of our county-quarter observations experience failure and the second method shows that 12.3% of our county-quarter observations experience failure. The third method shows that 6.6% of our county-quarter observations experience failure.

Table 2 Panels A and B show the average county has $2,539,000 in cash deposits in its branches. On average, the population is 100,157 people, half of which are female, and 13% are non-white. On average, 31.4% of the population of a county in a quarter is a sub-prime borrower. The average unemployment rate is 7.3% and the per capita income of our county-quarter observations is $35,444.

Panel A of Table 2 reports the county-quarter averages of reward-based crowdfunding projects. The average county with reward-based crowdfunding projects raises $7,774 in a quarter. Panel B of Table 2 shows that the average county with debt-based projects raises $87,622 in a quarter.

[TABLE 3 ABOUT HERE]

Table 3 Panel A reports our rewards-based project-level regression variable summary statistics. Instead of examining crowdfunding projects based on county aggregates, now we observe the projects at a far more granular level. Our matching procedure yielded 122,690 unique rewards-based crowdfunding projects which raise $4,692 on average. About 5% of those projects are in counties that experience bank failure; 24.3% of those projects are exposed to a technical failure; 42.3% to the NACR1 measure of failure; and 32.8% to the NACR2 measure of failure. Projects originate in counties that are more diverse than the county panel average would suggest; 25.3% of the population within a county in which a rewards-based crowdfunding project launches is non-white. Their credit is slightly better, too; on average, 27.1% of the population is subprime. The average per capita income is nearly twice the county panel average at $59,890. The county choropleth in figure 1 shows that California and New York dominate the crowdfunding sample; this is likely why the per capita income average is much higher than in the county panel summary.

Table 3 Panel B contains the subsample of debt-based crowdfunding projects. Our matching procedure yielded 665,138 unique debt-based crowdfunding projects that raise $13,291 on average. We isolate five categories of crowdfunding projects based on their loan characteristics. Lending Club and Prosper offer promotional rates for medical procedures, and thus medical loans are materially different than other types of crowdlending projects.

Our sample includes 8,068 crowdlending projects for medical procedures that raise $8,553 on average. Both Lending Club and Prosper offer loans for cars, boats, RV's and motorcycles that are secured loans, which raise $7,162 on average. Because these loans are secured, they are materially different than other types of crowdlending projects. There are 9,451 secured crowdfunding projects in our sample.

Lending Club and Prosper also offer a credit card consolidation product, which is a new revolving line of credit. Since revolving lines of credit are not fixed term loans like the other categories of crowdlending, they are materially different. Credit card debt consolidation crowdlending projects raise $14,716 on average and there are 102,888 credit card crowdlending projects in our sample.

Finally, we examine small-business loans separately because the application process for these loans is different than other types of loans. We are more interested in these loans for our study because they are directly to entrepreneurs and small business owners. There are 16,306 small business crowdlending projects in our sample and they raise $12,264 on average.

The remaining crowdlending projects, which represent the baseline in our crowdlending project level regressions, are personal loans for a variety of uses. They are homogenous in maximum loan term, loan amount maximum, and are sold to investors without a category assignment. Therefore, personal loans that don't belong to the previous four categories are analyzed as the baseline. There are 528,425 personal loan crowdlending projects that raise $13,227 on average. 3.6% of crowdlending projects in our sample are in counties that experience bank failure; 13.1% of those projects are exposed to a technical failure; 23.6% to the NACR1 measure of failure; and 17.1% to the NACR2 measure of failure. These projects originate from counties that are also more diverse than the county panel average; 22.4% of the population within a county in which a debt-based crowdfunding project launches is non-white. Similar to the rewards-based projects, the average population is 28.5% subprime. The average per capita income is also higher at $47,931.

[TABLE 4 ABOUT HERE]

Table 4 Panels A and B report correlations for our variables in the county panel regressions. Some of the variables are correlated at least at the 0.1 level but that is due to the temporal nature of the data. We checked the specifications in the next section for any bias associated with collinearity and did not find any material difference by including or excluding variables potentially affected by collinearity. We report the correlation coefficients with the caveat that most of our variables suffer from some degree of collinearity. Table 5 Panels A and B are similar to what we find in Table 4.

[TABLE 5 ABOUT HERE]

4. Empirical Tests

Table 6 presents panel data regressions by county and quarter of the amount of crowdfunding raised over the fourth quarter 2006 to fourth quarter 2014 time period. The regression uses time and county fixed effects and includes a number of control variables for county demographic characteristics, including county population, county per capita income levels, ethnicity, unemployment rates, as well as branch deposits and subprime amounts. We consider four alternative models with different measures of technical bank failure to assess robustness. Also, we have considered other specifications and robustness checks described further below in section 5 but not explicitly presented here.

In Table 6 (as well as for below for Tables 7 and 8), Panel A presents the regressions for funds raised in a county for rewards crowdfunding by itself. Panel B presents the regressions for debt crowdfunding only. We do not present regressions for donations crowdfunding and equity crowdfunding, as bank failures were statistically unrelated to those types of crowdfunding. In the case of donations, our bank failure measures are statistically insignificant, while, for equity crowdfunding, the available number of observations was too small to reliably test for the impact of bank failures.

Table 6 Panel A shows consistent evidence that bank failures in a county negatively affect the amount of crowdfunded capital for rewards-based projects. This effect is statistically significant at the 10% level in Model (2) and 5% level in Models (1), (3) and (4). The economic significance is large. A bank failure in a county quarter gives rise to a reduction in crowdfunding by 101.99% (relative to the average amount across all counties and all quarters in the data) in the most conservative estimate and 608.33% in the least conservative estimate. Overall, these regressions are consistent with Hypothesis 3, and not Hypotheses 1 and 2.

The other variables in Table 6 Panel A that are significant in the regressions is population, per capita income, percent subprime and branch deposits. A one standard deviation increase in population gives rise to a 47.47% increase in total crowdfunds raised in a county-quarter relative to the average county-quarter. A one standard deviation increase in per capita income gives rise to a 27.58% increase in total crowdfunds raised in a county-quarter relative to the average county-quarter. The data indicate that a one standard deviation increase in branch deposits gives rise to a 1.29% increase in total crowdfunds raised in a county-quarter relative to the average county-quarter. On the other hand, a one-standard-deviation increase in the percentage of the population of a county that is a subprime borrower decreases the total crowdfunds raised in a county-quarter relative to the average county-quarter by 1,010.3% in the most conservative estimate.

[Table 6 About Here]

Table 6 Panel B shows similar results as in Panel A for the subset of debt crowdfunding projects only. The effects from bank closures are statistically significant at the 1% level in all model specifications. The economic significance is such that a bank closure causes a 236.05% reduction in debt crowdfunding in the most conservative estimate (Model 3) and 369% in the least conservative estimate (Model 2) relative to the average amount of debt crowdfunding in a county quarter in the data. Again, the data support Hypothesis 3 and not Hypotheses 1 and 2.

The control variables in Table 6 Panel B show a significant effect of population (as in Panel A), with a 1-standard deviation increase giving rise to a 42.95% increase in debt crowdfunding relative to the county average. The percentage of the population that is classified as subprime is negative and significant whereby a one standard deviation increase is associated with approximately a 1,000% decrease in debt crowdfunding. Here too, the results support Hypothesis 3, and not Hypotheses 1 and 2.

Importantly, note that if bank closures were caused by crowdfunding, we would see a positive relation between crowdfunding and bank closures. The data indicate the exact opposite. As such, we do not have reason to believe that bank failures are caused by crowdfunding in the data, and hence endogeneity does not appear to be a significant factor influencing the regression results.

Table 7 Panels A and B presents analogous regressions as in Table 6 Panels A and B, with the difference in the dependent variable specified as the number of crowdfunding projects and not the total capital raised. The evidence is very similar to Table 6. Table 7 Panel A shows bank closure in a county causes the number of rewards-based crowdfunded projects to decline at the 5% level of significance in Models (1) and (3), and at the 1% level of significance in Models (2) and (4). The economic significance is most conservative in Model (3) with a 84.79% effect relative to the average number of projects in a county-quarter, and least conservative in Model (1) with a 465.71% effect relative to the average county-quarter. The control variables show population, per capita income and branch deposits are positive and statistically significant. Again, the data are consistent with Hypothesis 3, not Hypotheses 1 and 2. In unreported regressions, we test small business loans aggregated at the county level and find similar results.

[Table 7 About Here]

Table 7 Panel B shows the same regressions for number of debt crowdfunding projects. The effect of bank closures is statistically significant at the 1% level in all model specifications. The economic significance is most conservative in Model (3) at -220.95% relative to the average number of debt projects, and least conservative in Model (2) at -345.69%. This evidence is consistent with Hypothesis 3. The control variables show population is positive and statistically significant, while the percent of borrowers in a county which are subprime is negative and significant.

Tables 6 and 7 are presented for the county-level panel evidence. Table 8, by contrast, are at the crowdfunding project level. Table 8 measures the total project capital raised for rewards-based types of crowdfunding.

Table 8 shows that bank closures do not have a statistically significant impact on a crowdfunding project capital raise in Model (1), but the effect is positive and significant at the 1% level in Models (2), (3) and (4). The economic significance is such that a bank closure in a county causes a 7.5% increase in the amount of capital raised for a single crowdfunded project relative to the average project size in the most conservative estimate in Model (4) and a 9.19% increase in the least conservative estimate in Model (2). At first glance, the evidence may seem contradictory to Table 6, which were at the county-level and not the project level. The evidence is reconciled by the fact that bank failures reduce the number of crowdfunding projects (Table 7), leading to a reduction in the overall capital crowdfunded in a county (Table 6), but the remaining projects that can go ahead are larger (Table 7). In essence, bank failures are more detrimental and reduce economic opportunities for smaller entrepreneurs that do not otherwise have sources of capital to initiate crowdfunding projects. Larger capital raises through crowdfunding are nevertheless possible in the presence of a local bank failure among entrepreneurs less reliant on banks.

As expected, the control variables in Table 8 show that larger crowdfunding projects are statistically observed in counties with higher population, less unemployment, and greater per capital income.

[Table 8 About Here]

Table 9 Panel A shows the control variables for crowdlending projects. A one standard deviation increase in the proportion of a county's population that is non-white is associated with a 131.55% increase in funds raised, on average. A one standard deviation increase in unemployment is associated with a 64.26% increase in funds raised, on average.

[TABLE 9 ABOUT HERE]

Table 9 Panel B shows our measures of failure compared to the baseline as well as interacted with the 4 categories of crowdlending projects. Column 1 demonstrates that banks which actually fail and are located in the same county and in the same quarter as a crowdlending project cause those projects to raise an additional 0.81%, on average. The coefficient of fail is statistically significant at the 0.05 level. The only interaction term which has significance is the interaction of failure with secured loans, causing secured loans in counties which experience a bank failure to raise an additional 17.47% on average compared to the average secured crowdlending project, and the interaction coefficient is statistically significant at the 0.01 level. Column 2 presents our second measure of bank failure interacted with our four categories of crowdlending projects. While the measure of bank failure lacks significance, the interaction with medical loans is statistically significant at the 0.05 level and positive. On average, medical crowdlending projects raise 5.6% more funds than medical crowdlending projects located in counties which do not experience bank failure during the quarter. Similarly, secured loan projects raise 9.1% more funds on average than secured loan projects located in counties which do not experience bank failure during the quarter, and the interaction term is statistically significant at the 0.01 level. Credit card consolidation crowdlending projects raise 3.55% less on average than credit card consolidation crowdlending projects located in counties which do not experience bank failure during the quarter, and the interaction term is statistically significant at the 0.01 level. Small business loan crowdlending projects raise 2.79% more than small business loan crowdlending projects located in counties which do not experience bank failure during the quarter, and the interaction term is statistically significant at the 0.05 level. These findings are consistent with Table 8 and support our third hypothesis.

Table 9 Panel B columns 3 and 4 are consistent with column 2. Our measures of failure demonstrate the detrimental effect failed and failing banks have on crowdlending projects.

5. Other explanations

Different types of debt are available for investors on crowdlending platforms, however the predominant type is personal loans to individual borrowers. For example, Lending Club offers data on their website[5] which shows that 38% of Lending Club's investor base is banks, offering direct evidence that banks and crowdlending are complements. This partnership began in 2014, which is when the banking sector showed significant signs of improvement. Our data is comprised of over 400,000 Lending Club projects over our time sample, however the debt categories span 14 different types from weddings to small business loans.

Approximately 2.5% of our project-level observations are from New York County, New York, which encompasses Manhattan. To address the possibility that our results are affected by over-representation of a single county, we omit New York County from our analysis. In unreported project-level regressions, our results and conclusions are the same.

Finally, another alternative explanation is that independent factors may affect both bank finance and crowdlending. For example, tax policy (Keuschnigg and Neilsen, 2002), government support programs (McCahery and Vermeulen, 2016; Howell 2017), university programs (Lockett et al., 2005; Wright et al., 2006), and incubators (Rothaermel and Thursby, 2005 could affect the extent of crowdlending, crowdfunding and bank finance independently. Legal changes in one county versus another over time could further independently affect bank finance and crowdfunding. These and other possible variables, however, are largely controlled for with the use of county and time fixed effects in our panel regressions and platform, platform-year-quarter, county, and year-quarter fixed effects in our project level regressions. We have not observed subsets of counties or any other major policy shift in the time period and regions examined that would lead us to worry that the regression structure is not

[5] www.lendingclub.com/investing/institutional/banks

accounting for these and other possible explanations.

6. Summary, Conclusions and Directions for Future Research

In this paper, we offer three alternative hypotheses that bank finance is either negatively related to, unrelated to, or positively related to crowdfunding. We examine extensive data on two types of crowdfunding: debt and rewards-based projects. Our analysis shows strong and consistent support for the hypothesis that bank finance is a complement to, and not a substitute for, crowdfunding.

Our findings have current and relevant managerial and policy implications. Policymakers should promote stability in banking and banking efficiency to enhance entrepreneurial finance, crowdfunding, and entrepreneurship overall. Banks should embrace and promote lending as a way to encourage and foster entrepreneurial activity to make use of crowdfunding marketplaces. Fintech innovations through crowdfunding facilitate banking growth.

This growth through a positive association between bank finance and crowdfunding may come at the risk of loan repayment, among other unintended effects. Future research could examine this issue as more evidence on long-term success of crowdfunded projects becomes available. And future research could examine the role of equity crowdfunding and how it interplays with bank finance in other countries with a longer history of equity crowdfunding, and in the U.S. as more data become available. Also, future research could examine the impact of other types of fintech innovations other than crowdfunding. These findings may apply differentially in different institutional settings with legal, policy and cultural differences, and hence more international evidence would be useful to further guide policy and practice.

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Figure 1. Total crowdfunding dollars (in thousands) raised by rewards-based crowdfunding projects per county from 2007-2014

This county choropleth shows the total amount of dollars (in thousands) raised by crowdfunding projects in our sample from 2007-2014. The aggregate amounts have been winsorized at the upper 95% to aid in visualization.

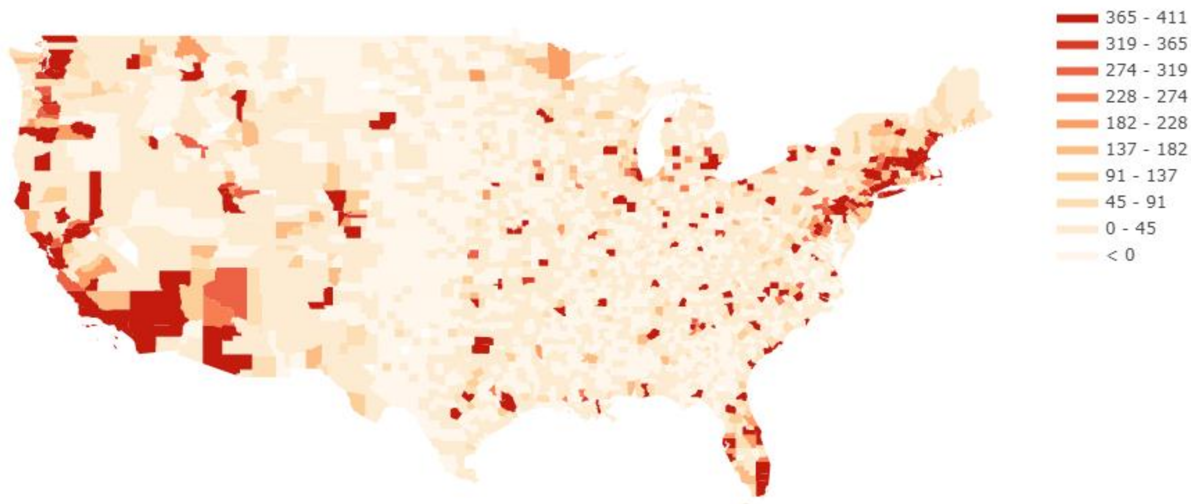

Figure 2. Total crowdfunding dollars (in thousands) raised by crowdlending projects per county from 2007-2014

This county choropleth shows the total amount of dollars (in thousands) raised by crowdlending projects in our sample from 2007-2014. The aggregate amounts have been winsorized at the upper 95% to aid in visualization.

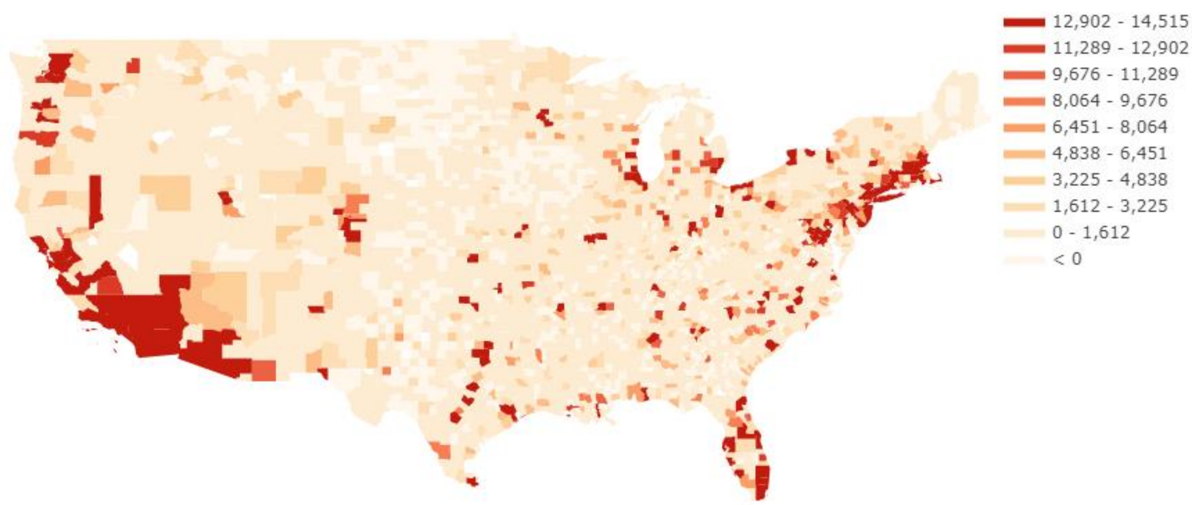

Figure 3. Total crowdfunding dollars (in thousands) raised by small business crowdlending projects per county from 2007-2014

This county choropleth shows the total amount of dollars (in thousands) raised by crowdlending projects in our sample from 2007-2014. The aggregate amounts have been winsorized at the upper 95% to aid in visualization.

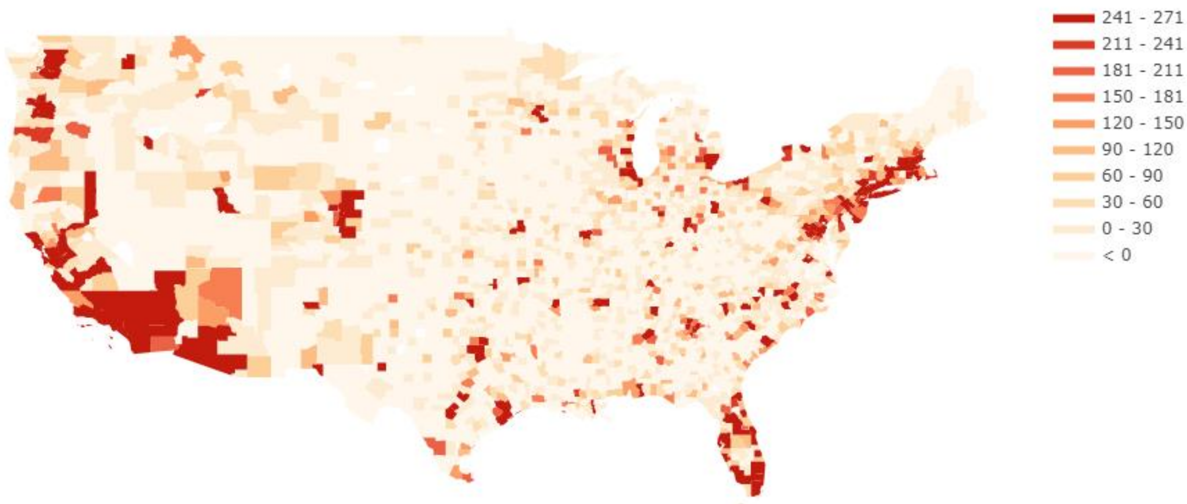

Figure 4. Counties which experience bank failure from 2007-2014

This county choropleth shows the counties which experienced bank failure, where a bank with at least one branch within a county failed according to the FDIC Failed Bank List. Red color indicates failure and gray color indicates that no bank failed within a county.

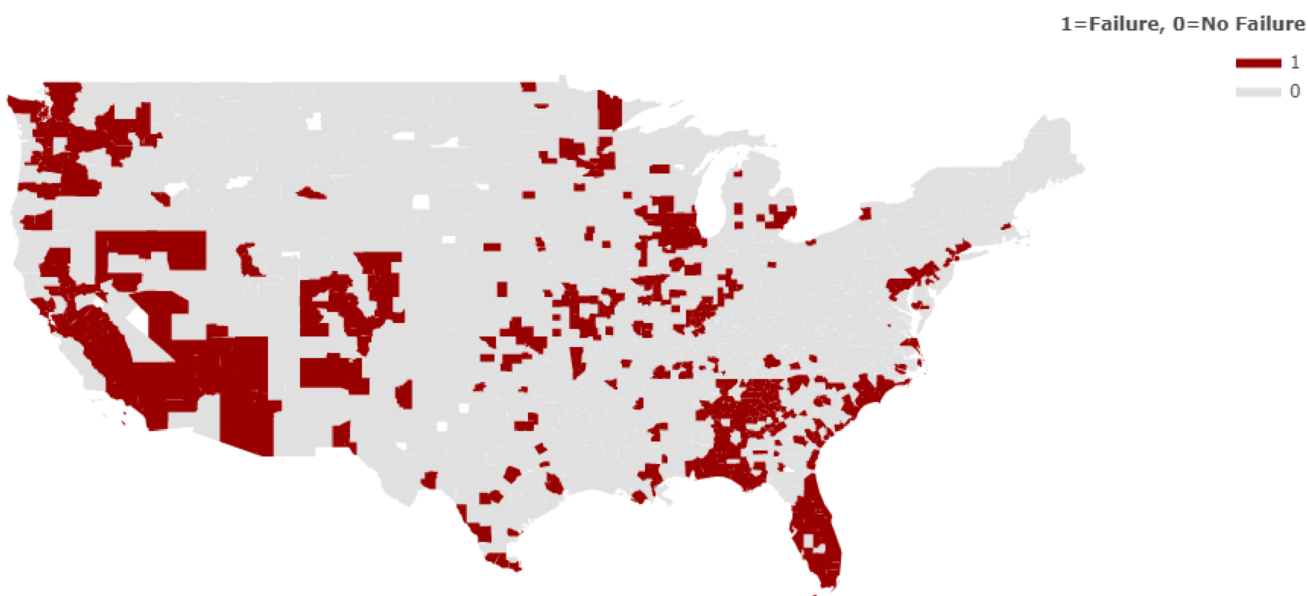

Table 1. Variable definitions and data sources

This table describes the variables related to crowdfunding and bank failure. The sources are in the table.

Variable	Description
Funds Raised	Project-level reported amount raised or the sum of all projects' reported funds raised in a county during a quarter, divided by 1000. From TAB Marketplace Finance Intelligence
No. Projects	Total number of projects started in a county during a quarter. From TAB Marketplace Finance Intelligence
Success Rate	Number of successful projects divided by the total number of projects in a county during a quarter
Interest Rate	Project-level reported interest rate for debt crowdfunding. From TAB Marketplace Finance Intelligence
Fail	Fail is an indicator variable equal to one if a bank with at least one branch in a county is reported as failed by the FDIC in a given quarter, otherwise the value is zero. From the FDIC Failed Bank List https://www.fdic.gov/bank/individual/failed/banklist.html
NACR Fail	NACR Fail is an indicator variable equal to one if a bank with at least one branch in a county in a given quarter reports that their sum of equity plus loan loss reserves was less than half of the value of its nonperforming assets, otherwise the value is zero. This method follows Cole and White (2012) and data comes from the quarterly Reports of Condition and Income (Call Reports) provided by the Federal Financial Institutions Examination Council (FFIEC) https://cdr.ffiec.gov/public/
NACR1 Fail	NACR1 Fail is an indicator variable equal to one if a bank with at least one branch in a county in a given quarter reports that their Nonperforming Assets Coverage Ratio (NACR) is below 2%, otherwise the value is zero. This method follows Equation 3 from Cole and White (2017) and data comes from the quarterly Reports of Condition and Income (Call Reports) provided by the Federal Financial Institutions Examination Council (FFIEC) https://cdr.ffiec.gov/public/
NACR2 Fail	NACR2 Fail is an indicator variable equal to one if a bank with at least one branch in a county in a given quarter reports that their Nonperforming Assets Coverage Ratio (NACR) is below 2%, otherwise the value is zero. This method follows Equation 5 from Cole and White (2017) and data comes from the quarterly Reports of Condition and Income (Call Reports) provided by the Federal Financial Institutions Examination Council (FFIEC) https://cdr.ffiec.gov/public/
Branch Deposits	Sum of all reported deposits of branches located in a county. From the Federal Deposit Insurance Corporation (FDIC) Summary of Deposits (SOD) file which is the annual survey of branch office deposits as of June 30th for all FDIC-insured institutions. https://www.fdic.gov/regulations/resources/call/sod.html
Population	Total population of a county divided by 1000. From the US Census Bureau
% Female	Percent of a county's population that is female. From the US Census Bureau
% Non-White	Percent of a county's population that is Non-White. From the US Census Bureau
% Subprime	Percent of a county's population that Equifax reports as having a 660 credit score or

	lower. From the Federal Reserve Bank of New York and Equifax, Equifax Subprime Credit Population retrieved from FRED, Federal Reserve Bank of St. Louis
Unemployment Rate	Percent of a county's total labor force that is unemployed. From the US Bureau of Labor Statistics
Per Capita Income	Average income earned in a county. From the US Bureau of Economic Analysis
Medical Loan	Medical Loan is an indicator variable equal to one if a crowdlending project is categorized by Lending Club or Prosper as a loan for a medical procedure and equal to zero otherwise
Secured Loan	Secured Loan is an indicator variable equal to one if a crowdlending project is categorized by Lending Club or Prosper as a loan for a car, boat, RV or motorcycle and equal to zero otherwise
Credit Card	Credit Card is an indicator variable equal to one if a crowdlending project is categorized by Lending Club as a revolving line of credit for consolidating credit card debt and equal to zero otherwise
Small Business	Small Business is an indicator variable equal to one if a crowdlending project is categorized by Lending Club or Prosper as a small business loan and equal to zero otherwise

Table 2. Panel A. Summary statistics - Rewards – County Level

This table reports summary statistics for the main variables in the data aggregated at the county level by quarter and includes only those crowdfunding projects which offer a reward for increased amounts of funding pledged to a project. Our Sample includes data for 3,216 counties in all 50 states, from the fourth quarter of 2006 through the fourth quarter of 2014. Variable definitions are contained in Table 1.

	N	Mean	St.Dev	p25	Median	p75
Funds Raised	100893	7.74	161.557	0	0	0
No. Projects	100893	1.085	16.27	0	0	0
Fail	100893	.011	.103	0	0	0
NACR Fail	100893	.043	.202	0	0	0
NACR1 Fail	100893	.123	.329	0	0	0
NACR2 Fail	100893	.066	.248	0	0	0
Branch Deposits	100893	2539.002	16000.24	166.511	378.861	940.927
Population	100893	100.157	318.546	11.328	26.077	67.761
% Female	100893	.5	.022	.496	.505	.511
% Non-White	100893	.13	.159	.025	.061	.173
% Subprime	100893	.314	.09	.248	.307	.377
Unemployment	100893	.073	.031	.05	.069	.092
Per Capita Inc.	100893	35.444	10.111	29.083	33.533	39.367

Table 2 Panel B. Summary statistics Debt – County Level

This table reports summary statistics for the main variables in the data aggregated at the county level by quarter and includes only those crowdfunding projects which are loans. Our Sample includes data for 3,216 counties in all 50 states, from the fourth quarter of 2006 through the fourth quarter of 2014. Variable definitions are contained in Table 1.

	N	Mean	St.Dev	p25	Median	p75
Funds Raised	100893	87.622	693.216	0	0	4.5
No. Projects	100893	6.305	48.803	0	0	0
Fail	100893	.011	.103	0	0	0
NACR Fail	100893	.043	.202	0	0	0
NACR1 Fail	100893	.123	.329	0	0	0
NACR2 Fail	100893	.066	.248	0	0	0
Branch Deposits	100893	2539.002	16000.24	166.511	378.861	940.927
Population	100893	100.157	318.546	11.328	26.077	67.761
% Female	100893	.5	.022	.496	.505	.511
% Non-White	100893	.13	.159	.025	.061	.173
% Subprime	100893	.314	.09	.248	.307	.377
Unemployment	100893	.073	.031	.05	.069	.092
Per Capita Inc.	100893	35.444	10.111	29.083	33.533	39.367

Table 3. Panel A. Summary statistics Rewards – Project Level
This table reports summary statistics by crowdfunding project that offer rewards for different funding levels. The data includes projects from June of 2007 through December of 2014. Definition of the variables is in Table 1.

	N	Mean	St.Dev	p25	Median	p75
Funds Raised	122690	6.365	53.302	.15	.972	3.595
Fail	122690	.05	.218	0	0	0
NACR Fail	122690	.243	.429	0	0	0
NACR1 Fail	122690	.423	.494	0	0	1
NACR2 Fail	122690	.328	.469	0	0	1
Branch Deposits	122690	139000	208000	7995.356	35019.19	219000
Population	122690	2153.014	2957.755	430.638	975.321	1848.347
% Female	122690	.511	.011	.505	.509	.517
% Non-White	122690	.253	.129	.163	.269	.334
% Subprime	122690	.271	.067	.222	.274	.314
Unemployment	122690	.074	.021	.059	.073	.085
Per Capita Inc.	122690	59.89	31.82	41.852	49.01	59.927

Table 3. Panel B. Summary statistics – Debt – Project Level
This table reports summary statistics by crowdfunding project that are funded as debt. The data includes projects from June of 2007 through December of 2014. Definition of the variables is in Table 1.

	N	Mean	St.Dev	p25	Median	p75
Funds Raised	665138	13.291	8.167	7	12	18
Fail	665138	.036	.185	0	0	0
NACR Fail	665138	.131	.337	0	0	0
NACR1 Fail	665138	.236	.424	0	0	0
NACR2 Fail	665138	.171	.376	0	0	0
Branch Deposits	665138	47659.47	95584.46	2893.236	12295.39	42096.95
Population	665138	1370.118	2107.506	213.484	662.647	1500.008
% Female	665138	.509	.011	.504	.509	.515
% Non-White	665138	.224	.141	.119	.212	.297
% Subprime	665138	.285	.065	.241	.282	.327
Unemployment	665138	.071	.024	.056	.066	.081
Per Capita Inc.	665138	47.931	15.815	38.441	44.419	53.098
Medical Loan	665138	.012	.109	0	0	0
Secured Loan	665138	.014	.118	0	0	0
Credit Card	665138	.155	.362	0	0	0
Small Business	665138	.025	.155	0	0	0

Table 4 Panel A. Rewards

This table presents correlations between the main variables in the data aggregated at the county level for crowdfunding projects that offer rewards for different funding levels. Due to the temporal nature of the data, all variables are correlated at least at the 0.10 level.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) Fnds Raised	1.000												
(2) No. Projects	0.878	1.000											
(3) Fail	0.012	0.027	1.000										
(4) NACR Fail	0.051	0.072	0.180	1.000									
(5) NACR1	0.043	0.066	0.168	0.563	1.000								
(6) NACR2	0.051	0.076	0.185	0.793	0.707	1.000							
(7) Branch	0.539	0.636	0.103	0.140	0.140	0.151	1.000						
(8) Pop	0.369	0.476	0.174	0.236	0.230	0.244	0.607	1.000					
(9) % Female	0.021	0.034	0.027	0.042	0.070	0.058	0.074	0.117	1.000				
(10)%Non-White	0.043	0.057	0.037	0.087	0.114	0.098	0.105	0.150	0.077	1.000			
(11) Sub-Prime	-0.034	-0.034	0.019	0.071	0.092	0.071	-0.045	-0.014	0.047	0.572	1.000		
(12) Unemp.	-0.003	0.001	0.076	0.128	0.207	0.160	-0.010	0.019	0.045	0.283	0.414	1.000	
(13) Per Capita	0.152	0.176	0.029	0.033	0.039	0.041	0.265	0.213	0.104	-0.119	-0.498	-0.343	1.000

Table 4 Panel B. Debt

This table presents correlations between the main variables in the data aggregated at the county level for crowdfunding projects that are loans. Due to the temporal nature of the data, all variables are correlated at least at the 0.10 level.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) Fnds Raised	1.000												
(2) No. Projects	0.997	1.000											
(3) Fail	0.026	0.032	1.000										
(4) NACR Fail	0.048	0.058	0.180	1.000									
(5) NACR1	0.035	0.045	0.168	0.563	1.000								
(6) NACR2	0.046	0.056	0.185	0.793	0.707	1.000							
(7) Branch	0.365	0.379	0.103	0.140	0.140	0.151	1.000						
(8) Pop	0.506	0.536	0.174	0.236	0.230	0.244	0.607	1.000					
(9) % Female	0.049	0.052	0.027	0.042	0.070	0.058	0.074	0.117	1.000				
(10)%Non-White	0.076	0.079	0.037	0.087	0.114	0.098	0.105	0.150	0.077	1.000			
(11) Sub-Prime	-0.043	-0.042	0.019	0.071	0.092	0.071	-0.045	-0.014	0.047	0.572	1.000		
(12) Unemp.	-0.016	-0.012	0.076	0.128	0.207	0.160	-0.010	0.019	0.045	0.283	0.414	1.000	
(13) Per Capita	0.165	0.165	0.029	0.033	0.039	0.041	0.265	0.213	0.104	-0.119	-0.498	-0.343	1.000

Table 5 Panel A. Rewards

This table presents correlations between the main variables in the data at the project level for crowdfunding projects that offer rewards for different funding levels. Due to the temporal nature of the data, all variables are correlated at least at the 0.10 level.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Fnds Raised	1.000											
(2) Fail	-0.007	1.000										
(3) NACR Fail	0.003	0.228	1.000									
(4) NACR1	-0.002	0.191	0.662	1.000								
(5) NACR2	0.000	0.217	0.812	0.815	1.000							
(6) Branch	0.025	-0.013	0.139	0.253	0.280	1.000						
(7) Pop	0.016	0.100	0.416	0.299	0.374	0.329	1.000					
(8) % Female	-0.012	0.015	0.025	0.163	0.157	0.456	-0.046	1.000				
(9) % Non-White	0.019	0.046	0.069	0.127	0.116	0.307	0.146	0.363	1.000			
(10) Sub-Prime	-0.036	0.145	0.211	0.127	0.123	-0.478	0.122	-0.087	0.056	1.000		
(11) Unemp.	-0.017	0.166	0.391	0.422	0.409	0.119	0.479	0.108	0.173	0.395	1.000	
(12) Per Capita	0.029	-0.080	-0.030	0.143	0.135	0.861	-0.047	0.463	0.329	-0.693	-0.136	1.000

Table 5 Panel B. Debt

This table presents correlations between the main variables in the data at the project level for crowdfunding projects that are loans. Due to the temporal nature of the data, all variables are correlated at least at the 0.10 level.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) Fnds Raised	1.000														
(3) Fail	-0.033	1.000													
(4) NACR Fail	-0.059	0.205	1.000												
(5) NACR1	-0.080	0.204	0.698	1.000											
(6) NACR2	-0.065	0.203	0.854	0.816	1.000										
(7) Branch	0.019	0.117	0.198	0.161	0.207	1.000									
(8) Pop	0.004	0.149	0.281	0.222	0.268	0.675	1.000								
(9) % Female	-0.005	0.019	0.047	0.060	0.070	0.128	0.031	1.000							
(10) % Non-White	0.015	0.056	0.108	0.102	0.117	0.216	0.223	0.344	1.000						
(11) Sub-Prime	-0.060	0.084	0.176	0.166	0.164	-0.156	-0.001	0.039	0.265	1.000					
(12) Unemp.	-0.076	0.093	0.218	0.266	0.241	0.069	0.188	-0.005	0.102	0.349	1.000				
(13) Per Capita	0.070	-0.020	-0.004	0.011	0.022	0.538	0.108	0.158	0.117	-0.623	-0.295	1.000			
(13) Medical Loan	-0.064	-0.001	0.003	0.000	0.001	-0.000	-0.002	-0.007	-0.003	0.008	-0.000	-0.002	1.000		
(14) Secured Loan	-0.090	0.015	0.030	0.038	0.032	-0.009	-0.004	-0.002	-0.003	0.020	0.033	-0.014	-0.013	1.000	
(15) Credit Card	0.075	-0.011	-0.004	-0.003	-0.003	0.016	0.010	0.001	-0.004	-0.029	-0.007	0.021	-0.047	-0.051	1.000
(16) Small Business	-0.020	0.024	0.043	0.055	0.047	0.003	0.006	0.001	0.005	0.026	0.024	-0.009	-0.018	-0.019	-0.068

Table 6. Panel A. Regression results – Rewards – County Level Funds Raised

This table presents the effect of *Fail*, *NACR Fail*, *NACR1 Fail*, and *NACR2 Fail* and other control variables on the aggregate amount of dollars raised by crowdfunding projects that offer a reward for increased levels of funding pledged to a project in a county. *Funds Raised* is the dependent variable in panel regressions with Year-Quarter and County fixed effects. Column 1 presents the regression on *Fail*, a dummy variable equal to one if a county experiences a bank failure and zero otherwise. Column 2 presents the regression on *NACR Fail*, a dummy variable equal to one if a bank with at least one branch in a county in a given quarter reports that their sum of equity plus loan loss reserves was less than half of the value of its nonperforming assets, otherwise the value is zero. Column 3 presents the regression on *NACR1 Fail*, a dummy variable equal to one if a bank with at least one branch in a county in a given quarter reports that their Nonperforming Assets Coverage Ratio (NACR) is below 2%, otherwise the value is zero. This method follows Equation 3 from Cole and White (2017). Column 4 presents the regression on *NACR2 Fail*, a dummy variable equal to one if a bank with at least one branch in a county in a given quarter reports that their Nonperforming Assets Coverage Ratio (NACR) is below 2%, otherwise the value is zero. This method follows Equation 5 from Cole and White (2017).

	(1) Funds Raised	(2) Funds Raised	(3) Funds Raised	(4) Funds Raised
Population	3.674*	3.695*	3.694*	3.693*
	(1.895)	(1.907)	(1.906)	(1.906)
% Female	-203.932	-205.001	-206.169	-203.685
	(242.379)	(243.121)	(243.430)	(242.910)
% Non-White	-1249.178	-1250.827	-1256.126	-1252.815
	(766.993)	(771.186)	(772.073)	(772.047)
Unemployment	79.845	73.811	77.325	76.567
	(73.042)	(67.224)	(66.891)	(66.790)
Per Capita Inc.	2.135**	2.137**	2.133**	2.136**
	(0.883)	(0.890)	(0.889)	(0.890)
% Subprime	-78.197**	-81.401**	-80.996**	-80.364**
	(33.033)	(34.285)	(34.194)	(34.441)
Branch Deposits	0.010*	0.010*	0.010*	0.010*
	(0.006)	(0.006)	(0.006)	(0.006)
Fail	-47.085**			
	(22.361)			
NACR Fail		-11.732*		
		(7.102)		
NACR1 Fail			-7.894**	
			(3.435)	
NACR2 Fail				-10.553**
				(4.650)
Constant	-159.792*	-159.779*	-158.622*	-160.457*
	(91.796)	(92.602)	(92.025)	(92.456)
Obs.	100,893	100,893	100,893	100,893
R-squared	0.518	0.517	0.517	0.517
Year-Quarter FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES

Standard errors are in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

Table 6. Panel B. Regression results Debt – County Level Funds Raised
This table presents the effect of *Fail*, *NACR Fail*, *NACR1 Fail*, and *NACR2 Fail* and other control variables on the aggregate amount of dollars raised by crowdfunding projects which are loans in a county. *Funds Raised* is the dependent variable in panel regressions with Year-Quarter and County fixed effects. Column 1 presents the regression on *Fail*, a dummy variable equal to one if a county experiences a bank failure and zero otherwise. Column 2 presents the regression on *NACR Fail*, a dummy variable equal to one if a bank with at least one branch in a county in a given quarter reports that their sum of equity plus loan loss reserves was less than half of the value of its nonperforming assets, otherwise the value is zero. Column 3 presents the regression on *NACR1 Fail*, a dummy variable equal to one if a bank with at least one branch in a county in a given quarter reports that their Nonperforming Assets Coverage Ratio (NACR) is below 2%, otherwise the value is zero. This method follows Equation 3 from Cole and White (2017). Column 4 presents the regression on *NACR2 Fail*, a dummy variable equal to one if a bank with at least one branch in a county in a given quarter reports that their Nonperforming Assets Coverage Ratio (NACR) is below 2%, otherwise the value is zero. This method follows Equation 5 from Cole and White (2017).

	(1) Funds Raised	(2) Funds Raised	(3) Funds Raised	(4) Funds Raised
Population	37.463***	37.685***	37.657***	37.629***
	(5.459)	(5.488)	(5.489)	(5.486)
% Female	490.303	467.169	437.616	501.897
	(900.559)	(903.365)	(904.007)	(903.105)
% Non-White	1358.560	1563.206	1410.825	1485.577
	(2553.762)	(2538.466)	(2550.537)	(2548.782)
Unemployment	-87.641	129.429	205.491	163.829
	(222.742)	(222.554)	(226.302)	(225.087)
Per Capita Inc.	2.617**	2.226*	2.153*	2.263*
	(1.293)	(1.256)	(1.262)	(1.264)
% Subprime	-1002.811***	-909.771***	-906.262***	-899.099***
	(326.425)	(313.857)	(320.062)	(316.442)
Branch Deposits	0.011*	0.011*	0.011*	0.011*
	(0.006)	(0.006)	(0.006)	(0.006)
Fail	-285.187***			
	(55.946)			
NACR Fail		-323.325***		
		(57.068)		
NACR1 Fail			-206.835***	
			(26.412)	
NACR2 Fail				-260.695***
				(39.234)
Constant	-3809.051***	-3871.009***	-3836.775***	-3879.497***
	(528.585)	(528.759)	(526.139)	(528.801)
Obs.	100,893	100,893	100,893	100,893
R-squared	0.563	0.567	0.566	0.566
Year-Quarter FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES

Standard errors are in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

Table 7. Panel A. Regression results Rewards – Number of Projects Launched
This table presents the effect of *Fail*, *NACR Fail*, *NACR1 Fail*, and *NACR2 Fail* and other control variables on the aggregate amount of crowdfunding projects which offer a reward for increased levels of funding pledged to a project which start fundraising in a county. *Funds Raised* is the dependent variable in panel regressions with Year-Quarter and County fixed effects. Column 1 presents the regression on *Fail*, a dummy variable equal to one if a county experiences a bank failure and zero otherwise. Column 2 presents the regression on *NACR Fail*, a dummy variable equal to one if a bank with at least one branch in a county in a given quarter reports that their sum of equity plus loan loss reserves was less than half of the value of its nonperforming assets, otherwise the value is zero. Column 3 presents the regression on *NACR1 Fail*, a dummy variable equal to one if a bank with at least one branch in a county in a given quarter reports that their Nonperforming Assets Coverage Ratio (NACR) is below 2%, otherwise the value is zero. This method follows Equation 3 from Cole and White (2017). Column 4 presents the regression on *NACR2 Fail*, a dummy variable equal to one if a bank with at least one branch in a county in a given quarter reports that their Nonperforming Assets Coverage Ratio (NACR) is below 2%, otherwise the value is zero. This method follows Equation 5 from Cole and White (2017).

	(1) No. Projects	(2) No. Projects	(3) No. Projects	(4) No. Projects
Population	0.465**	0.467**	0.467**	0.467**
	(0.196)	(0.197)	(0.197)	(0.197)
% Female	-14.147	-14.309	-14.405	-14.111
	(24.894)	(24.961)	(25.004)	(24.953)
% Non-White	-131.879	-131.450	-132.582	-132.134
	(80.159)	(80.497)	(80.716)	(80.678)
Unemployment	10.849	10.918	10.720	10.744
	(8.233)	(7.861)	(7.488)	(7.593)
Per Capita Inc.	0.173**	0.172**	0.172**	0.172**
	(0.080)	(0.081)	(0.081)	(0.081)
% Subprime	-4.400	-4.426	-4.649	-4.526
	(3.222)	(3.283)	(3.351)	(3.317)
Branch Deposits	0.001*	0.001*	0.001*	0.001*
	(0.001)	(0.001)	(0.001)	(0.001)
Fail	-5.053**			
	(2.389)			
NACR Fail		-1.971***		
		(0.490)		
NACR1 Fail			-0.920**	
			(0.386)	
NACR2 Fail				-1.311***
				(0.404)
Constant	-27.486***	-27.660***	-27.376***	-27.617***
	(9.508)	(9.544)	(9.541)	(9.554)
Obs.	100,893	100,893	100,893	100,893
R-squared	0.676	0.676	0.675	0.675
Year-Quarter FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES

Standard errors are in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

Table 7. Panel B. Regression results Debt – Number of Projects Launched
This table presents the effect of *Fail*, *NACR Fail*, *NACR1 Fail*, and *NACR2 Fail* and other control variables on the aggregate amount of crowdfunding projects from loans that begin project fundraising in a county. *Funds Raised* is the dependent variable in panel regressions with Year-Quarter and County fixed effects. Column 1 presents the regression on *Fail*, a dummy variable equal to one if a county experiences a bank failure and zero otherwise. Column 2 presents the regression on *NACR Fail*, a dummy variable equal to one if a bank with at least one branch in a county in a given quarter reports that their sum of equity plus loan loss reserves was less than half of the value of its nonperforming assets, otherwise the value is zero. Column 3 presents the regression on *NACR1 Fail*, a dummy variable equal to one if a bank with at least one branch in a county in a given quarter reports that their Nonperforming Assets Coverage Ratio (NACR) is below 2%, otherwise the value is zero. This method follows Equation 3 from Cole and White (2017). Column 4 presents the regression on *NACR2 Fail*, a dummy variable equal to one if a bank with at least one branch in a county in a given quarter reports that their Nonperforming Assets Coverage Ratio (NACR) is below 2%, otherwise the value is zero. This method follows Equation 5 from Cole and White (2017).

	(1) No. Projects	(2) No. Projects	(3) No. Projects	(4) No. Projects
Population	2.637***	2.653***	2.651***	2.649***
	(0.400)	(0.402)	(0.402)	(0.402)
% Female	31.815	30.250	28.261	32.592
	(63.972)	(64.182)	(64.258)	(64.162)
% Non-White	70.006	83.592	73.312	78.374
	(182.977)	(181.990)	(182.888)	(182.725)
Unemployment	-7.287	7.025	12.129	9.371
	(15.268)	(15.316)	(15.548)	(15.460)
Per Capita Inc.	0.151*	0.125	0.120	0.128
	(0.089)	(0.086)	(0.087)	(0.087)
% Subprime	-66.596***	-60.475***	-60.248***	-59.744***
	(21.901)	(21.110)	(21.516)	(21.282)
Branch Deposits	0.001*	0.001*	0.001*	0.001*
	(0.000)	(0.000)	(0.000)	(0.000)
Fail	-20.073***			
	(4.029)			
NACR Fail		-21.796***		
		(3.849)		
NACR1 Fail			-13.931***	
			(1.783)	
NACR2 Fail				-17.594***
				(2.645)
Constant	-263.675***	-267.800***	-265.489***	-268.379***
	(36.243)	(36.259)	(36.097)	(36.259)
Obs.	100,893	100,893	100,893	100,893
R-squared	0.587	0.591	0.590	0.591
Year-Quarter FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES

Standard errors are in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

Table 8. Regression Results Rewards – Project Level Funds Raised
This table presents the effect of *Fail*, *NACR Fail*, *NACR1 Fail*, and *NACR2 Fail* and other control variables on the amount of funds raised (winsorized at the 0.001 level) by crowdfunding projects offering a reward for increased levels of funding pledged to a project that begin fundraising in a county in a given quarter. *Funds Raised* is the dependent variable in panel regressions with Category, Platform, Platform-Year-Quarter, Year-Quarter and County fixed effects. Column 1 presents the regression on *Fail*, a dummy variable equal to one if a county experiences a bank failure and zero otherwise. Column 2 presents the regression on *NACR Fail*, a dummy variable equal to one if a bank with at least one branch in a county in a given quarter reports that their sum of equity plus loan loss reserves was less than half of the value of its nonperforming assets, otherwise the value is zero. Column 3 presents the regression on *NACR1 Fail*, a dummy variable equal to one if a bank with at least one branch in a county in a given quarter reports that their Nonperforming Assets Coverage Ratio (NACR) is below 2%, otherwise the value is zero. This method follows Equation 3 from Cole and White (2017). Column 4 presents the regression on *NACR2 Fail*, a dummy variable equal to one if a bank with at least one branch in a county in a given quarter reports that their Nonperforming Assets Coverage Ratio (NACR) is below 2%, otherwise the value is zero. This method follows Eq. 5 from Cole and White (2017).

	(1) Funds Raised	(2) Funds Raised	(3) Funds Raised	(4) Funds Raised
Branch Deposits	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
% Subprime	-1.740	-2.509	-1.177	-1.806
	(6.786)	(6.351)	(6.566)	(6.659)
Population	0.004**	0.006***	0.005**	0.005**
	(0.002)	(0.002)	(0.002)	(0.002)
% Female	-86.089	-76.261	-74.402	-75.811
	(88.874)	(86.009)	(85.473)	(84.782)
% Non-White	-22.350	-19.997	-22.182	-20.390
	(15.890)	(14.958)	(15.542)	(14.923)
Unemployment	-21.655	-24.988*	-23.415*	-24.305*
	(14.002)	(14.551)	(14.155)	(14.500)
Per Capita Inc.	0.082	0.080	0.084*	0.084*
	(0.053)	(0.051)	(0.051)	(0.050)
Fail	0.115			
	(0.177)			
NACR Fail		0.431***		
		(0.137)		
NACR1 Fail			0.363***	
			(0.132)	
NACR2 Fail				0.352**
				(0.142)
Constant	41.701	33.653	34.013	34.292
	(47.799)	(46.301)	(45.735)	(45.363)
Obs.	122,232	122,232	122,232	122,232
R-squared	0.118	0.118	0.118	0.118
Category FE	YES	YES	YES	YES
Platform FE	YES	YES	YES	YES
Platform-Year-Quarter FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES
Year-Quarter FE	YES	YES	YES	YES

Standard errors are in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

Table 9. Regression Results Rewards – Project Level Funds Raised

This table presents the effect of *Fail*, *NACR Fail*, *NACR1 Fail*, and *NACR2 Fail* and other control variables on the amount of funds raised by crowdfunding projects from loans that begin project fundraising in a county in a given quarter. *Funds Raised* is the dependent variable in panel regressions with Platform, Platform-Year-Quarter, Year-Quarter and County fixed effects. Column 1 presents the regression on *Fail*, a dummy variable equal to one if a county experiences a bank failure and zero otherwise. Column 2 presents the regression on *NACR Fail*, a dummy variable equal to one if a bank with at least one branch in a county in a given quarter reports that their sum of equity plus loan loss reserves was less than half of the value of its nonperforming assets, otherwise the value is zero. Column 3 presents the regression on *NACR1 Fail*, a dummy variable equal to one if a bank with at least one branch in a county in a given quarter reports that their Nonperforming Assets Coverage Ratio (NACR) is below 2%, otherwise the value is zero. This method follows Equation 3 from Cole and White (2017). Column 4 presents the regression on *NACR2 Fail*, a dummy variable equal to one if a bank with at least one branch in a county in a given quarter reports that their Nonperforming Assets Coverage Ratio (NACR) is below 2%, otherwise the value is zero. This method follows Eq. 5 from Cole and White (2017). **Panel B** presents the fail measures interacted with the following crowdlending categories: Medical Loans, Secured Loans, Credit Cards and Small Business. The dependent variable in all regressions is the amount of funds raised.

	(1) Funds Raised	(2) Funds Raised	(3) Funds Raised	(4) Funds Raised
Branch Deposits	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
% Subprime	-0.866	-0.777	-0.815	-0.802
	(1.726)	(1.705)	(1.708)	(1.696)
Population	-0.001	-0.002*	-0.001*	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)
% Female	-6.729	-9.372	-8.430	-8.814
	(14.579)	(14.529)	(14.593)	(14.605)
% Non-White	17.401***	17.181***	17.584***	17.438***
	(5.375)	(5.421)	(5.436)	(5.416)
Unemployment	8.474***	8.937***	8.469***	8.836***
	(2.562)	(2.472)	(2.520)	(2.491)
Per Capita Inc.	0.021*	0.020*	0.019*	0.019*
	(0.011)	(0.011)	(0.011)	(0.011)
Medical Loans	-4.386***	-4.436***	-4.504***	-4.436***
	(0.087)	(0.094)	(0.101)	(0.095)
Secured Loans	-4.465***	-4.537***	-4.709***	-4.590***
	(0.060)	(0.064)	(0.077)	(0.068)
Credit Cards	0.250***	0.318***	0.363***	0.338***
	(0.037)	(0.038)	(0.042)	(0.040)
Small Business	1.378***	1.306***	1.223***	1.273***
	(0.064)	(0.068)	(0.077)	(0.070)

Table 9
PANEL B

Variables of Interest	**Fail**	**NACR Fail**	**NACR1 Fail**	**NACR2 Fail**
Failure = 1	0.107**	-0.053	-0.036	-0.032
	-0.049	-0.043	-0.038	-0.041
X Medical Loans	0.489	0.479**	0.568***	0.381*
	-0.38	-0.23	-0.188	-0.212
X Secured Loans	1.144***	0.652***	0.847***	0.708***
	-0.281	-0.153	-0.123	-0.139
X Credit Cards	0.002	-0.522***	-0.477***	-0.514***
	-0.124	-0.08	-0.069	-0.073
X Small Business	0.104	0.342**	0.423***	0.390***
	-0.178	-0.156	-0.139	-0.151
Constant	13.108*	14.995**	14.373*	14.554*
	(7.595)	(7.589)	(7.639)	(7.638)
Obs.	664,922	664,922	664,922	664,922
R-squared	0.105	0.105	0.105	0.105
Platform FE	YES	YES	YES	YES
Platform-Year-Quarter FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES

Standard errors are in parenthesis
*** p<0.01, ** p<0.05, * p<0.1