Do Local Capital Market Conditions Affect Consumers' Borrowing Decisions?*

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Abstract

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Abstract

Studying consumer financing decisions is difficult because of endogeneity problems and scarce data. We use new data and an exogenous change in an interest rate ceiling facing consumers seeking loans from an online peer-to-peer lending intermediary to test how access to finance affects consumers' borrowing decisions. A differences-in-differences approach reveals that good access to local bank finance causes consumers to seek peer-to-peer loans at lower interest rates. We find that local *finance* plays a larger role in how consumers seek loans than local *economic* conditions like per capita income. Our results are particularly strong for borrowers with poor credit and those seeking small loans.

The Dodd-Frank Wall Street Reform and Consumer Protection Act is broad legislation that likely will have the most profound impact on financial market regulation since the Securities Act of 1933. One result of this legislation is the creation of a Bureau of Consumer Financial Protection.[1] This Bureau's mission is to "make markets for consumer financial products and services work for Americans."[2] However, because appropriate data are scarce, researchers have only a modest understanding of the machinery of consumer finance markets and the determinants of consumers' decisions within those markets. This paper sheds light on these subjects. We use a new data set and a novel identification strategy to examine how local capital market conditions affect consumers' borrowing decisions.

We use detailed loan request-level data from Prosper.com (hereafter, "Prosper"), a peer-to-peer consumer lending intermediary, to determine whether the supply of competing capital where consumers reside affects the price they are willing to take from this alternative source of finance. Prosper is one of the largest online peer-to-peer lending networks in the United States, providing consumers the opportunity to request loans from other consumers. (We explain in greater detail the mechanics of peer-to-peer lending in the Institutional Details section below.) Although peer-to-peer lending is a small market compared to other sources of consumer finance, the richness of the data allow us unique opportunities to study consumers' financing decisions.

We find that the lending capacity of local banks affects the interest rate borrowers request on a loan through Prosper. Specifically, we find that consumers with better access to bank financing seek loans at lower interest rates on Prosper. One hurdle to understanding how consumers choose their financing sources and terms is that a borrower's characteristics and the

[1] An article titled "The Uncertainty Principle" published in the Wall Street Journal on July 14, 2010 describes how the Dodd-Frank Wall Street Reform and Consumer Protection Act will require at least 243 new federal rule-makings by various new and existing regulatory agencies. The Bureau of Consumer Financial Protection will introduce an estimated 24 new rules related to consumer finance.

[2] Source: http://www.consumerfinance.gov/the-bureau/

financial environment where he resides may be jointly determined. Further, unobservable borrower characteristics such as savings rates, job prospects, education, or financial savvy may be correlated with the local financial environment. This paper overcomes this hurdle by exploiting a shift in the interest rate ceiling faced by Prosper borrowers residing in Florida on April 15, 2008. Prior to April 15, 2008, Prosper borrowers in Florida could request loans with interest rates no higher than 18 percent, per the state's usury rate ceiling. However, on April 15, 2008, Prosper partnered with WebBank, a Utah-chartered Industrial Bank. This partnership allowed Prosper to achieve nationwide lending (with the exceptions of South Dakota and Texas) with a maximum interest rate of 36 percent, removing a potentially binding constraint to Prosper borrowers in Florida by effectively doubling the maximum interest rate they could request. This merger affected Prosper's borrowers only, and we find that the 18 percent rate ceiling was a binding constraint for at least some Prosper borrowers.

This exogenous change in potential lending rates provides an opportunity to observe how areas with varying levels of financing availability satisfy consumers' demand for loanable funds. Our approach is a differences-in-differences analysis: do borrowers in counties with greater lending capacity seek financing at lower interest rates from a peer-to-peer lending network than similar borrowers in areas with lower lending capacity, and does the magnitude of the difference in requested interest rates change after the rate ceiling lifts? The rate ceiling shift represents an exogenous source of variation that only affects loan requests made on Prosper, and only for residents of certain states. It is independent of borrower-specific or geographic-specific characteristics which could be correlated with local banks' lending capacities. Thus, our approach mitigates the possibility of omitted variables driving a relation between the local lending capacity and the interest rate at which borrowers seek financing.

Following Becker (2007), Butler and Cornaggia (2011), and Cornaggia (2012), we proxy for local lending capacity with county-level bank deposits and other measures of financial development. We control for borrower-specific characteristics, including credit grade, debt-to-income ratio, and homeowner status. It is important also to control for economic conditions within the borrower's county of residence, including per capita income, the unemployment rate, the poverty rate, the per capita amount of mortgage, credit card, and auto loan debt held by consumers within the county, and the amount of this debt that is delinquent. We control for a variety of borrower characteristics based on the photographs borrowers include with their loan listings, including age, gender, and ethnicity. We find that Prosper borrowers residing in counties with greater lending capacity seek loans at lower interest rates, particularly after the rate ceiling lifts. Specifically, we find that borrowers living in counties with a level of bank deposits one standard deviation above average in Florida (i.e., counties with a greater supply of local bank finance) seek loans with interest rates 1.84 to 3.25 percent lower than similar borrowers in counties with average levels of bank deposits. That is, following the shift on April 15, 2008 to higher maximum interest rates, borrowers residing in counties with a greater supply of bank finance were less likely to seek loans closer to this higher potential interest rate.

We perform a number of falsification tests to confirm that the primary source of exogenous variation—the elevated rate ceiling—provides clean identification. The time period we study an economically dynamic one. So we use shorter horizon tests to rule out the possibility of confounding events, trends, or Tax Day affecting the results.[3] Likewise, for our longer horizon tests, we also pool loan requests from borrowers in Florida with loan requests made by borrowers residing in California to construct a differences-in-differences-in-differences analysis. For loan

[3] A report from the Federal Reserve Bank of St. Louis details a timeline of events and policy actions taken by regulators during the Financial Crisis (http://timeline.stlouisfed.org/pdf/CrisisTimeline.pdf). Notable events between March 15, 2008 and May 15, 2008 include a reduction in the federal funds rate by 75 basis points, the provision of term financing to facilitate JPMorgan Chase & Co.'s acquisition of The Bear Stearns Companies Inc., a reduction of the federal funds rate by 25 basis points to 2 percent, and an expansion of the list of eligible collateral for Schedule 2 TSLF auctions to include AAA/Aaa-rated asset-backed securities. Our difference-in-difference, difference-in-difference-in-difference, and synthetic controls tests, described below, net out these changes, allowing us to draw clean inferences about consumers' borrowing decisions on Prosper.

amounts greater than $2,550, Prosper borrowers in California could request loans at interest rates as high as 36 percent before April 15, 2008, per Prosper's California State Lending License.[4] Thus, in our sample period California borrowers requesting loans of $2,550 or more did not experience a change in the rate ceiling, making them a useful control group for which we expect to see no effect of the change around April 15, 2008. This result is what we find.

For California loans less than or equal to $2,550 the interest rate ceiling was 19.2 percent prior to April 15, 2008 and increased to 36 percent for Prosper loans after this date. We expect these "small" loan requests submitted by borrowers in California to behave similarly to all loan requests submitted by borrowers in Florida. Indeed, among loan requests for less than or equal to $2,550, we observe that after the rate ceiling lifted California borrowers residing in counties with bank deposits one standard deviation above the state average requested interest rates 3.58 to 6.16 percent lower than borrowers submitting loan requests in counties with average levels of bank deposits. This intra-state research design is useful because it dispels concerns that our findings are a result of omitted, unobservable time-varying variables at the state or county level. Moreover, to the extent that the Financial Crisis had similar effects in Florida and California (two states heavily affected by the housing bubble), these results also indicate the Financial Crisis does not explain our main finding.

To rule out more fully the possibility of unobserved confounding effects in our differences in differences tests we use a novel alternative identification strategy. We extend the *synthetic controls method* pioneered by Abadie and Gardeazabal (2003) and Abadie, Diamond, and Hainmueller (2010) to our setting. This approach allows us to estimate a counterfactual outcome for each county in Florida similar to a tracking portfolio approach. (We describe this method and our application of it in more detail in section 3.14 below.) We find results similar to our baseline findings: borrowers residing in counties with bank deposits one-standard deviation above the

[4] The usury rate in California is 19.2 percent for loans up to $2,550 and 36 percent for loans larger than $2,550.

Florida average increase their maximum requested rates by 2.38 percent less (relative to the synthetic controls) than borrowers residing in counties with average levels of bank deposits. We find no significant effect—as expected—in a placebo regression using April 2007 as the (false) intervention period.

We find qualitatively similar results if we proxy for local lending capacity with the number of bank branches within a county instead of the level of bank deposits. Further, our main results remain robust if we allow for the possibility that borrowers residing in areas with weak economic conditions (proxied by per capita income, unemployment rates, poverty rates, per capita consumer debt, and per capita delinquent consumer debt) were more likely to take advantage of the shift in the interest rate cap. Finally, our main results are particularly strong for borrowers who seek small loans (less than the median, which is about $4,500) and borrowers with poor credit, indicating that among our sample of Prosper borrowers, marginal borrowers—those that are relatively high risk borrowers and those seeking small loans—are more sensitive to the supply of bank financing than low risk borrowers.

Our findings are consistent with a positive link between banking competition and access to finance. Jayaratne and Strahan (1996) show that the removal of bank branching restrictions improves access to finance and facilitates economic development. Guzman (2000) shows that credit rationing is more likely to occur under a banking monopoly than a competitive banking market. Beck, Demirguc-Kunt, and Maksimovic (2005) find that banking concentration increases financing obstacles, but only in countries with low levels of economic and institutional development. Rice and Strahan (2010) find that state-level banking competition expands access to finance and lowers the cost of bank loans for small businesses. Although these studies focus on firms rather than consumers, our results are consistent with theirs—competitive banking environments provide better access to finance at a lower cost.

The rest of this paper is organized as follows. Section 1 provides institutional detail on the mechanics of peer-to-peer lending. Section 2 describes the data. Section 3 describes our methods and baseline results, as well as robustness tests and synthetic controls approach. Section 4 concludes.

1. Institutional Detail on Prosper's Peer-to-Peer Lending Function

Prosper is a new and growing alternative source of finance for consumers. Its distinguishing feature is that it connects consumers who are net savers with consumers who are net borrowers without the help of a traditional financial intermediary. As of September 2012, Prosper has over 1.5 million members and over $400 million of loans have been funded through its website.[5] Although this dollar amount is small relative to the consumer loan market in the United States, some analysts predict peer-to-peer lending websites will eventually account for $5 billion of the consumer lending market.[6] Consumers raise capital on peer-to-peer lending websites for a variety of reasons, including debt consolidation, home improvement, small business use, auto use, and so forth. The following paragraphs describe the auction format used by Prosper for funding loans.

When a prospective borrower applies for a loan on Prosper, he begins by creating a loan request which includes the amount he would like to borrow (a borrower can request loans ranging in size from $1,000 to $25,000) and the maximum interest rate he is willing to pay. The borrower writes a detailed description of the purpose of the loan and provides a host of personal information, including his income and occupation. The borrower has the option of including his city of residence. The borrower also has the option of including one or more photographs with the

[5] Source: Prosper. URL: http://www.prosper.com. Prosper is one of the largest peer-to-peer lending networks. Others include lendingclub.com and zopa.com. We focus on the mechanics of applying for a loan on Prosper, but many of the practices we describe here are similar to those of other peer-to-peer online lending networks.

[6] Source: http://www.prosper.com/about/

loan listing. Providing one's city of residence and photographs are voluntary decisions, which means our analysis could be susceptible to sample selection problems. We employ Heckman corrections in the robustness sections below, and we find selection issues do not limit the applicability of our results to a subset of Prosper borrowers.

After the borrower creates a loan request, Prosper retrieves a credit report for the borrower and includes it with the loan listing. The credit report includes a detailed description of the borrower's existing financial condition, including his credit score, delinquency history, and number and usage of existing credit lines. Prosper lists the loan request on its website after combining the borrower's loan request and credit report.

Lenders bid on the loans after they appear on Prosper. Prospective lenders create accounts with Prosper, and Prosper must verify that a lender has a bank account before the lender can bid. Lenders can bid amounts ranging from as little as $50 to the full amount of the borrower's loan request. Lenders also bid an interest rate which they wish to earn from the borrower. This interest rate will be less than or equal to the maximum amount of interest indicated by the borrower.

Lenders submit competitive bids and the bidding process follows the structure of a Dutch auction. The auction remains open for up to ten days. A loan listing will remain unfunded until the sum of lenders' bids equals or exceeds the total amount of the loan request. At this point, bidding may continue, as bids at lower interest rates take the place of bids at higher interest rates. The collection of bidders who ultimately fund the loan are those whose bids sum to the total amount of the loan request at the lowest interest rate. The winning bidders receive an interest rate equal to 0.05% less than the lowest interest rate bid by the losing bidders.[7] Because multiple bidders fund the loans on Prosper, we are unable to cleanly control for bidder characteristics in our tests.

[7] The loan origination process on Prosper has changed since the end of our sample period. As of December 2010, Prosper simplified its lending process so that borrowers receive pre-set rates. Source: Securities and Exchange Commission. URL: http://www.sec.gov/Archives/edgar/data/1416265/999999999510003619/9999999995-10-003619-index.htm.

Similarly, because the bidders may reside in a variety of areas across the country, we are unable to control for geographic characteristics related to the bidders' residences.

For loan requests that are completed, i.e., the amount of money pledged by lenders is at least the amount requested by the borrower, funds are transferred from the lenders' bank accounts to the borrower's bank account immediately after the auction closes. (No money changes hands for loan requests that receive only partial funding.) Prosper continues to service the loans, transferring funds from the borrower's bank account to the lenders' bank accounts on a monthly basis throughout the life of the loan. Each loan is a fully-amortized, three-year loan. Borrowers face a variety of consequences if they lack sufficient funds to repay the loans. These consequences include additional fees, notifications of past due accounts on their credit reports, and referral to a collection agency in the case of a default.

Our paper adds to a growing number of studies examining data from peer-to-peer lending networks in an effort to better understand how, why, and at what cost consumers access this new source of finance. These studies address a wide variety of research topics. For example, Everett (2008) finds that borrowers are less likely to default when they form groups because group membership holds the possibility of real-life personal connections. Ravina (2008) finds that physically attractive borrowers are more likely to secure loans at cheaper interest rates on Prosper. Duarte, Siegel, and Young (2012) find that lenders on Prosper are less likely to fund loan requests from borrowers whom they perceive as untrustworthy. Hildebrand, Puri, and Rocholl (2011) find that group leaders on Prosper do a better job of screening potential borrowers the more they participate in the loan. Lin, Prabhala, and Viswanathan (2011) find that online friendships of borrowers act as signals of credit quality, increasing the probability of receiving funding, lowering interest rates on completed loans, and mitigating the probability of default. Zhang and Lui (2012) find evidence of herding among lenders on Prosper. Pope and Sydnor (2011) find evidence that lenders favor certain ethnic groups over others, with systematic underestimation by lenders of the relative default rates between borrowers in different ethnic groups. Iyer, Khwaja, Shue, and Luttmer (2011) find that lenders on Prosper correctly infer one third of the variation in creditworthiness that borrowers' credit scores capture.

2. Data

This section describes the data sources we use in this study. We have data for 20,392 loan requests made by borrowers in Florida. Borrowers disclose their city of residence for 5,374 of those loan requests. We have data for 7,250 loan requests made by borrowers in California (the control state) that disclose their city of residence. Most loan requests in our sample originated before April 15, 2008 (the date the rate ceiling shifted), although several hundred originated after this date. The first loan request in our sample was made on January 3, 2007, and the last was made on July 23, 2008. Table 1 presents summary statistics. We match loan requests made by Prosper borrowers to county-level variables from January 2007 through July 2008.

2.1. Dependent Variables

Our primary dependent variable is the maximum interest rate (*Maximum rate*) a borrower on Prosper reports he is willing to pay. We also examine the dollar amount the borrower requests when applying for a loan on Prosper (*Amount requested*), the fraction of *Amount requested* funded by lenders on Prosper (*Percent funded*), and the interest rate paid by Prosper borrowers if the loan request received funding (*Realized rate*).

[Insert Table 1 here.]

2.2. Independent variables

Similar to Becker (2007), Butler and Cornaggia (2011), and Cornaggia (2012), we use county-level bank deposits from 2007 to 2008 to proxy for access to bank financing. For robustness purposes, we use the number of FDIC-insured bank branches within a county. Deposits and branches data come from the FDIC's website. *Bank deposits* represents the sum of all bank deposits held by FDIC-insured depository institutions within a county for a given year. *Bank branches* is the number of FDIC-insured bank branches within a county for a given year. We sum the number of branches and the level of deposits held by state and federally chartered bank branches within a county to compute this measure. We note, however, that our results are robust to restricting this measure to bank deposits held by either only state- or only federally-chartered bank branches. We suspect that bank deposits may reflect the general supply of financial services in a county. For instance, bank deposits may be correlated with number of bank branches and other financial intermediaries, and we find evidence that this is the case. For our Florida loan request observations, bank deposits are positively correlated with the presence of pawn shops (0.48), payday lenders (0.39), credit union branches (0.36), and bank branches (0.71). Bank deposits are not strongly related to measures of consumer loan demand: they are only weakly correlated with county-level credit card usage (0.07) and mortgage loans (0.11) and are negatively related to auto loans (-0.21).

We control for effects of credit rationing by scaling *Bank deposits* by county population and we control for effects of distance on lending relationships (e.g., Petersen and Rajan (2002)) by scaling this measure by county area measured in square miles. Population and area data come from the U.S. Census Bureau's website. The following example motivates these scaling adjustments. Consider a county containing one million dollars of bank deposits and one potential borrower within an area of one square mile. This county will provide better access to finance than a second county containing one million dollars of bank deposits and 1,000 potential borrowers within an area of one square mile. Similarly, the first county will provide better access to finance than a third county containing one million dollars of bank deposits and one potential borrower within an area of 1,000 square miles.

2.3. Control Variables

Each loan listing on Prosper includes a wealth of information that we use for control purposes. Specifically, we include controls for the borrowers' debt-to-income ratios (*Debt/income*), a dummy variable capturing whether or not a borrower owns a home (*Homeowner*), and a measure of borrowers' creditworthiness (*Credit grade*). We do not observe borrowers' actual credit scores. Rather, Prosper gives borrowers one of eight possible credit grades: AA, A, B, C, D, E, HR (high risk), and NC (no credit history). The credit grades are based upon credit scores from the Fair Isaac Corporation (FICO). Borrowers with FICO scores greater than 760 receive a grade of AA; 759 to 720 receive a grade of A; 719 to 680 receive a grade of B; 679 to 640 receive a grade of C; 639 to 600 receive a grade of D; 599 to 560 receive a grade of E; and 559 to 520 receive a grade of HR. We create the variable *Credit grade* by transforming the letter grades into a numerical score: AA becomes 7; A becomes 6; B becomes 5; C becomes 4; D becomes 3; E becomes 2; HR becomes 1; and NC becomes 0. This transformation assumes a one-to-one relationship between borrowers' FICO scores and creditworthiness, which may introduce measurement error. However, the results we describe below are robust to alternative transformations of *Credit grade*, including taking the log of this measure or including squared terms to capture nonlinearities. Further, our results are robust to including credit grade fixed effects instead of *Credit grade.*

Table 1 provides some insight into the characteristics of the typical Florida Prosper borrower in our sample. He (only 26% are female according to the photograph variables we describe below) asks for a loan of $4,500 (median) at an annual rate of up to 17% (median). He doesn't own a home (10% are homeowners), has a debt-to-income ratio of 21% (median), and has a FICO score in the neighborhood of 610 (the average credit grade is between D and E). For the sake of comparison, beginning on June 1, 2008, Fannie Mae established guidelines requiring borrowers of government-insured mortgage loans to have credit scores of at least 580.[8] This information indicates the typical borrowers in our sample have creditworthiness similar to that of many Americans who could secure bank loans. Consistent with the data, a recent article featuring an interview with Prosper CEO Chris Larsen concludes with the following statements:

> *So the profile of a peer-to-peer borrower probably isn't what some people might suspect. Certainly most of these individuals aren't fiscally irresponsible or people with bad credit ratings that could never get a bank loan. On the contrary, many of them are good credit risks and smart enough to know that the loan market is rapidly evolving, and that peer-to-peer loans are a viable option to traditional bank loans and credit.*[9]

For many tests we include control variables based on the photographs borrowers include with their loan listings. Table 1 indicates 3,821 out of 5,374 (5,070 out of 7,250) loan listings originating from Florida (California) included at least one photograph. Duarte, Siegel, and Young (2012) hand collected and provided the following variables to us based on these photographs; their paper provides details of the data collection procedure. *Obesity* is the obesity rating of the adult(s) in the photograph associated with a listing. If multiple photographs are associated with a listing, the variable represents the average across different photographs. *Obesity* estimates are expressed on a scale between one (not overweight) and three (definitely overweight). *Female indicator* equals one if at least one female adult appears in at least one of the photographs associated with a listing while no male adult was identified. The indicator equals zero otherwise. *Couple indicator* equals one if at least one photograph associated with a listing contains one female adult and one male adult and zero otherwise. *Kid(s) indicator* equals one if at least one person below the age of 18 in at least one of the photographs associated with a listing and zero otherwise. *Young adults* indicator equals one if at least one person above the age of 18, but below the age of 40 appears in at least one of the photographs associated with a listing or loan while no older adults were

[8] Source: https://www.efanniemae.com/sf/guides/ssg/annltrs/pdf/2008/0835.pdf

[9] Source: "Want a P2P Loan? See This Profile of a Typical Peer-to-Peer Borrower" (http://askthemoneycoach.com/2011/11/p2p-loan-profile-typical-peer-to-peer-borrower/).

identified. The indicator equals zero otherwise. *Old adults* indicator equals one if at least one person above the age of 60 appears in at least one of the photographs associated with a listing or loan while no younger adults were identified. The indicator equals zero otherwise. *Black* (*Asian*, *Hispanic*) indicator equals one if at least one Black (Asian, Hispanic) adult appears in at least one of the photographs associated with a listing and zero otherwise. *House* (*Car*, *Business*) equals one if a house (car, business establishment) appears in at least one of the photographs associated with a listing zero otherwise.

We include several county-level control variables in addition to the borrower-specific control variables. We include county-level per capita income (*Per capita income*), the percentage of the population that is unemployed (*Unemployment*), and the percentage of the population that lives below the poverty line (*Poverty*) to capture economic conditions where the borrowers reside for each year of the sample. We also control for county population (*Population*). We collect these measures from the U.S. Census Bureau's website. We control for average consumer debt levels with the variable *Consumer debt*, the sum of consumers' auto debt balance in dollars per capita, consumers' credit card debt balance in dollars per capita, and consumers' mortgage debt balance in dollars per capita within a county-year. We also control for average amount of delinquent consumer debt with the variable *Consumer debt delinquent*, the county-year sum of the following items: consumers' auto debt balance in dollars per capita that is at least 90 days delinquent, consumers' credit card debt balance in dollars per capita that is at least 90 days delinquent, and consumers' mortgage debt balance in dollars per capita that is at least 90 days delinquent. Data on consumer debt and delinquent consumer debt come from the New York Federal Reserve Board. We include county fixed effects in our regressions, which absorb unobservable, time invariant county-level effects. Table 2 displays a correlation matrix of dependent, independent, and control variables.

[Insert Table 2 here.]

3. Methods and Results

3.1. Motivation: was the 18 percent interest rate ceiling binding?

It is important to verify that the 18 percent interest rate ceiling was a binding constraint for at least some of the borrowers on Prosper. We begin by examining how the number of loan requests submitted by borrowers in Florida changed around the rate ceiling shift. We calculate the monthly percent change in the number of loan requests made by borrowers in Florida and the control state, California. Figure 1 displays the cumulative abnormal percent change in the number of loan requests made by borrowers in Florida relative to borrowers in California. The plot indicates the cumulative abnormal percent change in the number of loan requests was 21.8 percent in April 2008 and remained near this level through the end of the sample period.

[Insert Figure 1 here.]

We also examine loan requests submitted by the set of Prosper borrowers residing in Florida who submitted at least one loan request before April 15, 2008, and at least one loan request after April 15, 2008. We compare the maximum interest rates these borrowers requested before April 15, 2008 to the maximum interest rates they requested after April 15, 2008. We also compare the dollar amount requested by borrowers, the fraction of borrowers' loan requests filled by lenders, the interest rate paid by the borrowers if the loan request received funding, and the number of bids the loan requests received by potential lenders. We perform similar calculations for borrowers residing in California who submitted loan requests of at least $2,550. This group of loan requests provides a useful control group because the maximum interest rate these borrowers could request did not change around April 15, 2008. We report differences-in-differences to determine whether any changes in the outcomes for the sample of Florida loan requests are significant relative to similar changes in the control group. Table 3 presents the results.

[Insert Table 3 here.]

Panel A of Table 3 demonstrates that the 18 percent interest rate ceiling was indeed a binding constraint for this group of Florida borrowers. First, after the rate ceiling shift on April 15, 2008, the average maximum interest rate requested by this group of borrowers increased by over 11 percentage points, from 15.1 percent to 26.2 percent. This increase is significantly larger than the change in the average maximum interest rate requested by the California borrowers. Second, potential lenders on Prosper became more interested in forming lending relationships with these borrowers after April 15, 2008. The average percentage of the amount requested by borrowers that lenders offered to fund more than doubled from 11.9 percent to 27.0 percent, and the average number of bids per loan request more than quadrupled from 10.5 per loan to 45.4 per loan. Both of these increases are significant relative to changes among the California borrowers. These results indicate that the 18 percent interest rate ceiling prevented at least some Florida borrowers from receiving funding.

A potential concern with this approach is that some (particularly risky) borrowers may submit additional loan requests after April 15, 2008 because their earlier loan requests did not receive funding. We address this possibility by restricting the sample in Panel A to fully funded loan requests submitted by borrowers who submitted at least one fully funded loan request both before and after April 15, 2008. Although this filter dramatically reduces the sample size in both time periods, we continue to see patterns among this group of loan requests that are similar to the patterns we observe in the unrestricted sample. Specifically, the average maximum interest rate requested by this group of Florida borrowers increased significantly from 15.0 percent to 22.7 percent (Table 3, Panel B). Moreover, the average number of bids per loan jumped from 95.8 to 150.1 (the change is large in magnitude but statistically insignificant). These results indicate the rate ceiling was a binding constraint, even for borrowers with completed loan requests. Rigbi (2010) provides additional discussion of the extent to which this rate ceiling was binding for Prosper borrowers.

3.2 Do borrower characteristics change around the rate ceiling shift?

When the rate ceiling shifted from 18 percent to 36 percent for Florida borrowers, it may have induced new types of borrowers to participate on Prosper. We examine this possibility by testing whether the characteristics of borrowers in Florida changed around the rate ceiling shift relative to borrowers in California who requested loans greater than $2,550. We use these latter borrowers as a control group because they did not experience the rate ceiling shift. Thus, it is reasonable to assume that any changes to the pool of California borrowers who submitted loans greater than $2,550 do not result from the rate ceiling shift. We compute the difference between average loan request variables and photograph variables in pre-April 15, 2008 and post-April 15, 2008 time periods for loan requests submitted by Florida borrowers. We repeat this procedure for loan requests submitted by the control group and then we compute the differences-in-differences. Table 4 contains the results.

[Insert Table 4 here.]

The differences-in-differences calculations reveal that changes in the loan request variables and photograph variables were very similar around the rate ceiling shift among borrowers in Florida and borrowers in California who submitted loan requests greater than $2,550. These non-results are important because they indicate our findings below are a result of local access to finance and are not merely a result of changes to the pool of borrowers.

3.3. Regression specification: differences-in-differences

Using the sample of loan requests submitted by Florida borrowers and ordinary least squares (OLS) regressions, we regress *Maximum rate* on the variables appearing in Equation (1). The standard errors are robust to heteroskedasticity and we cluster them at the county level. The unit of observation for our dependent variable is individual loan requests. We include here subscripts l, c, and t to denote the loan request, county, and year, respectively, to clarify the structure of the variables.

$$
\begin{aligned}
\textit{Maximum rate}_{l,c,t} = {} & \beta_1 \textit{ Post-4/15/08}_t \times \textit{Log Bank deposits}_{c,t} + \\
& \beta_2 \textit{ Post-4/15/08}_t + \\
& \beta_3 \textit{ Log Bank deposits}_{c,t} + \\
& \beta_4 \text{ Vector of loan request variables}_{l,c,t} + \\
& \beta_5 \text{ Vector of geographic variables}_{c,t} + \\
& \beta_6 \text{ Vector of photograph variables}_{l,c,t} + \\
& \text{Constant} + \varepsilon_{l,c,t}
\end{aligned} \tag{1}
$$

Post-4/15/08 is an indicator variable taking a value of one if the loan request was made after April 15, 2008 and zero if the loan request was made before April 15, 2008. This variable should capture changes in the maximum interest rate borrowers are willing to pay as a result of the elevated rate ceiling. We interact this variable with independent variables that proxy for access to bank financing. If Florida borrowers residing in counties with a poor access to bank finance are willing to pay higher interest rates on loans from Prosper, then this discrepancy should be most pronounced after the rate ceiling lifts. In other words, borrowers residing in counties with good access to bank financing should be less likely to request loans at relatively higher rates on Prosper than borrowers in counties with poor access to bank financing. Therefore, we expect the interaction term to have a negative coefficient.

Panel A of Table 5 displays the regression results for loan requests made by borrowers in Florida. The coefficient on *Post-4/15/08 × Log Bank deposits* is negative and significant across specifications. Specifically, the regressions including *Post-4/15/08 × Log Bank deposits* indicate that for a one-standard deviation increase in county-level bank deposits, a borrower will request a loan with an interest rate 1.84 to 1.93 percent lower than a borrower residing in a county with an average level of bank deposits, depending on whether we include county fixed effects to control unobserved variation within counties. This result becomes economically larger (the effect increases to either 3.30 or 3.25 percent) when we control for the photograph variables. Further, the result remains qualitatively unchanged if we use the number of bank branches within a county as a proxy for the supply of bank financing. The coefficient on *Post-4/15/08 × Log Bank branches* narrowly misses significance at the 10% level in column (5) (the p-value is 0.11) and is significant at 10% when we include the photograph variables.

[Insert Table 5 here.]

We conduct similar tests for borrowers in California. We split the sample of loan requests from California borrowers into two groups based on the amount requested. The usury rate in California is 19.2 percent for loans up to $2,550 and 36 percent for loans larger than $2,550. Therefore, borrowers submitting loan requests for amounts less than or equal to $2,550 should react to the rate ceiling shift because the maximum rate they can request jumped from 19.2 percent to 36 percent. However, borrowers submitting loan requests above this amount should be insensitive to the shift because the maximum rate remains at 36 percent for this group. Based on these institutional details, we expect results among the "small" loan requests to be similar to our results among Florida borrowers, and we expect to see no results among the "large" loan requests. This result is precisely what we find, irrespective of whether we control for the photograph variables. Panel B of Table 5 contains the results. Borrowers submitting "small" loan requests in counties with bank deposits one-standard deviation above the state average request interest rates 3.58 to 6.16 percent lower than borrowers residing in counties with average levels of bank deposits. This intra-state research design is useful because it demonstrates that omitted, state-specific variables cannot drive the results.

3.4. The main findings are not a result of selection biases

One concern is that, because we only use data in which borrowers disclose their city of residence, our findings might not generalize to the larger population of Prosper borrowers. Likewise, a similar concern is that, for tests where we control for the photograph variables, we may introduce a selection bias if borrowers who include photographs with their loan requests are somehow different from the larger population of Prosper borrowers.

We examine these concerns with separate two-stage Heckman (1979) correction models. For the first, the Inverse Mill's Ratio is statistically significant at the 10% level, indicating that there is some selection bias associated with the decision to list one's city of residence. However, the coefficient on *Post-4/15/08* × *Log Bank deposits* remains nearly unchanged, indicating that any selection bias associated with the decision to disclose one's city of residence does not alter our results or conclusions. For the second, the Inverse Mill's Ratio is indistinguishable from zero, indicating that there is no selection bias associated with the decision to post a photograph(s). Further, the coefficient of on *Post-4/15/08* × *Log Bank deposits* remains nearly unchanged, indicating that any selection bias associated with the decision to include a photograph does not alter our results or conclusions. We do not tabulate these results.

3.5. The results obtain through a local finance channel, not a local economic conditions channel

Our baseline results include controls for local economic conditions, including county-level per capita income, unemployment rate, and poverty rate, but we do not let the loading on these conditions change around the shift in the interest rate ceiling. We relax this restriction in Table 6 to see if bank presence simply reflects local economic conditions. We multiply our measures of local economic conditions with *Post-4/15/08* and include the resulting interaction terms in our baseline regressions. Including these interaction terms allows the "lending capacity" channel and the "economic conditions" channel to compete with one another for explanatory power in the regressions. If our main result obtains not because of bank presence but rather because of economic conditions, the coefficients *Post-4/15/08* interacted with economic variables should be positive and significant and the coefficient on *Post-4/15/08* × *Log Bank deposits* should be insignificant. If, however, the supply of local bank financing explains our finding, including the additional interaction terms should not disturb the results. Indeed, we observe the latter pattern:

the coefficient on *Post-4/15/08* × *Log Bank deposits* remains negative and significant across specifications, indicating that local finance supply does not simply capture local economic conditions.

[Insert Table 6 here.]

3.6. The results are not an artifact of differences in consumer debt characteristics or local bank competition

If average consumer indebtedness in a county covaries with bank deposits, our measure of the supply of intermediated finance may simply proxy for borrowers' average financial distress. Our baseline regressions in Table 5 include two measures, per capita consumer debt (*Consumer debt*) and per capita delinquent consumer debt (*Consumer debt delinquent*), to control for this possibility. We delve deeper into this analysis by separately including these terms' interactions with *Post-4/15/08* in regressions explaining Florida borrowers' maximum rate requests. Columns (4) and (5) of Table 6 contain the results. The negative and significant coefficient on *Post-4/15/08* × *Log Bank deposits* remains negative and significant across specifications, indicating that our main finding is not driven by a correlation between bank deposits and consumer indebtedness.

Bank competition in the counties where borrowers reside may impact the rates that borrowers request on Prosper. In untabulated results, we add a measure of county-level bank competition, the Herfindahl-Hirschman Index (HHI) of branch-level deposits, for the county-year to our main regression specification. The coefficient on our main interaction variable of interest is qualitatively similar to the baseline specification in Table 5 and remain statistically significant. This result maintains whether we include the direct effect of HHI, only, or if we also include the interaction of *Post-4/15/08* and HHI. In the former case, the coefficient on HHI is negative and significant, indicating banking competition is associated with lower interest rate requests on Prosper. However, the effect is economically insignificant. In the latter case, the coefficient on the

HHI interaction variable is statistically indistinguishable from zero. We observe similar outcomes whether we compute HHI at the bank or branch level.

3.7 Local bank presence relates to whether Prosper borrowers mention banks in their loan requests

Having established that our results are not due to a local economic conditions effect, in untabulated results, we examine two different dependent variables that might support the idea that it is indeed bank presence, rather than some alternative channel, that drives our results. We construct two measures that may show a link between Prosper borrowers' choices and the local supply of bank financing. First, we machine-read every Prosper borrower's loan request and construct an indicator variable taking a value of one if the borrower writes the word "bank" or simple variations thereof in their loan request listing and zero otherwise. The idea behind this measure is that Prosper borrowers who tried to get a loan from a bank or considered obtaining bank finance are more likely to mention "bank" in their listing. (We note that there are other reasons a borrower might mention the word bank—they work at a bank, they are 'banking' on getting a good deal on Prosper, etc.—and these alternative reasons make this a potentially noisy proxy.) Second, we examine whether the number of Prosper loan requests per capita in a county-month relates to bank presence. We expect a higher usage of Prosper when there are poor alternatives to Prosper, and hence, to be correlated with a lack of bank loan supply. Admittedly, both of these variables are blunt proxies, but they have the potential to suggest a relation between bank presence and Prosper borrower choices. The results suggest that, as expected, there is a negative relation between whether Prosper borrowers mention the word "bank" and bank presence and a negative relation between bank presence and the number of Prosper requests in the county.

The negative relation is statistically significant for whether borrowers mention the word "bank" in their request, but is insignificant for the number of Prosper loan requests.[10]

3.8. The results are stronger for borrowers requesting small loans

We examine whether borrowers requesting larger or smaller loans are more sensitive to bank deposits in how they respond to the rate ceiling shift. Table 7 reproduces our Table 5 results with subsamples partitioned by requested loan size quartiles. The subsamples do not have equal numbers of observations due to lumpiness in the requested amounts. The average loan requests are $1,700, $3,374, $5,942, and $15,460 in the smallest to largest quartiles, respectively. We find that the coefficient on our interaction variable of interest is much smaller and statistically indistinguishable from zero in the largest loan request quintile. For the smallest two loan quintiles, the coefficient of interest is negative, large in magnitude, and statistically significant.

[Insert Table 7 here.]

3.9. The results are not an artifact of time trends or of Tax Day borrowing

In this section we establish that there is nothing inherently special about April 15th in terms of how consumers make loan requests on Prosper. We repeat the baseline regression in Table 5 after reducing the sample to the two-month period centered on April 15, 2008 (i.e., March 15, 2008 to May 15, 2008). Reducing the sample to a two-month period forces all regressors that vary by year to drop from the regression. Regressions (1) and (2) in Table 8 contains the results, with and without controlling for the photograph variables, respectively. We include county fixed effects and the standard errors are robust to heteroskedasticity and clustered at the county level.

[Insert Table 8 here.]

The baseline result continues to hold, and is larger in economic magnitude than the results from the full-sample regressions. These short horizon regressions provide stronger evidence that

[10] We lose statistical significance when we exclude important photo-related control variables, so we are reluctant to claim from this result more than a weak correlation in the expected direction.

time trends in consumer financing decisions are not driving the results and they provide supporting evidence that banking presence is an important determinant in the maximum interest rates that borrowers request.

Although this specification helps eliminate the concern that shocks other than the elevated rate ceiling are driving the main result, it does not eliminate the possibility that an alternative shock occurring on the same date is generating identification. One potential example is Tax Day. Since 1955, the United States federal and state governments have required U.S. citizens to submit annual tax returns by April 15th. It could be that many U.S. citizens require funds after remitting tax payments to the IRS, and this shift in demand is the actual source of variation driving the result rather than a change in the rate ceiling.

We test this hypothesis by repeating the short horizon regression using a two-month sample period centered on April 15, 2007, rather than April 15, 2008, and substituting *Post-4/15/07*, a dummy variable taking a value of one if the loan request was submitted after April 15, 2007, for *Post-4/15/08*. The results of this falsification test show that the coefficients on *Post-4/15/07 × Log Bank deposits* are small: one-tenth to one-quarter of the magnitude of coefficients on *Post-4/15/08 × Log Bank deposits*, depending on whether we control for the photograph variables. These results are consistent with the elevation of the rate ceiling as of April 15, 2008 being the primary force for changes in borrowers' loan rate requests.

Regressions (5) and (6) of Table 8 repeat the short horizon regression for loan requests for more than $2,550 made by borrowers in California during a two-month sample period centered on April 15, 2008. These tests further explore whether the changing interest rate ceiling was indeed unique to Florida. We find no evidence of a differential effect of access to bank financing on these loan requests in the month after April 15, 2008.

3.10. The change in the Florida rate ceiling affected loan prices but not quantities

The baseline tests reveal that access to bank finance has an effect on the *price* of funds which borrowers request. We repeat the baseline regression from the previous section with alternative dependent variables. Table 9 contains the results. The first regression uses *Amount requested* as the dependent variable. We intend regressions with this dependent variable to reveal whether the supply of bank finance has an effect on the *quantity* of funds which borrowers request.

The results suggest that access to bank financing does not play a role in the quantity of funds which borrowers request. This finding is consistent with Prosper borrowers having relatively inelastic demand for funds, a reasonable expectation because many borrowers on Prosper seek loans to pay off credit card bills.[11] That is, the quantity of funds which these borrowers request may be largely independent of the supply of financing in the counties where they reside. We use additional dependent variables to measure the quantity of funds which borrowers request, including the dollar sum of expected payments over the life of the loan (using *Amount requested* as the principal, *Maximum rate* as the discount rate, and a maturity of three years), the expected monthly payment (dividing the previous amount by 36), and the expected monthly interest (dividing the difference between the first and second amounts by 36). We find similar, insignificant coefficients on *Post-4/15/08* × *Log Bank deposits* under these specifications.

[Insert Table 9 here.]

The second regression uses *Percent funded* as the dependent variable. We find no evidence that access to bank finance leads to an increase in funding from lenders on Prosper. The third regression uses *Realized rate* as the dependent variable. The results of this regression are insignificant, indicating that although banking presence influences the rates borrowers request, it

[11] Source: Practical E-Commerce. (URL: http://www.practicalecommerce.com/articles/584-A-Lender-Or-Borrower-Be-Is-Prosper-com) This article is an interview with Prosper CEO Chris Larsen, who notes that majority of borrowers who receive funding on Prosper "are in the so-called sweet spot of credit cards…"

does not influence the interest rates borrowers ultimately receive on completed loans when requesting loans on Prosper.

3.11. Does banking presence affect the probability of default?

We address whether banking presence affects the probability of borrower default with probit regressions. The dependent variable is an indicator variable taking a value of one if the loan ultimately defaults (a loan defaults if it is charged-off or has interest payments that are more than two months late) and zero if the borrower repaid the loan, the loan is current, or the loan request was never completed. We regress this dependent variable on the independent variables in our baseline regression. This specification returns negative and significant coefficients on *Log Bank deposits*. However, we cannot use a differences-in-differences framework because none of the loans originating after April 15, 2008 default by the end of the sample period (July 2008). The results suggest that banking presence is correlated with a lower default probability, but we can make no stronger claims.

3.12. Triple-differences tests: Analysis with California, a control state

We compare the results for Florida to those for the control state, California. For loan requests greater than $2,550, the maximum interest rate that borrowers in California could request was 36 percent prior to April 15, 2008, and it remained at 36 percent after April 15, 2008. This group of loan requests provides a useful control group because these borrowers were not subject to the rate ceiling shift.

We pool loan requests from borrowers in Florida with loan requests from borrowers in California. We perform OLS regressions that are similar in spirit to the baseline tests, with the addition of a triple interaction term differentiating loan requests by their state of origin and other lower-ordered interactions. Equation (2) displays the regression equation. The standard errors are robust to heteroskedasticity and we cluster them at the county level. Subscripts l, c, and t denote loan request, county, and year, respectively.

$$
\begin{aligned}
\textit{Maximum rate}_{l,c,t} = {} & \beta_1\ \textit{Post-4/15/08}_t \times \textit{Log Bank deposits}_{c,t} \times \textit{Treated}_l + \\
& \beta_2\ \textit{Post-4/15/08}_t \times \textit{Log Bank deposits}_{c,t} + \\
& \beta_3\ \textit{Post-4/15/08}_t \times \textit{Treated}_l + \\
& \beta_4\ \textit{Log Bank deposits}_{c,t} \times \textit{Treated}_l + \\
& \beta_5\ \textit{Post-4/15/08}_t + \\
& \beta_6\ \textit{Log Bank deposits}_t + \\
& \beta_7\ \textit{Treated}_l + \\
& \beta_8\ \text{Vector of borrower-specific controls}_{l,c,t} + \\
& \beta_9\ \text{Vector of geographic-specific controls}_{c,t} + \\
& \text{Constant} + \varepsilon_{l,c,t}
\end{aligned}
\qquad (2)
$$

Treated is an indicator variable taking a value of one if the loan request was submitted by a Florida borrower or a borrower in California who requested less than or equal to $2,550. Treated takes a value of zero if the loan request was submitted by a California borrower who requested more than $2,550. We expect to find a negative coefficient on the triple interaction term. That is, we expect borrowers to request higher loan rates after April 15, 2008; the rate requests should change less in counties with greater access to bank finance; and only borrowers in the state of Florida or borrowers in California who seek small loans should exhibit changes in rate requests. Table 10 displays the regression results.

[Insert Table 10 here.]

Similar to the baseline result, we find a negative relation between banking presence and the maximum interest rate borrowers are willing to pay. The results indicate that after April 15, 2008, borrowers in Florida and borrowers in California who request small loans that live in counties with bank deposits one standard deviation above average requested loans at rates 2.09 percent lower than borrowers living in counties with average levels of bank deposits. Although this result is not statistically significant, it is close to being so: the p-value for the coefficient estimate is 0.13.

3.13. The results are stronger for borrowers with poor credit

We partition the Florida-California sample by borrowers' credit grades. Specifically, we create subsamples consisting of loan requests made by borrowers with credit grades of C or lower (NC, HR, E, D, or C), and we create other subsamples consisting of loan requests made by borrowers with credit grades of B or higher (B, A, or AA). We repeat the Florida-California pooled regression analysis in the previous section for each subsample. Regressions (2) and (3) of Table 10 contain the results.

The results indicate that banking presence affects the maximum interest rate borrowers with low credit grades are willing to pay. However, banking presence does not affect the maximum interest rate borrowers with good credit grades are willing to pay. These results are intuitive. The 18 percent rate ceiling was more likely a binding constraint for borrowers with low credit grades, as lenders demand higher interest rates from riskier borrowers. Our results indicate that once the rate ceiling shifted, these higher-risk borrowers sought financing at higher interest rates, particularly if they lived in counties with few banks to provide traditional financing. In contrast, the borrowers with good credit grades were likely able to secure financing at rates below 18 percent, even in counties with relatively poor access to bank financing.

3.14. Tests using the synthetic controls approach

Our baseline Florida-only differences-in-differences tests are appropriate for identifying a causal impact of the rate ceiling shift if there are no trends confounding the analysis. However, the possibility of trends seems likely, and motivates the tests in Table 9 where we use triple-differences tests with California as our control group. These tests relax the "no trends" assumption of a simple differences test and replace it with a "parallel trends" assumption. That is, we implicitly assume that any trend among borrowers in Florida is matched by a similar trend among borrowers in California, and differencing the two removes the effect of the trend.

In this section, we provide a robustness test that relaxes the parallel trends assumption. The method we use is the synthetic controls approach, introduced in Abadie and Gardeazabal (2003) and extended in Abadie, Diamond, and Hainmueller (2010). Although we discuss the intuition behind the method here, we refer the interested reader to the technical details in Abadie, Diamond, and Hainmueller (2010), where these authors discuss the method in depth.

This technique is a data-driven matching procedure, replacing a traditional researcher-selected control unit with a combination of control units. The following discussion draws heavily on Abadie et al. (2010, p. 494-496). Formally, suppose we seek to identify the causal effect of an intervention to an outcome variable of interest, Y, for unit i at time t. Define $\alpha_{it} = Y^{I}_{it} - Y^{N}_{it}$ as the difference between the treated outcome, denoted by superscript I and which we observe, and the counterfactual outcome that would have obtained in the absence of the intervention, denoted by superscript N. Furthermore, suppose we can describe the counterfactual outcome as $Y^{N}_{it} = \delta_t + \theta_t Z_i + \lambda_t \mu_i + \varepsilon_{it}$, where δ_t is an unknown common time-varying factor, θ_t is a vector of parameters, Z_i is a vector of observed covariates, λ_t is a vector of unobserved common factors, μ_i is a vector of factor loadings, and ε_{it} is the unit-level residual. A traditional differences-in-differences test requires parallel trends, $\lambda_t = \lambda$, so that unobserved confounders, μ_i, will not contaminate the results because they will be differenced out.

In addition to the treated observation, there are J untreated observations, which form a donor pool of observations that can be combined to create a control group. Consider a ($J \times 1$) vector of weights W, for the J untreated observations (the donor pool). Restrict the weights on individual donor pool observations, w_j, to be in the range [0, 1], and that the w_j's sum to one. Each value of W represents the composition of a potential synthetic control: $\sum_j(w_j Y_{jt}) = \delta_t + \theta_t \sum_j(w_j Z_i)+$

$\lambda_t \sum_j(w_j \mu_i) + \sum_j(w_j \varepsilon_{it})$, where $\sum_j$ is the summation operator, summing over J donor pool observations.

Suppose we can choose a particular W^* such that we can match the synthetic outcomes and covariates to the actual outcomes and covariates for each pre-treatment period. With a large set of pre-intervention outcomes to match, a synthetic control can match the outcomes and observed covariates *only* if it also matches the unobserved confounders. Thus, the synthetic controls method allows a researcher to control for the effect of unobserved confounders that influence the time trends of treatment and control groups. Moreover, the estimated effect of the shock can then be interpreted as a causal effect, because our synthetic control provides a compelling counterfactual outcome.

In practice, we cannot generally match all the outcomes and covariates exactly. Instead, we choose the W^* that minimizes the mean squared prediction error, the squared deviations between the outcome for the treated unit and the synthetic control unit summed over all pre-intervention periods. Then, an estimator of the treatment effect, α_{1t}, is $Y_{1t} - \sum_j(w_j^* Y_{jt})$. This method is similar in its intuition to the use of tracking portfolios in finance applications (e.g., Lamont (2001)).

To date, researchers have used the synthetic control approach to establish treatment effects for one unit (for example, one state or one country). We extend this approach to our setting: our shock, the rate ceiling shift, applied to many units (Florida counties), but the shock may have affected units differently.[12] Rather than denoting the state of Florida as our treated unit, we denote individual Florida counties as treated units. This approach makes better use of the granularity of our data than a state-level test and allows us to retain our ability to test the cross-sectional impact

[12] Acemoglu et al. (2010) extend the Abadie et al. (2010) method to the case of multiple treated observations. Unlike the Acemoglu et al. (2010) application, our interest is not whether the point estimate of the response to an event is non-zero, but rather the cross-sectional variation in the response.

of our variable of interest, *Log Bank deposits*, on the effect of interest rates requested by borrowers on Prosper, as in our baseline tests. We compute the average of the variables of interest for each county-month in the treated counties (Florida) and in our potential donor pool counties (California). We create a synthetic control for each county in Florida. This approach allows us to compute a treatment effect of the lifting of the interest rate ceiling, county-by-county.

Escambia County, Florida provides an example. The matching procedure identifies four counties in California that comprise Escambia's synthetic control: Del Norte (2.9%), Nevada (23.0%), San Bernardino (34.8%), and San Luis Obispo (39.3%). All other California counties are assigned a weight of zero, some because there were insufficient data to be in the donor pool. Table 11 reports these results, and Figure 2 plots the time series of the outcome variable, mean *Maximum rate*, for Escambia County and its synthetic control. The plot for Escambia County is representative; we typically see a close match during the pre-treatment period (i.e., prior to April 2008), a large jump in the treated county's outcome after the treatment period, and no obvious jump in the synthetic control outcome after the treatment period.[13]

[Insert Table 11 here.]

[Insert Figure 2 here.]

Having estimated the treatment effect for each county, we conduct a post-test where we regress the treatment effects on county-level bank deposits, an indicator variable taking a value of one in months after April 2008 and zero before, and the interaction of the two. This approach is similar to our baseline regression specification and it allows us to estimate how the (change in the) difference between the rates requested by Florida borrowers and their synthetic controls relates to bank deposits. *Gap*, the difference between the treated unit's outcome (mean *Maximum rate*) and

[13] In some settings, the closeness of the match can matter in a synthetic controls analysis, and researchers may cull the donor pool to improve the quality of the match between a treated unit and its synthetic control. See Abadie, et al. (2010) for a discussion. Our results are insensitive to excluding the observations that produce the highest 20% mean squared prediction errors.

its synthetic control's outcome, represents the treatment effect. We estimate the following regression, the results of which appear in Table 12:

$$
\begin{aligned}
Gap_{c,t} = {} & \beta_1\ \textit{Post-April 2008}_t \times \textit{Log Bank deposits}_{c,t} + \\
& \beta_2\ \textit{Post-April 2008}_t + \\
& \beta_3\ \textit{Log Bank deposits}_{c,t} + \\
& \text{Constant} + \varepsilon_{c,t}
\end{aligned}
\tag{3}
$$

[Insert Table 12 here.]

Consistent with our triple differences results reported above, we find that the effect of the shift in the rate ceiling attenuates in counties with more bank deposits. The result is not only qualitatively similar, but also similar in magnitude: the coefficient on our differences-in-differences estimator is statistically significant with a point estimate of -0.0238, which means that a one standard deviation increase in bank deposits attenuates the jump in requested rates by 2.38 percentage points.

We conduct a placebo test, treating April 2007 as if it were the intervention date, rather than the actual event in April 2008. We stop the sample period at March 2008 to avoid contaminating our placebo test with the real event. We report this test in the second column of Table 12. Consistent with the prediction that no intervention occurred in April 2007 and thus we should observe no results, the coefficient on the differences-in-differences estimator is statistically indistinguishable from zero.

4. Conclusion

This paper examines how local access to finance affects consumers' borrowing decisions using detailed loan request-level data from Prosper, a peer-to-peer consumer lending intermediary and an alternative to traditional sources of finance, such as banks and other consumer finance intermediaries. Using a novel identification strategy based on a plausibly exogenous shift in the maximum interest rate that borrowers could request when seeking loans on Prosper, we find that consumers with better access to bank financing seek loans at lower interest rates on Prosper. Our results are robust to a variety of alternative specifications, including a synthetic controls approach.

Our findings enhance our understanding of how consumers make financial decisions. Consumers do not make borrowing decisions in isolation from alternative sources of finance. To the contrary, we provide evidence that the competitive force of a greater banking presence causes consumers to seek loans at lower interest rates from alternative sources. This result is particularly strong for borrowers with poor credit, suggesting that riskier borrowers are more sensitive to the availability of competing sources of finance.

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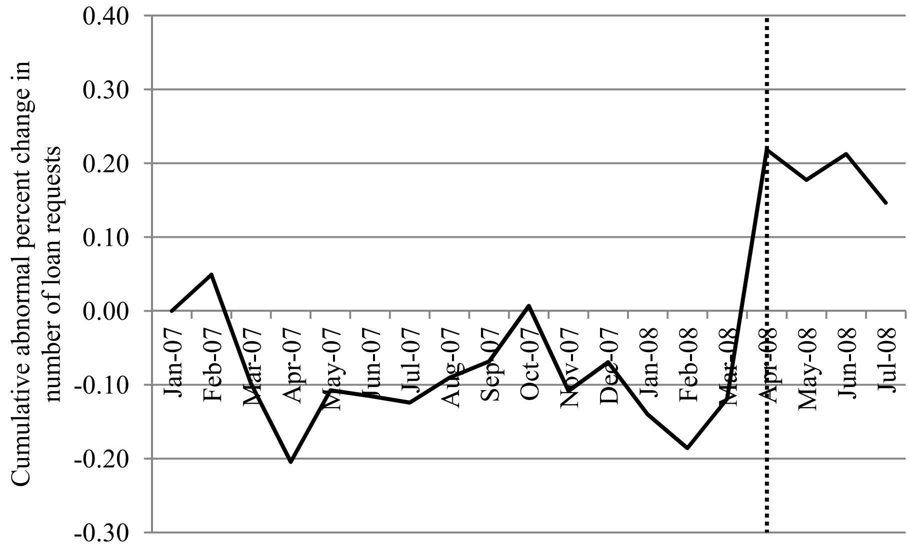

Figure 1 – Cumulative abnormal percent change in number of loan requests made by borrowers in Florida relative to borrowers in California

This figure reflects the difference between the number of loan requests made by borrowers in Florida relative to the number of loan requests made by borrowers in the control state, California. We begin by calculating the monthly percent change in the number of loan requests made by borrowers in both states, with January 2007 as the baseline month. The plot displays the cumulative abnormal percent change in the number of loan requests made by borrowers in Florida relative to borrowers in California. The vertical dotted line indicates April 2008, the month the rate ceiling shifted for borrowers in Florida.

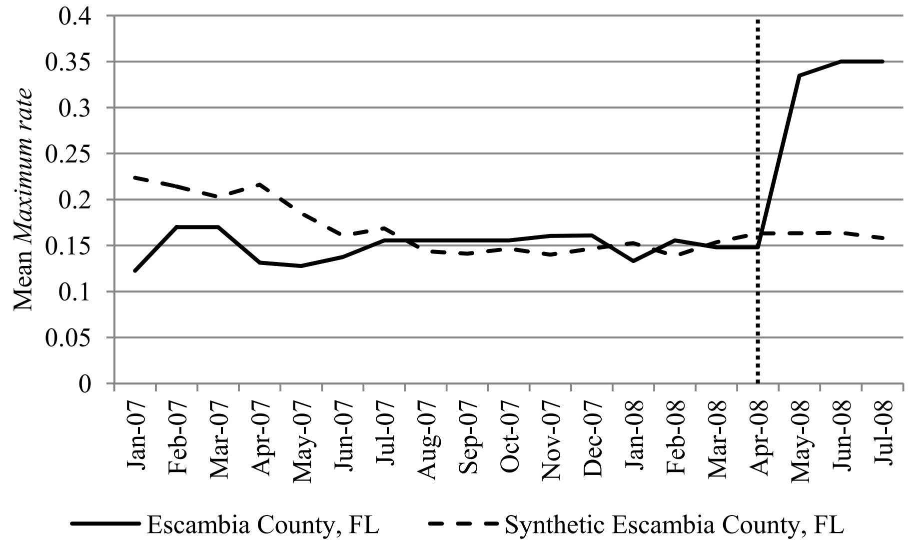

Figure 2 – Example of maximum rates requested by borrowers in a treatment county and the treatment county's synthetic control

This figure displays the monthly mean of *Maximum rate* for loan requests made by borrowers in Escambia County, FL and it synthetic control. The vertical dotted line indicates April 2008, the month the rate ceiling shifted for borrowers in Florida.

Table 1 – Summary Statistics

This table contains summary statistics for all borrower-county observations from the state of Florida and the control state, California. *Maximum rate* is the maximum interest rate the borrower is willing to pay when applying for a loan on Prosper. *Amount requested* is the dollar amount the borrower requests when applying for a loan on Prosper. *Percent funded* is the fraction of *Amount requested* funded by lenders on Prosper. *Credit grade* is the borrower's credit grade on a scale from zero (no credit) to seven (highest level of credit). *Debt/income* is the borrower's debt to income ratio. *Homeowner* is a dummy variable taking a value of one if the borrower owns a home, and zero otherwise. *Bank deposits* is the number of deposits (in millions of dollars) held by FDIC-insured bank branches in the county where the borrower lives. *Bank branches* is the number of FDIC-insured bank branches in the county where the borrower lives. *Per capita income* is the dollar amount of income per person in the county where the borrower lives. *Unemployment* is the unemployment rate in the county where the borrower lives. *Poverty* is the percentage of the population living below the poverty line in the county where the borrower lives. *Consumer debt* is the sum of consumers' auto debt balance in dollars per capita, consumers' credit card debt balance in dollars per capita, and consumers' mortgage debt balance in dollars per capita within a county-year. *Consumer debt delinquent* is the county-year sum of the following items: consumers' auto debt balance in dollars per capita that is at least 90 days delinquent, consumers' credit card debt balance in dollars per capita that is at least 90 days delinquent, and consumers' mortgage debt balance in dollars per capita that is at least 90 days delinquent. *Population* is the number of residents within a county for a given year (measured in thousands of residents). All of the geographic variables vary by county and year. *Obesity* is the average (across two workers) obesity rating of the adult(s) in the photograph associated with a listing. If multiple photographs are associated with a listing, the variable represents the average across different photographs. *Obesity* estimates are expressed on a scale between one (not overweight) and three (definitely overweight). *Female indicator* equals one if at least one worker identified at least one female adult in at least one of the photographs associated with a listing while no male adult was identified by any worker. The indicator equals zero otherwise. *Couple indicator* equals one if at least one photograph associated with a listing contains one female adult and one male adult and zero otherwise. *Kid(s) indicator* equals one if at least one worker identified at least one person below the age of 18 in at least one of the photographs associated with a listing and zero otherwise. *Young adults* indicator equals one if at least one worker identified at least one person above the age of 18, but below the age of 40 in at least one of the photographs associated with a listing or loan while no older adults were identified by any worker. The indicator equals zero otherwise. *Old adults* indicator equals one if at least one worker identified at least one person above the age of 60 in at least one of the photographs associated with a listing or loan while no younger adults were identified by any worker. The indicator equals zero otherwise. *Black* (*Asian*, *Hispanic*) indicator equals one if at least one worker identified at least one black (asian, hispanic) adult in at least one of the photographs associated with a listing and zero otherwise. *House* (*Car*, *Business*) equals one if at least one worker identified a house (car, business establishment) in at least one of the photographs associated with a listing and zero otherwise. The full sample period is from January 2007 through July 2008. We describe data sources in the text.

Panel A – Florida loan requests

	N	Mean	SD	25th Pct	Median	75th Pct
Loan request variables:						
Maximum rate	5,374	0.1626	0.0369	0.1555	0.1700	0.1700
Amount requested	5,374	6,438	6,029	2,500	4,500	8,000
Percent funded	5,374	0.10	0.26	0.00	0.00	0.03
Realized rate	376	0.1435	0.0379	0.1200	0.1496	0.1650
Credit grade	5,374	2.09	1.52	1	1	3
Debt/income	5,157	0.43	1.22	0.12	0.21	0.34
Homeowner	5,177	0.25	0.44	0	0	1
Geographic variables:						
Bank deposits	5,374	24,902	23,621	5,716	18,294	35,363
Bank branches	5,374	287.0	195.4	133	240	458
Per capita income	5,374	37,584	7,543	33,335	35,945	40,946
Unemployment	5,374	3.8	0.6	3.3	3.7	4.0
Poverty	5,374	12.4	2.8	10.6	11.9	13.7
Consumer debt	5,374	49,359	10,801	43,570	49,150	57,230
Consumer debt delinquent	5,374	2,218	2,136	914	1,204	3,033
Population	5,374	1,042	743	408	921	1,749
Photograph variables:						
Obesity	3,821	1.30	0.53	1	1	1.5
Female indicator	3,821	0.26	0.44	0	0	1
Couple indicator	3,821	0.11	0.31	0	0	0
Kid(s) indicator	3,821	0.32	0.47	0	0	1
Young adults indicator	3,821	0.48	0.50	0	0	1
Old adults indicator	3,821	0.01	0.10	0	0	0
Black indicator	3,821	0.21	0.41	0	0	0
Asian indicator	3,821	0.07	0.26	0	0	0
Hispanic indicator	3,821	0.17	0.37	0	0	0
House	3,821	0.10	0.29	0	0	0
Business	3,821	0.10	0.30	0	0	0
Car	3,821	0.10	0.30	0	0	0

Panel B – California loan requests

	N	Mean	SD	25th Pct	Median	75th Pct
Loan request variables:						
Maximum rate	7,250	0.2320	0.0667	0.1900	0.2460	0.2900
Amount requested	7,250	7,587	6,431	3,000	5,000	10,000
Percent funded	7,250	0.19	0.35	0.00	0.01	0.13
Realized rate	1,066	0.1996	0.0710	0.1410	0.1991	0.2600
Credit grade	7,250	2.12	1.59	1	1	3
Debt/income	6,950	0.58	1.53	0.14	0.23	0.38
Homeowner	6,818	0.16	0.37	0	0	0
Geographic variables:						
Bank deposits	7,250	74,534	83,479	17,974	47,258	89,137
Bank branches	7,250	605.3	596.1	224	302	684
Per capita income	7,250	43,484	12,433	36,782	42,521	48,576
Unemployment	7,250	5.1	1.2	4.4	4.7	5.1
Poverty	7,250	12.2	3.1	9.8	11.7	14.6
Consumer debt	7,250	81,508	17,449	70,180	80,810	91,600
Consumer debt delinquent	7,250	2,592	1,965	1,089	1,981	3,284
Population	7,250	3,307	3,471	799	1,982	2,977
Photograph variables:						
Obesity	5,070	1.24	0.47	1	1	1.25
Female indicator	5,070	0.22	0.41	0	0	0
Couple indicator	5,070	0.12	0.33	0	0	0
Kid(s) indicator	5,070	0.36	0.48	0	0	1
Young adults indicator	5,070	0.49	0.49	0	0	1
Old adults indicator	5,070	0.01	0.09	0	0	0
Black indicator	5,070	0.16	0.36	0	0	0
Asian indicator	5,070	0.15	0.36	0	0	0
Hispanic indicator	5,070	0.17	0.37	0	0	0
House	5,070	0.12	0.33	0	0	0
Business	5,070	0.14	0.35	0	0	0
Car	5,070	0.07	0.25	0	0	0

Table 2 – Correlation Matrix

This table contains correlation coefficients for borrower-county observations from the state of Florida related to borrowers' loan requests, characteristics of the county in which the borrower resides, and personal characteristics gleaned from borrowers' photographs. Variable definitions are available in the legend of Table 1. Italic font indicates significance at the 10 percent level, bold font indicates significance at the 5 percent level, and bold and italic font indicates significance at the 1 percent level.

	Maximum rate	Amount requested	Percent funded	Realized rate	Credit grade	Debt/income	Homeowner	Bank deposits	Bank branches	Per capita income	Unemployment	Poverty	Consumer debt	Consumer debt delinquent	Population	Obesity	Female indicator	Couple indicator	Kid(s) indicator	Young adults indicator	Old adults indicator	Black indicator	Asian indicator	Hispanic indicator	House	Business
Amount requested	***-.10***																									
Percent funded	-.00	-.00																								
Realized rate	***.95***	***-.09***	***-.08***																							
Credit grade	***-.19***	***.37***	***.46***	***-.19***																						
Debt/income	**-.03**	***.14***	***-.03***	**-.03**	***.08***																					
Homeowner	***-.04***	***.21***	***.16***	***-.04***	***.38***	.01																				
Bank deposits	-.02	***.04***	**.03**	-.01	***.07***	-.01	***.05***																			
Bank branches	-.01	***.04***	**.03**	-.01	***.06***	-.01	**.03**	***.94***																		
Per capita income	.00	***.04***	-.01	.00	-.02	-.02	***-.04***	***.12***	***-.08***																	
Unemployment	***.19***	***.10***	**.03**	***.20***	***.13***	***.08***	***.09***	**-.01**	**-.03**	.02																
Poverty	*.02*	-.01	.02	***.03***	***.06***	***.02***	***.04***	***.43***	***.27***	***-.45***	.00															
Consumer debt	.01	***.08***	**.03**	.01	***.05***	***.03***	-.02	***.42***	***.54***	***.61***	***-.08***	***-.38***														
Consumer debt delinquent	***.24***	***.06***	***.05***	***.25***	***.18***	**.03**	***.12***	***.43***	***.46***	***.18***	***.33***	***.12***	***.53***													
Population	*-.02*	**.03**	**.03**	-.02	***.06***	-.01	***.04***	***.95***	***.97***	***.10***	***-.07***	***.36***	***.48***	***.44***												
Obesity	.00	-.02	***-.05***	-.00	**-.03**	.01	***-.05***	***-.09***	***-.08***	***.06***	*.03*	***-.08***	***-.05***	***-.08***	***-.09***											
Female indicator	.00	***-.09***	***-.06***	.01	***-.06***	-.02	-.00	***.14***	***.14***	***.05***	-.02	***.06***	***.07***	***.14***	***.14***	***.11***										
Couple indicator	-.03	.02	***.04***	-.02	**.04**	***.06***	***-.05***	**-.03**	**-.03**	.02	.02	**-.03**	***-.04***	***-.05***	***-.05***	***.18***	***-.21***									
Kid(s) indicator	-.01	***-.05***	-.02	.00	***-.07***	*-.03*	***-.07***	***-.06***	***-.09***	**-.04**	.02	-.00	***-.13***	***-.14***	***-.09***	-.01	**-.04**	***-.07***								
Young adults indicator	.00	***-.04***	-.02	.02	-.02	-.01	***-.07***	***.10***	***.08***	*-.03*	.01	***.08***	*.02*	***.11***	***.08***	.03	***.20***	***.08***	-.00							
Old adults indicator	-.02	-.02	***.07***	*-.03*	*.03*	-.02	.00	.01	.03	.00	-.02	.00	*-.02*	**-.02**	.01	***.06***	*-.03*	***.10***	***-.06***	***-.10***						
Black indicator	**-.04**	***-.10***	***-.07***	**-.04**	***-.17***	**.04**	***-.13***	***.10***	***.08***	***-.09***	*-.03*	***.13***	*-.03*	**-.03**	***.11***	***.06***	***.16***	***-.06***	-.03	***.14***	***-.05***					
Asian indicator	***.06***	***.06***	***-.04***	***.09***	**.03**	-.00	**.04**	***.11***	***.08***	.01	.00	***.07***	***.11***	***.27***	***.08***	**-.04**	***.09***	.02	***-.07***	***.08***	-.00	***-.05***				
Hispanic indicator	***.04***	.01	-.01	***.06***	.02	***.05***	.02	***.15***	***.14***	***-.05***	-.02	***.13***	***.11***	***.27***	***.14***	**-.04**	.02	***.10***	**-.04**	***.15***	*-.03*	***-.06***	***.25***			
House	-.02	**.04**	.02	-.02	.02	-.01	***.07***	***-.06***	***-.06***	***.04***	***.05***	**-.04**	*.03*	***.16***	***-.06***	**.04**	-.00	-.00	***.07***	*-.03*	-.02	-.00	***.05***	***-.04***		
Business	-.01	***.10***	***.06***	-.01	***.06***	***.08***	***.05***	-.01	-.00	.01	**.04**	.00	-.01	***-.04***	-.02	***-.04***	***-.09***	**.04**	***-.08***	***-.09***	-.01	***-.05***	.01	-.00	.01	
Car	***.05***	-.01	-.00	***.07***	***.04***	-.00	***.11***	***.05***	.02	-.02	***-.06***	***.05***	***.06***	***.19***	.02	-.02	**.04**	-.02	**-.04**	*.03*	-.01	*.03*	***.27***	***.21***	***.10***	-.01

Table 3 – Comparisons of Loan Outcomes for Borrowers Submitting Loan Requests Before and After April 15, 2008

This table contains results from t-tests comparing average outcomes related to loan requests made by borrowers on Prosper residing in Florida and California (the control state) who requested loans both before and after April 15, 2008. For the sample of California borrowers, we require the amount requested to be greater than $2,550. Variable definitions are available in the legend of Table 1. Standard errors appear below differences and differences-in-differences in parentheses. *, **, and *** indicate the difference is significant at the 10, 5, or 1 percent level, respectively.

Panel A – All loan requests

	Florida			California			
	Before 4/15/08	After 4/15/08	Difference (SE)	Before 4/15/08	After 4/15/08	Difference (t-stat)	Diff-in-Diff (SE)
Maximum rate	0.151	0.262	0.111*** (0.017)	0.216	0.259	0.042*** (0.007)	0.068*** (0.011)
Amount requested	6,586	6,873	286 (681)	8,825	7,461	-1,363** (668)	1,650* (959)
Percent funded	0.119	0.270	0.151*** (0.056)	0.241	0.247	0.007 (0.039)	0.145*** (0.054)
N bids received by each loan request	10.5	45.4	34.9*** (3.9)	37.5	32.8	-4.7 (8.5)	39.6*** (3.2)
N loan requests	300	113		234	136		

Panel B – Completed loan requests, only

	Florida			California			
	Before 4/15/08	After 4/15/08	Difference (SE)	Before 4/15/08	After 4/15/08	Difference (t-stat)	Diff-in-Diff (SE)
Maximum rate	0.150	0.227	0.077*** (0.022)	0.206	0.244	0.038** (0.018)	0.039 (0.028)
Amount requested	4,047	6,240	2,193 (1,754)	7,596	6,087	-1,509 (1,450)	3,701 (2,270)
Percent funded	1.000	1.000	0.000 (--)	1.000	1.000	0.000 (--)	0.000 (--)
Realized rate	0.127	0.179	0.052** (0.029)	0.180	0.194	0.014 (0.018)	0.038 (0.028)
N bids received by each loan request	95.8	150.1	54.3 (42.4)	153.6	151.0	-2.5 (35.7)	56.8 (58.6)
N loan requests	20	20		40	23		

Table 4 – Dynamics of Borrower Characteristics around the Rate Ceiling Shift

This table displays average loan request characteristics and personal characteristics gleaned from borrowers' photographs for borrowers on Prosper residing in Florida and the control state, California. For the sample of California borrowers, we require the amount requested to be greater than $2,550. The table displays differences in these characteristics before and after the rate ceiling shift, and the differences-in-differences. Variable definitions are available in the legend of Table 1. Standard errors appear below differences and differences-in-differences in parentheses. *, **, and *** indicate the difference or difference-in-difference is significant at the 10, 5, or 1 percent level, respectively.

	Florida			California			
	Before 4/15/08	After 4/15/08	Diff. (SE)	Before 4/15/08	After 4/15/08	Diff. (SE)	Diff.-in-Diff. (SE)
Credit grade	2.609	3.074	0.465***	2.631	3.224	0.594***	-0.128
			(0.183)			(0.122)	(0.183)
Debt/income	0.328	0.314	-0.014	0.431	0.348	-0.083**	0.069
			(0.012)			(0.053)	(0.077)
Homeowner	0.418	0.391	-0.028	0.229	0.141	-0.088***	0.061
			(0.048)			(0.032)	(0.048)
Obesity	1.328	1.341	0.013	1.171	1.197	0.026	-0.013
			(0.057)			(0.062)	(0.084)
Female indicator	0.405	0.305	-0.100**	0.178	0.164	-0.014	-0.086
			(0.050)			(0.054)	(0.077)
Couple indicator	0.062	0.084	0.022	0.101	0.164	0.063*	-0.041
			(0.033)			(0.036)	(0.048)
Kid(s) indicator	0.267	0.295	0.027	0.304	0.370	0.066	-0.038
			(0.052)			(0.057)	(0.077)
Young adults indicator	0.635	0.589	-0.046	0.491	0.548	0.057	-0.103
			(.056)			(0.062)	(0.084)
Old adults indicator	0.007	0.011	0.003	0.006	-0.000	-0.006	0.009
			(0.009)			(0.010)	(0.014)
Black indicator	0.175	0.116	-0.059	0.130	0.041	-0.089**	0.030
			(0.039)			(0.043)	(0.059)
Asian indicator	0.208	0.179	-0.029	0.097	0.096	-0.001	-0.027
			(0.040)			(0.044)	(0.059)
Hispanic indicator	0.243	0.305	0.063	0.093	0.123	0.030	0.033
			(0.042)			(0.046)	(0.062)
House	0.072	0.084	0.012	0.134	0.110	-0.024	0.036
			(0.035)			(0.038)	(0.052)
Business	0.053	0.074	0.021	0.154	0.205	0.051	-0.030
			(0.036)			(0.039)	(0.053)
Car	0.192	0.168	-0.024	0.085	0.110	0.024	-0.048
			(0.039)			(0.042)	(0.057)

Table 5 – OLS Regressions of Maximum Rate

This table contains results from OLS regressions of borrowers' maximum rates (*Maximum rate*) regressed on variables related to borrowers' loan requests, characteristics of the county in which the borrower resides, and personal characteristics gleaned from borrowers' photographs. *Post-4/15/08* is an indicator variable taking a value of 1 if the loan request was made after April 15, 2008, and zero otherwise. Other variable definitions are available in the legend of Table 1. Standard errors are robust to heteroskedasticity and we cluster them at the county level. Standard errors appear in parentheses below coefficient estimates. *, **, and *** indicate the coefficient is significant at the 10, 5, or 1 percent level, respectively.

Panel A – Florida loan requests

	(1)	(2)	(3)	(4)	(5)	(6)
Post-4/15/08 × Log Bank deposits	-0.0184	-0.0330	-0.0193	-0.0325		
	(0.0065)***	(0.0107)***	(0.0066)***	(0.0102)***		
Log Bank deposits	0.0002	0.0001	0.0178	0.0141		
	(0.0005)	(0.0005)	(0.0103)*	(0.0102)		
Post-4/15/08 × Log Bank branches					-0.0172	-0.0191
					(0.0104)	(0.0103)*
Log Bank branches					-0.0053	-0.0289
					(0.0242)	(0.0279)
Post-4/15/08	0.1225	0.1377	0.1207	0.1372	0.1189	0.1266
	(0.0088)***	(0.0127)***	(0.0086)***	(0.0100)***	(0.0104)***	(0.0127)***
Credit grade	-0.0062	-0.0052	-0.0060	-0.0049	-0.0059	-0.0049
	(0.0005)***	(0.0005)***	(0.0005)***	(0.0005)***	(0.0005)***	(0.0005)***
Debt/income	0.0000	-0.0003	0.0001	-0.0002	0.0000	-0.0002
	(0.0003)	(0.0004)	(0.0003)	(0.0004)	(0.0003)	(0.0004)
Homeowner	0.0014	0.0003	0.0018	0.0009	0.0017	0.0011
	(0.0018)	(0.0015)	(0.0018)	(0.0014)	(0.0018)	(0.0014)
Per capita income	-0.0001	0.0001	-0.0047	-0.0039	-0.0042	-0.0043
	(0.0001)	(0.0001)	(0.0018)**	(0.0021)*	(0.0016)**	(0.0022)*
Unemployment	0.0016	-0.0007	0.0073	0.0052	0.0094	0.0089
	(0.0016)	(0.0019)	(0.0028)**	(0.0036)	(0.0038)**	(0.0051)*
Poverty	-0.0003	-0.0004	-0.0004	-0.0039	0.0001	-0.0033
	(0.0002)	(0.0003)	(0.0017)	(0.0019)**	(0.0018)	(0.0021)
Consumer debt	-0.0001	-0.0007	-0.0019	-0.0075	-0.0018	-0.0063
	(0.0009)	(0.0008)	(0.0050)	(0.0054)	(0.0051)	(0.0072)
Consumer debt delinquent	-0.0017	-0.0019	0.0034	0.0041	0.0024	0.0047
	(0.0010)*	(0.0012)	(0.0020)*	(0.0027)	(0.0023)	(0.0030)
Population	0.0000	0.0001	-0.2730	-0.3694	-0.3344	-0.3897
	(0.0008)	(0.0007)	(0.1370)*	(0.1591)**	(0.1760)*	(0.1980)*
Obesity		-0.0009		-0.0009		-0.0007
		(0.0018)		(0.0019)		(0.0020)
Female indicator		-0.0003		-0.0005		-0.0006
		(0.0015)		(0.0015)		(0.0015)
Couple indicator		-0.0011		-0.0006		-0.0007
		(0.0017)		(0.0019)		(0.0020)
Kid(s) indicator		-0.0011		-0.0014		-0.0013
		(0.0009)		(0.0009)		(0.0010)
Young adults indicator		-0.0004		0.0003		0.0001
		(0.0012)		(0.0013)		(0.0013)
Old adults indicator		-0.0032		-0.0029		-0.0045
		(0.0057)		(0.0059)		(0.0057)
Black indicator		-0.0038		-0.0045		-0.0049
		(0.0017)**		(0.0017)**		(0.0016)***
Asian indicator		0.0032		0.0034		0.0031
		(0.0020)		(0.0024)		(0.0024)
Hispanic indicator		0.0003		0.0005		0.0002
		(0.0024)		(0.0025)		(0.0022)
House		-0.0023		-0.0022		-0.0021
		(0.0015)		(0.0013)*		(0.0013)
Business		-0.0008		-0.0015		-0.0014
		(0.0017)		(0.0019)		(0.0019)
Car		0.0035		0.0021		0.0024
		(0.0029)		(0.0036)		(0.0036)
Constant	0.1710	0.1771	0.6067	0.7326	0.6363	0.7460
	(0.0076)***	(0.0092)***	(0.1801)***	(0.2204)***	(0.2150)***	(0.2609)***
Fixed effects	None	None	County	County	County	County
N	4,960	3,638	4,960	3,638	4,960	3,638
Adjusted-R^2	0.44	0.43	0.45	0.45	0.45	0.44

Panel B – California loan requests

	Amount requested is less than or equal to \$2,550		*Amount requested* is greater than \$2,550	
	(1)	(2)	(3)	(4)
Post-4/15/08 × Log Bank deposits	-0.0358	-0.0616	-0.0040	0.0034
	(0.0085)***	(0.0229)**	(0.0047)	(0.0069)
Post-4/15/08	0.0940	0.1258	0.0029	-0.0006
	(0.0126)***	(0.0156)***	(0.0088)	(0.0195)
Log Bank deposits	-0.0784	-0.2595	0.1843	0.1622
	(0.3163)	(0.3077)	(0.1730)	(0.1889)
Credit grade	-0.0254	-0.0251	-0.0224	-0.0228
	(0.0018)***	(0.0019)***	(0.0009)***	(0.0007)***
Debt/income	0.0004	0.0016	-0.0002	-0.0000
	(0.0019)	(0.0019)	(0.0006)	(0.0007)
Homeowner	-0.0115	0.0125	0.0042	0.0016
	(0.0082)	(0.0109)	(0.0038)	(0.0040)
Per capita income	0.0003	-0.0027	0.0060	0.0047
	(0.0017)	(0.0023)	(0.0012)***	(0.0011)***
Unemployment	-0.0271	-0.0845	0.0096	0.0044
	(0.0177)	(0.0181)***	(0.0088)	(0.0086)
Poverty	0.0014	-0.0042	0.0033	0.0027
	(0.0048)	(0.0045)	(0.0018)*	(0.0020)
Consumer debt	-0.0106	-0.0122	-0.0299	-0.0209
	(0.0190)	(0.0287)	(0.0132)**	(0.0168)
Consumer debt delinquent	-0.0096	0.0074	0.0154	0.0147
	(0.0069)	(0.0065)	(0.0044)***	(0.0036)***
Population	-0.0048	0.2690	-0.0886	-0.0784
	(0.1607)	(0.1226)**	(0.0827)	(0.0896)
Obesity		-0.0088		0.0019
		(0.0060)		(0.0026)
Female indicator		0.0061		0.0033
		(0.0033)*		(0.0024)
Couple indicator		0.0075		-0.0030
		(0.0074)		(0.0032)
Kid(s) indicator		-0.0035		-0.0028
		(0.0046)		(0.0026)
Young adults indicator		0.0016		-0.0001
		(0.0036)		(0.0025)
Old adults indicator		0.0042		0.0010
		(0.0145)		(0.0054)
Black indicator		0.0095		0.0036
		(0.0062)		(0.0033)
Asian indicator		-0.0102		0.0014
		(0.0094)		(0.0029)
Hispanic indicator		0.0101		-0.0057
		(0.0037)**		(0.0025)**
House		0.0007		0.0029
		(0.0072)		(0.0048)
Business		0.0042		0.0045
		(0.0074)		(0.0042)
Car		0.0031		0.0001
		(0.0089)		(0.0064)
Constant	0.3836	0.0057	0.2403	0.2857
	(0.4998)	(0.3118)	(0.2581)	(0.2802)
Fixed effects	County	County	County	County
N	997	735	5,540	4,078
Adjusted-R^2	0.42	0.50	0.33	0.34

Table 6 – OLS Regressions of Maximum Rate: Local Banking Presence versus Local Economic Conditions or Consumer Debt Characteristics

This table contains results from OLS regressions of Florida borrowers' maximum rates (*Maximum rate*) regressed on variables related to borrowers' loan requests, characteristics of the county in which the borrower resides, including banking presence and economic conditions, and personal characteristics gleaned from borrowers' photographs. *Post-4/15/08* is an indicator variable taking a value of 1 if the loan request was made after April 15, 2008, and zero otherwise. Other variable definitions are available in the legend of Table 1. Standard errors are robust to heteroskedasticity and we cluster them at the county level. Standard errors appear in parentheses below coefficient estimates. *, **, and *** indicate the coefficient is significant at the 10, 5, or 1 percent level, respectively.

	(1)	(2)	(3)	(4)	(5)
Post-4/15/08 × Log Bank deposits	-0.0358	-0.0331	-0.0464	-0.0325	-0.0307
	(0.0099)***	(0.0094)***	(0.0114)***	(0.0106)***	(0.0151)**
Post-4/15/08 × Per capita income	0.0012				
	(0.0015)				
Post-4/15/08 × Unemployment		0.0136			
		(0.0075)*			
Post-4/15/08 × Poverty			-0.0075		
			(0.0050)		
Post-4/15/08 × Consumer debt				0.0006	
				(0.0142)	
Post-4/15/08 × Consumer debt delinquent					0.0022
					(0.0095)
Post-4/15/08	0.0920	0.0743	0.2463	0.1343	0.1295
	(0.0616)	(0.0330)**	(0.0727)***	(0.0760)*	(0.0403)***
Log Bank deposits	0.0150	0.0117	0.0137	0.0141	0.0142
	(0.0104)	(0.0098)	(0.0108)	(0.0103)	(0.0104)
Credit grade	-0.0049	-0.0048	-0.0048	-0.0049	-0.0049
	(0.0005)***	(0.0005)***	(0.0005)***	(0.0005)***	(0.0005)***
Debt/income	-0.0002	-0.0002	-0.0002	-0.0002	-0.0002
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Homeowner	0.0010	0.0010	0.0012	0.0009	0.0010
	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0014)
Per capita income	-0.0040	-0.0026	-0.0028	-0.0039	-0.0038
	(0.0019)**	(0.0019)	(0.0016)*	(0.0020)*	(0.0020)*
Unemployment	0.0046	-0.0003	0.0009	0.0052	0.0051
	(0.0031)	(0.0030)	(0.0032)	(0.0036)	(0.0034)
Poverty	-0.0035	-0.0034	-0.0029	-0.0038	-0.0036
	(0.0015)**	(0.0020)*	(0.0012)**	(0.0016)**	(0.0017)**
Consumer debt	-0.0058	-0.0053	-0.0043	-0.0074	-0.0068
	(0.0041)	(0.0046)	(0.0034)	(0.0049)	(0.0046)
Consumer debt delinquent	0.0035	0.0029	0.0022	0.0040	0.0036
	(0.0021)*	(0.0029)	(0.0017)	(0.0018)**	(0.0017)**
Population	-0.3492	-0.2520	-0.2584	-0.3687	-0.3641
	(0.1426)**	(0.1347)*	(0.1074)**	(0.1574)**	(0.1562)**
Constant	0.7110	0.5753	0.5779	0.7307	0.7202
	(0.1944)***	(0.1941)***	(0.1432)***	(0.2135)***	(0.2118)***
Photograph variables?	Yes	Yes	Yes	Yes	Yes
Fixed effects	County	County	County	County	County
N	3,638	3,638	3,638	3,638	3,638
Adjusted-R^2	0.45	0.45	0.45	0.45	0.45

Table 7 – OLS Regressions of Maximum Rate by Amount Requested Quartiles

This table contains results from OLS regressions of Florida borrowers' maximum rates (*Maximum rate*) regressed on variables related to borrowers' loan requests, characteristics of the county in which the borrower resides, and personal characteristics gleaned from borrowers' photographs. We perform these regressions by quartiles according to the amount of money requested by the borrowers. The first (second, third, fourth) column includes loan requests with an average requested amount of $1,700 ($3,374, $5,942, $15,460). *Post-4/15/08* is an indicator variable taking a value of 1 if the loan request was made after April 15, 2008, and zero otherwise. Other variable definitions are available in the legend of Table 1. Standard errors are robust to heteroskedasticity and we cluster them at the county level. Standard errors appear in parentheses below coefficient estimates. *, **, and *** indicate the coefficient is significant at the 10, 5, or 1 percent level, respectively.

	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Post-4/15/08 × Log Bank deposits	-0.0548	-0.0405	-0.0658	-0.0166
	(0.0149)***	(0.0173)**	(0.0505)	(0.0266)
Post-4/15/08	0.1359	0.1643	0.1347	0.1001
	(0.0209)***	(0.0107)***	(0.0221)***	(0.0295)***
Log Bank deposits	0.0064	0.0616	0.0178	-0.0371
	(0.0096)	(0.0247)**	(0.0213)	(0.0288)
Credit grade	-0.0090	-0.0056	-0.0038	-0.0028
	(0.0021)***	(0.0008)***	(0.0006)***	(0.0006)***
Debt/income	-0.0019	-0.0003	-0.0010	0.0008
	(0.0017)	(0.0008)	(0.0010)	(0.0005)
Homeowner	0.0039	-0.0048	0.0012	0.0022
	(0.0042)	(0.0023)**	(0.0022)	(0.0023)
Per capita income	-0.0037	-0.0061	-0.0005	0.0009
	(0.0036)	(0.0040)	(0.0020)	(0.0026)
Unemployment	0.0116	-0.0010	0.0049	0.0037
	(0.0051)**	(0.0051)	(0.0021)**	(0.0051)
Poverty	-0.0013	-0.0048	-0.0024	-0.0015
	(0.0025)	(0.0021)**	(0.0020)	(0.0033)
Consumer debt	-0.0094	-0.0025	-0.0075	-0.0145
	(0.0101)	(0.0080)	(0.0048)	(0.0116)
Consumer debt delinquent	0.0028	0.0046	-0.0043	0.0039
	(0.0028)	(0.0032)	(0.0026)	(0.0055)
Population	-0.5194	0.3039	-0.0564	-0.8609
	(0.2316)**	(0.1664)*	(0.1767)	(0.3256)**
Constant	0.8110	0.1362	0.2509	1.0619
	(0.3342)**	(0.2854)	(0.2241)	(0.3627)***
Photograph variables?	Yes	Yes	Yes	Yes
Fixed effects	County	County	County	County
N	1,029	814	939	856
Adjusted-R^2	0.64	0.55	0.49	0.16

Table 8 – Short Horizon OLS Regressions of Maximum Rate

This table contains results from OLS regressions of borrowers' maximum rates (*Maximum rate*) regressed on variables related to borrowers' loan requests, characteristics of the county in which the borrower resides, and personal characteristics gleaned from borrowers' photographs. *Post-4/15/07* (*Post-4/15/08*) is an indicator variable taking a value of 1 if the loan request was made after April 15, 2007 (April 15, 2008), and zero otherwise. Other variable definitions are available in the legend of Table 1. Standard errors are robust to heteroskedasticity and we cluster them at the county level. Standard errors appear in parentheses below coefficient estimates. *, **, and *** indicate the coefficient is significant at the 10, 5, or 1 percent level, respectively.

	Florida loan requests issued from:				California loan requests with *Amount requested* greater than $2,550 issued from:	
	3/15/08 to 5/15/08	3/15/08 to 5/15/08	3/15/07 to 5/15/07	3/15/07 to 5/15/07	3/15/08 to 5/15/08	3/15/08 to 5/15/08
	(1)	(2)	(3)	(4)	(5)	(6)
Post-4/15/08 × Log Bank deposits	-0.0262	-0.0744			0.0129	0.0129
	(0.0088)***	(0.0067)***			(0.0112)	(0.0315)
Post-4/15/08	0.1153	0.1500			-0.0231	-0.0424
	(0.0197)***	(0.0064)***			(0.0081)**	(0.0451)
Post-4/15/07 × Log Bank deposits			-0.0059	-0.0066		
			(0.0029)**	(0.0027)**		
Post-4/15/07			-0.0061	-0.0045		
			(0.0023)***	(0.0021)**		
Credit grade	-0.0186	0.0006	-0.0063	-0.0056	-0.0230	-0.0327
	(0.0040)***	(0.0019)	(0.0012)***	(0.0013)***	(0.0078)***	(0.0111)**
Debt/income	0.0133	0.1588	0.0004	0.0001	-0.0051	0.0077
	(0.0578)	(0.0484)***	(0.0006)	(0.0005)	(0.0100)	(0.0052)
Homeowner	0.0325	0.0255	0.0092	0.0053	-0.0136	-0.0617
	(0.0211)	(0.0213)	(0.0027)***	(0.0049)	(0.0160)	(0.0556)
Constant	0.1864	0.1081	0.1711	0.1688	0.3576	0.4682
	(0.0228)***	(0.0268)***	(0.0030)***	(0.0069)***	(0.0226)***	(0.1535)***
Photograph variables?	No	Yes	No	Yes	No	Yes
Fixed effects	County	County	County	County	County	County
N	147	83	521	399	276	104
Adjusted-R^2	0.59	0.79	0.13	0.14	0.33	0.71

Table 9 – OLS Regressions with Alternative Dependent Variables

This table contains results from OLS regressions of dependent variables regressed on variables related to borrowers' loan requests, characteristics of the county in which the borrower resides, and personal characteristics gleaned from borrowers' photographs. *Post-4/15/08* is an indicator variable taking a value of 1 if the loan request was made after April 15, 2008, and zero otherwise. Other variable definitions are available in the legend of Table 1. Standard errors are robust to heteroskedasticity and we cluster them at the county level. Standard errors appear in parentheses below coefficient estimates. *, **, and *** indicate the coefficient is significant at the 10, 5, or 1 percent level, respectively.

Dependent variable:	Amount requested (1)	Percent funded (2)	Realized rate (3)
Post-4/15/08 × Log Bank deposits	-491	0.0395	-0.0096
	(753)	(0.0273)	(0.0080)
Post-4/15/08	-199	0.1334	0.0643
	(539)	(0.0572)**	(0.0091)***
Log Bank deposits	-3,058	0.0044	0.0510
	(1,820)*	(0.0691)	(0.0275)*
Credit grade	1,208	0.0968	-0.0122
	(108)***	(0.0048)***	(0.0011)***
Debt/income	503	-0.0199	0.0066
	(154)***	(0.0043)***	(0.0011)***
Homeowner	1,158	-0.0140	0.0000
	(445)**	(0.0155)	(0.0034)
Per capita income	-22	-0.0180	-0.0020
	(301)	(0.0125)	(0.0036)
Unemployment	477	0.0150	0.0098
	(336)	(0.0123)	(0.0058)
Poverty	-173	0.0007	-0.0047
	(243)	(0.0086)	(0.0043)
Consumer debt	4,792	0.0190	0.0050
	(849)***	(0.0418)	(0.0099)
Consumer debt delinquent	-1,762	-0.0103	-0.0088
	(296)***	(0.0135)	(0.0034)**
Population	-16,562	-1.6153	-0.5504
	(19,083)	(0.8108)*	(0.3390)
Constant	21,772	2.2230	0.8904
	(26,340)	(1.0786)**	(0.4822)*
Photograph variables?	Yes	Yes	Yes
Fixed effects	County	County	County
N	3,638	3,638	227
Adjusted-R^2	0.20	0.26	0.53

Table 10 – OLS Regressions of Maximum Rate with Pooled Florida and California Loan Requests

This table contains results from OLS regressions of borrowers' maximum rate (*Maximum rate*) regressed on variables related to borrowers' loan requests, characteristics of the county in which the borrower resides, and personal characteristics gleaned from borrowers' photographs. Regression (1) pools loan requests from borrowers in Florida and borrowers in California who request loans larger than $2,550. Regression (2) uses a subsample loan requests from borrowers with credit grades of "C" and below from the sample of pooled Florida and California loan requests. Regression (3) uses a subsample of loan requests from borrowers with credit grades of "B" and above from the sample of pooled Florida and California loan requests. *Post-4/15/08* is an indicator variable taking a value of 1 if the loan request was made after April 15, 2008, and zero otherwise. *Treated* is an indicator variable taking a value of 1 if the loan request was made by a borrower in Florida or a borrower in California who requested an amount less than or equal to $2,550. *Treated* takes a value of zero if the loan request was made by a borrower in California who requested more than $2,550. Other variable definitions are available in the legend of Table 1. Standard errors are robust to heteroskedasticity and we cluster them at the county level. Standard errors appear in parentheses below coefficient estimates. *, **, and *** indicate the coefficient is significant at the 10, 5, or 1 percent level, respectively.

	All loan requests	All loan requests	Bad credit	Good credit
	(1)	(2)	(3)	(4)
Post-4/15/08 × Log Bank deposits × Treated	-0.0289	-0.0209	-0.0433	-0.0044
	(0.0120)**	(0.0128)	(0.0133)***	(0.0196)
Post-4/15/08 × Log Bank deposits	0.0025	0.0004	0.0126	0.0056
	(0.0084)	(0.0081)	(0.0081)	(0.0081)
Post-4/15/08 × Treated	0.0764	0.0858	0.0796	0.0483
	(0.0177)***	(0.0193)***	(0.0175)***	(0.0347)
Log Bank deposits × Treated	0.0013	-0.0001	0.0007	0.0079
	(0.0037)	(0.0025)	(0.0026)	(0.0028)***
Post-4/15/08	0.0354	0.0222	0.0375	-0.0155
	(0.0155)**	(0.0176)	(0.0150)**	(0.0207)
Log Bank deposits	-0.0043	0.0164	0.0052	0.1124
	(0.0041)	(0.0143)	(0.0107)	(0.0654)*
Treated	-0.0458	-0.0088	-0.0084	-0.0341
	(0.0057)***	(0.0029)***	(0.0027)***	(0.0086)***
Credit grade	-0.0163	-0.0158	-0.0100	-0.0231
	(0.0018)***	(0.0019)***	(0.0019)***	(0.0025)***
Debt/income	-0.0004	-0.0004	-0.0012	0.0014
	(0.0005)	(0.0004)	(0.0005)**	(0.0015)
Homeowner	0.0013	0.0030	0.0010	-0.0007
	(0.0028)	(0.0026)	(0.0025)	(0.0042)
Per capita income	0.0005	0.0028	0.0033	0.0034
	(0.0004)	(0.0011)**	(0.0010)***	(0.0039)
Unemployment	0.0107	-0.0004	-0.0008	0.0210
	(0.0015)***	(0.0035)	(0.0036)	(0.0098)**
Poverty	-0.0025	-0.0002	0.0000	-0.0070
	(0.0007)***	(0.0016)	(0.0015)	(0.0038)*
Consumer debt	-0.0023	-0.0137	-0.0169	-0.0298
	(0.0024)	(0.0075)*	(0.0070)**	(0.0143)**
Consumer debt delinquent	0.0005	0.0048	0.0033	0.0036
	(0.0018)	(0.0027)*	(0.0026)	(0.0049)
Population	0.0026	0.0201	0.0273	0.1312
	(0.0003)***	(0.0944)	(0.0865)	(0.2393)
Constant	-0.0016	0.0842	0.0395	-0.1960
	(0.0018)	(0.2176)	(0.1975)	(0.5362)
Photograph variables?	Yes	Yes	Yes	Yes
Fixed effects	None	County	County	County
N	8,451	8,451	7,714	737
Adjusted-R^2	0.46	0.52	0.53	0.30

Table 11 – California Counties' Weights in Synthetic Escambia County, Florida

This table displays the weights assigned to counties in the control state, California, that comprise synthetic Escambia County, Florida. '--' indicates insufficient data are available to include the county in the donor pool.

County	Weight	County	Weight
Alameda	0	Orange	0
Alpine	--	Placer	0
Amador	0	Plumas	--
Butte	0	Riverside	0
Calaveras	--	Sacramento	0
Colusa	--	San Benito	0
Contra Costa	0	San Bernardino	0.393
Del Norte	0.029	San Diego	0
El Dorado	0	San Francisco	0
Fresno	0	San Joaquin	0
Glenn	--	San Luis Obispo	0.348
Humboldt	0	San Mateo	0
Imperial	--	Santa Barbara	0
Inyo	--	Santa Clara	0
Kern	0	Santa Cruz	0
Kings	0	Shasta	0
Lake	0	Sierra	--
Lassen	--	Siskiyou	--
Los Angeles	0	Solano	0
Madera	0	Sonoma	0
Marin	0	Stanislaus	0
Mariposa	--	Sutter	0
Mendocino	0	Tehama	0
Merced	0	Trinity	--
Modoc	--	Tulare	0
Mono	--	Tuolumne	--
Monterey	0	Ventura	0
Napa	0	Yolo	0
Nevada	0.230	Yuba	0

Table 12 – Synthetic Controls Post-Test Regressions

This table presents results from OLS regressions where the dependent variable is the difference between a treated county's average *Maximum rate* in a given month and its synthetic control. *Maximum rate* is the maximum interest rate the borrower is willing to pay when applying for a loan on Prosper. *Post-April 2008* (*Post-April 2007*) is an indicator variable taking a value of one if the loan request was made after April, 2008 (2007), and zero if the loan request was made before April, 2008 (2007). *Log Bank deposits* is the logged number of deposits (in thousands of dollars) held by FDIC-insured bank branches in the county where the borrower lives scaled by county population and area in square miles. *Log Bank deposits* is standardized to follow a mean-zero, unit-variance distribution. Standard errors are robust to heteroskedasticity and we cluster them at the county level. Standard errors appear in parentheses below coefficient estimates. *, **, and *** indicate the coefficient is significant at the 10, 5, or 1 percent level, respectively.

	Standard regression (1)	Placebo regression (2)
Post-April 2008 × Log Bank deposits	-0.0238	
	(0.0099)**	
Post-April 2008	0.0214	
	(0.0076)***	
Post-April 2007 × Log Bank deposits		-0.0014
		(0.056)
Post-April 2007		0.0275
		(.0055)***
Log Bank deposits	-0.0018	0.0350
	(0.0022)	(0.217)
Constant	-0.0315	-0.0537
	(0.0049)***	(0.0044)***
Fixed effects	County	County
N	1,045	825
Adjusted-R^2	0.41	0.60