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Do Local Capital Market Conditions Affect Consumers' Borrowing Decisions?

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Abstract. This paper uses detailed data from an online peer-to-peer lending intermediary to test whether local access to finance affects consumers' willingness to pay for loans. After controlling for local economic conditions and borrower credit quality, we find that borrowers who reside in areas with good access to bank finance request loans with lower interest rates. This effect is stronger for borrowers with poor credit and those seeking small loans, suggesting that local access to finance is more important for marginal borrowers. Overall, our findings shed light on how consumers substitute between alternative sources of finance.

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1. Introduction

Whereas there is a large and well-established literature studying corporate decisions about external financing, consumer financing decisions are more difficult to study because of a lack of appropriate data. We study how borrowers' local consumer finance alternatives affect consumer finance decisions made by users of Prosper.com (hereafter, "Prosper"), a peer-to-peer consumer lending intermediary. 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 allows us unique opportunities to study consumers' financing decisions.

We find that the lending capacity of local banks is associated with 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, suggesting that consumers do not make borrowing decisions in isolation from alternative sources of finance. Our paper differs in important ways from other papers that use the Prosper data. Other papers tend to focus on how borrower characteristics affect loan outcomes,[1] or how Prosper's market structure affects loan outcomes.[2] In contrast, our paper studies how borrowers' local consumer finance alternatives affect their behavior—in particular, reservation interest rates that borrowers state they are willing to pay.

Following Becker (2007), Butler and Cornaggia (2011), and Cornaggia (2013), we proxy for local lending capacity with county-level bank deposits and other measures of financial development. Our main hurdle to understanding how consumers choose their financing sources and terms is that a borrower's characteristics and the 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. One of the advantages of the Prosper data is the richness of covariates we are able to use. We saturate our regressions with vectors of control variables that capture borrower attributes and local economic conditions. Although this approach may not fully resolve endogeneity concerns, the richness of the data mitigates the possibility that omitted variables could drive our results.

To isolate the effect of local consumer finance alternatives from borrower characteristics, we control for borrower-specific characteristics, including credit grade, debt-to-income ratio, and homeowner status. We also control for other, more detailed variables that capture borrowers' credit profiles. Examples include the borrower's amount of delinquent debt, bank card utilization, number of credit lines, etc. We describe these variables in greater detail in the data section. We also 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 fractions of these sources of debt that are delinquent. As in Iyer et al. (2016), we use splines in regressions to allow our local economic control variables to have a nonlinear relation with our outcome variables.

We find that Prosper borrowers residing in counties with greater lending capacity seek loans at lower interest rates. Specifically, we find that borrowers living in counties with a level of bank deposits one standard deviation above average seek loans with interest rates 61 to 74 basis points lower than similar borrowers in counties with average levels of bank deposits. 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. Our results are particularly strong for borrowers who seek small loans (less than the median, which is $5,000) 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.

A critical assumption behind our ordinary least squares (OLS) regressions is that county-level bank deposits only affect borrowers' willingness to pay through local lending conditions. In other words, we assume our measure of local bank financing is uncorrelated with unobserved economic conditions and borrower quality. If this assumption is valid, then county-level bank deposits should not predict loans' propensities to become distressed. To test this directly, we use a sample of completed loan requests and regress measures of loan repayment on our measure of local bank financing, the realized interest rate set for the loans, and the same set of controls as in our baseline OLS regressions. The relationship between county-level bank deposits and the probability that loans fall into distress is statistically indistinguishable from zero. Our main measure of distress captures loans that default, are charged-off, or have late payments. However, we also run separate tests, looking for a relation between county-level bank deposits and each of these three individual measures of distress. We find no relation in each case. These non-results support our assumption that county-level bank deposits only affect borrowers' willingness to pay through local lending conditions.

We provide further support for this assumption by testing for a relation between county-level bank deposits and other loan outcome variables. We repeat our baseline OLS regressions with the fraction of each loan request that is actually funded by lenders on Prosper as the dependent variable. We find no evidence that access to bank finance leads to an increase in funding from lenders on Prosper. We also use the realized rate on loan requests, rather than borrowers' reservation rates, as the dependent variable. Likewise, we find no evidence that access to bank finance is correlated with this variable. These non-results show that competitive Prosper lenders, who operate at the national level, do not view borrower creditworthiness as correlated with local deposit levels. Instead, borrower willingness to pay is related to local deposit levels.

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 et al. (2004) 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.

One recent paper that also studies borrowers' reservation prices is Kawai et al. (2014). This paper uses six months of completed Prosper loans to examine whether borrowers use low reservation prices as signals of their quality. In this paper's setup, low reservation prices can serve to separate good borrowers from the bad because stating a low reservation price should lead to a lower probability of the loan being funded. Our results, that local banking markets are an important determinant of borrowers' stated reservation prices, shows that the cost of the signal is a function of geography and therefore is, at least in part, independent of their individual characteristics. Because separating signals cannot be overly productive (i.e., making the bad types better, as in Spence 1973), our finding that local banking markets are an important determinant of borrowers' reservations prices could help lenders (and researchers) determine where, geographically, such attempts to create a separating signal will be most effective.

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

Prosper is a growing alternative source of finance for consumers. As of September 2013, Prosper has over two million members and over $1 billion of loans have been funded through its website.[3] 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.[4] 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 during our sample period 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 loan listing.

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 that 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 14 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.[5] Because multiple bidders fund the loans on Prosper, we are unable to cleanly control for bidder characteristics in our tests. 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. (During our sample period, 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.

3. Data

We start with all loan requests made by borrowers on Prosper.com. We drop loan requests made before April 15, 2008. Prior to April 15, 2008, the maximum rate a borrower could request varied on a state-by-state basis, depending on the license Prosper had with the state. On April 15, 2008, Prosper partnered with WebBank, a Utah-chartered industrial bank. This partnership allowed Prosper to achieve nationwide lending with a maximum interest rate of 36%. The lack of uniformity across states in maximum interest rates prior to this date would make it difficult to disentangle borrowers' willingness to pay for loans from mechanical variation in maximum interest rates set by Prosper's state-by-state lending licenses.[6] We drop loan requests made by borrowers in South Dakota and Texas because the rate ceiling shift applied to all states except these two. We also drop loan requests made on or after December 19, 2010. Prior to December 19, 2010, interest rates on loans were set according to the Dutch auction process described above. As of December 19, 2010, however, Prosper changed its business model so that interest rates are determined by a formula that evaluates a borrower's credit risk. Prosper's new business model removes the opportunity for borrowers to reveal their willingness to pay by stating a maximum interest rate, a necessary characteristic for us to conduct our tests. We further require that borrowers reveal their city of residence in their loan requests so that we can map the loan requests to measures of local access to finance and other geography-based controls. Applying all of these filters leaves us with 5,069 loan requests, which we use for our main tests.

3.1. 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*).

3.2. Independent Variables

Similar to Becker (2007), Butler and Cornaggia (2011), and Cornaggia (2013), we use county-level bank deposits from 2008 through 2010 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. *Deposits* represents the sum of all bank deposits held by FDIC-insured depository institutions within a county for a given year. *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-chartered or only federally-chartered bank branches. We standardize both *Deposits* and *Branches* across the sample of 5,069 loan requests to follow mean-zero, unit-variance distributions.

3.3. Control Variables

Our tests include controls for per capita income, the percentage of the population that is unemployed, and the percentage of the population that lives below the poverty line. Together, these measures capture economic conditions in counties where the borrowers reside for each year of the sample. We control for per capita levels of auto, credit card, and mortgage debt, as well as the fractions of these amounts that are delinquent. These measures come from the Federal Reserve Bank of New York Consumer Credit Panel. All of the controls for economic conditions and measures of consumer debt and delinquent debt vary by county and year. We define each of them and describe how we use them in our tests in the appendix. To allow control variables for local economic conditions to have a nonlinear relation with our outcome variables, we use spline regressions. We use five-part splines; our results are robust if we use continuous versions of these variables instead of splines, or if we vary the number of splines into which we translate each variable. (For example, our results are robust if we use two-, seven-, or ten-part splines.)

Each loan listing on Prosper includes a wealth of information that we use for control purposes. Specifically, we include controls for loan requests characteristics, including indicator variables that capture the number of days (seven or 14) that the loan request remains open for funding, an indicator variable taking a value of one if the loan listing includes at least one picture and zero if the loan listing includes no pictures, and loan category indicator variables. Loan categories include debt consolidation, home improvement, business, personal loan, student use, auto, other, and not available.

Prosper also provides information on borrowers' credit profiles. We include basic borrower controls such as the borrowers' debt-to-income ratios, an indicator variable capturing whether or not a borrower owns a home, and indicator variables that capture the borrowers' credit grade at the time the listings are created. 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 Missing (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. Our results are robust if, instead of using indicator variables, we include one control variable that imparts a linear transformation on borrowers' credit scores, such that it takes a value of 0 for borrowers with no credit history, 1 for HR borrowers, etc., up to 7 for AA borrowers. Prosper also provides many additional data items that characterize borrowers' credit profiles. We include detailed borrower controls such as the borrower's amount of delinquent debt, bank card utilization, and number of credit lines, to name a few. We collectively refer to these characteristics as *Detailed borrower controls*. We define each of them and describe how we use them in our tests in the appendix.

4. Methods and Results

4.1. Data Description

Table 1 summarizes the loan requests we use in our main sample. This table also contains summary statistics for local economy controls, basic borrower controls, and detailed borrower controls. To conserve space, we only report summary statistics for the variables most pertinent to our analysis in this table. Complete summary statistics for all variables used in our analysis are provided in the Internet appendix, available at http://www.jesscornaggia.com and as supplemental material at https://doi.org/10.1287/mnsc.2016.2560. Panel A summarizes characteristics for all loan requests, and panel B restricts the sample to loan requests that receive funding. Panel B is identical to panel A, except it contains summary statistics on *Realized rate*, the actual rate paid by borrowers on completed loans, in addition to *Maximum rate*.

4.2. Baseline Regressions

Using the sample of loan requests in Table 1, panel A, 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

Table 1. Summary Statistics

	Mean	SD	10th pct.	Median	90th pct.
		Panel A: All loan requests			
Maximum rate	0.2670	0.0904	0.1200	0.3000	0.3500
Amount requested	6,395	5,262	1,500	5,000	15,000
Percent funded	27.8	40.4	0	3.3	100.0
Deposits	42.1	70.3	1.1	14.8	137.0
Branches	339.8	432.2	30	200	716
Local economy controls					
Per capita income	42,915	11,952	30,808	40,351	57,336
Unemployment	7.26	2.57	4.60	6.50	10.80
Poverty	13.30	4.59	7.60	13.40	18.30
Auto debt	3,138	751	2,210	3,170	4,100
Credit card debt	3,739	753	2,780	3,710	4,660
Mortgage debt	48,076	21,887	21,220	47,660	75,520
Auto debt delinquent	4.6	2.1	2.2	4.4	7.2
Credit card debt delinquent	11.2	3.9	7.1	10.5	16.2
Mortgage debt delinquent	6.3	4.7	2.1	5.0	12.3
Basic borrower controls					
Debt/Income	0.31	0.55	0.08	0.24	0.49
Homeowner indicator	0.40	0.49	0	0	1
Credit grade indicators					
AA	0.03	0.17	0	0	0
A	0.04	0.20	0	0	0
B	0.05	0.22	0	0	0
C	0.10	0.30	0	0	0
D	0.13	0.34	0	0	1
E	0.09	0.29	0	0	0
HR	0.20	0.40	0	0	1
Missing	0.35	0.48	0	0	1
Detailed borrower controls					
Amount delinquent	2,727	40,627	0	0	5,240
Bank card utilization	0.59	0.42	0.00	0.66	1.00
Current credit lines	9.19	6.07	2	8	17
Current delinquencies	2.02	4.56	0	0	6
Delinquencies last 7 years	7.43	14.02	0	1	23
Inquiries last 6 months	2.81	3.73	0	2	7
Employment length status in months	12.01	39.01	0	0	35
Public records last 12 months	0.05	0.27	0	0	0
Public records last 10 years	0.57	1.02	0.00	0.00	2.00
Revolving credit balance	14,374	41,320	0	4,704	30,011
Total credit lines	26.92	15.68	10	25	46

Notes. This table reports summary statistics for variables associated with loan requests submitted by borrowers on Prosper.com. The sample include 5,069 loan requests (panel A), 966 of which are completed (panel B). Variable definitions and data sources are in the appendix.

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.

$$\begin{aligned} \textit{Maximum rate}_{l,c,t} &= \beta_1 \textit{Deposits}_{\,c,t} \\ &\quad + \beta_2 \text{Vector of Local economy controls}_{c,t} \\ &\quad + \beta_3 \text{Vector of Loan request controls}_{l,c,t} \\ &\quad + \beta_4 \text{Vector of Basic borrower controls}_{l,c,t} \\ &\quad + \beta_5 \text{Vector of Detailed borrower controls}_{l,c,t} \\ &\quad + \text{Constant} + \varepsilon_{l,c,t}. \end{aligned} \tag{1}$$

Deposits is our primary independent variable of interest. If borrowers residing in counties with poor access to bank finance are willing to pay higher interest rates on loans from Prosper, then this term should have a negative coefficient. Table 2 displays the results.[7]

Indeed, panel A shows that for a one-standard-deviation increase in county-level bank deposits, borrowers request interest rates on Prosper that are 61 basis points lower than borrowers residing in counties with average levels of bank deposits. This magnitude increases to 74 basis points if we include the vector of detailed borrower controls. Columns (3) and (4) repeat the analysis in columns (1) and (2), respectively, but with *Branches* as the independent variable of interest. The results are similar: For a one-standard-deviation increase in county-level bank branches, borrowers request interest rates on Prosper that are 58 to 68 basis points lower than borrowers residing in counties with average levels of bank branches, depending on whether we include the vector of detailed borrower controls. These results indicate that borrowers' willingness to pay for loans on Prosper is negatively correlated with local access to bank finance.

Table 1. (Continued)

	Mean	SD	10th pct.	Median	90th pct.
	Panel B: Completed loan requests				
Maximum rate	0.2428	0.0971	0.1004	0.2575	0.3500
Realized rate	0.2000	0.0950	0.0835	0.1865	0.3500
Amount requested	4,743	4,096	1,000	3,500	10,000
Percent funded	100.0	0	100.0	100.0	100.0
Deposits	44.1	74.0	1.1	14.5	143.0
Branches	344.3	443.2	30	199	716
Local economy controls					
Per capita income	44,197	13,006	31,346	41,113	58,837
Unemployment	7.49	2.76	4.50	6.80	11.10
Poverty	13.16	4.61	7.50	13.15	18.00
Auto debt	3,040	754	2,110	3,045	3,920
Credit card debt	3,733	747	2,800	3,695	4,640
Mortgage debt	49,227	21,913	21,540	47,810	78,740
Auto debt delinquent	4.5	2.0	2.1	4.1	7.1
Credit card debt delinquent	11.0	3.8	7.0	10.3	16.3
Mortgage debt delinquent	5.9	4.3	2.1	4.7	11.0
Basic borrower controls					
Debt/Income	0.23	0.22	0.07	0.20	0.38
Homeowner indicator	0.43	0.50	0	0	1
Credit grade indicators					
AA	0.07	0.26	0	0	0
A	0.08	0.26	0	0	0
B	0.08	0.27	0	0	0
C	0.11	0.32	0	0	1
D	0.10	0.30	0	0	1
E	0.04	0.19	0	0	0
HR	0.07	0.26	0	0	0
Missing	0.44	0.50	0	0	1
Detailed borrower controls					
Amount delinquent	831	3,942	0	0	1,224
Bank card utilization	0.54	0.40	0	0.58	0.97
Current credit lines	9.73	5.46	4	9	16
Current delinquencies	0.78	2.62	0	0	2
Delinquencies last 7 years	4.02	10.38	0	0	12
Inquiries last 6 months	1.80	2.89	0	1	4
Employment length status in months	13.78	44.43	0	0	42
Public records last 12 months	0.02	0.16	0	0	0
Public records last 10 years	0.33	0.82	0	0	1
Revolving credit balance	13,904	29,963	90	5,661	31,938
Total credit lines	25.20	14.46	9	23	45

Panel A of Table 2 uses state fixed effects to control for unobservable influences on borrowers' requested interest rates that vary geographically. This approach allows the results to derive from within-state or within-county time series variation. Panel B repeats the regressions in panel A with county fixed effects. This approach forces identification from within-county time series variation only. The negative relation between bank deposits and requested interest rates remains weakly robust under this specification. Although this approach eliminates alternative explanations for our results based on unobserved, time-invariant characteristics at the county level, it limits degrees of freedom in the data. Our regressions include over 100 control variables, and our sample features loan requests from 567 different counties. For the remainder of the paper, we report results with state fixed effects because they provide a reasonable compromise between controlling for unobserved geographic variation without overly constraining degrees of freedom.

4.3. Are the Results Stronger for Borrowers Requesting Small Loans?

We next examine whether borrowers seeking larger or smaller loans are more sensitive to levels of local bank deposits. Panel A of Table 3 replicates the regressions in Table 2 after splitting the sample by loan size. Column (1) includes observations with requested amounts greater than \$5,000. Column (2) includes observations with requested amounts less than or equal to \$5,000. We find no relation between county-level bank deposits and borrowers' willingness to pay for

Table 2. Local Access to Finance and Borrowers' Willingness to Pay for Loans on Prosper

	(1)	(2)	(3)	(4)
	Panel A: State fixed effects			
Deposits	−0.0061***	−0.0074***		
	(0.0021)	(0.0018)		
Branches			−0.0058***	−0.0068***
			(0.0021)	(0.0020)
Local economy controls?	Yes	Yes	Yes	Yes
Loan request controls?	Yes	Yes	Yes	Yes
Basic borrower controls?	Yes	Yes	Yes	Yes
Detailed borrower controls?	No	Yes	No	Yes
State fixed effects?	Yes	Yes	Yes	Yes
County fixed effects?	No	No	No	No
Year fixed effects?	Yes	Yes	Yes	Yes
Adjusted R^2	0.31	0.42	0.31	0.41
N	5,069	5,069	5,069	5,069
	Panel B: County fixed effects			
Deposits	−0.0445*	−0.0395*		
	(0.0267)	(0.0229)		
Branches			0.0361	0.0098
			(0.1552)	(0.1358)
Local economy controls?	Yes	Yes	Yes	Yes
Loan request controls?	Yes	Yes	Yes	Yes
Basic borrower controls?	Yes	Yes	Yes	Yes
Detailed borrower controls?	No	Yes	No	Yes
State fixed effects?	No	No	No	No
County fixed effects?	Yes	Yes	Yes	Yes
Year fixed effects?	Yes	Yes	Yes	Yes
Adjusted R^2	0.31	0.42	0.31	0.42
N	5,069	5,069	5,069	5,069

Notes. This table reports results from OLS regressions of *Maximum rate* on measures of local banking conditions and controls. *Maximum rate* is the maximum interest rate the borrower is willing to pay when applying for a loan on Prosper. *Deposits* is the level of deposits held by FDIC-insured bank branches in the county where the borrower lives. *Branches* is the number of FDIC-insured bank branches in the county where the borrower lives. Variable definitions and data sources are in the appendix. Panel A controls for unobserved geographic variation with state fixed effects, whereas panel B uses county fixed effects. Standard errors, which we cluster at the county level, appear in parentheses below regression coefficients.

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

borrowers requesting large loans. However, for small loans, we see that for a one-standard-deviation increase in county-level bank deposits, borrowers request interest rates on Prosper that are 65 basis points lower than borrowers residing in counties with average levels of bank deposits.

Column (3) in panel A of Table 3 more rigorously tests whether the correlation between *Deposits* and *Maximum rate* is indeed stronger for borrower requesting small loans. We construct an indicator variable, *Small loan*, that takes a value of one if the loan request is for less than or equal to \$5,000 and zero if the loan request is for greater than \$5,000. We pool the subsamples in columns (1) and (2) and interact *Small loan* with *Deposits*. We run the following regression:

$$
\begin{aligned}
\mathit{Maximum\ rate}_{l,c,t} &= \beta_1 \mathit{Deposits}_{c,t} \times \mathit{Small\ loan}_l \\
&\quad + \beta_2 \mathit{Deposits}_{c,t} + \beta_3 \mathit{Small\ loan}_l \\
&\quad + \beta_4 \text{Vector of Local economy controls}_{c,t} \\
&\quad + \beta_5 \text{Vector of Loan request controls}_{l,c,t} \\
&\quad + \beta_6 \text{Vector of Basic borrower controls}_{l,c,t} \\
&\quad + \beta_7 \text{Vector of Detailed borrower controls}_{l,c,t} \\
&\quad + \text{Constant} + \varepsilon_{l,c,t}. \qquad (2)
\end{aligned}
$$

If borrowers seeking smaller loans are more sensitive to local bank deposits, then the coefficient on this interaction term should be negative. Indeed, we observe that, for a one-standard-deviation increase in county-level bank deposits, borrowers request interest rates on Prosper that are 57 basis points lower than borrowers residing in counties with average levels of bank deposits. More importantly, the coefficient on the interaction term reveals that this effect is 40 basis points larger for borrowers requesting small loans.

4.4. Are the Results Stronger for Borrowers with Poor Credit?

We also examine whether borrowers with poor credit are more sensitive to local levels of bank deposits. Panel B of Table 3 replicates the regressions in Table 2

Table 3. Local Banking Conditions and Willingness to Pay by Loan Size and Credit Quality

Panel A: Sample split by loan size

	Requested amount is greater than \$5,000 (1)	Requested amount is less than or equal to \$5,000 (2)	Pooled (3)
Deposits × *Small loan*			−0.0040*
			(0.0022)
Deposits	−0.0048	−0.0065***	−0.0057**
	(0.0033)	(0.0024)	(0.0024)
Small loan			0.0013
			(0.0028)
Local economy controls?	Yes	Yes	Yes
Loan request controls?	Yes	Yes	Yes
Basic borrower controls?	Yes	Yes	Yes
Detailed borrower controls?	Yes	Yes	Yes
State fixed effects?	Yes	Yes	Yes
Year fixed effects?	Yes	Yes	Yes
Adjusted R^2	0.35	0.48	0.42
N	2,197	2,872	5,069

Panel B: Sample split by borrower credit quality

	AA, A, or B (1)	C, D, E, HR, or missing (2)	Pooled (3)
Deposits × *Bad credit*			−0.0003
			(0.0059)
Deposits	−0.0049	−0.0085***	−0.0077
	(0.0088)	(0.0020)	(0.0054)
Bad credit			0.0632***
			(0.0064)
Local economy controls?	Yes	Yes	Yes
Loan request controls?	Yes	Yes	Yes
Basic borrower controls?	Yes, except credit grade indicators	Yes, except credit grade indicators	Yes, except credit grade indicators
Detailed borrower controls?	Yes	Yes	Yes
State fixed effects?	Yes	Yes	Yes
Year fixed effects?	Yes	Yes	Yes
Adjusted R^2	0.41	0.33	0.41
N	638	4,431	5,069

Notes. This table reports results from OLS regressions of *Maximum rate* on measures of local banking conditions and controls. *Maximum rate* is the maximum interest rate the borrower is willing to pay when applying for a loan on Prosper. *Deposits* is the level of deposits held by FDIC-insured bank branches in the county where the borrower lives. Panel A splits the sample by whether the loan request is for more than \$5,000 or less than or equal to \$5,000. *Small loan* is an indicator variable taking a value of one if the loan request is for less than or equal to \$5,000 and zero if the loan request is for greater than \$5,000. Panel B splits the sample by borrower credit quality. *Bad credit* is an indicator variable taking a value of one if the borrower's credit grade is C, D, E, HR, or Missing and zero if the borrower's credit grade is AA, A, or B. Variable definitions and data sources are in the appendix. Standard errors, which we cluster at the county level, appear in parentheses.

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

after splitting the sample by borrowers' credit grades. A key difference between these regressions and those in Table 2 is that we do not include credit grade fixed effects. Column (1) includes loan requests from borrowers with credit grades of AA, A, or B. Column (2) includes loan requests from borrowers with credit grades of C, D, E, HR, or Missing. We find no relation between county-level bank deposits and borrowers' willingness to pay for borrowers with good credit. However, for borrowers with bad credit, we see that for a one-standard-deviation increase in county-level bank deposits, borrowers request interest rates on Prosper that are 85 basis points lower than borrowers residing in counties with average levels of bank deposits.

Column (3) in panel B of Table 3 more rigorously tests whether the correlation between *Deposits* and *Maximum rate* is indeed stronger for borrower with poor credit. We construct an indicator variable, *Bad credit*, that takes a value of one if the borrower's credit grade is C, D, E, HR, or Missing and zero if the borrower's credit grade is AA, A, or B. We pool the subsamples in columns (1) and (2) and interact *Bad credit* with *Deposits*. If borrowers with poor credit are more sensitive to local bank deposits, then the coefficient on this interaction term should be negative. Although we observe a negative coefficient on the interaction term, it is small in magnitude and is statistically insignificant. Therefore, although columns (1) and (2) provide suggestive evidence that borrowers with poor credit are more sensitive to local bank finance, we can make no stronger claims.

4.5. Does Local Access to Finance Affect Loan Quantity?

The baseline tests reveal that access to bank finance has an effect on the *price* of funds that borrowers request. We repeat the baseline regressions from above (columns (1) and (2) from Table 2) with alternative dependent variables. We begin with *Amount requested* as the dependent variable. Regressions with this dependent variable reveal whether the supply of bank finance has an effect on the *quantity* of funds that borrowers request. We find that access to bank financing does not play a role in the quantity of funds that 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.[8] 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 that 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 *Deposits* under these specifications.

We also use *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. Finally, we use *Realized rate* as the dependent variable. The coefficients on *Deposits* are insignificant in these specifications as well. These results could differ from those in our main tests because of differences in statistical power (our main tests use 5,069 loan requests; these tests use 966 completed loans). However, they suggest that although banking presence influences the rates borrowers request, it does not influence the interest rates borrowers ultimately receive on completed loans when requesting loans on Prosper.

4.6. Does Banking Presence Affect the Probability of Default?

A critical assumption behind our OLS regressions is that *Deposits* only affects borrowers' willingness to pay through local lending conditions. In other words, we have assumed thus far that *Deposits* is uncorrelated with unobserved economic conditions and borrower quality. If this assumption is true, then *Deposits* should not predict borrowers' propensities to default on their loans. To test this directly, we begin with our sample of 966 completed loan requests and construct an indicator variable, *Bad loan*, which takes a value of one if the loan's status ever indicates distress or bankruptcy, and zero if the borrower repays his loan in full and on time. Specifically, *Bad loan* takes a value of one if the loan's status is ever "Default (bankruptcy)," "Charge-off," "Late," "1 month late," "2 months late," "3 months late," or "4+ months late." Of the 966 completed loans we use in this analysis, 204 receive a value of one for *Bad loan*. We regress *Bad loan* on *Deposits*, *Realized rate*, and the same set of controls as in the baseline OLS regressions. Column (1) in Table 4 displays the results. The small (0.0018) and insignificant coefficient on *Deposits* confirms our assumption that *Deposits* only affects borrowers' willingness to pay through local lending conditions. Not surprisingly, the coefficient on *Realized rate* is positive and significant, indicating loans with higher interest rates are more likely to exhibit distress in the future.

For robustness, we decompose *Bad loan* into three indicator variables: *Default* (*bankruptcy*) takes a value of one if the loan request's status is ever "Default (bankruptcy)," *Charge-off* takes a value of one if the loan request's status is ever "Charge-off," and *Late* takes a value of one if the loan's status is ever "Late," "1 month late," "2 months late," "3 months late," or "4+ months late." We repeat the regression in Table 4,

Table 4. Local Banking Conditions and Loan Repayment

	OLS (1)	Probit (2)
Deposits	0.0018	−0.0599
	(0.0223)	(0.1118)
Realized rate	0.0542***	3.8861***
	(0.0193)	(0.8963)
Local economy controls?	Yes	Yes
Loan request controls?	Yes	Yes
Basic borrower controls?	Yes	Yes
Detailed borrower controls?	Yes	Yes
State fixed effects?	Yes	Yes
Year fixed effects?	Yes	Yes
Adjusted R^2 or Pseudo R^2	0.18	0.33
N	966	803

Notes. This table reports results from regressions of *Bad loan* on *Deposits* and controls. *Bad loan* is an indicator variable taking a value of one if the loan's status is ever "Default (bankruptcy)," "Charge-off," "Late," "1 month late," "2 months late," "3 months late," or "4+ months late." *Deposits* is the level of deposits held by FDIC-insured bank branches in the county where the borrower lives. *Realized rate* is rate the borrower pays on his completed loan. Variable definitions and data sources are in the appendix. Standard errors, which we cluster at the county level, appear in parentheses.

***Indicates statistical significance at the 1% level.

separately using each of these three indicators as the dependent variable.

We find that the coefficient on *Deposits* is insignificant under all three specifications. By breaking *Bad loan* into its components, these non-results show that *Deposits* is uncorrelated with several alternative definitions of distress. However, we do not report these results because the alternative dependent variables are highly correlated with one another and *Bad loan*. For example, many loans that eventually earn a status of "Charge-off" first had statuses of "1 month late," "2 months late," etc.

The regression in column (1) in Table 4 is identical in structure to the regression in column (2) of Table 2. It is an OLS regression with identical control variables. One advantage of this approach is that it facilitates comparison across specifications. That is, it allows us to confirm our assumption that *Deposits* only affects borrowers' willingness to pay through local lending conditions without introducing the possibility that the insignificant coefficient on *Deposits* in Table 4 could be driven by different modeling choices. However, a drawback to this approach is that the dependent variable is an indicator variable, and thus a probit model may be more desirable. Therefore, for robustness, we repeat the test in this section using a probit model. Column (2) contains the results. As under the OLS specification, we continue to see that *Deposits* does not predict borrowers' propensities to default on their loans.[9]

Finally, for additional robustness purposes, we conduct Cox proportional hazard models. The dependent variable is the number of days between origination and the earliest date the loan's status becomes "Default (bankruptcy)," "Charge-off," "Late," "1 month late," "2 months late," "3 months late," or "4+ months late." For loans that borrowers pay off in full and on time, the dependent variable is right-censored at the number of days between origination and maturity of the loan. We include all of the same controls in Table 4 (including *Realized rate*), with the exception of the five-part splines for the measures of consumer auto, credit card, and mortgage debt, and the fraction of those measures that are delinquent. (When we include these splines, the Cox proportional hazard models are unable to converge because of flat regions resulting in missing likelihoods.) We include the continuous versions of these variables instead. We cluster standard errors at the county level, just as in the baseline OLS regressions. Under this specification, the coefficient on *Deposits* is again small and statistically insignificant. Specifically, we find that the instantaneous probability of a loan having a *Bad loan* outcome is only 0.1% higher in counties with bank deposits one standard deviation above the average.

5. Conclusion

This paper examines how local access to finance affects consumers' willingness to pay for loans on Prosper .com, a peer-to-peer consumer lending intermediary and an alternative to traditional sources of finance, such as banks and other consumer finance intermediaries. We find that consumers with better access to bank financing seek loans at lower interest rates on Prosper. A challenge to understanding how consumers choose their financing sources and terms is that a borrower's characteristics and the 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. One advantage of the Prosper data is the richness of covariates we are able to use. We saturate our regressions with vectors of control variables that capture borrower attributes and local economic conditions. Although this approach may not fully resolve endogeneity concerns, the richness of the data mitigates the possibility that omitted variables could drive our results.

Our findings enhance our understanding of how consumers make financial decisions. We show that 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 is associated with borrowers exhibiting less willingness to pay for loans 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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Appendix. Variable Definitions and Data Sources

Variable name	Definition and source
Maximum rate	Maximum interest rate the borrower is willing to pay when applying for a loan on Prosper. Source: Prosper.com
Realized rate	The interest rate paid by Prosper borrowers if the loan request received funding. Source: Prosper.com
Amount requested	Dollar amount the borrower requests when applying for a loan on Prosper. Source: Prosper.com
Percent funded	The fraction of Amount requested funded by lenders on Prosper. Source: Prosper.com
Deposits	Number of deposits (in millions of dollars) held by FDIC-insured bank branches in the county-year where the borrower lives. We standardize this variable to follow a mean-zero, unit-variance distribution in our tests. Source: Federal Deposit Insurance Corporation
Branches	Number of FDIC-insured bank branches in the county-year where the borrower lives. We standardize this variable to follow a mean-zero, unit-variance distribution in our tests. Source: Federal Deposit Insurance Corporation
Local economy controls	
Per capita income	Dollar amount of income per person in the county-year where the borrower lives. Source: U.S. Bureau of Economic Analysis
Unemployment	Unemployment rate in the county-year where the borrower lives. Source: U.S. Bureau of Labor Statistics
Poverty	Percentage of the population living below the poverty line in the county-year where the borrower lives. Source: U.S. Census Bureau
Auto debt	Auto debt per capita in the county-year where the borrower lives. Source: Board of Governors of the Federal Reserve System
Credit card debt	Credit card debt per capita in the county-year where the borrower lives. Source: Board of Governors of the Federal Reserve System
Mortgage debt	Mortgage debt per capita in the county-year where the borrower lives. Source: Board of Governors of the Federal Reserve System
Auto debt delinquent	Percentage of auto debt per capita that is delinquent in the county-year where the borrower lives. Source: Board of Governors of the Federal Reserve System
Credit card debt delinquent	Percentage of credit card debt per capita that is delinquent in the county-year where the borrower lives. Source: Board of Governors of the Federal Reserve System
Mortgage debt delinquent	Percentage of mortgage debt per capita that is delinquent in the county-year where the borrower lives. Source: Board of Governors of the Federal Reserve System
Loan request controls	
7 day duration indicator	An indicator variable taking a value of one if the loan listing is valid for seven days and zero if the loan listing is valid for 14 days. Source: Prosper.com
14 day duration indicator	An indicator variable taking a value of one if the loan listing is valid for 14 days and zero if the loan listing is valid for seven days. Source: Prosper.com
Image(s)indicator	An indicator variable taking a value of one if the loan listing includes at least one picture and zero if the loan listing includes no pictures. Source: Prosper.com
Loan category indicators	Indicator variables for each category of loan listing. Categories include Debt consolidation, Home improvement, Business, Personal loan, Student use, Auto, Other, and Not available. Source: Prosper.com
Basic borrower controls	
Debt/Income	The debt to income ratio of the borrower at the time the listing was created. This value is null if the debt to income ratio is not available. This value is capped at 10.01 (so any actual debt to income ratio larger than 1000% will be returned as 1001%). Source: Prosper.com
Homeowner indicator	An indicator variable taking a value of one if the borrower is a verified homeowner at the time the listing was created. Source: Prosper.com
Credit grade indicators	Indicator variables for the borrower's credit grade at the time the listing was created. Credit grades include AA, A, B, C, D, E, HR, and Missing. Source: Prosper.com

Appendix. (Continued)

Variable name	Definition and source
Detailed borrower controls	
Amount delinquent	Monetary amount delinquent at the time the listing was created. We use the log of one plus this variable in our tests. Source: Prosper.com
Bank card utilization	Percentage of available revolving credit that is utilized at the time the listing was created. Source: Prosper.com
Current credit lines	Number of current credit lines at the time the listing was created. We use the log of one plus this variable in our tests. Source: Prosper.com
Current delinquencies	Number of current delinquencies at the time the listing was created. We use the log of one plus this variable in our tests. Source: Prosper.com
Delinquencies last 7 years	Number of delinquencies in the last seven years at the time the listing was created. We use the log of one plus this variable in our tests. Source: Prosper.com
Inquiries last 6 months	Number of inquires in the last six months at the time the listing was created. We use the log of one plus this variable in our tests. Source: Prosper.com
Employment length status in months	Length in months of the employment status at the time the listing was created. We use the log of one plus this variable in our tests. Source: Prosper.com
Public records last 12 months	Number of public records in the last 12 months at the time the listing was created. We use the log of one plus this variable in our tests. Source: Prosper.com
Public records last 10 years	Number of public records in the last 10 years at the time the listing was created. We use the log of one plus this variable in our tests. Source: Prosper.com
Revolving credit balance	Monetary amount of revolving credit balance at the time the listing was created. We use the log of one plus this variable in our tests. Source: Prosper.com
Total credit lines	Number of total credit lines at the time the listing was created. We use the log of one plus this variable in our tests. Source: Prosper.com
Occupation indicators:	Indicator variables for the borrower's occupation at the time the listing was created. There are 63 different occupation indicator variable. Source: Prosper.com
Employment status indicators	Indicator variables for the borrower's employment status at the time the listing was created. Employment status categories include employed, full-time, not employed, other, part-time, retired, and self-employed. Source: Prosper.com
Income range indicators:	Indicator variables for the borrower's income range at the time the listing was created. Income range categories include $0 or unable to verify, $1–24,999, $25,000–49,999, $50,000–74,999, $75,000–99,999, $100,000+, and not employed. Source: Prosper.com

Note. This table defines the variables we use in our analysis and indicates our data sources.

Endnotes

[1] Examples of papers that focus on borrower characteristics include the following: Ravina (2012) finds that physically attractive borrowers are more likely to secure loans at cheaper interest rates. Duarte et al. (2012) find that borrowers whom lenders perceive to be untrustworthy are less likely to receive funding. Lin et al. (2013) find that borrowers' online friendships act as signals of credit quality, increasing the probability that borrowers receive funding, lowering interest rates on completed loans, and mitigating the probability of default. Everett (2010) finds that borrowers are less likely to default when they form groups because group membership holds the possibility of real-life personal connections. Pope and Sydnor (2011) find that certain ethnic groups receive more funding than others, and that lenders systematically underestimate the relative default rates of borrowers in different ethnic groups.

[2] Examples of papers that focus on Prosper's market structure include the following: Hildebrand et al. (2011) find that screening improves with the extent to which group leaders participate in loans on Prosper. Iyer et al. (2016) find that lenders on Prosper predict borrowers' probabilities of default with 45% greater accuracy than borrowers' credit scores. Zhang and Liu (2012) find evidence of herding among lenders on Prosper. Freedman and Jin (2011) argue that during it start-up period, Prosper improved lenders' ability to screen high-risk borrowers by changing the information it provided. Miller (2015) finds that lenders improved their abilities to screen borrowers after Prosper added additional metrics related to borrower credit quality in April 2006.

[3] Source: Prosper (http://www.prosper.com/about/, accessed July 1, 2014). 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.

[4] Source: http://www.nolo.com/legal-encyclopedia/peer-peer-lending-p2p-small-businesses.html (accessed July 1, 2014).

[5] The loan origination process on Prosper changed on December 19, 2010. Prosper simplified its lending process so that borrowers receive rates determined by a formula. Source: Securities and Exchange Commission (http://www.sec.gov/Archives/edgar/data/1416265/999999999510003619/9999999995-10-003619-index.htm, accessed July 1, 2014).

[6] Rigbi (2013) discusses the extent to which states' rate ceilings were binding for Prosper borrowers.

[7] To conserve space, Table 2 suppresses coefficients on all control variables and the constant. We provide complete output for these regressions in the Internet appendix.

[8] Source: Practical E-Commerce (http://www.practicalecommerce.com/articles/584-A-Lender-Or-Borrower-Be-Is-Prosper-com, accessed July 1, 2014) 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. . . "

[9] The reduction in observations between the OLS and probit models occurs because some completed loans are uniquely identified by just one control variable. For example, only one of the completed loan requests was made by an attorney. These observations drop during the maximum likelihood estimation procedure for the probit model.

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