THE ACCOUNTING REVIEW
Vol. 87, No. 4
2012
pp. 1385–1413

American Accounting Association
DOI: 10.2308/accr-50159

Do Unverifiable Disclosures Matter? Evidence from Peer-to-Peer Lending

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ABSTRACT: The role of disclosure in attenuating market inefficiencies has been the subject of extensive research. While costless, voluntary, and unverifiable disclosures are unlikely to be credible sources of information, prior research demonstrates that individuals' decisions can be influenced by uninformative content. I use a unique dataset from a peer-to-peer lending website, Prosper.com, to demonstrate an economically large effect of voluntary, unverifiable disclosures in reducing the cost of debt. My results show an additional unverifiable disclosure is associated with a 1.27 percentage point reduction in interest rate and an 8 percent increase in bidding activity.

Keywords: *voluntary disclosure; cost of debt; asymmetric information; microfinance; behavioral economics; Prosper.com.*

Data Availability: *All data are publicly available from sources identified in the paper.*

I. INTRODUCTION

The role of disclosure in attenuating inefficiencies in financial markets has been the subject of extensive research.[1] Generally, these studies focus on mandated and audited financial reports. The lack of good measures for voluntary disclosures limits empirical work in this area. In the absence of any cost, it is unclear that voluntary disclosures could be seen as a credible source of information and thus should not influence investment decisions. However, prior research in psychology and behavioral economics demonstrates that people incorporate objectively uninformative content into their decisions in certain circumstances (Nisbett et al. 1981; Gilbert

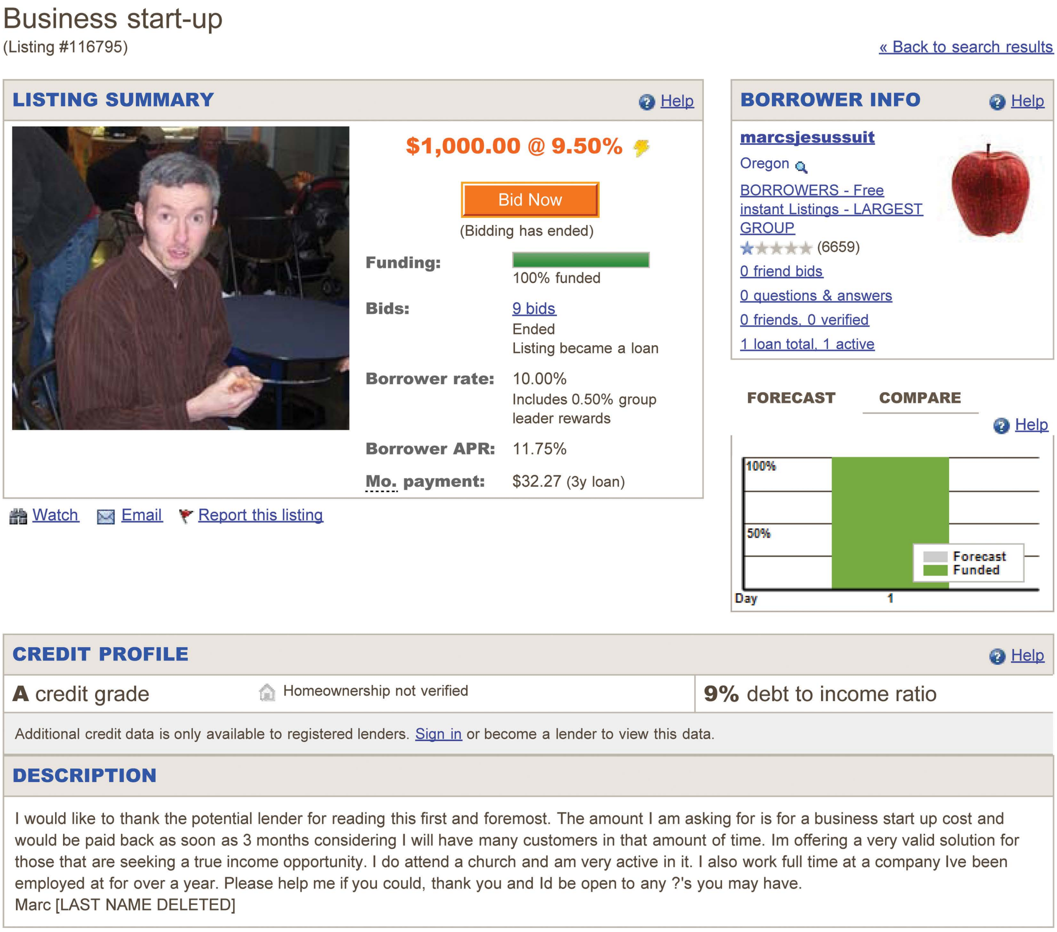
I thank John Harry Evans III and Steven Kachelmeier (the editors), Alan Jagolinzer, Bjorn Jorgensen, John Lynch, Paul Madsen (discussant), Steve Rock, and Lisa Sedor (discussant) for many insightful remarks as well as seminar participants at the University of Colorado at Boulder, 2010 Western Regional American Accounting Association Meeting, 2011 American Accounting Association Annual Meeting, and two anonymous reviewers for their helpful comments. I also gratefully acknowledge financial support from the AAA/Grant Thornton Doctoral Dissertation Award for Innovation in Accounting Education.

Editor's note: Accepted by John Harry Evans III, with thanks to Steven Kachelmeier for serving as editor on a previous version.

Submitted: September 2010
Accepted: January 2012
Published Online: March 2012

[1] See Healy and Palepu (2001) for a review of this literature.

FIGURE 1
Example Loan Listing on Prosper.com



et al. 1993; DellaVigna and Gentzkow 2009). Therefore, the influence of voluntary, unverifiable disclosures on investing decisions is an interesting empirical question.

In this study, I use a unique dataset of unsecured personal loans, made to individuals, originated through Prosper.com[2] to investigate the relationship between voluntary, unverifiable disclosures and the cost of debt. Prosper.com is an online, peer-to-peer lending marketplace that provides a service for lending that is similar to eBay.com's service for consumer products. On the Prosper website, potential borrowers apply for a loan by creating a loan listing. The loan listing states the amount of money they wish to borrow and the maximum interest rate they are willing to pay. Figures 1 and 2 give examples of loan listings. Potential lenders[3] bid on portions of loans by setting the minimum interest rate that they are willing to receive and the amount of the loan they wish to fund.

[2] All data used in this study are publicly available at http://www.prosper.com/tools/

[3] Lenders, as they are referred to here, are actually purchasing loans, making them technically loan buyers. However, for simplicity I refer to them as lenders throughout the paper.

FIGURE 2
Example Loan Listing on Prosper.com

SAFE INVESTMENT(Despite Credit Grade)!
(Listing #140068)

« Back to search results

LISTING SUMMARY Help

$3,200.00 @ 29.00%

Bid Now

(Bidding has ended)

Funding: 100% funded

Bids: 33 bids
Ended
Listing became a loan

Borrower APR: 30.56%

Mo. payment: $134.10 (3y loan)

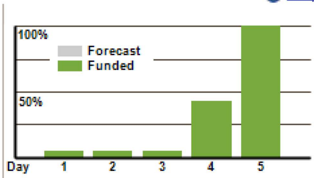
Watch Email Report this listing

BORROWER INFO Help

TweetyGirl
DOUGLASVILLE, GA
0 friend bids
2 questions & answers
1 friend, 0 verified
1 loan total, 1 active

FORECAST **COMPARE**

Help



CREDIT PROFILE Help

E credit grade Homeowner **61%** debt to income ratio

Additional credit data is only available to registered lenders. Sign in or become a lender to view this data.

DESCRIPTION

Purpose of loan:
This is a very safe investment for anyone bidding on this listing. I will use this loan to payoff two very high interest credit cards that I have with Household Bank. They went over the limit and I was charge extra fees(reason for $289 deliquent). I want to pay them off to begin reducing my debt burden and increse my credit score for the future.

My financial situation:
I am currently a doctoral student with a full-time job, a part-time job, two kids and a husband. My husband and I are homeowners with very recent credit issues due his hospitilization at the beginning of the this year. This caused us to use all available and excess funds to maintain. My dti doesn't reflect my part-time income because it is to new to verify. I can assure you that I would have no problem paying this loan and more than likely it will be paid off sooner than the total time allowed. I really want to get rid of these Household cards and begin to rebuild my credit back to its original state. I barely missed the "D" credit grade by two points.

Monthly net income: $ 2100 ($1200 part-time)

Monthly expenses: $ 1733
Housing: $ 0 (husband pays this)
Insurance: $ 130 (my half of auto and life)
Car expenses: $ 401
Utilities: $ 140 (my half)
Phone, cable, internet: $ 127
Food, entertainment: $ 150 (my half)
Clothing, household expenses $ 100 (my half)
Credit cards and other loans: $ 525
Other expenses: $ 260 (my half of daycare)

As you can see, once the part-time income kicks in there will be plenty left to pay this loan. Also, when I pay the two Household cards, it will free up about $200 which can go towards the prosper loan.

While Prosper verifies borrowers' identities and provides certain information obtained from their credit reports, a borrower's loan listing may also include voluntary and unverified personal information, such as intended use of proceeds, interest rates on other debts, explanations for poor credit ratings, or a picture. Using the natural variation in the amount of these voluntary, unverified disclosures in the loan listings, I identify the effect these disclosures have on the number of bids a loan listing receives and the final interest rate on a loan. Data are available for both successful loan listings that resulted in a loan and unsuccessful ones that did not receive enough bids to fund the listing.

My results show that these voluntary disclosures made in loan listings do affect the loans' interest rates. More unverifiable disclosures are associated with a lower interest rate on a loan. Additionally, more unverifiable disclosures increase the bidding activity on a loan listing. These effects are economically large: an additional disclosure is associated with a 1.27 percentage point reduction in interest rate and an 8 percent increase in bidding activity. Given that these essentially costless disclosures reduce interest costs for borrowers, it may seem surprising that not all borrowers make as many voluntary disclosures as possible, regardless of their truthfulness. At least two explanations may account for this behavior. First, the borrowers on Prosper may not fully understand the effectiveness of disclosures in reducing their interest costs. If the market had persisted,[4] then it is possible that learning would have occurred and the amount of disclosures made would have increased. Second, borrowers may be reluctant to use misleading disclosures to reduce their interest rates. This second argument is consistent with work demonstrating an aversion to lying, even when truth-telling is costly (Evans et al. 2001; Gneezy 2005).

My results contribute to a literature that demonstrates the role of presentation and persuasion in decision making by showing that unverifiable disclosures influence investors' decisions in a natural setting with large economic consequences. These findings may interest regulators as these nontraditional financial markets grow in prevalence. Since Prosper's inception in 2006, several other peer-to-peer lending sites have been established, such as Lending Club and Loanio. These online markets have already garnered the attention of the U.S. Securities and Exchange Commission, which imposed a cease-and-desist order against Prosper in 2008, determining that the website must register under the Securities Act of 1933.[5]

This study's findings also have implications for banking and microfinance. Prior research demonstrates the importance of relationships between borrowers and lenders when information asymmetries are severe (Petersen and Rajan 1994; Berger and Udell 1995). In the absence of a relationship, many microfinance institutions rely on group lending and liability to overcome adverse selection issues. While groups of affiliated lenders exist on Prosper, these groups do not have joint liability for the loans of their members. In the absence of group liability, methods developed by microfinance institutions to manage incentives include offering very small, but successively larger loans, and threatening to cut off access to future credit in the case of default (Armendariz de Aghion and Morduch 2010). However, in the context of Prosper, competition among lenders, and other lending websites, is likely to undermine the success of such efforts. Also, repeated borrowing is observed to only a limited degree. Thus, the Prosper marketplace offers an opportunity to study adverse selection problems in lending when traditional remedies are not available. Results indicate participants in the Prosper marketplace appear to be willing to rely on unverifiable disclosures to overcome informational asymmetries.

Finally, this study's setting offers several advantages over studies of voluntary disclosures by publicly traded firms. First, the direction of causality is clearer in the current study than in those using publicly traded firms. In this paper's setting, the disclosures must precede any investment

[4] Loans on Prosper are no longer priced through the bidding process analyzed in this study.
[5] Prosper has since registered and is again operational. All data in this study precede this action.

decision. In studies using publicly traded firms, the timing of events (that is, the disclosure and change in firm performance or value) is often less clear. Further, disclosure measures in studies of publicly traded firms are often incomplete, as firms can make disclosures through many alternative avenues, such as annual reports, management forecasts, or conference calls. In this study, all information available to potential lenders is contained in the loan listing, reducing the potential for incomplete measures. Last, most disclosures made by public firms, such as management forecasts, are verifiable in at least an *ex post* sense, giving them some level of credibility. Truly unverifiable disclosures by public firms compose such a small portion of the total information surrounding the firm that it is difficult to identify the effect of these disclosures. A natural solution to this problem is to examine disclosure effects in less developed markets (Verrecchia 2001). My paper contributes to the accounting literature by using such a setting to understand the impact of unverifiable disclosures on participants in a real world market. As Verrecchia (2001, 174) notes, "[A]s the theory of disclosure matures, it seems reasonable to inquire whether the empirical literature can provide additional insights into the economic consequences of disclosure."

The remainder of the paper is organized as follows. Section II outlines prior research related to disclosure and develops hypotheses. Section III describes the data source. Section IV discusses the research design. Section V details the main results, while Section VI presents alternative models to test for robustness. Section VII examines the association of unverifiable disclosures and loan performance. Section VIII concludes.

II. RELATED RESEARCH AND HYPOTHESIS DEVELOPMENT

Several contemporaneous working papers also examine the setting of the Prosper marketplace. Some of these studies examine the social aspects of Prosper, such as whether membership in a group of affiliated borrowers affects the success of loan listings (Freedman and Jin 2008; Lin et al. 2009).[6] Other studies examine aspects of the pictures of borrowers included in loan listings to investigate the effect of demographic characteristics such as gender, age, or race (Herzenstein et al. 2008; Pope and Sydnor 2011). Duarte et al. (2010) examine even more subjective aspects of borrower pictures, including trustworthiness and attractiveness. Herzenstein et al. (2011) examine claims of similarly subjective characteristics, such as trustworthiness or piety, in listings. Klafft (2008) offers an overview of how credit information and borrower-provided pictures are related to listing success, while Iyer et al. (2010) investigate how closely lenders can infer actual credit scores. Several of these studies attempt to control for information in the narrative description of the loan listings. Proxies used include word count (Freedman and Jin 2008; Lin et al. 2009), indicator variables for "general" or "specific" personal information (Herzenstein et al. 2008), or the residual of a regression of interest rate on credit variables (Iyer et al. 2010). Note this last measure is only available for successful listings that result in loans.

The present study differs from these works in that I code for the presence of specific disclosures in the loan listings. The unverifiable disclosure measure that I develop allows me to investigate specifically which elements of the loan listing description lenders respond to. I discuss this disclosure measure in detail in Section IV. I am aware of no other study that codes for the presence of particular disclosures in the loan listings.

Empirical studies of disclosure typically focus on firms listed on major exchanges, where voluntary disclosures represent a small fraction of the available information relative to mandatory, regulated filings. This research generally finds that costs of capital are decreasing in the amount of disclosure (Botosan 1997; Sengupta 1998). Sivakumar and Waymire (1994) offer some insight into

[6] Groups on Prosper do not have joint liability for the loans of their members, unlike some other micro-lending settings.

the effects of disclosures in an unregulated environment by investigating stock market reactions to voluntary disclosures for companies listed on the New York Stock Exchange during 1905–1910. Reporting requirements were minimal during this time. Annual earnings disclosures were mandatory; however, there were no accounting standards or audit requirements. Nonetheless, significant changes in price and trading volume are observed in association with discretionary disclosures during this period, suggesting that the disclosures were seen as at least partially credible. In a similar vein, Price (2000) investigates the association between earnings-related disclosures by franchisers and the fees they charge to franchisees. Disclosure of earnings by franchisers is optional. If disclosed, then the earnings claim is not subject to verification. The study indicates that franchisers who disclose earnings charge their franchisees higher fees. The willingness of franchisees to accept these fees suggests that they perceive these earnings disclosures to be credible. In the context of initial public offerings (IPOs), Leone et al. (2007) demonstrate that firms that volunteer more detailed intended-use-of-proceeds disclosures enjoy less IPO underpricing. Lang and Lundholm (2000) find firms increase voluntary disclosures before seasoned equity offerings to "hype" their stock. Upon the announcement of the offering, the market penalizes these firms, as it suspects their ulterior motive for the increase in disclosure. However, the reduction in stock price is incomplete, suggesting firms can use "hype" to reduce their cost of equity capital.

In summary, empirical research on unverifiable disclosures generally indicates market participants perceive such disclosures as being at least partially credible. However, voluntary disclosures made by firms, such as management forecasts, are often verifiable in an *ex post* sense. It is not clear that these results would generalize to a setting in which there is no opportunity for *ex post* settling up. While shareholders may have the opportunity to sue for misleading information, lenders on Prosper have no recourse against borrowers who may have used misleading information in their loan listings. Borrowers are never individually identified to lenders, and Prosper pursues all collection efforts on the lender's behalf. Thus, this setting offers a unique opportunity to further our understanding of how investors use unverifiable disclosures in decisions that have large economic consequences.

Analytical research on disclosures has typically focused on models where disclosures must be made truthfully. Early work in bargaining typically assumes signals are costless and verifiable (Grossman 1981; Milgrom 1981). However, since the seminal paper of Crawford and Sobel (1982), several analytical papers have explored scenarios in which the assumption that disclosures must be made truthfully is relaxed. In these so-called "cheap-talk" games, disclosures that are made may be false. Gigler (1994) shows that even when disclosures are unverifiable, the tension between proprietary costs and the wish to signal favorable information can make disclosures credible. That is, the cost associated with making the disclosure lends it credibility. However, in the setting of Prosper, one would not expect there to be proprietary costs associated with disclosing personal information for the purpose of obtaining a personal loan. Stocken (2000) considers a model in which a manager can make unverifiable disclosures to a potential investor. In this model the manager gives an unverifiable signal to an investor concerning the potential payoff of a project. In a single period game, no informative disclosures occur in equilibrium. In a repeated game, however, the manager will most likely disclose, and do so truthfully, as benefits exist to developing a reputation for telling the truth. While repeated interaction could produce credible disclosures on Prosper, the incidence of repeat borrowing is relatively low. During my sample period, 7 percent of borrowers obtained more than one loan through Prosper; however, less than 1 percent obtained more than two loans. Further, Stocken's (2000) result depends on both the number of interactions and the manager's discount factor being sufficiently high. A reading of the loan listings on Prosper indicates that many borrowers are financially distressed and already have large debts. This revealed preference for consumption over savings implies a low discount factor.

Models from the cheap-talk literature recognize that unverifiable disclosures are only relevant when agents' incentives are at least partially aligned (Farrell and Rabin 1996). However, evidence from both experiments and empirical studies demonstrates that people fail to fully account for conflicts of interest (Cain et al. 2005; Malmendier and Shanthikumar 2007). The tendency of people to rely on false or irrelevant information in decision making has been well established in the psychology literature. People behave as if their first reaction is to believe any information they are presented with (Gilbert 1991; Gilbert et al. 1993) and have difficulty ignoring irrelevant information in making decisions (Nisbett et al. 1981; Kahneman et al. 1982). Experimental research in marketing has produced results consistent with these findings. Carpenter et al. (1994) show that consumers value differentiating, but irrelevant, product attributes. Mandel and Johnson (2002) find changing only the background colors and images on a website influences product choices. Also, in psychology, Scharlemann et al. (2001) demonstrate subjects in a one-shot "trust" game exhibit more (potentially costly) cooperative behavior when their counterpart is represented by a picture of a smiling face. Overall, this stream of research suggests that lenders on Prosper would be influenced by the presence of unverifiable information in loan listings, especially given its prominent display in the listings (see Figures 1 and 2).

In related work in behavioral economics, Mullainathan et al. (2008) develop a model, in the spirit of the cheap-talk literature, that highlights how uninformative material can influence choice. Motivated by the psychology and marketing literature, they argue that rather than fully updating on new information, people think "coarsely" in that they partition potential outcomes into categories. The authors then demonstrate how this mental simplification strategy can result in useless information influencing choice, either through the misapplication of information within a partition, or by influencing the partition choice. Their model is consistent with results observed in experimental settings (for example, see Krueger and Clement 1994). A field experiment by Bertrand et al. (2010) also examines the effect of uninformative content on consumer choice. In loan offer letters sent to potential borrowers, the authors find that either including a picture of a smiling female, offering only one example of loans terms (versus several examples), or not suggesting a use for the loan increases offer acceptance by the same amount as a two-percentage point decrease in the interest rate of the loan. This result demonstrates that uninformative material can significantly affect behavior.

In sum, while traditional work in disclosure argues that unverifiable disclosures should be irrelevant, behavioral studies demonstrate that objectively uninformative content affects individual behavior. In the context of Prosper, if lenders are influenced by the voluntary, unverifiable disclosures made by borrowers in their loan listings, then I expect to see interest rates decreasing in the amount of disclosure. This leads to the following hypothesis:

H1: Interest rates are decreasing in the amount of voluntary, unverifiable disclosures in a loan listing.

If unverifiable disclosures in a loan listing are seen as convincing, then they should not only result in lower interest rates, but also greater bidding activity as well (Beaver 1968; Bamber 1986; Kim and Verrecchia 1991). That is, if these disclosures increase perceptions of quality regarding the loan listing, then I expect a listing with more disclosures to generate more bids. This prediction is consistent with work in auction theory that allows for entry of bidders (rather than assuming a fixed number of bidders). In this literature, it is costly to submit a bid. This cost is often interpreted as the cost of preparing the bid and processing information to learn what the object in question is worth. The number of entrants in an auction is decreasing in this cost (Samuelson 1985; McAfee and McMillan 1987; Levin and Smith 1994). If the unverifiable disclosures in a loan listing are perceived to be credible, then they should decrease the effort of learning the value of the loan, thus increasing the amount of bidding. This leads to my second hypothesis:

H2: The number of bids on a loan listing is increasing in the amount of voluntary, unverifiable disclosures in a loan listing.

Finally, I expect the relations in H1 and H2 to be stronger for loan listings by borrowers with relatively poor credit. Borrowers with good credit are likely able to obtain sufficient bids to fund their loan and a favorable rate by virtue of verifiable information alone (for example, their credit reports). Potential borrowers with poor credit will likely rely more heavily on the descriptive portion of the loan listing (that is, the section where they tell their personal story, which is unverifiable) in an effort to differentiate themselves from other competing borrowers with poor credit. Additionally, unverifiable disclosures may be more important for potential borrowers with poor credit quality because credit scores are based in part on the length of credit history. Therefore, a low credit score may reflect a dearth of verifiable information about a potential borrower. These predictions are formalized in the following hypotheses:

H3a: The relation between interest rates and the amount of voluntary, unverifiable disclosures in a loan listing is stronger for listings with relatively poor credit quality.

H3b: The relation between the number of bids and the amount of voluntary, unverifiable disclosures in a loan listing is stronger for listings with relatively poor credit quality.

Note that my measure of voluntary, unverifiable disclosure is a count of the number of specific items disclosed in the loan listing. While the specific content of what is revealed in a given disclosure is also likely to be important in determining its effect, I code only for the presence of a disclosure to increase objectivity. An indicator variable for the presence of a disclosure is a noisy proxy for its content. So to the extent the specific content of disclosures is important, my measure simply offers less powerful tests, biasing against finding a result. In additional analysis, I also investigate which types of disclosures have the greatest effect on lenders' decisions.

III. DATA

As outlined in Section I, the dataset of personal loan listings is collected from Prosper.com. All loans made through Prosper are three-year unsecured loans. Potential borrowers submit personal information to Prosper, enabling Prosper to verify their identity and obtain their credit reports. Prosper assigns a credit grade to each potential borrower based on his or her credit score.[7] Prosper also calculates a debt-to-income ratio (DTI) for each potential borrower by dividing the borrower's nonhousing debt payments (taken from their credit report) by his or her income. Income is self-reported by the borrower. Employment status,[8] length of employment, and occupation (chosen from a list) are also self-reported by potential borrowers.

After Prosper has obtained their credit information, potential borrowers can make loan listings by selecting the size of the loan they wish to obtain (maximum loan size is $25,000) and the maximum interest rate they are willing to pay (the maximum rate allowed is 35 percent). This information, along with their credit grade,[9] DTI ratio, employment status, length of employment, occupation, and stated income become part of the loan listing. Additionally, potential borrowers are encouraged to include in their loan listing a picture and additional personal information as to why

7 AA = 760 and up, A = 720–759, B = 680–719, C = 640–679, D = 600–639, E = 560–599, HR (high risk) = 520–559. Persons with scores below 520 are not allowed to create a loan listing.

8 Full-time, part-time, self-employed, retired, or not employed.

9 Lenders have the ability to view a variety of credit information in addition to the credit grade, including number of accounts currently delinquent, amount delinquent, delinquencies in last seven years, public records in last 12 months, public records in last ten years, inquiries in last six months, first credit line, current credit lines, open credit lines, total credit lines, revolving credit balance, and bankcard utilization.

they are good loan candidates in a free-form text field. This additional information often includes items such as the purpose of the loan (intended use of proceeds), current interest rates on other debts, explanations for poor credit grades, and monthly budgets. The picture and additional personal information are not verified by Prosper. Examples of loan listings are given in Figures 1 and 2.[10]

Once the borrower has made the loan listing, lenders may place bids on the listing. Lenders bid on loans by stating the amount of the loan they wish to fund (minimum of $50) and the minimum interest rate they are willing to receive (their reservation rate). Importantly, many different lenders may bid on and fund a loan listing. If, when the loan listing closes, the amount of money bid by lenders meets or exceeds the amount of the loan listing, then the listing becomes a loan. Winning bidders fund the loan in the amount of their bid and receive a note also equal to the amount of their winning bid. In the case that the total amount of bids exceeds the amount of the loan, the bidders with the lowest reservation rates are given priority in funding the loan. In this way, competition among lenders can lower the interest rate on a loan below the borrower's maximum acceptable rate.

Prosper makes money on this process by charging a closing fee to borrowers and a servicing fee to lenders. Penalties for default on Prosper loans are similar to those on other consumer debt. Delinquencies are reported to credit-reporting agencies, so borrowers' credit reports are adversely affected. Prosper also pursues collection efforts (through collections agencies) on behalf of the lenders. In no case can individual lenders pursue collection efforts themselves. Borrowers and lenders are identified to each other on the website only by screen names. Personal identities are not revealed.

The population of loan listings used in this study is all loan listings created on Prosper between February 12, 2007, and October 31, 2008. This period was selected because Prosper's informational policies remained constant over this time. In total, this includes 246,841 loan listings, 21,450 of which were successfully funded and 225,391 of which were not funded. The analysis that follows is based on a stratified random sample of 500 funded listings and 500 unfunded listings (1,000 listings in total).[11] I use a random sample rather than the entire population of listings because each loan listing must be read and hand-coded in developing the disclosure measure. I stratify over-funded and unfunded listings to ensure sufficient variation in each type of listing.

IV. RESEARCH DESIGN

Disclosure Measures

To evaluate the effect that voluntary, unverifiable disclosures have on the interest rate at which a loan listing funds, I must first develop a measure of such disclosures. To do this I grade each loan listing for the presence of specific voluntary and unverified information. One point is awarded for each item disclosed. Items scored are the purpose of the loan, income amount, income source, education, amount of other debt, interest rate on other debt, explanation for poor credit grade, listing of monthly expenses, and a picture of a person (presumably the borrower). All information I code is from the description section of the loan listing, which is not subject to verification.

The sum of all points awarded to a loan listing is its disclosure score (*DSCORE*). A summary of the definitions of the components of *DSCORE* is given in Panel A of Table 1, along with

[10] Some features of Prosper.com have changed since the time period examined in this study. All features described here relate to the operation of Prosper prior to November 2008. Many of the details of Prosper's operations during this time period are still available in the firm's SEC filings.

[11] Weights are not used in the following analysis; however, all inferences are robust to using sampling weights.

TABLE 1
Disclosure Score (*DSCORE*) Components

Panel A: Variable Definitions

Variable	Definition
Purpose	1 if purpose of loan given, 0 otherwise
Income	1 if income given, 0 otherwise
Inc Source	1 if income source given, 0 otherwise
Education	1 if education level given, 0 otherwise
Other Debt	1 if amount of other debt given, 0 otherwise
Other Debt Rate	1 if interest rate on other debt given, 0 otherwise
Poor Credit Expl	1 if explanation for poor credit grade given, 0 otherwise
Expenses	1 if monthly expenses listed, 0 otherwise
Picture	1 if picture of person included in listing, 0 otherwise

Panel B: Summary Statistics

	Unfunded			Funded			Difference in Means	
Variables	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Diff.	Std. Err.
Purpose	500	0.87	0.34	500	0.93	0.25	−0.07***	(0.019)
Income	500	0.79	0.41	500	0.74	0.44	0.05+	(0.027)
Inc Source	500	0.30	0.46	500	0.39	0.49	−0.09**	(0.030)
Education	500	0.07	0.26	500	0.10	0.30	−0.02	(0.018)
Other Debt	500	0.12	0.32	500	0.17	0.37	−0.05*	(0.022)
Other Debt Rate	500	0.05	0.21	500	0.11	0.31	−0.06***	(0.017)
Poor Credit Expl	500	0.21	0.41	500	0.21	0.41	0.00	(0.026)
Expenses	500	0.80	0.40	500	0.71	0.45	0.09**	(0.027)
Picture	500	0.50	0.50	500	0.59	0.49	−0.09**	(0.031)

Panel C: *DSCORE* Frequencies

	Frequency		
DSCORE	Unfunded	Funded	Total
0	18	8	26
1	25	38	63
2	57	56	113
3	123	90	213
4	130	113	243
5	86	108	194
6	41	56	97
7	16	23	39
8	4	6	10
9	0	2	2
Total	500	500	1,000

+, *, **, *** $p < 0.10$, $p < 0.05$, $p < 0.01$, and $p < 0.001$, respectively (for two-tailed tests).
DSCORE for each loan listing in the sample equals the sum of the nine indicator variables listed in Panel A.

summary statistics in Panel B. Below I describe each of the components of the disclosure score in some detail.

Purpose: A point is awarded if the borrower states the intended use for the proceeds of the loan. If the purpose of the loan is debt consolidation, then I create an additional indicator variable, *DEBT*. Debt consolidation is the most commonly stated purpose for borrowing, and I expect loans with this purpose to be perceived as relatively less risky than other loans, because a borrower's financial situation is likely to improve if he or she can consolidate debt. Therefore, I include *DEBT* as a separate covariate outside of *DSCORE* in several of my model specifications.

Income Amount: Income amount refers to a disclosure of a specific monthly or yearly income number. This may include other income, such as that coming from a spouse or self-employment, which is not used in calculating the borrower's debt-to-income ratio (DTI). I include DTI as a separate control in the analysis. Because the borrower's self-reported income only indicates a \$25,000 interval in which his or her income falls, a disclosure of a specific income value will provide incremental information to the lender. Thus a point is awarded for this disclosure.

Income Source: This disclosure specifies the source of the borrower's income. This may refer to additional sources of income beyond the mandatory job title given in the loan listing. It may also provide a more detailed description of the borrower's position. A point is not awarded for this disclosure if the borrower simply indicates the industry in which he or she is employed.

Education: A point is awarded if the borrower states in the listing the level of education he or she has achieved. However, statements such as "I need a loan to pay off student loans" or "pay for my last semester of tuition" do not earn points, as it is not clear if the borrower has completed or will complete the educational program.

Amount of other Debt: A point is awarded if the borrower reports outstanding balances of other debt.

Interest Rate on other Debt: A point is awarded if the listing reports the interest rate on at least one of the borrower's other debts. A specific interest rate must be stated. For example, simply stating that the borrower wants to use the loan to consolidate other high-interest debt does not earn a point without explicitly stating at least one rate.

Explanation of Poor Credit: A point is awarded if the borrower explains why his or her credit grade is low. The statement must be specific with respect to the reason the credit grade is low. For example, the statement "I need the loan because I have fallen behind on my mortgage payments" would not earn a point by itself, even though this is likely at least partially the source of the poor credit grade. Stating "I was injured in a car accident and have been unable to work, thus have trouble keeping up with bills" would earn a point.

Monthly Expenses: A point is awarded if the borrower lists their monthly expenses, for example, a budget.

Picture: A point is awarded if the listing includes a picture of a person, independent of who the picture represents.

Figures 1 and 2 offer examples of these disclosures. The loan listings in Figures 1 and 2 earn a point for the *Picture* disclosure. Likewise, both listings earn a point for stating the purpose of the loan, which is "for a business start up" in Figure 1 and "to payoff [sic] two very high interest credit cards" in Figure 2. The loan listing in Figure 2 also includes *Explanation of Poor Credit* as "credit issues due his hospitilization [sic]," *Income,* and *Monthly Expenses*. In particular, note that the listing in Figure 2 discloses income that would not be used in calculating the borrower's DTI.

Panel B of Table 1 reports summary statistics for the components of the disclosure score (*DSCORE*) in the sample. As noted previously, each element of the score is an indicator variable taking a value of 1 if the disclosure is present in the loan listing, and 0 otherwise. Most elements of the disclosure score display significant variation, although *Purpose, Education,* and *Other Debt Rate* have relatively low variation.

Panel B of Table 1 also reports that, for the nine disclosure components, disclosure frequency is greater for funded loans in six components, and five of these differences are statistically significant. Panel C of Table 1 reports the frequency of different levels of *DSCORE*. The median number of disclosures across all loan listings is 4. Successfully funded loans have a higher frequency than unfunded loans in each *DSCORE* category above 4. This preliminary evidence suggests lenders consider these unverifiable disclosures in the bidding process.

Control Variables

The variables used to control for other likely sources of variation in the rate at which a loan listing is funded and the number of bids it receives are auto-funding, maximum interest rate, loan amount, credit grade, homeownership, DTI, two-year Treasury bond yield, group membership, and prior loan performance. Each of these variables is described next.

Auto-Funding (AUTOF): A listing with automatic funding is closed as soon as the requested amount is met by bidders, so that additional bidders cannot bid down the rate once the loan is fully funded. This is an option for borrowers who want to fund a loan quickly. I expect auto-funded loans to have higher interest rates, as there is less opportunity for competition among bidders. This variable is an indicator variable taking value of 1 if the loan uses auto-funding, and 0 otherwise.

Maximum Interest Rate (MAXR): The borrower sets the maximum interest rate above which bids for funding the loan will not be accepted. It is not clear what effect this variable will have on the final rate of a loan. While *MAXR* places a cap on how high the rate can be, higher values could attract more bids, pushing the final interest rate lower.

Loan Amount (LAMT): Loan amount is the natural logarithm of the principal amount of the loan requested. I expect larger loans to have higher interest rates because larger payments should increase the risk of default. Larger loans should also attract more bids, because, holding bid size equal, it takes more bids to fund the loan.

Credit Grade (CRDG): The credit grade assigned to the borrower by Prosper is based on the borrower's credit score (see footnote 7). Grades range from AA (best) to HR or High Risk (worst). For the purposes of analysis, grades are assigned an integer value ranging from 1 to 7, with 1 reflecting the best credit grade (AA). I expect interest rates to be increasing with the credit grade.[12]

Homeownership (HOME): This variable indicates whether the borrower is a homeowner, as indicated by an active mortgage loan on the borrower's credit report. The effect of homeownership on the funded interest rate is not clear. Homeowners may be perceived as being more financially stable and may have greater access to other funding by using their house as collateral. Alternatively, the greater expense and inflexibility associated with a mortgage payment may increase risk. This variable is an indicator variable taking value of 1 if homeownership has been verified, and 0 otherwise.

Debt-to-Income Ratio (DTI): The debt-to-income ratio is the borrower's nonhousing debt payments, including both principal and interest components as taken from their credit report, divided by self-reported income. I expect interest rates to be increasing in DTI.

Bond Yield (BOND): This variable is the two-year Treasury bond yield on the date the listing was posted.[13] Listings fund quickly, usually within seven days. Even though all Prosper loans have three-year maturities, I use the two-year bond as there are no prepayment penalties, so I expect some loans to be paid back early. I expect interest rates charged on loans to increase with bond yields, as the opportunity cost of lending is greater. Additionally, bond yields are generally

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[12] Conclusions from the analysis are unchanged if I use an array of indicator variables for credit score in place of the index variable *CRDG*.

[13] Taken from http://www.federalreserve.gov/releases/h15/data.htm

increasing with expected inflation, so higher bond yields are also a proxy for inflation risk, which should increase the funded interest rate.

Group Membership (GROUP): Groups on Prosper are collections of people with a common interest, including professional, ethnic, religious, geographic, or athletic. The concept is that a group whose members consistently make on-time loan payments will develop a reputation, allowing the group's members to attract more bids and lower interest rates to their loan listings. Likewise, the social pressure of maintaining the group's reputation could reduce the likelihood of default for borrowers in the group. However, groups do not guarantee the loans of their members and members are in no way jointly liable for the loans of other group members. Several contemporaneous working papers show membership in a group of affiliated members on Prosper may affect the success of loan listings (Freedman and Jin 2008; Lin et al. 2009). Therefore, I include a control variable indicating group membership.

Prior Loan Performance (PR_G and PR_B): During my sample period, about 7 percent of borrowers had obtained loans previously through Prosper. Because prior loans are visible to lenders, I include control variables indicating the presence and performance of a prior loan. I expect that having either a loan on which all payments are current or having a fully paid prior loan (*PR_G*) to decrease the interest rate on a listing, while having a loan in default or with late payments (*PR_B*) should increase the interest rate on a listing.

Panel A of Table 2 reports summary statistics for all regression variables. *DSCORE* has a median of 4 of a possible of 9 for both funded and unfunded listings. The mean of *DSCORE* is slightly higher for funded loans at 3.95, compared to 3.70 for unfunded listings. Panel B of Table 2 gives the correlations between all regression variables.[14] For funded loans, the Pearson correlation of 0.203 between *RATE* and *DSCORE* is statistically significant, reflecting a positive relation between *RATE* and *DSCORE* before controlling for any other variables. Although this positive association is contrary to the hypothesis that the interest rate charged will be decreasing in disclosures, *DSCORE* is also strongly correlated with *CRDG*, the borrower's credit score, which may explain this result, as *CRDG* has a strong positive correlation with *RATE*. Indeed, the partial correlation between *RATE* and *DSCORE*, holding *CRDG* constant, is significantly negative at –0.084. The positive correlation between *DSCORE* and *CRDG* is consistent with the argument in Section II that the descriptive portion of the loan listing is relatively more important for borrowers with relatively poor credit.

Model

To test the effect of unverifiable disclosures on the interest rate at which a loan is funded (H1), I use a Tobit regression of the interest rate at which a loan listing is funded on the disclosure score and control variables. If lenders perceive the unverifiable disclosures in the loan listings as credible, then I expect to see the interest rate decreasing in the disclosure score. For unfunded loans, the interest rate limit is set at 35 percent, the maximum allowable rate. This assumes all loans would be funded at some interest rate if rates were allowed to exceed 35 percent. As noted in Section III, the sample has 500 funded loans (uncensored) and 500 unfunded loans (right-censored at $RATE \geq 0.35$). As previously described, the control variables used are auto-funding, maximum interest rate, loan amount, credit grade, homeownership, DTI, two-year Treasury bond yield, group membership, and prior loan performance. That is:

$$RATE_i = f(\beta_0, \beta_1 AUTOF_i, \beta_2 MAXR_i, \beta_3 LAMT_i, \beta_4 CRDG_i, \beta_5 HOME_i, \beta_6 DTI_i, \beta_7 BOND_i,$$

[14] All Variance Inflation Factors (VIFs) associated with the independent variables used in subsequent models are less than 2, indicating multicollinearity is unlikely to pose a problem (Menard 1995; Kennedy 2008).

TABLE 2
Regression Variables

Panel A: Summary Statistics

Variable[a]	Obs.	Mean	Std. Dev.	Median	Min.	Max.
Unfunded Listings						
RATE	NA	NA	NA	NA	NA	NA
BIDS	500	0.54	1.52	0.00	0.00	13.00
AUTOF	500	0.26	0.44	0.00	0.00	1.00
MAXR	500	0.21	0.09	0.20	0.04	0.35
LAMT	500	8.67	0.78	8.61	6.91	10.13
CRDG	500	5.58	1.61	6.00	1.00	7.00
HOME	500	0.30	0.46	0.00	0.00	1.00
DTI	500	0.69	1.44	0.32	0.02	10.01
BOND	500	3.40	1.14	3.17	1.43	5.08
GROUP	500	0.19	0.39	0.00	0.00	1.00
PR_G	500	0.03	0.17	0.00	0.00	1.00
PR_B	500	0.02	0.14	0.00	0.00	1.00
DEBT	500	0.45	0.50	0.00	0.00	1.00
DEFAULT	NA	NA	NA	NA	NA	NA
DSCORE	500	3.70	1.60	4.00	0.00	8.00
Funded Listings						
RATE	500	0.18	0.08	0.16	0.04	0.35
BIDS	500	22.09	21.64	16.00	0.00	134.00
AUTOF	500	0.21	0.41	0.00	0.00	1.00
MAXR	500	0.21	0.08	0.20	0.04	0.35
LAMT	500	8.44	0.90	8.52	6.91	10.13
CRDG	500	3.66	1.79	4.00	1.00	7.00
HOME	500	0.46	0.50	0.00	0.00	1.00
DTI	500	0.37	0.95	0.23	0.01	10.01
BOND	500	3.25	1.14	2.89	1.35	5.08
GROUP	500	0.29	0.46	0.00	0.00	1.00
PR_G	500	0.10	0.30	0.00	0.00	1.00

(continued on next page)

TABLE 2 (continued)

Variable[a]	Obs.	Mean	Std. Dev.	Median	Min.	Max.
PR_B	500	0.02	0.15	0.00	0.00	1.00
DEBT	500	0.45	0.50	0.00	0.00	1.00
DEFAULT	500	0.34	0.47	0.00	0.00	1.00
DSCORE	500	3.95	1.72	4.00	0.00	9.00

Panel B: Correlations[b]

	RATE	*BIDS*	*AUTOF*	*MAXR*	*LAMT*	*CRDG*	*HOME*	*DTI*	*BOND*	*GROUP*	*PR_G*	*PR_B*	*DEBT*	*DEFAULT*	*DSCORE*
Unfunded Loans															
RATE	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
BIDS	NA	1.000	−0.039	**0.114**	**0.165**	**−0.448**	**0.099**	−0.042	−0.004	0.059	0.040	−0.043	−0.061	NA	0.026
AUTOF	NA	−0.032	1.000	**−0.103**	0.027	**0.124**	−0.054	−0.054	**0.341**	0.017	−0.016	−0.018	0.004	NA	0.032
MAXR	NA	**0.086**	**−0.113**	1.000	**−0.102**	**0.154**	−0.030	0.039	**−0.267**	0.056	0.024	0.025	**0.077**	NA	**0.088**
LAMT	NA	**0.173**	0.029	**−0.108**	1.000	**−0.403**	**0.116**	**0.264**	**0.131**	**−0.108**	**−0.081**	−0.051	−0.040	NA	0.006
CRDG	NA	**−0.401**	**0.124**	**0.167**	**−0.411**	1.000	**−0.221**	**−0.174**	**0.122**	0.056	−0.017	0.000	0.064	NA	0.072
HOME	NA	0.048	−0.054	−0.032	**0.117**	**−0.219**	1.000	0.066	−0.036	**−0.075**	−0.005	0.062	**−0.101**	NA	**−0.075**
DTI	NA	−0.032	−0.007	−0.035	**0.078**	−0.062	**0.088**	1.000	−0.034	−0.039	**−0.106**	−0.045	0.044	NA	0.002
BOND	NA	−0.027	**0.358**	**−0.320**	**0.125**	**0.124**	−0.050	**0.114**	1.000	**0.205**	−0.055	**−0.105**	−0.060	NA	0.011
GROUP	NA	**0.079**	0.017	0.050	**−0.118**	0.059	**−0.075**	0.027	**0.223**	1.000	**0.164**	**0.221**	**0.090**	NA	**0.179**
PR_G	NA	0.036	−0.016	0.020	**−0.079**	−0.008	−0.005	−0.053	−0.059	**0.164**	1.000	−0.024	0.066	NA	−0.032
PR_B	NA	−0.041	−0.018	0.023	−0.057	0.002	0.062	−0.038	**−0.110**	**0.221**	−0.024	1.000	0.043	NA	0.034
DEBT	NA	−0.057	0.004	**0.080**	−0.050	0.071	**−0.101**	−0.058	−0.058	**0.090**	0.066	0.043	1.000	NA	**0.249**
DEFAULT	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
DSCORE	NA	0.051	0.040	**0.100**	0.015	0.061	**−0.078**	−0.070	0.002	**0.166**	−0.021	0.027	**0.273**	NA	1.000
Funded Loans															
RATE	1.000	**−0.349**	**0.383**	**0.890**	**−0.164**	**0.738**	**−0.196**	**0.290**	−0.048	**0.095**	−0.037	**0.175**	0.062	**0.349**	**0.237**
BIDS	**−0.324**	1.000	**−0.462**	**−0.175**	**0.740**	**−0.534**	**0.281**	0.038	−0.018	−0.033	0.012	−0.054	0.031	0.021	−0.020
AUTOF	**0.393**	**−0.324**	1.000	**0.183**	**−0.135**	**0.251**	**−0.086**	0.019	**0.210**	0.012	−0.021	**0.124**	0.023	**0.132**	−0.003
MAXR	**0.882**	**−0.162**	**0.176**	1.000	**−0.158**	**0.682**	**−0.148**	**0.286**	**−0.118**	**0.089**	−0.035	**0.160**	0.051	**0.331**	**0.276**
LAMT	**−0.197**	**0.737**	**−0.121**	**−0.163**	1.000	**−0.462**	**0.285**	**0.173**	0.045	0.010	0.012	0.023	**0.097**	**0.107**	−0.039
CRDG	**0.724**	**−0.495**	**0.251**	**0.690**	**−0.440**	1.000	**−0.330**	**0.092**	0.066	**0.199**	0.006	0.064	**0.105**	**0.215**	**0.356**

(continued on next page)

TABLE 2 (continued)

	RATE	*BIDS*	*AUTOF*	*MAXR*	*LAMT*	*CRDG*	*HOME*	*DTI*	*BOND*	*GROUP*	*PR_G*	*PR_B*	*DEBT*	*DEFAULT*	*DSCORE*
HOME	**−0.192**	**0.290**	**−0.086**	**−0.152**	**0.273**	**−0.329**	1.000	0.072	0.014	−0.028	**0.084**	−0.003	0.022	0.060	**−0.173**
DTI	0.052	0.040	0.002	0.072	**0.099**	−0.001	0.041	1.000	−0.067	**0.115**	−0.027	**0.084**	**0.187**	**0.202**	0.044
BOND	**−0.084**	−0.044	**0.219**	**−0.150**	0.056	0.070	0.005	**0.098**	1.000	**0.367**	**−0.082**	**−0.121**	0.029	0.061	**0.157**
GROUP	**0.082**	−0.068	0.012	**0.078**	0.022	**0.193**	−0.028	**0.077**	**0.389**	1.000	**0.097**	**0.083**	0.064	0.052	**0.253**
PR_G	−0.038	−0.025	−0.021	−0.030	0.011	0.014	**0.084**	0.031	**−0.093**	**0.097**	1.000	−0.049	−0.030	**−0.106**	0.023
PR_B	**0.203**	−0.071	**0.124**	**0.170**	0.016	**0.074**	−0.003	0.010	**−0.125**	**0.083**	−0.049	1.000	0.055	**0.182**	−0.026
DEBT	0.053	−0.011	0.023	0.044	**0.101**	**0.115**	0.022	0.005	0.028	0.064	−0.030	0.055	1.000	−0.002	**0.185**
DEFAULT	**0.331**	0.048	**0.132**	**0.320**	**0.114**	**0.222**	0.060	**0.100**	0.070	0.052	**−0.106**	**0.182**	−0.002	1.000	−0.059
DSCORE	**0.203**	−0.037	−0.011	**0.259**	−0.012	**0.355**	**−0.158**	−0.023	**0.163**	**0.247**	0.025	−0.027	**0.195**	−0.058	1.000

Bold indicates significance at the 10 percent level or better.

[a] *RATE* is the interest rate at which the loan funded. *BIDS* is the number of bids on the loan divided by the number of days the loan listing was open, rounded to the nearest integer. *AUTOF* is an indicator variable for auto-funding. *MAXR* is the maximum interest rate that the borrower will accept for his loan listing. *LAMT* is the natural log of loan principal amount. *CRDG* is borrower's credit score. *HOME* is an indicator variable for homeownership. *DTI* is borrower's debt-to-income ratio. *BOND* is the two-year Treasury bond yield on loan listing date. *GROUP* is an indicator variable for membership in a Prosper Group. *PR_G* is an indicator variable for having a prior Prosper loan that was paid off. *PR_B* is an indicator variable for having a prior Prosper loan that defaulted. *DEBT* is an indicator variable for the borrower claiming that the purpose of the loan is debt consolidation/refinancing. *DEFAULT* is an indicator variable for the loan resulting from the listing eventually defaulting. *DSCORE* is the borrower's disclosure score (see Table 1).

[b] Pearson correlations are below the diagonal, Spearman correlations are above.

$$\beta_8 GROUP_i, \beta_9 PR\_G_i, \beta_{10} PR\_B_i, \beta_{11} DSCORE_i) + \varepsilon_i \tag{1}$$

where:

RATE = interest rate at which the loan was funded;
AUTOF = indicator variable, taking value of 1 if loan used auto-funding, 0 otherwise;
MAXR = maximum interest rate the borrower will accept for his or her loan listing;
LAMT = natural logarithm of principal amount of the loan;
CRDG = borrower's credit score; takes integer values 1 through 7, with 1 being best score (or AA, see footnote 7);
HOME = indicator variable, taking value of 1 if borrower is homeowner, 0 otherwise;
DTI = borrower's debt-to-income ratio;
BOND = yield on two-year Treasury bond on date loan listing was posted;
GROUP = indicator variable, taking value of 1 if borrower is a member of a Prosper group, 0 otherwise;
PR_G = indicator variable, taking value of 1 if the borrower has a prior loan that has been paid off or is current at the time of the listing, 0 otherwise;
PR_B = indicator variable, taking value of 1 if the borrower has a prior loan that defaulted or has late payments at the time of the listing, 0 otherwise; and
DSCORE = borrower's disclosure score (see Table 1).

The coefficient of primary interest is β_{11}. Alternatively, I estimate this model using each level of disclosure, rather than the index variable *DSCORE*.

I use a Poisson regression to test the effect of unverifiable disclosures on the number of bids a loan listing receives (H2). For this model, the dependent variable is the number of bids per day a listing receives (*BIDS*). Formally, I define *BIDS* as the number of bids on a loan divided by the number of days the loan listing was open, rounded to the nearest integer. If the lenders perceive the additional information provided in the unverifiable disclosures represented in *DSCORE* as credible, I expect to see *BIDS* increasing in *DSCORE*, as the lender's assessment of the loan listing is improved. Note that *BIDS* is not censored for unfunded loans. I use a Poisson regression due to the count nature of the *BIDS* variable.[15] Thus, the second model is:

$$\begin{aligned} BIDS_i = g(&\beta_0, \beta_1 AUTOF_i, \beta_2 MAXR_i, \beta_3 LAMT_i, \beta_4 CRDG_i, \beta_5 HOME_i, \beta_6 DTI_i, \beta_7 BOND_i, \\ &\beta_8 GROUP_i, \beta_9 PR\_G_i, \beta_{10} PR\_B_i, \beta_{11} DSCORE_i) + \varepsilon_i \end{aligned} \tag{2}$$

Control variables are as defined in Model (1). Again, the coefficient of primary interest is β_{11}. I also estimate this model using each level of disclosure, rather than the index variable *DSCORE*.

To test H3a and H3b, I define a new variable, *POOR*, as an indicator variable taking a value of 1 if *CRDG* is greater than or equal to 5.[16] Thus, *POOR* is an indicator for loan listings where the borrower has relatively poor credit. I then re-estimate Models (1) and (2) adding *POOR* and the interaction of *POOR* with all other independent variables. The coefficient of primary interest is that on the interaction *DSCORE***POOR*.

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[15] Results are robust to using a zero-inflated Poisson or negative binomial regression.
[16] I partition around *CRDG* = 5, as 5 is the median value of this variable. Defining *POOR* to indicate $CRDG \geq 5$ creates the most equal partitions. However, inferences from tests are unchanged if I define *POOR* to indicate $CRDG \geq 4$. Inferences are again unchanged if I define *POOR* to indicate $CRDG \geq 6$ in the Poisson models; however, the interaction term $DSCORE * POOR$ becomes statistically insignificant in the Tobit models under this definition.

TABLE 3

Tobit Regression Results

Variable[a]	(1)	(2)	(3)
Constant	−0.4206***	−0.4075***	−0.4122***
	(0.0499)	(0.0494)	(0.0495)
AUTOF	0.0206+	0.0180+	0.0183+
	(0.0106)	(0.0105)	(0.0105)
MAXR	−0.2258***	−0.1857**	−0.1914**
	(0.0626)	(0.0623)	(0.0624)
LAMT	0.0611***	0.0629***	0.0639***
	(0.0053)	(0.0053)	(0.0053)
CRDG	0.0689***	0.0704***	0.0710***
	(0.0032)	(0.0032)	(0.0032)
HOME	−0.0062	−0.0095	−0.0090
	(0.0087)	(0.0087)	(0.0087)
DTI	0.0176***	0.0165***	0.0164***
	(0.0041)	(0.0041)	(0.0041)
BOND	−0.0135**	−0.0118**	−0.0122**
	(0.0044)	(0.0043)	(0.0043)
GROUP	−0.0419***	−0.0330**	−0.0324**
	(0.0102)	(0.0103)	(0.0102)
PR_G	−0.0531***	−0.0518***	−0.0524***
	(0.0154)	(0.0152)	(0.0151)
PR_B	0.0373	0.0308	0.0326
	(0.0287)	(0.0284)	(0.0283)
DEBT			−0.0168*
			(0.0083)
DSCORE		−0.0127***	−0.0116***
		(0.0026)	(0.0026)
Model Chi-Squared	702.26***	726.60***	730.68***
Number of Obs.	1,000	1,000	1,000

+, *, **, *** $p < 0.10$, $p < 0.05$, $p < 0.01$, and $p < 0.001$, respectively (for two-tailed tests).
Tobit regression of interest rate at which loan was funded on disclosure score and control variables. Interest rate limit for unfunded loans is set at 35 percent, the maximum allowable rate. The sample has 500 funded loans (uncensored) and 500 unfunded loans (right-censored at $r \geq 0.35$). Standard errors in parentheses.
Dependent variable is *RATE*.
[a] *RATE* is the interest rate at which the loan funded. *AUTOF* is an indicator variable for auto-funding. *MAXR* is the maximum interest rate that the borrower will accept for his loan listing. *LAMT* is the natural log of loan principal amount. *CRDG* is borrower's credit score. *HOME* is an indicator variable for homeownership. *DTI* is borrower's debt-to-income ratio. *BOND* is the two-year Treasury bond yield on loan listing date. *GROUP* is an indicator variable for membership in a Prosper Group. *PR_G* is an indicator variable for having a prior Prosper loan that was paid off. *PR_B* is an indicator variable for having a prior Prosper loan that defaulted. *DEBT* is an indicator variable for the borrower claiming that the purpose of the loan is debt consolidation/refinancing. *DSCORE* is the borrower's disclosure score (see Table 1).

V. RESULTS

Table 3 presents the results for Model (1). The sign on the *DSCORE* coefficient is negative and statistically significant, consistent with H1. This suggests that the voluntary, unverifiable disclosures in a loan listing do affect the loan's interest rate. The coefficient on *DSCORE* of

−0.0127 indicates each additional disclosure is associated with a reduction in the loan's interest rate of 1.27 percentage points. Thus, all else equal, a loan listing with a *DSCORE* at the 75th percentile (*DSCORE* of 5) could expect to obtain an interest rate 2.54 percentage points lower than a loan listing with a *DSCORE* at the 25th percentile (*DSCORE* of 3).

The signs on the coefficients of the control variables are largely as expected. All but *HOME* and *PR_B* are statistically significant. The lack of significance on *PR_B* is surprising. While the positive and significant coefficient on *PR_G* indicates that lenders give lower rates to borrowers with good payment histories on prior loans, the lack of significance on *PR_B* suggests lenders do not punish borrowers for late payments or defaults on prior loans. Lenders may choose to ignore this negative information in the listing, or it may be subsumed by the other credit information in *CRDG*. Alternatively, lenders may believe that all borrowers on Prosper are likely to have poor payment histories, so they do not update their beliefs after observing late payments. As expected, the coefficient on *DEBT* is negative, indicating borrowers who state the purpose of their loan is debt consolidation receive a significantly lower rate than other borrowers. This is again consistent with unverifiable disclosures in the loan listings affecting lender behavior. The negative and significant coefficient on *BOND* is also surprising. This indicates that lower two-year bond yields are associated with higher loan rates. This may reflect lenders' heightened concern regarding the creditworthiness of borrowers who seek financing through Prosper when bank loan rates are low.

In untabled analysis, I estimate Model (1) using levels of the *DSCORE* variable in the regression, rather than the index variable. Every level of *DSCORE* is negatively associated with interest rates, consistent with the result from Table 3 that interest rates are decreasing with disclosure. While the increase in the magnitude of coefficients as the number of disclosures increases is not monotonic, the general trend is that more disclosures are associated with more negative coefficients. F-tests reveal the change in interest rate for an additional disclosure is relatively constant over different levels of disclosure. However, the decrease in rate for an increase from four to five disclosures is significantly greater than the change in rate for an increase from three to four disclosures. The impact of disclosures on rate is not statistically significant until five disclosures are present in the listing.

I also estimate several variations of Model (1) to demonstrate that the results are robust to alternative ways of controlling for the credit quality of potential borrowers. First, I replace the variable *CRDG*, which takes values of 1 to 7, with each value corresponding to a specific credit grade, with an array of dummy variables for each category of credit grade. Using *CRDG* to control for credit worthiness could be problematic because it equalizes the effect of credit grade on interest rate across every credit category. This could introduce a bias in *DSCORE* if interest rates are increasing in credit grade but at a decreasing rate, as *DSCORE* is also associated with credit grades. However, results are largely unchanged when using dummy variables to control for credit grades in a more general way, with the coefficient on *DSCORE* being −0.0123 and remaining significant at the 0.1 percent level. Second, I add all additional employment and credit report data that are available to lenders, as outlined in footnotes 8 and 9, as controls in the analysis. If these additional credit data are negatively associated with interest rates and positively associated with disclosures, then omitting it would introduce a negative bias to the *DSCORE* coefficient. Again, however, the results are robust to the inclusion of these additional controls, with the coefficient on *DSCORE* being −0.0120 and statistically significant at the 0.1 percent level.

Table 4 presents the results for regression Model (2). The coefficient on *DSCORE* is positive and statistically significant, indicating that more voluntary disclosures increase the bidding activity on a loan, consistent with H2. Again, this suggests that lenders consider the voluntary, unverifiable disclosures in the loan listings in their investment decisions. The coefficient on *DSCORE* of 0.08 in this regression indicates, all else equal, that an additional disclosure in the loan listing is associated with an 8 percent increase in the number of bids on the listing. The coefficient on *DEBT* is insignificantly

TABLE 4

Poisson Regression Results

Variable[a]	**(1)**	**(2)**	**(3)**
Constant	−0.54	−0.58	−0.57
	(0.380)	(0.376)	(0.381)
AUTOF	−0.71***	−0.69***	−0.68***
	(0.121)	(0.122)	(0.122)
MAXR	5.32***	5.06***	5.12***
	(0.544)	(0.550)	(0.551)
LAMT	0.40***	0.38***	0.38***
	(0.042)	(0.043)	(0.044)
CRDG	−0.51***	−0.52***	−0.53***
	(0.025)	(0.025)	(0.025)
HOME	0.21**	0.23**	0.22**
	(0.079)	(0.079)	(0.079)
DTI	−0.18+	−0.18+	−0.18+
	(0.101)	(0.103)	(0.104)
BOND	0.08*	0.07	0.07+
	(0.040)	(0.041)	(0.041)
GROUP	0.23**	0.17+	0.17+
	(0.087)	(0.090)	(0.090)
PR_G	0.22*	0.19+	0.19+
	(0.102)	(0.100)	(0.102)
PR_B	−0.21	−0.16	−0.17
	(0.270)	(0.264)	(0.259)
DEBT			0.07
			(0.071)
DSCORE		0.08***	0.08***
		(0.022)	(0.022)
Model Chi-Squared	1022.63***	1085.00***	1102.28***
Number of Obs.	1,000	1,000	1,000

+, *, **, *** $p < 0.10$, $p < 0.05$, $p < 0.01$, and $p < 0.001$, respectively (for two-tailed tests).
Poisson regression of number of bids per day listing was open on disclosure score and control variables. Robust standard errors in parentheses.
Dependent variable is *BIDS*.
[a] *BIDS* is the number of bids on the loan divided by the number of days the loan listing was open, rounded to the nearest integer. *AUTOF* is an indicator variable for auto-funding. *MAXR* is the maximum interest rate that the borrower will accept for his loan listing. *LAMT* is the natural log of loan principal amount. *CRDG* is borrower's credit score. *HOME* is an indicator variable for homeownership. *DTI* is borrower's debt-to-income ratio. *BOND* is the two-year Treasury bond yield on loan listing date. *GROUP* is an indicator variable for membership in a Prosper Group. *PR_G* is an indicator variable for having a prior Prosper loan that was paid off. *PR_B* is an indicator variable for having a prior Prosper loan that defaulted. *DEBT* is an indicator variable for the borrower claiming that the purpose of the loan is debt consolidation/refinancing. *DSCORE* is the borrower's disclosure score (see Table 1).

different from zero, indicating that, while borrowers stating loan consolidation as the purpose of their loan may receive lower rates, they do not generate more bidding activity on their listings.

As with Model (1), in untabulated results I estimate Model (2) with categories of *DSCORE* rather than the index variable. More extreme disclosure categories lack significance, perhaps due to limited power in these categories (see Table 1, Panel C). Disclosures in the listings do not affect the bidding on a listing until five disclosures are present. While the effect of an additional disclosure is

TABLE 5

Interacted Tobit Regression Results

Variable[a]	(1)		(2)		(3)	
Constant	−0.3452***	(0.0626)	−0.3417***	(0.0617)	−0.3526***	(0.0617)
AUTOF	0.0398*	(0.0167)	0.0382*	(0.0164)	0.0350*	(0.0164)
MAXR	−0.0735	(0.0960)	−0.0611	(0.0947)	−0.0883	(0.0950)
LAMT	0.0532***	(0.0067)	0.0543***	(0.0067)	0.0562***	(0.0067)
CRDG	0.0506***	(0.0059)	0.0521***	(0.0059)	0.0542***	(0.0059)
HOME	−0.0164	(0.0111)	−0.0175	(0.0109)	−0.0150	(0.0109)
DTI	0.0205***	(0.0052)	0.0200***	(0.0051)	0.0200***	(0.0051)
BOND	−0.0092	(0.0061)	−0.0084	(0.0060)	−0.0088	(0.0060)
GROUP	−0.0330*	(0.0154)	−0.0286+	(0.0153)	−0.0285+	(0.0153)
PR_G	−0.0445*	(0.0201)	−0.0441*	(0.0198)	−0.0456*	(0.0197)
PR_B	0.0488	(0.0513)	0.0396	(0.0507)	0.0487	(0.0507)
DEBT					−0.0281*	(0.0112)
DSCORE			−0.0063+	(0.0034)	−0.0048	(0.0034)
POOR	−0.3308**	(0.1211)	−0.2910*	(0.1208)	−0.2751*	(0.1204)
*AUTOF * POOR*	−0.0296	(0.0218)	−0.0329	(0.0216)	−0.0301	(0.0216)
*MAXR * POOR*	−0.2000	(0.1310)	−0.1453	(0.1302)	−0.1164	(0.1300)
*LAMT * POOR*	0.0259*	(0.0115)	0.0268*	(0.0115)	0.0244*	(0.0115)
*CRDG * POOR*	0.0464***	(0.0102)	0.0445***	(0.0102)	0.0419***	(0.0102)
*HOME * POOR*	0.0304	(0.0185)	0.0242	(0.0183)	0.0219	(0.0183)
*DTI * POOR*	−0.0121	(0.0082)	−0.0147+	(0.0083)	−0.0147+	(0.0082)
*BOND * POOR*	−0.0152+	(0.0090)	−0.0125	(0.0089)	−0.0119	(0.0089)
*GROUP * POOR*	−0.0160	(0.0207)	−0.0076	(0.0208)	−0.0078	(0.0207)
*PR_G * POOR*	−0.0089	(0.0317)	−0.0074	(0.0313)	−0.0054	(0.0312)
*PR_B * POOR*	−0.0193	(0.0623)	−0.0123	(0.0617)	−0.0216	(0.0616)
*DEBT * POOR*					0.0321+	(0.0170)
*DSCORE * POOR*			−0.0139**	(0.0053)	−0.0157**	(0.0054)
Model Chi-Squared	733.81***		761.81***		768.23***	
Number. of Obs.	1,000		1,000		1,000	

+, *, **, *** $p < 0.10$, $p < 0.05$, $p < 0.01$, and $p < 0.001$, respectively (for two-tailed tests).
Tobit regression of interest rate at which loan was funded on disclosure score and control variables. Interest rate limit for unfunded loans set at 35 percent, the maximum allowable rate. The sample has 500 funded loans (uncensored) and 500 unfunded loans (right-censored at $r \geq 0.35$). Standard errors in parentheses.
Dependent variable is *RATE*.
[a] *RATE* is the interest rate at which the loan funded. *AUTOF* is an indicator variable for auto-funding. *MAXR* is the maximum interest rate that the borrower will accept for his loan listing. *LAMT* is the natural log of loan principal amount. *CRDG* is borrower's credit score. *HOME* is an indicator variable for homeownership. *DTI* is borrower's debt-to-income ratio. *BOND* is the two-year Treasury bond yield on loan listing date. *GROUP* is an indicator variable for membership in a Prosper Group. *PR_G* is an indicator variable for having a prior Prosper loan that was paid off. *PR_B* is an indicator variable for having a prior Prosper loan that defaulted. *DEBT* is an indicator variable for the borrower claiming that the purpose of the loan is debt consolidation/refinancing. *DSCORE* is the borrower's disclosure score (see Table 1). *POOR* is an indicator variable for *CRDG* $\geq$ 5.

similar across most levels of disclosure, the effect of an increase from both three to four disclosures and four to five disclosures is significantly different from the effect of the previous increase.

Finally, I also estimate Model (2) including additional credit worthiness controls. As with Model (1), all inferences remain unchanged in the presence of these additional controls. The coefficient on *DSCORE* is 0.07 when controlling for credit grade with an array of dummy variables

TABLE 6

Interacted Poisson Regression Results

Variable[a]	(1)		(2)		(3)	
Constant	−1.3921**	(0.4288)	−1.4097***	(0.4234)	−1.4036**	(0.4277)
AUTOF	−0.7476***	(0.1554)	−0.7348***	(0.1569)	−0.7306***	(0.1569)
MAXR	3.9034***	(0.6779)	3.7520***	(0.6789)	3.7853***	(0.6825)
LAMT	0.4895***	(0.0483)	0.4807***	(0.0485)	0.4796***	(0.0492)
CRDG	−0.3556***	(0.0426)	−0.3631***	(0.0420)	−0.3658***	(0.0425)
HOME	0.2617**	(0.0859)	0.2706**	(0.0858)	0.2667**	(0.0860)
DTI	−0.1684	(0.1124)	−0.1667	(0.1129)	−0.1670	(0.1133)
BOND	0.0537	(0.0456)	0.0431	(0.0465)	0.0431	(0.0463)
GROUP	0.1319	(0.1029)	0.0995	(0.1038)	0.0996	(0.1036)
PR_G	0.1291	(0.0980)	0.1109	(0.0933)	0.1109	(0.0939)
PR_B	−0.3153	(0.3718)	−0.2442	(0.3806)	−0.2499	(0.3755)
DEBT					0.0274	(0.0779)
DSCORE			0.0491*	(0.0225)	0.0477*	(0.0223)
POOR	5.9371***	(1.2856)	5.4611***	(1.2675)	5.5955***	(1.2566)
AUTOF ∗ POOR	0.0126	(0.2147)	0.0808	(0.2206)	0.0632	(0.2226)
MAXR ∗ POOR	3.1874*	(1.4573)	2.7812+	(1.4294)	2.7575+	(1.4269)
LAMT ∗ POOR	−0.5096***	(0.1226)	−0.5340***	(0.1196)	−0.5514***	(0.1164)
CRDG ∗ POOR	−0.7047***	(0.1101)	−0.6885***	(0.1039)	−0.6940***	(0.1045)
HOME ∗ POOR	−0.3425+	(0.1971)	−0.2190	(0.1957)	−0.1934	(0.1996)
DTI ∗ POOR	0.0006	(0.2082)	0.0616	(0.2032)	0.0586	(0.2084)
BOND ∗ POOR	0.2722**	(0.1022)	0.2251*	(0.1010)	0.2301*	(0.1010)
GROUP ∗ POOR	0.3949*	(0.1817)	0.2933	(0.1827)	0.2924	(0.1827)
PR_G ∗ POOR	0.4491+	(0.2348)	0.4246+	(0.2399)	0.4399+	(0.2360)
PR_B ∗ POOR	0.2946	(0.5194)	0.1620	(0.4933)	0.1536	(0.4851)
DEBT ∗ POOR					0.1132	(0.1743)
DSCORE ∗ POOR			0.1821**	(0.0596)	0.1757**	(0.0609)
Model Chi-Squared	1083.08***		1151.07***		1163.56***	
Number of Obs.	1,000		1,000		1,000	

+, *, **, *** $p < 0.10$, $p < 0.05$, $p < 0.01$, and $p < 0.001$, respectively (for two-tailed tests).

Poisson regression of number of bids per day listing was open on disclosure score and control variables. Robust standard errors in parentheses.

Dependent variable is *BIDS*.

[a] *BIDS* is the number of bids on the loan divided by the number of days the loan listing was open, rounded to the nearest integer. *AUTOF* is an indicator variable for auto-funding. *MAXR* is the maximum interest rate that the borrower will accept for his loan listing. *LAMT* is the natural log of loan principal amount. *CRDG* is borrower's credit score. *HOME* is an indicator variable for homeownership. *DTI* is borrower's debt-to-income ratio. *BOND* is the two-year Treasury bond yield on loan listing date. *GROUP* is an indicator variable for membership in a Prosper Group. *PR_G* is an indicator variable for having a prior Prosper loan that was paid off. *PR_B* is an indicator variable for having a prior Prosper loan that defaulted. *DEBT* is an indicator variable for the borrower claiming that the purpose of the loan is debt consolidation/refinancing. *DSCORE* is the borrower's disclosure score (see Table 1). *POOR* is an indicator variable for $CRDG \geq 5$.

and 0.08 when including all additional creditworthiness controls, outlined in footnotes 8 and 9. Both are statistically significant at the 0.1 percent level. In addition, all results from subsequent analysis in this paper are robust to including these additional control variables. For parsimony, I only discuss results using *CRDG* as the credit quality control in subsequent analysis.

The results from the models testing H3a and H3b are presented in Table 5 and Table 6, respectively. In Table 5 the coefficient on the interaction *DSCORE* $*$ *POOR* of -0.0139 is statistically significant, indicating that an additional disclosure reduces a listing's interest rate by 1.39 percentage points more for borrowers with relatively poor credit. This is consistent with H3a. Table 6, consistent with H3b, shows that the coefficient on the interaction *DSCORE*$*$*POOR* is 0.1821, which is statistically significant. This indicates an additional disclosure increases bidding activity by 18.21 percent more for borrowers with relatively poor credit. Collectively, these results indicate that unverifiable disclosures are relatively more important for borrowers with relatively poor credit.

VI. ALTERNATIVE SPECIFICATIONS

In this section, I test the robustness of my results. First, I use a two-step model, rather than a Tobit model, to analyze separately whether a loan is funded and, if it is funded, which interest rate it receives. Next, I allow for the possibility that certain components of my disclosure measure may be correlated with information that is verified elsewhere in the loan listing. I separate from my disclosure measure those components that in limited instances may be verified in other sections of the loan listing to ensure I am measuring only the effect of truly unverifiable items in influencing lender behavior.

Table 7 shows the results of the two-step model. First, I estimate a probit model, regressing an indicator for a listing successfully funding on *DSCORE* and control variables. The results show that, for the average listing, an additional unverifiable disclosure increases the likelihood of funding by 3.28 percent. Next, for the subsample of successfully funded loans, I regress the actual interest rate on *DSCORE* and control variables. This shows that, given a loan is funded, an additional disclosure decreases the interest rate by 0.22 percentage points. Finally, I estimate a Heckman two-step model, where the inverse-Mills ratio from the funding equation is added to the rate regression to control for selection effects. I omit *GROUP* from the rate regression in the Heckman model to avoid identification only through nonlinearities. I use this as the identifying variable because group membership, while having a large effect on whether the loan receives enough bids to fund (as seen in the selection model), may have little direct impact on the rate of the loan.[17] Results from the Heckman model show that an additional disclosure decreases the interest rate on a loan by 0.31 percentage points.

Table 8 shows the results of Models (1) and (2) with the *DSCORE* disclosure index replaced with an array of indicator variables for each specific disclosure included in the index. Many individual disclosures do not have a statistically significant effect when considered in isolation. *Purpose*, *Other Debt Rate*, and *Poor Credit Expl* appear the most important in determining interest rates, while *Purpose, Other Debt*, and *Poor Credit Expl* have the greatest effect on bidding activity.

In limited instances Prosper may verify other borrower-provided information in the loan listing, such as income, employment, or occupation. While the information I code in developing *DSCORE* comes only from the descriptive portion of the loan listing, which is not subject to verification, this information is likely to be consistent with the information provided by the borrower elsewhere in the listing. Thus, these disclosures could be considered at least partially verified. Therefore, to ensure that lenders' responses to *DSCORE* are reflecting reliance on unverifiable information, I

[17] The fact that I am able to control for all information in a loan listing available to potential lenders mitigates the concern of selection bias. Identifying an exogenous instrument is difficult in this setting, as only information potentially relevant in the lending decision is likely to be included in the loan listing. Note results from the Heckman model are robust to not excluding a variable in the second stage, which may be a preferred specification when reasonable exclusion restrictions do not exist (Li and Prabhala 2007).

TABLE 7

Two-Step and Heckman Selection Models

Variable[b]	Model: Probit *FUNDED*[a]	Model: OLS *RATE*[a]	Model: Heckman *RATE*[a]
Constant		−0.0237	−0.0532*
		(0.0148)	(0.0255)
AUTOF	0.0495+	0.0430***	0.0417***
	(0.0299)	(0.0030)	(0.0037)
MAXR	1.4486***	0.6793***	0.6365***
	(0.1691)	(0.0346)	(0.0389)
LAMT	−0.1915***	0.0039*	0.0083*
	(0.0150)	(0.0018)	(0.0035)
CRDG	−0.1734***	0.0096***	0.0140***
	(0.0052)	(0.0015)	(0.0032)
HOME	0.0344	−0.0020	−0.0027
	(0.0254)	(0.0030)	(0.0030)
DTI	−0.0372***	−0.0000	0.0013
	(0.0106)	(0.0013)	(0.0017)
BOND	0.0335**	−0.0026+	−0.0036*
	(0.0128)	(0.0013)	(0.0016)
GROUP	0.0971**	0.0011	
	(0.0304)	(0.0034)	
PR_G	0.1682***	−0.0042	−0.0080
	(0.0504)	(0.0044)	(0.0054)
PR_B	−0.0140	0.0173	0.0172+
	(0.0760)	(0.0106)	(0.0096)
DSCORE	0.0328***	−0.0022**	−0.0031**
	(0.0075)	(0.0008)	(0.0011)
MILLS			−0.0143
			(0.0097)
Model Chi-Squared	549.93***		2580.61***
Adj. R^2		0.85	
Number of Obs.	1,000	500	1,000

+, *, **, *** $p < 0.10$, $p < 0.05$, $p < 0.01$, and $p < 0.001$, respectively (for two-tailed tests).
Average marginal effects reported for probit regression. Standard errors in parentheses.
[a] Dependent variables: *FUNDED* is an indicator for the loan listing resulting in a loan. *RATE* is the interest rate at which the loan funded.
[b] *AUTOF* is an indicator variable for auto-funding. *MAXR* is the maximum interest rate that the borrower will accept for his loan listing. *LAMT* is the natural log of loan principal amount. *CRDG* is borrower's credit score. *HOME* is an indicator variable for homeownership. *DTI* is borrower's debt-to-income ratio. *BOND* is the two-year Treasury bond yield on loan listing date. *GROUP* is an indicator variable for membership in a Prosper Group. *PR_G* is an indicator variable for having a prior Prosper loan that was paid off. *PR_B* is an indicator variable for having a prior Prosper loan that defaulted. *DSCORE* is the borrower's disclosure score (see Table 1). *MILLS* is the inverse Mills ratio.

partition *DSCORE* into two measures. *D_VER* includes disclosures that may be verified in other parts of the listing in limited instances (income, income source, other debt, and interest rate on other debt), while *D_UNV* includes disclosures that are most likely to be unverifiable in all cases (purpose, education, poor credit explanation, expenses, and picture). Table 8 shows that in both determining the interest rate and the number of bids on a loan, *D_UNV* is greater than *D_VER* in

TABLE 8

***DSCORE* Component Analysis**

Variable[a]	Tobit Regression Dependent Variable is *RATE* (1)	(2)	(3)	Poisson Regression Dependent Variable is *BIDS* (4)	(5)	(6)
Constant	−0.4075***	−0.4021***	−0.4069***	−0.5840	−0.8989*	−0.6792+
	(0.0494)	(0.0510)	(0.0497)	(0.3762)	(0.4037)	(0.3749)
AUTOF	0.0180+	0.0181+	0.0180+	−0.6908***	−0.6786***	−0.6928***
	(0.0105)	(0.0105)	(0.0105)	(0.1219)	(0.1210)	(0.1227)
MAXR	−0.1857**	−0.1946**	−0.1857**	5.0611***	5.3902***	5.1061***
	(0.0623)	(0.0630)	(0.0623)	(0.5502)	(0.5411)	(0.5476)
LAMT	0.0629***	0.0628***	0.0629***	0.3813***	0.3722***	0.3846***
	(0.0053)	(0.0053)	(0.0053)	(0.0430)	(0.0420)	(0.0427)
CRDG	0.0704***	0.0701***	0.0704***	−0.5221***	−0.5310***	−0.5280***
	(0.0032)	(0.0033)	(0.0032)	(0.0255)	(0.0267)	(0.0261)
HOME	−0.0095	−0.0081	−0.0096	0.2269**	0.2247**	0.2283**
	(0.0087)	(0.0087)	(0.0087)	(0.0792)	(0.0780)	(0.0780)
DTI	0.0165***	0.0165***	0.0165***	−0.1775+	−0.1754+	−0.1755+
	(0.0041)	(0.0041)	(0.0041)	(0.1029)	(0.1011)	(0.1002)
BOND	−0.0118**	−0.0113**	−0.0118**	0.0665	0.0769+	0.0723+
	(0.0043)	(0.0044)	(0.0043)	(0.0409)	(0.0395)	(0.0410)
GROUP	−0.0330**	−0.0313**	−0.0331**	0.1683+	0.1437	0.1744+
	(0.0103)	(0.0105)	(0.0103)	(0.0896)	(0.0888)	(0.0900)
PR_G	−0.0518***	−0.0513***	−0.0519***	0.1911+	0.2024*	0.1926+
	(0.0152)	(0.0153)	(0.0152)	(0.1002)	(0.1008)	(0.0998)
PR_B	0.0308	0.0362	0.0308	−0.1599	−0.1628	−0.1646
	(0.0284)	(0.0285)	(0.0284)	(0.2643)	(0.2560)	(0.2652)
DSCORE	−0.0127***			0.0800***		
	(0.0026)			(0.0222)		
Purpose		−0.0274+			0.5281**	
		(0.0152)			(0.1884)	
Income		0.0068			−0.1325	
		(0.0143)			(0.1292)	
Inc Source		−0.0102			0.0464	
		(0.0090)			(0.0773)	
Education		−0.0025			0.1229	
		(0.0140)			(0.1099)	
Other Debt		−0.0185			0.2065*	
		(0.0124)			(0.0892)	
Other Debt Rate		−0.0258+			−0.1357	
		(0.0146)			(0.1237)	
Poor Credit Expl		−0.0227*			0.2173*	
		(0.0107)			(0.0945)	
Expenses		−0.0185			0.2062	
		(0.0141)			(0.1316)	
Picture		−0.0099			0.0020	
		(0.0085)			(0.0692)	

(continued on next page)

TABLE 8 (continued)

Variable[a]	Tobit Regression Dependent Variable is *RATE* (1)	(2)	(3)	Poisson Regression Dependent Variable is *BIDS* (4)	(5)	(6)
D_VER			−0.0122*			0.0243
			(0.0050)			(0.0415)
D_UNV			−0.0130**			0.1329**
			(0.0045)			(0.0428)
Model Chi-Squared	726.60***	732.12***	726.61***	1085.00***	1263.39***	1079.23***
Number of Obs.	1,000	1,000	1,000	1,000	1,000	1,000

+, *, **, *** $p < 0.10$, $p < 0.05$, $p < 0.01$, and $p < 0.001$, respectively (for two-tailed tests).

[a] *RATE* is the interest rate at which the loan funded. *BIDS* is the number of bids on the loan divided by the number of days the loan listing was open, rounded to the nearest integer. *AUTOF* is an indicator variable for auto-funding. *MAXR* is the maximum interest rate the borrower will accept for his loan listing. *LAMT* is the natural log of loan principal amount. *CRDG* is borrower's credit score. *HOME* is an indicator variable for homeownership. *DTI* is borrower's debt-to-income ratio. *BOND* is the two-year Treasury bond yield on loan listing date. *GROUP* is an indicator variable for membership in a Prosper Group. *PR_G* is an indicator variable for having a prior Prosper loan that was paid off. *PR_B* is an indicator variable for having a prior Prosper loan that defaulted. *DSCORE* is the borrower's disclosure score (see Table 1). *Purpose–Picture* are individual components of *DSCORE* (see Table 1). *D_VER* is a subset of *DSCORE* (the sum of *Income*, *Inc Source*, *Other Debt*, and *Other Debt Rate*). *D_UNV* is another subset of *DSCORE* (the sum of *Purpose*, *Education*, *Poor Credit Expl*, *Expenses*, and *Picture*).

both magnitude and statistical significance. This offers additional evidence that borrowers respond to truly unverifiable information in loan listings.

VII. LOAN OUTCOME ANALYSIS

Given that unverifiable disclosures in loan listings significantly influence the decisions of lenders, a natural extension is to examine how these disclosures relate to loan performance. To accomplish this, I perform a probit regression of an indicator for eventual loan default on *DSCORE* and control variables. Table 9 shows the results of this model, with average marginal effects reported. This analysis is limited to listings that resulted in loans. The size of the loan strongly predicts future default, as does having a prior loan with poor performance. Of all control variables, only having a prior loan with current payments is significantly associated with a lower risk of future default. Interestingly, rate does not predict default. *DSCORE,* however, has a strong negative association with future defaults. An additional disclosure is associated with a 5.37 percent less chance of future default. Partitioning *DSCORE* into two components, as in Table 8, demonstrates that it is the most unverifiable of the disclosures that are driving this result. Thus, lenders' reliance on unverifiable disclosures in the loan listings appears to be validated in an *ex post* sense.

VIII. CONCLUSION

This study analyzes the impact of voluntary, unverifiable disclosures with a unique dataset of peer-to-peer loans. This setting allows for more powerful tests of unverifiable disclosures than are possible with publicly traded firms. The results indicate that such disclosures influence lenders by both decreasing the interest rate charged and increasing the bidding activity on a loan. Additional analysis shows the effect of these disclosures is stronger for borrowers with relatively poor credit. Further, unverifiable disclosures are negatively associated with future loan defaults.

TABLE 9
Loan Outcome Analysis

Variable[a]	(1)	(2)	(3)	(4)
AUTOF	0.0108	0.0175	−0.0076	−0.0137
	(0.0558)	(0.0481)	(0.0547)	(0.0552)
MAXR	0.7458	1.4099***	1.0146+	1.0009+
	(0.5441)	(0.3341)	(0.5322)	(0.5330)
LAMT	0.1104***	0.1270***	0.1247***	0.1243***
	(0.0262)	(0.0254)	(0.0256)	(0.0256)
CRDG	0.0420*	0.0642***	0.0588**	0.0594**
	(0.0192)	(0.0181)	(0.0190)	(0.0190)
HOME	0.0869*	0.0647	0.0663	0.0650
	(0.0411)	(0.0407)	(0.0407)	(0.0407)
DTI	0.0281	0.0209	0.0212	0.0215
	(0.0228)	(0.0221)	(0.0222)	(0.0222)
BOND	0.0378+	0.0477*	0.0490*	0.0477*
	(0.0206)	(0.0201)	(0.0201)	(0.0202)
GROUP	−0.0574	−0.0302	−0.0307	−0.0370
	(0.0488)	(0.0484)	(0.0483)	(0.0487)
PR_G	−0.1610*	−0.1554*	−0.1513*	−0.1519*
	(0.0727)	(0.0712)	(0.0710)	(0.0709)
PR_B	0.3932*	0.3756*	0.3667*	0.3656*
	(0.1607)	(0.1584)	(0.1584)	(0.1574)
RATE	0.8101		0.5668	0.6057
	(0.5986)		(0.5860)	(0.5883)
DSCORE		−0.0537***	−0.0525***	
		(0.0122)	(0.0123)	
D_VER				−0.0356
				(0.0232)
D_UNV				−0.0674**
				(0.0212)
Model Chi-Squared	106.72***	123.07***	124.01***	124.74***
Number of Obs.	500	500	500	500

*, **, *** $p < 0.05$, $p < 0.01$, and $p < 0.001$, respectively (for two-tailed tests).
+ $p < 0.10$ (for two-tailed tests).
Probit regression of an indicator for default on disclosure score and control variables. Average marginal effects reported. Standard errors in parentheses.
Dependent variable is *DEFAULT*.
[a] *DEFAULT* in an indicator variable for the loan resulting from the successful listing eventually defaulting. *AUTOF* is an indicator variable for auto-funding. *MAXR* is the maximum interest rate that the borrower will accept for his loan listing. *LAMT* is the natural log of loan principal amount. *CRDG* is borrower's credit score. *HOME* is an indicator variable for homeownership. *DTI* is borrower's debt-to-income ratio. *BOND* is the two-year Treasury bond yield on loan listing date. *GROUP* is an indicator variable for membership in a Prosper Group. *PR_G* is an indicator variable for having a prior Prosper loan that was paid off. *PR_B* is an indicator variable for having a prior Prosper loan that defaulted. *RATE* is the interest rate at which the loan funded. *DSCORE* is borrower's disclosure score (see Table 1). *D_VER* is a subset of *DSCORE* (the sum of *Income*, *Inc Source*, *Other Debt*, and *Other Debt Rate*). *D_UNV* is another subset of *DSCORE* (the sum of *Purpose*, *Education*, *Poor Credit Expl*, *Expenses*, and *Picture*).

These results can be interpreted as being consistent with a desire of borrowers to develop a reputation for truth telling in their disclosures so that they can continue to benefit from using these disclosures in future loan listings (Stocken 2000). However, this interpretation requires the possibility of repeated borrowing, which is observed only to a limited degree in the data. The results are also consistent with work in psychology and behavioral economics that shows objectively uninformative material can influence individual choice. Developing an appreciation for how individuals value and react to these types of disclosures is important in understanding and predicting the behavior of market participants.

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