Policy Uncertainty and Household Credit Access:

Evidence from Peer-to-Peer Crowdfunding

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Abstract

This paper studies how policy uncertainty affects household credit access. Using crowdfunding data from a major peer-to-peer (P2P) crowdfunding platform, Prosper.com, and a news-based policy uncertainty index developed by Baker, Bloom, and Davis (2016), we find that policy uncertainty negatively affects households' access to small loans. Using an instrument variable based on partisan conflicts and a difference-in-differences analysis relying on plausibly exogenous variation in policy uncertainty generated by gubernatorial elections, we show that the relation is likely causal. Investors' increased caution on deal selection and enhanced value of the "wait-and-see" option appear to be two plausible underlying channels through which policy uncertainty affects P2P crowdfunding. Further evidence suggests that policy uncertainty increases loan interest rates and default probabilities.

Key words: policy uncertainty; credit access; peer-to-peer crowdfunding

JEL number: G18; G21; D14

1. INTRODUCTION

Recent research suggests that policy uncertainty is an important source of risk and affects various firm decisions and the macro economy. For example, during the period of high policy uncertainty, firms cut investment expenditure (Julio and Yook, 2012; Gulen and Ion, 2016; Jens, 2017), engage in less in M&A activities (Bonaime, Gulen, and Ion, 2017; Nguyen and Phan, 2017), generate fewer patents (Bhattacharya et al., 2017), and are less likely to go public (Colak, Durnev, and Qian, 2017). These changes in firm fundamentals are also reflected in the stock market as stock prices drops as policy uncertainty rises (Pastor and Veronesi, 2013; Liu, Shu, and Wei, 2017). At the macro level, policy uncertainty foreshadows drops in GDP, drives business cycles (Bloom et al., 2016), and hampers economic recovery (Baker, Bloom, and Davis, 2012). It also decreases bank lending activities (Bordo, Duca, and Koch, 2016). Despite of the rich evidence on how firms respond to policy uncertainty, however, we know little about how this macro uncertainty affects households' financial decision making. Specifically, it is unclear that how the supply of credit in the microloan market, and the borrowing capacity of households, are influenced by policy uncertainty. This is an important but under-researched question in the literature on consumer finance (Tufano, 2009).

In this paper, we attempt to fill in this void and investigate the effect of policy uncertainty on the peer-to-peer (henceforth P2P) crowdfunding activities, which provide small credit to households and individuals. In P2P, prospective borrowers post their borrowing needs and personal information in electronic online platforms. Investors then review and make decisions on funding the loan requests (Morse, 2015). In this context, information on loan requests, origination, and performance, along with the profiles of the borrowers are available to the public, enabling us to gauge households' credit access directly and estimate the effect of policy uncertainty on it. Meanwhile, P2P crowdfunding, as an alternative financing marketplace for households and individuals, is of growing importance itself. It is one of the fast growing segments in the financial service sector in recent years, and is expected to grow to a $150-490 billion market by 2020.[1] Prior studies on this market mainly focus on contracting mechanisms that alleviate information asymmetry between borrowers and investors (lenders),

[1] For more details, see http://www.nasdaq.com/article/the-rise-of-peertopeer-p2p-lending-cm685513.

and market players' behavioral patterns.[2] A study on how macro-level uncertainty influences P2P dynamics could complement our understanding of the burgeoning market.

In this study, we examine the relation between policy uncertainty and household credit access in terms of P2P crowdfunding in a major P2P crowdfunding platform, Prosper.com, during the period between 2007 and 2016. Our data on P2P crowdfunding include 879,627 loan requests from 659,601 individual borrowers, 408,857 of which are successfully funded and become P2P loans. We use the news-based index developed by Baker, Bloom, and Baker (2016) (henceforth BBD) as a proxy for economic policy uncertainty.[3] This news-based BBD index is constructed as a count of newspaper articles in 10 major newspapers containing key terms related to policy uncertainty. To first get a visual observation between policy uncertainty and household access to P2P loans, we plot daily credit allocated to households on Propser.com, measured as the number and amount of loans made to borrowers, against the natural logarithm of the BBD index from 2007 to 2016 in Figure 1. A simple visual check suggests that after de-trending, daily crowdfunding activities (loan amount in the top panel and loan count in the bottom panel) are seemingly negatively correlated with the policy uncertainty proxy. The correlation between the BBD index and loan amount (number) is -0.3541 (-0.3531), which is significant at the 1% level. This negative relation appears pervasive from 2009 to 2016 and is not restricted to the period of poor economic conditions.[4]

Formally, we conjecture that P2P crowdfunding activities are significantly reduced during the period of high policy uncertainty. We argue that P2P investors are able to respond to the new information about increased credit risk on the loans caused by high policy uncertainty, and reduce their credit supply to peer households accordingly. There may be two plausible underlying channels in play. The disciplinary mechanism argues that policy uncertainty induces investors' risk-averse behavior (Panousi and Papanikolaou, 2012). P2P investors avoid risky loans to manage their overall credit risk exposure, which results in fewer

[2] See Morse (2015) for an excellent survey on studies on the P2P crowdfunding market.
[3] Earlier version of the Baker, Bloom, and Davis (2016) index is constructed as a weighted average of four components related to news, tax code changes, and dispersion in forecasts of monetary and fiscal policies. In our study, we follow the method in Baker, Bloom, and Davis (2016) to report results with the index from the newspaper approach, and results with the overall index are qualitatively the same.
[4] For example, in the five-year period following the Great Recession of 2007- 2008, policy uncertainty is at all-time highs while the crowdfunding activities remain suppressed, even though general economic conditions improved significantly.

funded loans. The real option channel argues that since P2P investments are irreversible (Duart, Siegel, and Young, 2012), the "wait-and-see" option value increases during the period of high policy uncertainty. Hence, investors are more likely to delay their P2P investments, loan requests are less likely to be funded, and the time it takes to fund a request is lengthened. Meanwhile, on the demand side, since households' cash flow could be lower during the period of high policy uncertainty, we expect that they cut current consumption and investment, and hence are less likely to borrow from the P2P market.

In our baseline analysis, we regress P2P crowdfunding outcomes (including whether a loan request is funded, the amount funded, and the time it takes to fund the request) on the BBD policy uncertainty index and a vector of macro- and loan request-level control variables. Our main results show that policy uncertainty is significantly and negatively correlated with investors' propensity to lend and thus households' access to credit in the P2P market. Our findings suggest investors cut their supply of small loans when they are exposed to high policy uncertainty.

It is reasonable to suspect that the negative relation we observed is driven by omitted variables. We attempt to address the endogeneity concern and establish causality using the instrumental variable (IV) approach and the difference-in-differences (DiD) approach. First, in the IV analysis we use the partisan-conflict index developed by Azzimonti (2018) as an instrument for policy uncertainty. The conflicts between Democratic and Republican legislators reflect uncertainty in future policies, but they are unlikely to directly affect P2P borrowing/lending behaviors. Therefore, the instrument should reasonably satisfy the exclusion restriction. The two-stage least squares (2SLS) regressions with the proposed instrument suggest a negative and causal link between policy uncertainty and crowdfunding activities. Second, we use plausibly exogenous variation in policy uncertainty generated by gubernatorial elections to tackle the identification issue. Gubernatorial elections increase policy uncertainty and are staggered across business and economic cycles. Our DiD analysis shows that loan requests from borrowers in states with forthcoming gubernatorial elections (and thus high policy uncertainty) are less likely to be fully funded. Again, these results suggest the negative relation between policy uncertainty and P2P crowdfunding activities is likely causal.

Our findings continue to hold in a number of robustness checks. First, to address the concern that there exists a switch by Prosper.com from auction-based loan pricing to platform- or model-based pricing on December 20, 2010 (see Subsection 4.3.1 for more details), we split our sample into an auction subsample and a posted-price subsample. We then re-estimate the 2SLS regressions in both subsamples, and obtain results that are consistent with those from the full sample. Second, to address the concern that possible confounding macroeconomic forces from the BBD index could drive our results, we replace the BBD index with the residuals from the regression of the US BBD index on the Canadian BBD index in our analyses, given the close tie between the US and Canadian economies. We still observe a negative relation between policy uncertainty and P2P crowdfunding activities. Finally, we include year fixed effects and use alternative measures for investment opportunities and economic uncertainties in the regressions. We observe qualitatively similar results in different specifications.

We then test how policy uncertainty affects household credit access through the two proposed channels, i.e., the disciplinary mechanism and the real option mechanism. We find that during the period of high policy uncertainty, investors are more likely to fund loan requests with higher credit ratings and requests from borrowers with higher FICO scores and income, which is consistent with the predictions of the disciplinary mechanism. We also show that when there is a secondary market for loans and thus P2P investment is more reversible or the cost of delaying an investment is high due to fierce competition among investors, the negative effect of policy uncertainty on P2P crowdfunding activities is less pronounced. These findings are consistent with the predictions of the real option mechanism.

Next, we explore how aggregate crowdfunding activities on Prosper.com respond to changes in policy uncertainty by counting the amount and number of requests and loans made in the platform in each month. This setting enables us to estimate the effect of policy uncertainty on households' demand for small loans, along with the impact on crowdfunding outcomes in the P2P market. Both the instrumental variable approach and the DiD approach suggest that high policy uncertainty leads to reduced borrowing demand and P2P loans made at the aggregate level. That is, during the period of high policy uncertainty, households are more reluctant to borrow. Since investors are more reluctant to lend in the same time as we discussed above, we observe a smaller crowdfunding volume in the P2P market.

In the final part of the paper, we address three remaining questions: 1) the effects of policy uncertainty on loan pricing and performance; 2) the effects of different types of policy uncertainty; and 3) how long the policy uncertainty effect lasts. First, we find that during the period of high policy uncertainty, the interest rates offered by borrowers, the contract rates that clear the deals, and the yields to investors all increase. This observation is consistent with Pastor and Veronesi (2013) in the sense that policy uncertainty commands a risk premium, and suggests that investors bear larger risk when policy uncertainty is higher even though they are able to mitigate it to some extent by either carefully selecting loans (the disciplinary channel we document before) or delaying riskier investments (the real option channel we document before). Our results on default rates show that high policy uncertainty leads to higher default probability and larger default amount. This finding is consistent with the notion that policy uncertainty does increase credit risk and worsen *ex post* loan performance. Second, we investigate the effects of uncertainty generated by various types of policies on P2P crowdfunding activities using a set of category-specific indices of policy uncertainty constructed by Baker, Bloom, and Davis (2016). We find that policy uncertainty related to fiscal policy (tax and government spending), general and financial regulation, health care, entitlement programs, and sovereign debt matters, while uncertainty related to trade policy and national security are relatively less important. Last, we find the negative effect of policy uncertainty on P2P crowdfunding is long-lasting for up to 22 months.

Our paper contributes to two growing strands of literature. First, it provides a new perspective on the impact of macro policy uncertainty. Prior studies mainly focus on how firms or institutional investors responds to shocks in policy uncertainty (e.g., Bloom (2009), Julio and Yook (2012), Gulen and Ion (2016), and Tian and Ye (2017)). To the best of our knowledge, this paper is the first study that looks into the micro-loan market and investigates how households' investment and borrowing decisions are affected by policy uncertainty. Households and individuals are players with equal importance to firms in the financial market, but attract less attention from researchers. We complement the policy uncertainty literature by establishing a causal link from macro uncertainty to households' credit access to P2P crowdfunding, which is a central topic in household finance.

Second, our study adds to the P2P crowdfunding literature on how this market responds to shocks from macroeconomic conditions. The existing literature argues that P2P investors are able to take advantages of technology and eliminate information asymmetry using various sources like social networks, narratives, and local information, leading to more active crowdfunding activities (Morse, 2015). This literature, however, has largely ignored the role played by governments and policies, among other macro shocks. Our paper fills in this gap by showing that both borrowers and investors are able to collect information from outside, and macro policy uncertainty reduces P2P crowdfunding activities.

The rest of our paper proceeds as follows. Section 2 reviews the literature and develops our hypotheses. Section 3 describes our data and sample. Section 4 reports main results. Section 5 discusses plausible underlying channels. Section 6 presents results on aggregate crowdfunding volume. Section 7 conducts additional analyses, and Section 8 concludes.

2. LITERATURE AND HYPOTHESIS

In this section, we review two growing bodies of literature: the economic impact of policy uncertainty and factors affecting P2P crowdfunding activities. Based on the existing theories and evidence, we attempt to combine these two strands of research and develop our hypothesis on the effect of policy uncertainty on P2P crowdfunding.

2.1 Related literature

2.1.1 Literature on the real effects of policy uncertainty

Theories predict that macro uncertainties suppress investment and employment at the firm and macro levels (Bloom, 2009). Among these uncertainties, it has been shown that policy uncertainty has a significant, real impact on various corporate decisions (investment in particular) and the real economy. Specifically, Julio and Yook (2012) document that policy uncertainty is negatively correlated with capital expenditure, using an international sample. Gulen and Ion (2016) use a news-based index of policy uncertainty constructed by Baker, Bloom, and Davis (2016), and find similar negative relation in US. Jens (2017) relies on the gubernatorial elections and establishes a causal link between policy uncertainty and reductions in corporate investment. Besides investments, Bonaime, Gulen, and Ion (2017) and Nguyen and Phan (2017) find that policy uncertainty is strongly and negatively associated with M&A

activities. Bhattacharya et al. (2017) show that innovation activities drop significantly during times of national elections with an international sample. Fundraising (IPO) activities are also dampened when policy uncertainty is high (Colak, Durnev, and Qian, 2017). At the macro level, policy uncertainty foreshadows drops in GDP and drives business cycles (Bloom et al., 2016), hampers economic recovery (Baker, Boom, and Davis, 2012), and influences cross-border flows of capital (Julio and Yook, 2016).

The impact of policy uncertainty on individual firms is also reflected in the financial market. The model in Pastor and Veronesi (2012) suggests that policy changes cause drops in prices, increases in volatilities and correlations among stocks. With respect to empirical evidence, Pastor and Veronesi (2013) find that there is a risk premium for policy uncertainty. Policy uncertainty predicts market returns and affects return volatilities (Brogaard and Detzel, 2015; Boutchkova et al., 2011). In a recent work by Liu, Shu, and Wei (2017), using a political scandal in China, they document a negative, causal effect of policy (political) uncertainty on stock prices. In the bond market, Kaviani et al. (2017) show that policy uncertainty is positively correlated to corporate credit spreads.

There are very few studies on how policy uncertainty influences capital demand or supply. Tian and Ye (2017) suggest policy uncertainty increases the value of the option to wait, reduces VC investments, and negatively affect VC investment outcomes. Bordo, Duca, and Koch (2016) find policy uncertainty is negatively related to bank credit growth.

2.1.2 Literature on factors affecting P2P crowdfunding

There is a nascent strand of literature on P2P crowdfunding as a disintermediation of consumer finance serving households' financing needs (Morse, 2015; Tufano, 2009). One central topic of the literature is on factors affecting the access to credit in this social marketplace. The general idea is that the crowd could use the proximity between borrowers and investors (lenders) generated in various scenarios in the P2P market, to produce useful information.

First, the proximity can be generated in social networks among borrowers, or between borrowers and investors. Lin, Prabhala, and Viswanathan (2013) suggest borrowers on Prosper.com with high-credit friends are more likely to be funded, receive lower interest rates, and default less. Freedman and Jin (2017) find online friendships between borrowers and investors have similar impacts. Second, narratives provided by the borrowers on the P2P platform can generate proximity. Herzenstein, Sonenshein, and Dholakia (2011) find trustworthy and successful identity claims in narratives increase funding and improve funding terms. Gao and Lin (2017) show that well-established linguistic features regarding creditworthiness all meaningfully relate to loan repayment. Some studies on photo-based discrimination, e.g., Duarte, Siegel, and Young (2012), find that borrowers who appear more trustworthy have larger probabilities of having loans funded and default less. Third, local market or economic information could also generate proximity. Crowe and Ramcharan (2013) show homeowners in states with declining house prices experience higher interest rates, greater credit rationing, and faster delinquency in the P2P market due to increased credit risk. Butler, Cornaggia, and Gurun (2017) find borrowers residing in areas with better access to bank finance request P2P loans with lower interest rates. Last, investors can become proximate by rational herding (Zhang and Liu, 2012), and home bias (Lin and Viswanathan, 2016). In addition, the market mechanism (auction versus platform-mandated pricing) can also affect P2P crowdfunding outcomes (Wei and Lin, 2017).

2.2 Hypothesis development

We conjecture that policy uncertainty reduces crowdfunding activities and thus households' access to credit in the P2P market because investors are more reluctant to lend. This argument is based on the supply side of P2P crowdfunding, and is consistent with previous findings on the effect of policy uncertainty on bank credit and VC investment (Bordo, Duca, and Koch, 2016; Tian and Ye, 2017).

Specifically, we argue that during the period of high policy uncertainty, a household's future cash flow and financial conditions are less certain, which translates to increased credit risk exposed to their creditors. Since P2P investors are able to respond to new information on credit risk and adjust their investment strategies in a timely manner as documented in the previous literature, it is likely that they are aware of and respond to the macro policy uncertainty that negatively affects the borrower's capacity to repay the loan in the future.[5,6] On the other hand, P2P investors' future cash flow is negatively affected by policy uncertainty as well, which may also make them more cautious when making investment in the P2P market.

There are two plausible underlying channels that are in play. First, policy uncertainty can affect P2P investors' propensity to lend through a disciplinary channel. Uncertainty could induce agents' risk-averse behavior (Panousi and Papanikolaou, 2012), because they anticipate exacerbated financial constraints (Bordo, Duca and Koch, 2016). In the P2P context, investors could actively manage the overall credit risk they bear with more careful portfolio selection. Similar to the investors in the stock market, during the period of high policy uncertainty, P2P investors become more prudent and delay large and risky investments (Nguyen and Phan, 2017). This argument suggests that policy uncertainty leads to fewer funded loans to households.

Second, policy uncertainty could affect P2P crowdfunding through a real option channel. Existing studies (e.g., Bernanke (1983), Rodrik (1991), Dixit and Pindyck (1994)) argues that if investment projects are irreversible, firms are more likely to delay them during the period of high uncertainty because of increased value of the "wait-and-see" option. Bonaime, Gulen, and Ion (2017) find the similar real option channel in the M&A setting. Given the high risk and the irreversibility of P2P investments (Duart, Siegel, and Young, 2012), we expect a negative relation between policy uncertainty and the probability of a loan request being funded since investors' incentives to wait increase. Another direct prediction is that the time it takes to fund a request will be lengthened when policy uncertainty is high.

Besides the supply of funds, we conjecture that policy uncertainty could negatively affect households' demand for small loans in the P2P market. This conjecture is based on the demand side of the P2P market. When facing greater uncertainty on future income, a rational household is likely to cut current consumption or investment and hence reduce their borrowing needs. Evidence on the negative relation between policy uncertainty and firms' capital expenditure in Gulen and Ion (2016) suggests that firms' capital needs decrease as policy

[5] For example, they actively collect and extract information on a loan's credit risk from social networks, soft information in the borrower's narratives, or local financial and economic status.

[6] According to an article in *Financial Times* (October 5,2014), as of 2014, 80% of investment going into Prosper.com and Lending Club is from institutional investors, who are able to collect, process, and respond to information about their investments more timely and correctly.

uncertainty is high. In addition, firms raise less capital under high policy uncertainty (Colak, Durnev, and Qian (2017)). In the same spirit, it is reasonable to argue that households spend and invest less during the period of high policy uncertainty, and are less likely to borrow using P2P crowdfunding.

3. DATA AND SAMPLE

In this section, we describe how P2P crowdfunding works on Prosper.com and summarize the data on borrowing requests and loans we obtain from the platform. We also provide descriptions on the construction and properties of the news-based policy uncertainty index from Baker, Bloom, and Davis (2016).

3.1 Prosper.com and data on P2P crowdfunding

Our data on borrowing requests and loans are obtained from a leading P2P crowdfunding platform, Prosper.com. In practice, prospective individual borrowers post their loan requests (i.e., listings), along with selected personal information related to their credit profiles, in the online platform. Investors, including institutions and individuals, then review the information and make lending decisions.

Our data set contains all transactions on the website from February 2007 to December 2016, including both funded and failed loan requests. We exclude observations with missing information, and end up with a sample of 879,627 requests posted on the website and 408,857 successfully funded requests that later become household loans. For each request, we obtain an extensive set of variables including requested amount, initial interest rate, loan terms, and funding status.[7] For each funded loan, we obtain information on the loan origination date, contract interest rate, and repayment record. For each borrower, we collect information on her profile, including her credit rating rated by Prosper.com, FICO score, debt-to-income ratio, number of credit lines, delinquency history, revolving credit balance, and bankcard utilization.

We report detailed variable definitions in Table A1 in the Appendix. Table 1 reports

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[7] For loan requests using the auction mechanism before December 20, 2010, we define initial rate as the borrower's reserve rate. For requests using the posted-price mechanism, we use the rate determined by Prosper.com as initial rate. See Subsection 4.3.1 for more details.

summary statistics of our key variables. Panel A shows that, in a typical loan request, a borrower requests to borrow \$13,117. She is willing to pay an annual interest rate of 15.6% and make monthly payments in the next 43 months to pay back the debt. 67.5% of the requests are successfully funded.[8] In a funded loan, the borrower is able to fulfil 93.5% of her funding target by raising \$12,495. Panel B shows that borrowers finally pay a 15.1% interest rate on the loan, and the investors receive a 14.1% yield after fees. The default rate is 12.2% for all loans, and 23.2% for due loans. Panel C presents information on borrowers. In our sample, there are 659,601 individual borrowers with an average debt-to-income ratio of 1.0. 47.7% of the borrowers are homeowners. An average borrower has 0.3 and 3.5 delinquencies at the time the loan request is made and in the past 7 years, respectively. Currently she has 10 active bank accounts (open credit lines) and uses 54.3% of her credit line. Her revolving credit balance is \$11,347. About one out of every 100 borrowers used to be a lender on Prosper.com.

3.2 Data on policy uncertainty

We measure policy-related economic uncertainty using the news-based Baker, Bloom, and Davis (2016) index (*BBD*), which is constructed based on newspaper coverage frequency. The BBD index includes policy uncertainty related to all types of policies, as long as these events are covered in the news. Specifically, since 1985 the BBD index measures policy uncertainty identified through an automated search of 10 major newspapers.[9] For each newspaper, a monthly count of articles that contain the following triple: 'uncertainty' or 'uncertain'; 'economic' or 'economy'; and one of the following policy terms: 'congress', 'deficit', 'Federal Reserve', 'legislation', 'regulation' or 'white house' is obtained. To be counted, an article must contain terms in all three categories pertaining to uncertainty, the economy, and policy. This count is then scaled by the total number of articles reported in the same newspaper in that month, resulting in 10 time series of monthly percentages of news

[8] On Prosper.com a prospective borrowers can target at either fully (100%) funding or partially funding. The threshold for a successful partial funding is currently set at 70%. That is, if the total bidding amount exceed 70% of the requested amount, the request will be categorized as "*Funded*", and a loan will be made. We control for the fully funding and partially funding targets in our regressions.

[9] These newspapers include the *Boston Globe*, the *Chicago Tribune*, the *Dallas Morning News*, the *Los Angeles Times*, the *Miami Herald*, the *New York Times*, the *San Francisco Chronicle*, the *Wall Street Journal*, the *Washington Post* and the *USA Today*.

articles related to policy uncertainty. These 10 time series are normalized to unit standard deviation and added up for each month. The resulting monthly index is then re-normalized to a mean value of 100 from 1985 to 2009.

Panel D of Table 1 shows that the mean news-based BBD index during our sample period (from 2007 to 2016) is 121.7, and the standard deviation is 47.9. Panel D also reports the summary statistics for other macroeconomic variables we use as controls in our analyses.

4. POLICY UNCERTAINTY AND P2P CROWDFUNDING

We conjecture that with greater policy uncertainty, investors are more reluctant to fund borrowers' loan requests due to higher expected credit risk, resulting in less credit provided to households in the P2P crowdfunding market. In this section, we test this conjecture by examining the effect of policy uncertainty on the supply of funds to households.

4.1 Baseline results

To formally test the effect of policy uncertainty on whether and how households' loan requests are funded on Prosper.com, we estimate various forms of the following model:

$$FundingStatus_i = \alpha + \beta \times BBD_i + \theta \times Macro_i + \gamma \times Control_i + FE + \epsilon_i \qquad (1)$$

where *i* indexes loan requests, and *FundingStatus* represents the funding results of a request. Specifically, we use four proxies for *FundingStatus*: a successful funding dummy (*Funded*) that equals one if a request is funded, and zero otherwise; the fraction of requested amount that is funded (*Percent funded*); the natural logarithm of the borrowed amount in dollars (*Amount funded*); and the number of days it takes to successfully fund the request normalized by the requested amount in thousand dollars (*Funding duration*).

The key independent variable is the natural logarithm of the monthly news-based policy uncertainty index, *BBD*. We match each request with *BBD* one calendar month ahead of the creation of the loan request. We use the logit model to estimate the specification with *Funded* as the dependent variable, and use the OLS method to estimate specifications with *Percent funded*, *Amount funded*, and *Funding duration* as the dependent variables. Because *Funding duration* is only observable among funded loans, we correct this potential selection bias by using the two-step Heckman model.[10] Because funding duration is fixed by the platform in auctions, we use the posted-price subsample after December 2010 to estimate the *Funding duration* regression.

Since we rely on the time series variation in *BBD* to estimate equation (1), we control for other possible confounding macroeconomic forces that may drive spurious relations by including *Macro,* a vector of various proxies for investment opportunities and general economic uncertainty in regressions, following Gulen and Ion (2016).

First, given the extant evidence that policy uncertainty tends to be countercyclical (e.g., Bloom et al. (2016)), periods of high policy uncertainty may coincide with poor economic conditions or low capital availability, which could affect crowdfunding outcomes. In our regressions, we employ a series of macro-level variables to proxy for expectations about future economic conditions: 1) the University of Michigan index of consumer confidence; 2) the Conference Board's proprietary Leading Economic Indicator; 3) the National Activity Index from the Chicago Federal Reserve Board; and 4) the average one-year ahead GDP growth forecast from the Livingstone Survey of Professional Forecasters. To avoid multicollinearity issues, we include the lagged first principal component of the four proxies in our regressions.

Second, to address the concern that *BBD* is correlated with uncertainty generated by other macroeconomic factors, we control for uncertainty in the macro economy by including four additional proxies: 1) the Jurado, Ludvigson, and Ng (2015) monthly index of macroeconomic uncertainty constructed with a system of 279 macroeconomic variables; 2) the VXO implied volatility index, released by the Chicago Board Options Exchange; 3) the cross-sectional standard deviations of monthly returns from CRSP as suggested in Bloom (2009); and 4) the cross-sectional standard deviations of year-on-year sales growth from Compustat as suggested in Bloom (2009). To avoid multicollinearity, we include the lagged first principal component of these four proxies in regressions.

Besides macroeconomic conditions, we also include a large vector of control variables

[10] Specifically, we follow Lin, Prabhala and Viswanathan (2013) to use *Spikedays*, a dummy that equals one if a request is posted in a week when the search volume on Google Trends for "Prosper" was above the 75th percentile in our sample period and zero otherwise, as the instrument in the first-stage probit model that predicts the probability of a listing being successfully funded. Then we include the inverse mills ratio in the second step regression to adjust for the selection bias. In untabulated analyses, our main findings continue to hold if we don't correct for the bias and use the OLS method instead.

across regressions. First, we follow the fin-tech literature to control for loan request and borrower characteristics that may influence crowdfunding results, including the interest rate offered by the borrower, loan maturity, the borrower's income-to-debt ratio, credit profile, and her access to and utilization of banking service. We further include a time trend variable, and several dummy variables defined based on the purpose of the loan, the type of the funding target (full or partial), the borrower's FICO score, income level, and employment status. State and occupation fixed effects are also included to absorb any influences varying only with borrowers' locations and occupation.

We report estimation results of the *FundingStatus* regressions in Table 2. To facilitate interpretation, we report the marginal effects of the coefficient estimates for the logit regression in column (1) and coefficient estimates for OLS regressions in columns (2) - (4). The marginal effects (coefficient estimates) on the news-based policy uncertainty index (*BBD*) are negative and significant at the 1% level in all regressions, which is consistent with our hypothesis that increased political uncertainty significantly reduces households' access to small loans in the P2P market.[11]

4.2 Identification

We have observed a negative association between the policy uncertainty index and successful crowdfunding outcomes on Prosper.com. It is possible that the relation could be driven by omitted variables. Though we have controlled for two most possible confounding driving forces for P2P crowdfunding (investment opportunity and macroeconomic uncertainty), time trend, and a large set of loan and borrower characteristics in our previous analyses, the endogeneity concern could still exist. In this subsection, we attempt to alleviate endogeneity issues with the instrument variable approach and the difference-in-differences (DiD) method.

4.2.1 The instrument variable approach

Following Baker, Bloom, and Davis (2016) and Bonaime, Gulen, and Ion (2017), we use

[11] In the *Funding duration* regression, from the first-step probit regression predicting funding probability, we find that the instrument, *Spikedays*, has a positive coefficient with Z-value of 70.53 satisfying the Staiger and Stock (1997) criterion for a strong instrument.

the partisan-conflict index from the Federal Reserve Bank of Philadelphia, developed by Azzimonti (2018), as an instrument for the BBD index. The partisan-conflict index is based on a frequency count of newspaper articles containing terms related to lawmakers' policy disagreement. This index captures the frequency of newspaper coverage of articles documenting political disagreement both within and between national parties about government policy. According to Azzimonti (2018), compared to the existing low-frequency measures of partisan conflict, this index can capture not only general ideological differences in the liberal-conservative spectrum, but also the degree of disagreement over particular topics at high frequencies.[12]

In our research setting, partisan-conflict index should be a valid instrument for policy uncertainty. The conflicts between Democratic and Republican legislators and the within-party disagreements directly reflect uncertainty in future policies. It is, however, unclear that how the number of disagreements on lawmaking affects borrowing/lending behaviors in a way other than through its effect on policy uncertainty, because this instrument captures only the intensity of the debate rather than the content. Thus, the partisan-conflict index as our instrument should reasonably satisfy the exclusion restriction.

We use the two-stage least squares (2SLS) regression with the proposed instrument variable to estimate the effect of policy uncertainty on P2P crowdfunding. Specifically, in the first stage, we regress *BBD* on the partisan-conflict index and all the control variables in equation (1). In the second stage, we replace *BBD* with the fitted values from the first stage and re-estimate equation (1).

Table 3 reports the two-stage regression results. Column (1) shows that, in the first-stage regression, the coefficient estimate on the instrument, *Partisan Conflict*, is positive and significant at the 1% level with a *t*-statistic well above 6, suggesting that the instrument is highly correlated with the endogenous right-hand side variable in the second stage and do not appear to suffer from the weak instrument problem. Columns (2) - (5) report the second-stage regression results on crowdfunding outcomes. The marginal effect (coefficient estimates) on

[12] For example, the partisan polarization measure based on the DW NOMINATE scores developed by McCarty (2004) tracks legislators' ideological positions over time. The measure is used as an instrument in Gulen and Ion (2016).

the instrumented *BBD* is negative and significant at the 1% level in columns (2), (3), and (4), suggesting that greater policy uncertainty leads to a lower probability a loan being funded and a smaller amount a borrower can raise. The coefficient estimate on the instrumented *BBD* in column (5) is positive and significant at the 1% level, suggesting that greater policy uncertainty leads to a longer time to fund a loan request. The economic effect is also significant. For example, with a one standard deviation (0.32) increase in the instrumented *BBD*, the probability that a loan request is funded decreases by 0.6% (about 0.9% of the mean of 67.5%), the funded amount decreases by $1,022 (about 8.2% of the mean of $12,495), and the funding duration increases by 0.27 days (about 31.4% of the mean of 0.86 days). Overall, the above evidence suggests that policy uncertainty appears to have a negative and causal effect on P2P crowdfunding activities.

4.2.2 The difference-in-differences approach

Our second attempt to tackle the endogeneity issue use the DiD approach by relying on plausibly exogenous variation in policy uncertainty generated by gubernatorial elections, following the existing literature (e.g., Colak, Durnev, and Qian (2017); Jens (2017)). Gubernatorial elections increase policy uncertainty and are staggered across business and economic cycles. A key advantage of this identification strategy is that these elections are able to generate multiple shocks to policy uncertainty in different states at different times, which avoids a common identification difficulty faced by studies with a single shock, i.e., the existence of potential omitted variables coinciding with the shock that directly affect P2P crowdfunding activities.

We obtain information on gubernatorial elections from the Voting and Elections Collection database in the CQ Press library. This database provides detailed information on each gubernatorial election, including the election date, the name of winning candidate and party, whether the candidate is an incumbent or the challenger, and the voting margin. There are 118 gubernatorial elections that take place in our sample period between 2007 and 2016.

To implement the DiD analysis, we compare funding results of loan requests posted by borrowers residing in states with and without gubernatorial elections before their postings. We first identify whether there is a gubernatorial election in the month after a borrower posts her requests. We then estimate the following model:

$$FundingStatus_i = \alpha + \beta \times Elect_i^{-1} + \theta \times Macro_i + \gamma \times Control_i + FE + \epsilon_i \quad (2)$$

where i indexes loan requests, and *FundingStatus* represents crowdfunding outcomes as in equation (1). The key independent variable is the gubernatorial election dummy ($Elect^{-1}$) that equals one if a gubernatorial election occurs in the state the borrower resides during the month immediately after the request is created, and zero otherwise. Other control variables are the same as in equation (1). We include state, occupation, and year-month fixed effects in regressions.

Table 4 reports the results estimating equation (2). To facilitate interpretation, we report the marginal effect instead of raw coefficient estimates of the logistic model. The marginal effect of $Elect^{-1}$ is negative and significant at the 1% level, suggesting that in the month immediately before a gubernatorial election, the probability that a loan request being funded decreases. The coefficient estimates on $Elect^{-1}$ are -0.70 and -0.05 in columns (2) and (3), respectively. These estimates are both significant at the 1% level, suggesting the funded amount drops by 0.7%, or \$633. The result on *Funding duration* in column (4) is consistent with our conjecture, though statistically insignificant.

We also include an election month dummy ($Elect^{0}$) that equals one if a gubernatorial election occurs in the state the borrower resides during the month when the request is created and a post-election month dummy ($Elect^{+1}$) that equals one if a gubernatorial election occurs during the month prior to the creation of the request in the analysis to check whether the pattern we observe is reversed when policy uncertainty caused by gubernatorial elections is significantly reduced. Marginal effects (coefficient estimates) are insignificant across regressions, suggesting that when the difference in policy uncertainty diminishes, the funding results of the treated requests are similar to those of the control requests. Thus, the DiD results confirm that increased policy uncertainty decreases crowdfunding activities on Prosper.com.

4.3 Robustness Checks

4.3.1 Changes in market mechanism

One reasonable concern is that our main results could be driven by a regime change in the market mechanism of Prosper. Specifically, on December 20, 2010, Prosper.com unexpectedly abandoned its well-known auction model and switched to a posted-price mechanism (see, for example, Zhang and Liu (2012) and Lin, Prabhala, and Viswanathan (2013) for more discussions on this change). Before the change, a second-price proxy auction is conducted until a request is either funded or expired. In those bids, investors specify the amount of funds they would like to invest, and the minimum interest rate at which they are willing to lend. Since December 20, 2010, the interest rate is pre-set by Prosper.com based on a few factors, including: 1) Prosper's credit ratings, 2) loan terms, 3) economic environment, and 4) competitive conditions.[13] With this new pricing regime, investors only need to specify a dollar amount for their investment when bidding, implicitly accepting the pre-set interest rate. Along with the regime change, Prosper.com extended the maximum funding duration for all listings from 7 days to 14 days as well.

It has been documented that the regime change from the auction system to the posted-price system is correlated with larger funding probability and increased initial and contract rate (Wei and Lin, 2017). In order to rule out the possibility that our findings are driven by the regime change, we split our sample into two subsamples: an auction subsample consisting of requests posted before December 20, 2010, and a posted-price subsample consisting of requests posted after that date. We then test whether our findings hold in these two subsamples.

Table 5 reports the second-stage regression results for equation (1) in the two subsamples. The marginal effects (coefficient estimates) on the instrumented BBD index exhibit consistent signs with those obtained from the full sample regressions and are significant at the 1% level. This observation suggests that the negative effect of policy uncertainty on P2P crowdfunding probabilities holds under both the auction system and the posted-price system, and our results are robust after considering the regime change.

4.3.2 Measurement error in the BBD index

Another reasonable concern is that our policy uncertainty proxy could capture economic uncertainty that is not related to policy but affects P2P crowdfunding. Though with the instrumental variable approach we have shown that the policy-related variation in the BBD

[13] https://prosper.zendesk.com/hc/en-us/articles/210013663-What-are-loan-interest-rates-and-estimated-investor-returns-

index affects crowdfunding activities, we further address this measurement error concern by following Gulen and Ion (2016) and using data on Canadian economic policy uncertainty. Since US and Canada economies are closely tied (Romalis, 2007), the two nations should share similar economic shocks. Therefore, if the US BBD index captures other economic information than policy-related uncertainty, we are able to extract them from the US BBD index by identifying the common component of the US and Canadian BBD indices. Then we can better measure US policy uncertainty with the residual part of the US BBD index, which is not related to economic uncertainty shared by these two nations.

Following Gulen and Ion (2016), we regress the monthly news-based U.S. BBD policy uncertainty index on the Canadian news-based policy uncertainty measure, monthly average interest rate, and several macroeconomic control variables including the VXO implied volatility index, the return on the CRSP value-weighted market index, the spread between the Baa rate and the federal funds rate, Robert Shiller's Cyclically Adjusted Price Earnings Ratio (CAPE), and a linear time trend variable. We obtain the regression residual (labeled as *RPU*), which is the difference between the actual and the predicted U.S. news-based policy uncertainty measure. We then replace *BBD* with *RPU* in equation (1) and re-estimate the model.

Table 6 reports the OLS regression results. The marginal effect (coefficient estimates) on *RPU* exhibit consistent signs with those we reported in Table 2, and are significant at the 1% level. Therefore, the results with an arguably cleaner measure for policy uncertainty suggest that our main results are unlikely driven by measurement errors in the BBD index.

4.3.3 Other robustness tests

We run several other tests to check the robustness of our main findings and report the results in the Appendix. Panel A in Table A2 shows that our main results stay qualitatively unchanged, if we further include year fixed effects and control for investment opportunities and general economic uncertainty with the original set of proxies instead of the first principal components in equation (1). Our results are also robust to clustering standard errors by both state and year.

In Table A2 Panel B, we re-run our baseline regressions using the daily *BBD* data. Specifically, we match each loan request with the policy uncertainty variable for the day prior to the request is posted. This new approach captures the extent of policy uncertainty more precisely. Results show that policy uncertainty reduces crowdfunding activities, which is consistent with the results estimated with the monthly data, and support our hypothesis.

5. UNDERLYING CHANNELS

In this section, we investigate plausible underlying channels through which policy uncertainty affects P2P crowdfunding activities. Specifically, we propose two possible mechanisms. First, the disciplinary mechanism suggests that during the period of high policy uncertainty, agents (P2P investors in our setting) are disciplined more intensively and hence pick higher quality investment opportunities. We conjecture that the impact of policy uncertainty is more pronounced for loans requested by borrowers with lower credit status. Second, the real option mechanism argues that higher levels of uncertainty can increase the value of the real option to delay investments (e.g., Bloom (2009)), and enhance the investors' incentives to postpone P2P investments. Thus, we expect the relation between policy uncertainty and P2P crowdfunding is more pronounced if the real option value is larger.

5.1 The disciplinary channel

The external disciplinary force theory in corporate finance suggests that policy uncertainty exacerbates financial constraints (Bordo, Duca and Koch, 2016), which can substitute for corporate governance in mitigating managerial discretion and overinvestment (Masulis, Wang, and Xie, 2007; Nguyen and Phan, 2017). In the same spirit, during the period of high policy uncertainty, P2P investors are more likely to fund high-quality requests or borrowers because of greater credit risk. Thus, to the extent that investors' risk aversion does not vary across time, we conjecture that the relation between policy uncertainty and P2P crowdfunding activities is more pronounced for requests or borrowers with lower credit status.

To test the disciplinary channel, we interact three request/borrower credit status proxies with instrumented *BBD* in equation (1): 1) a Prosper credit grade dummy, *Grade*, that equals one if the in-house credit ratings of a request by Prosper.com is better than average, and zero otherwise;[14] 2) a borrower income dummy, *Income*, that equals one if a borrower's income range is above sample mean, and zero otherwise;[15] and 3) a borrower FICO dummy, *FICO*, that equals one if the borrower's FICO score is above average, and zero otherwise.[16] Intuitively, loan requests with high *Grade* posted by borrowers with high *Income* and *FICO* are associated with lower credit risk.

The first three columns in Panel A of Table 7 reports the second-stage regressions results of funding probability (*Funded*). The marginal effects of the interaction terms (*BBD*Grade, BBD*Income, BBD*FICO*) are all positive and statistically significant. The first three columns in Panel B reports results on funding amount (*Percent funded*). The coefficient estimates on the interaction terms are also positive and significant at the 1% level across regressions. That is, the effect of policy uncertainty on P2P crowdfunding is more pronounced for low-credit requests from borrowers that are more likely to default. These results are consistent with the disciplinary channel, as investors appear to be more cautious on investing in low-credit borrowing requests in the P2P market when policy uncertainty is high.

5.2 The real option channel

The real option theory suggests that during the periods of heightened uncertainty, the value of the option to delay an investment increases. In this subsection, we run two cross-sectional tests to examine this channel. Specifically, according to the real option channel, the negative relation between policy uncertainty and the probability of a request being funded depends on 1) the extent to which the loan investment can be reversed, and 2) the cost of delaying the loan. We conjecture that, if it is less costly to reverse a loan investment, the effect of policy uncertainty on P2P crowdfunding would be less pronounced because the option to wait is less valuable. Similarly, with a higher cost of delaying the investment the value of the

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[14] Prosper.com gives deals one of seven possible credit grades: AA (low risk), A, B, C, D, E, HR (high risk). The assessment of the credit grade decision includes FICO, loan term (shorter term is considered better), proprietary models, and the loan amount requested by the borrower. We re-measure seven possible credit grades on a scale between one (AA) and seven (HR) and calculate the average credit grades in our analysis.

[15] On Prosper.com, borrowers are required to disclose which of the six possible income ranges they belong to: $0 or unable to verify, $1–24,999, $25,000–49,999, $50,000–74,999, $75,000–99,999, $100,000+. We re-measure these six possible income range on a scale between one ($0 or unable to verify) and six ($100,000+).

[16] Prosper.com requires borrowers to disclose which of the thirteen possible FICO ranges they belong to: <600, 600-619, 620-639, 640-659, 660-679, 680-699, 700-719, 720-739,740-759, 760-779, 780-799, 800-819, 820-850. We redefine these thirteen possible FICO ranges on a scale between one (<600) and thirteen (820-850).

option decreases, and therefore we expect a less pronounced effect of policy uncertainty on P2P crowdfunding activities.

We use the secondary market liquidity provided by Prosper.com to proxy for a loan request's (expected) investment irreversibility. This practice is motivated by Kessides (1990) and Farinas and Ruano (2005) who argue that the sunk costs should be lower for firms whose assets have an active second-hand market and hence a higher resale value, resulting in higher asset reversibility. We define a secondary market liquidity dummy, *Illiquid*, that equals one after Prosper.com closes down their secondary market on October 27, 2016 or before Prosper.com starts running a secondary market via FOLIOfn since 2009, and zero otherwise.[17] We use *Funding duration* defined in Subsection 4.1.1 as a proxy for the cost of delaying investment on Prosper.com. The rationale is that, because a hot request will be funded in a very short time, the funding duration of a loan request reflects the competition among investors. Since the costs of delaying investment is higher when the competition is fiercer (Grenadier, 2002), the option to delay is less valuable for requests with many competing investors.

We add interaction terms between *Illiquid* (*Funding duration*) and the instrumented *BBD* in equation (1) to test the real option channel. Columns (4) and (5) in Table 7 Panel A report the second-stage regression results on *Funded*, and the same two columns in Panel B reports the results on *Percent funded*. The marginal effects of *BBD*Illiquid* is negative and significant at the 1% level in column (4) of Panel A, suggesting that the effect of policy uncertainty on P2P crowdfunding probability is more pronounced when investments on Prosper.com cannot be reversed via the secondary market and hence the value of the option to delay is high. Similarly, the marginal effect of *BBD*Funding duration* is negative and significant at the 1% level in column (5), suggesting that the impact of policy uncertainty on P2P funding probability is stronger when the bidding competition is less fierce and hence the "wait and see" option value is high. In Panel B, we also find that the effect on funded amount is stronger for high option value requests in column (5). Therefore, the real option channel appears a plausible mechanism through which policy uncertainty affects P2P crowdfunding activities.

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[17] FOLIOfn, Inc. is a brokerage and investment company serving U.S. investors, financial advisors, and financial institutions.

6. POLICY UNCERTAINTY AND AGGREGATE CROWDFUNDING VOLUME

So far, we have shown that policy uncertainty decreases the probability and amount that a borrowing request is funded on Prosper.com using loan request-level data. These results are conditional on that the borrower has posted her request in the platform, and hence reflect the effect of policy uncertainty on the supply side of the P2P crowdfunding market. In this section, we explore how aggregate crowdfunding activities in the P2P market respond to policy uncertainty changes. Since we are able to count the number and amount of loan requests in each month, we are able to gauge the effect of policy uncertainty on households' demand for funds (and test our hypothesis on the demand side), besides the credit allocation results in this setting.

Specifically, our prior is that higher policy uncertainty leads to lower borrowing demand and crowdfunding volume because: 1) on the demand side, households are less likely to borrow due to uncertainty in their future cash flow; and 2) on the supply side, conditional on a loan request is made, investors are less willing to lend because of increased credit risk, which we have documented in Section 4.

6.1 2SLS regression results

To test this conjecture, we run a monthly time series regression. The dependent variables include the natural logarithm of the number of loan requests in a month posted on Prosper.com (*Request number*), the natural logarithm of the total dollar amount requested in millions (*Request amount*), the natural logarithm of the total number of loans made (*Loan number*), and the natural logarithm of the total amount of loans in millions (*Loan amount*). The independent variable of interest is *BBD*, measured at one month ahead. We include following control variables in regressions: 1) the VXO implied volatility index from the Chicago Board Options Exchange (CBOE), 2) the return on the CRSP value-weighted market index, 3) the spread between the Baa rate and the federal funds, 4) Robert Shiller's Cyclically Adjusted Price Earnings Ratio (*CAPE*), 5) the mean value of borrower rate, and 6) a linear time trend variable. To address the endogeneity issue, we use *partisan conflict* as an instrument and run 2SLS instrumental variable regressions.

We report the second-stage regression results in Table 8. The coefficient estimates on instrumented *BBD* are negative and significant at the 1% level in all regressions, suggesting that the aggregate demand for borrowings and loans made to the borrowers decrease significantly during the period of high policy uncertainty. The economic magnitude is sizable. Results in columns (1) and (2) suggest that a one standard deviation increase in the instrumented *BBD* is associated with a decrease of $64.2 million from 5,298 loan requests in the next month. Columns (3) and (4) show that the amount and number of funded loans decrease by $24.8 million and 1,952, respectively.

6.2 Difference-in-difference analysis results

We further address the endogeneity issue by using gubernatorial elections and run DiD analysis following Subsection 4.2.2. Specifically, we estimate the following equation

$$Volume_s = \alpha + \beta \times Elect_s^{-1} + FE + \epsilon_i \quad (3)$$

where s indexes state, and *Volume* represents loan requests and loans from state s in a given month. The key independent variable is the gubernatorial election dummy ($Elect^{-1}$) that equals one if a gubernatorial election occurs in state s in the next month, and zero otherwise. We include state and year-month fixed effects in regressions. We also require a state to have at least four P2P loans in each month to be included in our sample.

Table 9 reports estimation results with equation (3). The coefficient estimates on $Elect^{-1}$ are negative and significant across regressions. Results suggest that in a state that will hold a gubernatorial election in the next month, the total amount and number of loan requests decrease by $924,971 and 62.3, respectively; and the amount and number of funded loans decrease by $169,902 and 12.2, respectively. These results are consistent with previous findings with the 2SLS approach, and support our conjectures on how borrowers and investors in the P2P market respond to policy uncertainty.

Note that in the DiD tests, we focus on the shocks to the policy uncertainty faced by borrowers rather than investors, because we use policy uncertainty generated by gubernatorial elections in borrowers' states. These tests provide further support to our conjecture that P2P investors are able to internalize the information on increased credit risk of the loan (and the borrowers) during the period of high policy uncertainty and cut credit supply accordingly.

In untabulated analysis, we follow Bonaime, Gulen, and Ion (2017) and re-estimate the effect of policy uncertainty on P2P crowdfunding activities at the aggregate level using a Vector Autoregression (VAR) model. The results are qualitatively similar to those from the 2SLS regressions.

7. ADDITIONAL ANYLYSES

7.1 Evidence on interest rate and default probability

Besides non-pricing terms of P2P crowdfunding, such as deal completion probability and investment amount, we are also interested in how policy uncertainty affects the pricing and performance of loans in the P2P market. These tests examine a basic assumption of our hypothesis, that is, higher policy uncertainty is associated with increased credit risk. Considering investors command a risk premium of policy uncertainty (Pastor and Veronesi, 2013), we conjecture that policy uncertainty increases loan interest rate and default probability due to a larger credit risk.

7.1.1 Policy uncertainty and interest rate

Testing the effect of policy uncertainty on loan interest rates is empirically challenging, because there is a major regime change for loan pricing on Prosper.com in 2010. As we discussed earlier, before December 20, 2010, interest rates are determined in an auction system; after that, Prosper.com pre-sets interest rates for loans using an in-house risk model (See Subsection 4.3.1 for more details). The determination of interest rates in the later period is based on a model and seems to be mechanical. To address this concern, we follow the method in Subsection 4.3.1 to divide the sample into an auction subsample and a posted-price subsample to estimate our models.

We use three proxies for the interest rate of a loan: the rate a borrower initially offers (*Initial rate*), the finalized borrowing rate that closes the deal (*Contract rate*), and the yield to lenders after subtracting the platform's fees from *Contract Rate* (*Lender yield*).[18] We estimate equation (1) with interest rates as the dependent variables. To address potential selection bias, we follow Subsection 4.1.1 and estimate a Heckman model. We then use the 2SLS regressions

[18] See Footnote 7 for details on *Initial rate*.

with the previously proposed instrumental variable to address the endogeneity concern.

Table 10 reports the second-stage regression results with *Partisan conflict* as the instrument. The coefficient estimates on instrumented *BBD* in all regressions are positive and statistically significant in both subsamples, suggesting that policy uncertainty leads to increased borrowing cost in the P2P market regardless of the pricing mechanism. The economic impact is also significant. For example, in the auction subsample, with a one standard deviation increase in instrumented *BBD* (0.32), *Initial rate*, *Contract rate*, and *Lender yield* increase by 0.20%, 1.05%, 1.07%, respectively. This finding is consistent with Pastor and Veronesi (2013) in the sense that policy uncertainty commands a risk premium, and suggests that investors are perceived to bear larger risk when policy uncertainty is higher even though they are able to mitigate it to some extent by either carefully selecting loans (the disciplinary channel we document before) or delaying riskier investments (the real option channel we document before).

7.1.2 Policy uncertainty and default rate

We test the effect of policy uncertainty on loan defaults using a sample of completed loans on Prosper.com. We construct two dependent variables: *Default amount*, defined as the natural logarithm of the dollar amount a borrower fails to pay back, and *Default*, a dummy that equals one if a loan's status is "defaulted" or "charge-off" and zero otherwise. The independent variable of interest is *BBD*, measured as one month before the loan is initiated. We include the same set of control variables as in equation (1) in our analyses. We estimate the *Default* regressions with a logit model, and the *Default amount* regressions with the OLS method. We use the 2SLS with the previously proposed instrument variable to address the endogeneity issue.

Table 11 reports the second-stage regression results for loan performance. The marginal effects/coefficient estimates on instrumented *BBD* in *Default amount* and *Default* regressions are positive and significant in both subsamples, suggesting that policy uncertainty leads to increased default risk for P2P loans. For example, in the auction subsample, the coefficient estimate on the instrumented *BBD* in column (1) is 0.266 and significant at the 1% level, suggesting that with a one standard deviation increase in the instrumented *BBD*, the default rate for a loan increases by 10.5%. Similarly, column (2) shows that the default amount on a loan increases by $1,022 with a one standard deviation increase in the instrumented *BBD*.

Therefore, our results on loan default rates show that high policy uncertainty indeed leads to a higher loan default probability and a larger default amount, which is consistent with the notion that policy uncertainty increases credit risk. Our results are also consistent with Kaviani et al. (2017) who find that increases in policy uncertainty are associated with higher default probability of corporate bond.

7.2 The impacts of different policy types

The results in the previous sections support the hypothesis that general policy uncertainty, proxied by the BBD index, affects P2P crowdfunding activities and households' credit access. In this subsection, we further investigate the effects of uncertainty generated by various types of policies on P2P crowdfunding. Our empirical tests rely on a set of category-specific indices of policy uncertainty constructed by Baker, Bloom, and Davis (2016), including indices related to fiscal policy, taxes, government spending, monetary policy, regulation, financial regulation, health care, entitlement programs, sovereign debt, trade policy, and national security.[19]

We use a specification analogous to the baseline regression in equation (1), with the only exception that we replace the overall BBD proxy with category-specific BBD indices. Table 12 reports the estimation results.[20] Columns (1) - (4) reveal that uncertainty related to fiscal policy (including taxes and government spending) and monetary policy negatively affects P2P crowdfunding activities. Columns (5) and (6) show that policy uncertainty related to regulation (financial regulation in particular) has a strong and negative effect on funding probability. Columns (7), (8), and (9) suggest that policy uncertainty related to health care, entitlement programs, and sovereign debt affects P2P crowdfunding as well. In contrast, the last two columns suggest that policy uncertainty related to trade policy and national security does not

[19] To obtain these measures, Baker, Bloom, and Davis (2016) count newspaper articles that contain search terms related to the specific type of policy in question in addition to the original search terms for the overall policy-uncertainty index. For example, to measure policy uncertainty related to taxes, the authors count the number of newspaper articles that contain not only the original keywords related to policy, uncertainty and economics (see Subsection 3.2 for details on this process), but also one or more of the following keywords: "taxes," "tax," "taxation," and "taxed."

[20] We show, in the last row, information on the sources of the overall policy uncertainty by reporting the percentage of newspapers articles mentioning policy uncertainty that also mention the keywords pertaining to the specific type of policy. For example, fiscal policy, monetary policy, national security, regulation, health care, and entitlement programs generate relatively large policy uncertainty, while trade policy and sovereign debt are relatively less important sources of policy uncertainty.

appear to affect subsequent crowdfunding activities. In summary, our results reveal that the relation between uncertainty and crowdfunding activity is complex: not all sources of macroeconomic uncertainty affect crowdfunding and credit access in the same manner.

7.3 The lasting of policy uncertainty effect

In this subsection, we take a closer look at how the relation between policy uncertainty and investments evolves over time. Specifically, we re-estimate equation (1) but lag the *BBD* proxy by more months to examine how long the effect of policy uncertainty can last.

Figure 2 plots the coefficient estimates and the associated confidence intervals obtained from the logit regressions of *Funded* on the news-based BBD index lagged by 1-24 months. We observe that the negative effect of policy uncertainty on P2P crowdfunding activities peaks at the 12^{th} month, and can last for up to 22 months. After it, the coefficient estimate turns to be positive, suggesting that P2P crowdfunding activities recover and become more active when policy uncertainty is largely resolved.

8. CONCLUSION

We examine the effect of policy uncertainty on household credit access in terms of P2P crowdfunding on Prosper.com, using a news-based policy uncertainty index developed by Baker, Bloom, and Baker (2016). Our results show that policy uncertainty significantly reduces crowdfunding activities and hence households' access to small credit in the P2P market. This finding is robust to a variety of model specifications. Using the partisan conflict index as an instrument variable and a DiD approach replying on plausibly exogenous variation in policy generated by gubernatorial elections, we show that the effect of policy uncertainty on P2P crowdfunding appears causal. Investors' increased caution on deal selection and enhanced value of the "wait-and-see" option appear two plausible underlying channels through which policy uncertainty affects P2P crowdfunding. At the aggregate level, policy uncertainty decreases overall crowdfunding activities and dampens households' incentives to borrow.

We also find the policy uncertainty leads to higher loan interest rates and default probabilities. In addition, policy uncertainty related to fiscal policy (tax and government spending), general and financial regulation, health care, entitlement programs, and sovereign debt has more significant effects. The effect of policy uncertainty is long-lasting for up to 22 months.

Our paper contributes to the policy uncertainty literature by showing the effect of policy uncertainty on households and investors at the micro-loan market, which is an important player in the financial market. Our paper also sheds new light on the factors affecting P2P crowdfunding by linking macro shocks to crowdfunding outcomes.

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Figure 1. Policy uncertainty and loans made on Prosper.com

This figure plots the natural logarithm of total loan amount (top panel) and number of loans (bottom panel) on Prosper.com against the news-based Baker, Bloom, and Davis (2016) policy uncertainty index from January 2007 to December 2016. Both of the time series are de-trended by regressing the index on a linear time trend variable.

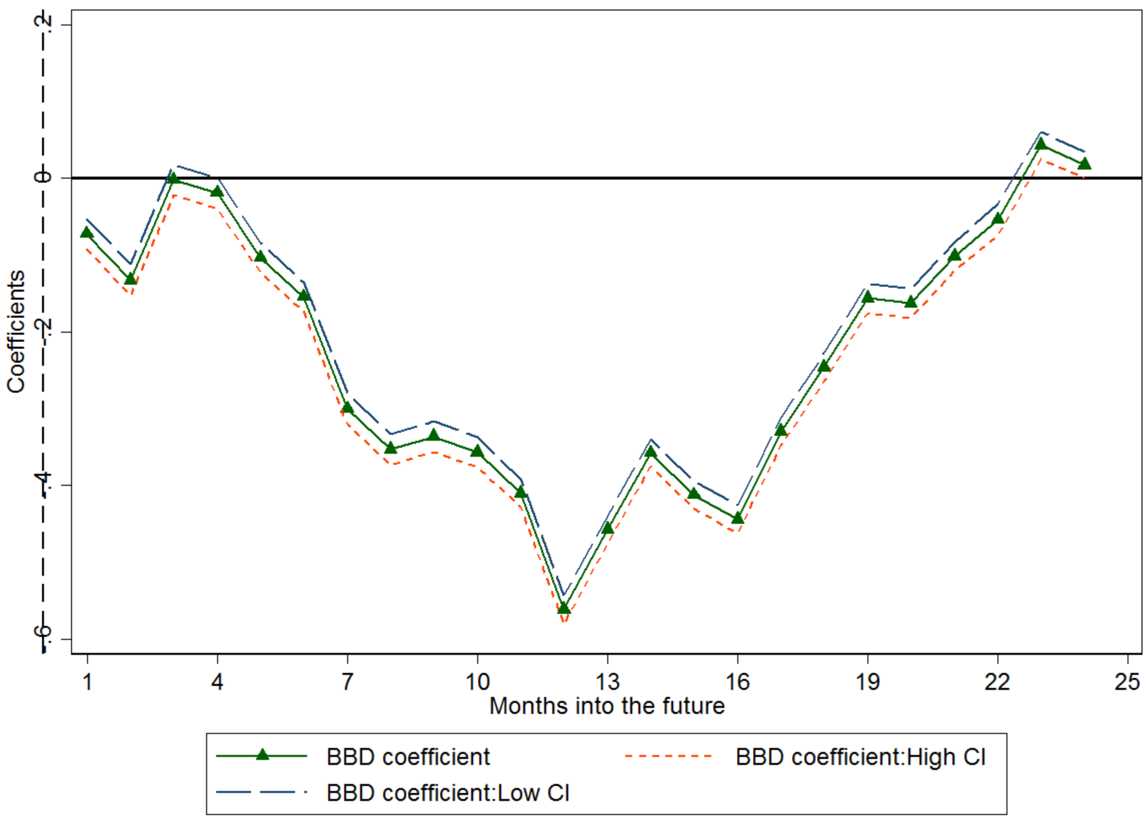

Figure 2. The effect of policy uncertainty on future crowdfunding outcome

This figure depicts the effect of policy uncertainty on future P2P funding probability. The vertical axis represents coefficient estimates obtained from regressions of the *Funded* dummy in future months on the current *BBD* index with a logistic model. The horizontal axis represents months into the future. See equation (1) for detailed model specification.

Table 1. Summary statistics

This table presents summary statistics for listings, loans, borrowers, and macroeconomic variables. Data on listings, loans, and borrowers is from Proper.com. The policy uncertainty index is from Baker, Bloom, and Davis (2016). The sample period is February, 2007 to December, 2016. Borrowers' information is as of their first appearance in our data. See Appendix A for definition of variables.

Variable	N	Mean	Median	SD	P5	P95
Panel A: Loan requests						
Amount requested (thousand dollars)	879,627	13.117	12.000	8.004	3.000	30.000
Term (months)	879,627	42.897	36.000	11.017	36.000	60.000
Borrower rate	879,627	0.156	0.142	0.068	0.070	0.300
Amount funded (thousand Dollars)	879,627	12.495	10.000	8.361	0.526	30.000
Percent funded	879,627	0.935	1.000	0.235	0.093	1.000
Funding indicator	879,627	0.675	1.000	0.468	0.000	1.000
Panel B: Loans						
Contract rate	408,857	0.151	0.141	0.061	0.070	0.270
Lender yield	408,857	0.141	0.131	0.061	0.060	0.260
Estimated return	408,857	0.066	0.069	0.051	0.042	0.115
Default amount (thousand dollars)	215,511	2.122	0.000	5.001	0.000	13.914
Default indicator (due loans)	215,511	0.232	0.000	0.422	0.000	1.000
Default Indicator	408,424	0.122	0.000	0.328	0.000	1.000
Funding duration (days)	407,530	0.860	0.020	2.307	0.00005	7.001
Panel C: Borrowers						
Debt-to-income Ratio	659,601	1.025	0.240	149.109	0.080	0.470
Homeowner indicator	659,601	0.477	0.000	0.499	0.000	1.000
Number of delinquencies (Current)	659,601	0.298	0.000	0.956	0.000	2.000
Number of delinquencies (last 7 years)	659,601	3.472	0.000	8.795	0.000	22.000
Amount delinquent (thousand dollars)	659,601	0.526	0.000	2.962	0.000	1.312
Current credit lines	659,601	10.676	10.000	5.059	4.000	20.000
Open credit lines	659,601	9.956	9.000	4.786	4.000	19.000
Revolving credit balance (thousand dollars)	659,601	19.279	11.347	24.685	1.191	64.420
Bankcard utilization	659,601	0.543	0.560	0.270	0.060	0.950
Lender indicator	659,601	0.011	0.000	0.102	0.000	0.000
Panel D: Uncertainty and macro variables						
News-based *BBD* index	126	121.721	108.893	47.923	59.841	214.952
VXO index	126	18.510	16.295	7.500	10.870	29.620
Shiller's PE Ratio	126	24.012	23.695	2.771	19.669	27.283
CRSP index return	126	0.008	0.011	0.041	-0.062	0.068
Rate spread	126	4.405	4.795	1.617	1.140	6.200

Table 2. The effect of policy uncertainty on P2P crowdfunding results

This table reports results for regressions of P2P crowdfunding status on policy uncertainty. Column (1) reports the logit regression results and marginal effects. Columns (2) - (3) report OLS regression results. Column (4) reports the second-step regression results of the Heckman model, in which the first step is a probit regression predicting funding probability using the *Spikedays* instrument by Lin, Prabhala, and Viswanathan (2013) and untabulated. See Appendix A for definitions of variables. Standard errors are adjusted for heteroscedasticity and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Dependent variable	*Funded*	*Percent funded*	*Amount funded*	*Funding duration*
Policy uncertainty (*BBD*)	-0.015***	-2.074***	-0.225***	0.025***
	(0.002)	(0.088)	(0.007)	(0.002)
Borrower rate	-0.801***	-26.157***	2.432***	-0.968***
	(0.022)	(1.798)	(0.153)	(0.045)
Listing term	0.0004***	0.010***	0.012***	0.008***
	(0.0005)	(0.002)	(0.000)	(0.000)
Investment opportunity	-0.068***	-5.817***	-0.250***	-0.332***
	(0.001)	(0.095)	(0.007)	(0.015)
Macro uncertainty	-0.011***	-3.660***	-0.193***	-0.277***
	(0.001)	(0.040)	(0.003)	(0.012)
Bankcard utilization	0.084***	0.487***	-0.116***	0.394***
	(0.002)	(0.119)	(0.009)	(0.017)
Debt-To-Income ratio	5.74e-08***	-5.886***	-0.518***	0.291***
	(2.87e-09)	(0.179)	(0.014)	(0.013)
Lender indicator	0.057***	0.715***	-0.101***	0.377***
	(0.003)	(0.227)	(0.018)	(0.019)
Homeowner Indicator	0.039***	0.423***	0.059***	0.135***
	(0.001)	(0.044)	(0.004)	(0.006)
Current delinquencies	0.006***	-0.026	-0.014***	0.025***
	(0.001)	(0.031)	(0.002)	(0.001)
Past delinquencies	0.002***	0.007***	-0.001***	0.006***
	(0.0001)	(0.002)	(0.000)	(0.000)
Amount delinquent	-0.003***	-0.100***	-0.009***	-0.013***
	(0.0003)	(0.012)	(0.001)	(0.001)
Current credit lines	0.006***	0.017	-0.021***	0.027***
	(0.0004)	(0.019)	(0.002)	(0.001)
Open credit lines	-0.004***	-0.003	0.023***	-0.022***
	(0.0004)	(0.020)	(0.002)	(0.001)
Revolving credit balance	-0.008***	-0.092***	0.049***	-0.043***
	(0.0004)	(0.027)	(0.002)	(0.002)
Time trend	0.005***	0.269***	0.023***	0.021***
	(0.0001)	(0.003)	(0.000)	(0.001)

Inverse Mills ratio				3.174***
				(0.138)
Intercept		129.885***	9.582***	-1.656***
		(1.999)	(0.230)	(0.147)
Loan purpose dummies	Yes	Yes	Yes	Yes
Credit grade dummies	Yes	Yes	Yes	Yes
FICO dummies	Yes	Yes	Yes	Yes
Income dummies	Yes	Yes	Yes	Yes
Employment dummies	Yes	Yes	Yes	Yes
Target type dummies	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes
N	878,024	879,627	879,627	822,993
Adjusted/Pseudo R^2	0.069	0.373	0.377	0.309

Table 3. Endogeneity test using the two-stage instrument variable regressions

This table reports the two-stage regression results on the effect of policy uncertainty on P2P crowdfunding. The instrument is the partisan conflict index from Azzimonti (2018). All control variables and fixed effects in Table 2 are included across regressions. Marginal effects from the logistic regression are reported in column (2), and OLS estimates are reported in columns (3) - (5). In column (5), the selection bias is corrected with the same Heckman model in Table 2 and the second-step regression results are reported. See Appendix A for definition of variables. Standard errors are adjusted for heteroscedasticity and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	First stage	Second stage			
	(1)	(2)	(3)	(4)	(5)
Dependent variable	*BBD*	*Funded*	*Percent funded*	*Amount funded*	*Funding duration*
Partisan conflict	0.756***				
	(0.002)				
Instrumented *BBD*		-0.019***	-0.570***	-0.263***	0.067***
		(0.005)	(0.207)	(0.017)	(0.003)
Controls	Yes	Yes	Yes	Yes	Yes
State and Occu. FEs	Yes	Yes	Yes	Yes	Yes
N	879,627	878,024	879,627	879,627	822,993
Adj./Pseudo R^2	0.360	0.069	0.372	0.377	0.308

Table 4. Endogeneity test using the difference-in-differences (DiD) approach

This table reports results of the difference-in-differences analysis on the effect of policy uncertainty on P2P crowdfunding. $Elect^{-1}$/$Elect^{0}$/$Elect^{+1}$ is a dummy that equals one if a gubernatorial election occurs in state a borrower resides in during the month after/when/before a loan request is posted, and zero otherwise. All control variables in Table 2 are included across regressions. Marginal effects from the logistic regression are reported in column (1), and OLS estimates are reported in columns (2) - (4). In column (4), the selection bias is corrected with the same Heckman model in Table 2 and the second-step regression results are reported. See Appendix A for definition of variables. Standard errors are adjusted for heteroscedasticity and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Dependent variable	*Funded*	*Percent funded*	*Amount funded*	*Funding duration*
$Elect^{-1}$	-0.010*	-0.700***	-0.052***	0.001
	(0.006)	(0.223)	(0.019)	(0.003)
$Elect^{0}$	-0.001	-0.177	-0.023	0.00002
	(0.006)	(0.227)	(0.018)	(0.004)
$Elect^{+1}$	0.007	0.122	0.002	-0.001
	(0.006)	(0.195)	(0.016)	(0.004)
Controls	Yes	Yes	Yes	Yes
State and Occu. FEs	Yes	Yes	Yes	Yes
Year-month FEs	Yes	Yes	Yes	Yes
N	879,353	879,627	879,627	822,993
Adj./Pseudo R^2	0.057	0.500	0.472	0.195

Table 5. Subsample analysis

This table reports the second-stage regression results on the effect of policy uncertainty on P2P crowdfunding with two subsamples. The auction subsample consists of loan requests posted before December 20, 2010 and funded with an auction system, and the posted-price subsample consists of requests posted after that date and funded with a preset price by the platform. Model specifications and estimation methods and controls are the same as those in Table 3. Marginal effects from the logistic regressions are reported in columns (1) and (5), and OLS estimates are reported in other columns. See Appendix A for definition of variables. Standard errors are adjusted for heteroscedasticity and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Auction			Posted-Price		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	*Funded*	*Percent funded*	*Amount funded*	*Funded*	*Percent funded*	*Amount funded*
Instrumented *BBD*	-0.238***	-43.511***	-4.720***	-0.046***	-4.760***	-0.430***
	(0.014)	(1.941)	(0.160)	(0.005)	(0.164)	(0.015)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State and Occu. FEs	Yes	Yes	Yes	Yes	Yes	Yes
N	55,036	56,634	56,634	822,988	822,993	822,993
Adj./Pseudo R^2	0.513	0.484	0.402	0.043	0.142	0.195

Table 6. Regression results using residual policy uncertainty index as the independent variable
This table reports results for regressions of P2P crowdfunding status on policy uncertainty. The main independent variable is the residual of the regression of the US BBD index on Canadian BBD index and control variables. Column (1) reports the logit regression results and marginal effects. Columns (2) and (3) report OLS regression results. Column (4) reports the second-step regression results of the Heckman model. Model specifications and estimation methods are as those in Table 2. See Appendix A for definition of variables. Standard errors are adjusted for heteroscedasticity and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Dependent variable	*Funded*	*Percent funded*	*Amount funded*	*Funding duration*
RPU	-0.060***	-1.751***	-0.150***	0.016***
	(0.011)	(0.118)	(0.009)	(0.002)
Controls	Yes	Yes	Yes	Yes
State and Occu. FEs	Yes	Yes	Yes	Yes
N	879,552	879,627	879,627	822,993
Adj./Pseudo R^2	0.035	0.372	0.375	0.310

Table 7. Mechanism tests

This table reports results for mechanism tests. The dependent variable is *Funded*, a dummy variable that equals one if a loan request is funded, and zero otherwise in Panel A; and *Percent funded*, defined as the fraction of requested amount that is funded in Panel B. *Grade*, *Income*, and *FICO* are dummy variables measuring the credit status of a loan request or a borrower. *Illiquid* is a dummy that equals one if a loan cannot be sold in Prosper's secondary market, and zero otherwise. Controls and fixed effects are the same as those in Table 3. Marginal effects from the logistic regressions are reported in Panel A, and OLS estimates are reported in Panel B. See Appendix A for definition of variables. Standard errors are adjusted for heteroscedasticity and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A Dependent variable: *Funded*					
	(1)	(2)	(3)	(4)	(5)
IR=	*Grade*	*Income*	*FICO*	*Illiquid*	*Funding duration*
*Instrumented BBD*IR*	0.042***	0.067***	0.085***	-0.560***	-0.003***
	(0.007)	(0.006)	(0.010)	(0.083)	(0.0001)
IR	-0.051	-0.538***	-0.554***	2.626***	0.001***
	(0.031)	(0.050)	(0.058)	(0.382)	(0.000)
Instrumented BBD	-0.094***	-0.099***	-0.097***	-0.072***	-0.032***
	(0.006)	(0.006)	(0.011)	(0.005)	(0.005)
Controls	Yes	Yes	Yes	Yes	Yes
State and Occu. FEs	Yes	Yes	Yes	Yes	Yes
N	879,552	879,552	878,024	879,552	820,763
Pseudo R^2	0.040	0.040	0.068	0.040	0.047
Panel B Dependent variable: *Percent funded*					
	(1)	(2)	(3)	(4)	(5)
IR=	*Grade*	*Income*	*FICO*	*Illiquid*	*Funding duration*
*Instrumented BBD*IR*	9.188***	8.115***	16.642***	-1.841	-1.149***
	(0.462)	(0.345)	(0.362)	(2.136)	(0.126)
IR	-25.215***	-30.154***	-90.045***	3.830	4.470***
	(2.117)	(1.913)	(2.322)	(9.785)	(0.623)
Instrumented BBD	-14.751***	-13.858***	-20.766***	-0.707***	-3.441***
	(0.478)	(0.354)	(0.386)	(0.209)	(0.166)
Controls	Yes	Yes	Yes	Yes	Yes
State and Occu. FEs	Yes	Yes	Yes	Yes	Yes
N	879,627	879,627	879,627	879,627	820,765
Adj. R^2	0.394	0.394	0.393	0.372	0.171

Table 8. Second-stage regression results on the effect of policy uncertainty on aggregate crowdfunding activities

This table reports the 2SLS regression results of monthly P2P crowdfunding volume on policy uncertainty. The dependent variables include the amount and number of loan requests and funded loans for each month. The main independent variable is the mean BBD index for the previous month. See Appendix A for definition of variables. Standard errors are adjusted for heteroscedasticity and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable	(1) *Request amount*	(2) *Request number*	(3) *Loan amount*	(4) *Loan number*
Instrumented *BBD*	-2.477***	-2.314***	-1.476**	-1.461***
	(0.816)	(0.769)	(0.598)	(0.522)
VXO index	0.119***	0.113***	0.070***	0.064***
	(0.030)	(0.029)	(0.021)	(0.019)
Shiller's PE ratio	0.183**	0.174**	0.215***	0.171***
	(0.083)	(0.078)	(0.068)	(0.064)
CRSP index return	9.021**	8.418**	3.989	3.993
	(4.017)	(3.819)	(3.096)	(2.779)
Rate spread	-0.210*	-0.197	-0.151	-0.106
	(0.126)	(0.119)	(0.097)	(0.089)
Time trend	0.039***	0.031***	0.058***	0.047***
	(0.010)	(0.009)	(0.007)	(0.007)
Initial rate	7.451	9.525	9.385	9.616
	(10.405)	(9.867)	(7.119)	(6.646)
Intercept	19.927***	10.452***	12.257***	4.810
	(3.968)	(3.684)	(3.424)	(3.109)
N	126	126	126	126
Adjusted R^2	0.607	0.507	0.860	0.817

Table 9. DiD analysis on the effect of policy uncertainty on aggregate crowdfunding activities

This table reports results of the difference-in-difference analysis on the effect of policy uncertainty on monthly P2P crowdfunding volume at the state level. $Elect^{-1}$ is a dummy that equals one if a gubernatorial election occurs in state a borrower resides in during the month before a loan request is posted, and zero otherwise. See Appendix A for definition of variables. Standard errors are adjusted for heteroscedasticity and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Dependent variable	*Request amount*	*Request number*	*Loan amount*	*Loan number*
$Elect^{-1}$	-0.319***	-0.283***	-0.077*	-0.074*
	(0.099)	(0.095)	(0.043)	(0.040)
State and Year-month FEs	Yes	Yes	Yes	Yes
N	2,408	2,408	2,408	2,408
Adj. R^2	0.877	0.843	0.913	0.887

Table 10. The effect of policy uncertainty on P2P loan interest rate

This table reports the second-stage regression results on the effect of policy uncertainty on P2P loan interest rates with two subsamples. The auction subsample consists of loan requests posted before December 20, 2010 and funded with an auction system, and the posted-price subsample consists of requests posted after that date and funded with a preset price by the platform. The Heckman two-step model is used to adjust for the selection issue. Control variables and fixed effects are the same as those in Table 3. See Appendix A for definition of variables. Standard errors are adjusted for heteroscedasticity and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Auction			Posted-Price		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	*Initial rate*	*Contract rate*	*Lender yield*	*Initial rate*	*Contract rate*	*Lender yield*
Instrumented *BBD*	0.611**	3.286***	3.356***	0.452***	1.551***	1.550***
	(0.286)	(0.197)	(0.199)	(0.015)	(0.018)	(0.018)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State and Occu. FEs	Yes	Yes	Yes	Yes	Yes	Yes
N	56,634	56,634	56,634	822,993	822,993	822,993
Adjusted R^2	0.617	0.954	0.953	0.953	0.970	0.970

Table 11. The effect of policy uncertainty on P2P loan default rate

This table reports the second-stage regression results on the effect of policy uncertainty on P2P loan default rates with two subsamples. The auction subsample consists of loan requests posted before December 20, 2010 and funded with an auction system, and the posted-price subsample consists of requests posted after that date and funded with a preset price by the platform. Only completed loans are included in the sample. Columns (1) and (3) are estimated with the logistic regressions, and columns (2) and (4) are estimated with the OLS method. Marginal effects are reported in column (1) and (3). Control variables and fixed effects are the same as those in Table 3. See Appendix A for definition of variables. Standard errors are adjusted for heteroscedasticity and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Auction		Posted-Price	
	(1)	(2)	(3)	(4)
Dependent variable	*Default*	*Default amount*	*Default*	*Default amount*
Instrumented *BBD*	0.266***	1.889***	0.040***	0.317***
	(0.045)	(0.315)	(0.010)	(0.089)
Controls	Yes	Yes	Yes	Yes
State and Occu. FEs	Yes	Yes	Yes	Yes
N	19,920	19,920	195,591	195,591
Adjusted/Pseudo R^2	0.131	0.153	0.080	0.082

Table 12. The effects of uncertainty generated by different types of policies

This table reports logistic regression results on the effects of uncertainty generated by different types of policies on P2P crowdfunding. The independent variables are a set of category-specific policy uncertainty indices constructed by Baker, Bloom, and Davis (2016). Control variables are the same as those in Table 2. Marginal effects are reported. See Appendix A for definition of variables. Standard errors are adjusted for heteroscedasticity and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Dep. var. = *Funded*	*Fiscal policy*	*Taxes*	*Gov. spending*	*Monetary policy*	*Regulation*	*Financial regulation*	*Health care*	*Entitlement programs*	*Sovereign debt*	*Trade policy*	*National security*
BBD type	-0.171***	-0.164***	-0.083***	-0.047***	-0.188***	-0.155***	-0.252***	-0.047***	-0.006**	-0.001	0.013
	(0.008)	(0.008)	(0.005)	(0.006)	(0.010)	(0.005)	(0.006)	(0.006)	(0.003)	(0.003)	(0.011)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State and Occu. FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	878,024	878,024	878,024	878,024	878,024	878,024	878,024	878,024	860,808	878,024	878,024
Pseudo R^2	0.067	0.067	0.068	0.067	0.068	0.068	0.069	0.067	0.063	0.067	0.084
% of total BBD	46.1%	40.3%	17.1%	28.1%	17.4%	3.3%	17.3%	12.4%	1.6%	3.8%	23.8%

Appendix A

Table A1. Variable definitions

Variable	*Definition*
Funded	An indicator that equals one if a listing is funded and becomes a loan, and zero otherwise.
Amount requested	The natural logarithm of the dollar amount ($) that a prospective borrower requests to borrow.
Amount funded	The natural logarithm of the dollar amount ($) which has been funded.
Percent funded	The fraction of requested amount (in percentage) that is funded.
Borrower Rate (*Initial rate* /*Contract rate*)	The rate the borrower pays on the loan (in decimals). The rate is computed as the lender rate plus the group leader reward rate (if applicable) and the bank draft fee annual rate (if applicable). *Initial rate* is an ex-ante rate of a loan request preset by the borrowers or Prosper.com. *Contract rate* is a realized interest rate after a request is successfully funded.
Lender yield	The rate that lenders receive on the loan (in decimals).
Default	An indicator that equals one if the loan status is "Defaulted," "Charge-off," and zero otherwise.
Default amount	The dollar amount ($) loss on a loan (0 if fully repaid).
Funding duration	Funding duration is calculated as the time length (in days) it takes to reach full funding. We standardize this variable by dividing it by the requested amount in thousand dollars.
News-based BBD index (*BBD*)	The natural logarithm of the policy uncertainty index based on the frequency of articles related to policy uncertainty in ten leading U.S. newspapers developed by Baker, Bloom, and Davis (2016).
Credit Grade indicators	A set of dummy variables for the borrower's credit grade at the time the request is created provided by Prosper. Credit grades include AA (lowest risk), A, B, C, D, E, HR (high risk), and Missing.
FICO indicators	A set of dummy variables for the borrower's binned FICO score range. FICO takes values between <600 and 820-850.
Debt-to-income Ratio	The debt-to-income ratio (in decimals) of the borrower at the time the listing is created.
Homeowner indicator	An indicator variable that equals one if the borrower is a verified homeowner at the time the request is created, and zero otherwise.
No. of delinquencies (currently)	Number of current delinquencies at the time the request is created.
No. of delinquencies (last 7 years)	Number of delinquencies in the last 7 years at the time the request is created.
Amount delinquent	The past due amounts ($) owed by the borrower at the time the request is created.
Current credit lines	The number of credit lines (open or closed accounts) of the borrower at the time the request is created.
Open credit lines	The number of open credit lines (lines that are active now) of the borrower

	at the time the request is created.
Revolving credit balance	Borrower's dollar amount ($) of revolving credit balance at the time the request is created.
Bankcard utilization	The sum of the balances owed by the borrower on open bankcards divided by the sum of the cards' credit limits at the time the request is created (in decimals).
Income level indicators	A set of dummy variables for the borrower's income range at the time the request is 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.
Employment status indicators	A set of dummy variables for the borrower's employment status at the time the request is created. Employment status categories include employed, not employed, retired and not available.
State	The state of the address of the borrower at the time the request is created.
Occupation indicators	A set of dummy variables for the borrower's occupation at the time the request is created. There are 67 occupations.
Lender indicator	Lender indicator equals one if a borrower used to be an investor/lender, and zero otherwise.
Request purpose indicators	A set of dummy variables for each category of loan requests. Categories include debt consolidation, home improvement, business, personal loan, student use, auto and so on. There are 21 different types.
Funding target indicators	Two dummy variables for each type of funding target, fractional and whole.
Term	Months over which the loan amortizes.
Investment opportunities	The first principal component of the following four variables: consumer confidence, leading economic indicator, the Chicago Fed National Activity Index (CFNAI), expected GDP growth.
Macroeconomic uncertainty	The first principal component extracted from the following four variables: JLN uncertainty index developed by Jurado, Ludvigson and Ng (2015), VXO index, the cross-sectional standard deviation of cumulative returns from the past three months, the cross-sectional standard deviation of year-on-year sales growth.
VXO index	Daily index of implied volatility released by the Chicago Board Options Exchange, calculated based on trading of S&P 100 options.
Shiller's PE Ratio	The Cyclically Adjusted Price Earnings Ratio (CAPE) developed by Robert Shiller.
CRSP Index Return	The monthly return on the CRSP value-weighted market index.
Rate Spread	The monthly spread between Baa rated bonds and the Federal Funds rate.

Table A2. Baseline regression results with alternative model specifications and data frequency
This table reports results for regressions of P2P crowdfunding status on policy uncertainty. Model specifications and estimation methods are as those in Table 2. Panel A includes year fixed effects, and controls for investment opportunities and general economic uncertainty with the original set of proxies instead of the first principal components. Panel B estimates the baseline regression with daily data. Marginal effects from the logistic regression are reported in column (1), and OLS estimates are reported in other columns. Standard errors are adjusted for heteroscedasticity and clustering at state and year, and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Include year fixed effect, and use the original macro proxies				
	(1)	(2)	(3)	(5)
Dependent variable	*Funded*	*Percent funded*	*Amount funded*	*Funding duration*
Policy uncertainty (*BBD*)	-0.045***	-0.404**	-0.029**	0.020***
	(0.015)	(0.170)	(0.012)	(0.003)
Controls	Yes	Yes	Yes	Yes
State and Occupation FEs	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	866,839	879,627	879,627	822,993
Adj./Pseudo R^2	0.085	0.484	0.465	0.345
Panel B: Use daily BBD data				
	(1)	(2)	(3)	(5)
Dependent variable	*Funded*	*Percent funded*	*Amount funded*	*Funding duration*
Policy uncertainty (*BBD*)	-0.031***	-0.555***	-0.060***	0.002***
	(0.005)	(0.040)	(0.003)	(0.001)
Controls	Yes	Yes	Yes	Yes
FEs	Yes	Yes	Yes	Yes
N	878,024	879,627	879,627	822,993
Adj./Pseudo R^2	0.067	0.372	0.376	0.309