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Distrust in Banks and Fintech Participation: The Case of Peer-to-Peer Lending

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Abstract

What has boosted crowdfunding's growth? In the case of peer-to-peer (P2P) lending, we highlight the role of consumers' distrust in banks. We offer evidence that distrust in banks likely triggers individuals to supply funding toward crowdfunding and away from bank deposits. We highlight that a distrust mindset promotes questioning default choices and considering alternatives, and fosters comparisons focusing on dissimilarities. Our findings suggest US states whose residents express greater distrust in banks are more likely to fund P2P loans and, conditional on funding, lend higher amounts. This relationship is more pronounced when funding small loans or borrowers with less banking access.

Keywords

crowdfunding, peer-to-peer lending, distrust in banks, fintech, technology adoption

By expanding funding opportunities, crowdfunding offers the promise of democratizing access to funding for many entrepreneurs (Bruton et al., 2015), especially underprivileged ones and those in underfunded regions (Sorenson et al., 2016). Successfully attracting funding from a large crowd requires understanding what drives their contributions (McKenny et al., 2017). This question lies at the core of crowdfunding's sustained growth as an alternative arrangement, hailed by policymakers who seek ways to grow the entrepreneurial ecosystem as a means of revitalizing their economies and creating jobs.

This paper examines distrust in traditional financial institutions as a factor behind the rise of crowdfunding. More specifically, we assess whether distrust in banks and other financial

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institutions boosts peer-to-peer (P2P) lending contributions. We chose this context for several reasons. First, P2P lending is the most widespread form of crowdfunding,[1] and banks and P2P lenders perform similar functions, as both extend debt financing to consumers. Second, trust is a crucial component in banking (Thakor & Merton, 2018; Zucker, 1986). However, in the wake of the recent financial crisis of 2008–2009, trust in banks has nosedived (Sapienza & Zingales, 2012; see also Guiso, 2010; Knell & Stix, 2015), a phenomenon that has been linked to predatory lending methods directed at vulnerable communities (Agarwal et al., 2014), breaching banks' obligations to protect consumers. Against the backdrop of financial institutions falling out of favor, popular media have touted P2P lending as a strong contender for the consumer lending market.

To investigate how distrust in banks is associated with higher inflows to P2P lending, we draw from extant literature on the "distrust mindset" from social psychology, which studies information processing under conditions of distrust (for a review, see Mayo, 2015). A central tenet of the distrust mindset is questioning one's default state of mind while activating, generating, and selecting creative alternatives to default positions and perspectives (e.g., Mayer & Mussweiler, 2011; Posten & Mussweiler, 2013; Schul et al., 2004). A fundamental difference exists between information processing under trust versus distrust mindsets. Whereas trust mindsets assume routine information processing and uncritically accept default positions, distrust leads people to engage in non-routine processing in which they carefully consider alternative options rather than uncritically hold onto their initial perspectives and interpretations (Posten & Mussweiler, 2013). Additionally, the distrust mindset induces dissimilarity-focus comparisons (Posten & Mussweiler, 2013), which describe judgments about a target that contrast with a comparison benchmark, rather than judgments about a target to be assimilated into a comparison benchmark (Mussweiler, 2001, 2003). Accordingly, distrust mindsets selectively activate information indicating that the target and benchmark are dissimilar on some selective dimensions of interest. These theoretical insights yield the following hypotheses: (a) Distrust in banks increases the provision of P2P lending as an alternative option, and (b) this supply-motivated relationship is more pronounced towards borrowers under-served by banks: borrowers with less access to banking or those who seek small loans. These moderating factors are consistent with how distrust in banks nurtures a focus on dissimilarities between banks (the benchmark comparison) and P2P lending (the alternative). We use data from Prosper.com, one of the largest U.S.-based P2P platforms, to test these hypotheses.

We find that residents of states with higher levels of distrust in banks are more likely to participate in P2P loans and allocate greater sums toward P2P loans—while distrust in banks is negatively correlated with bank deposits. The effect of distrust in banks on lending supply relative to that of general trust (i.e., whether most people can be trusted) is between 60% and 116% across different specifications. Furthermore, the relationship between lenders' distrust in banks and flows to P2P loans is stronger for loan applications whose borrowers seek small loans or live in areas that provide relatively lower access to bank branches.

Background Literature

P2P Lending

As an alternative means of access to funding for individuals including entrepreneurs, crowdfunding is organized in several models that are still evolving: reward-based crowdfunding; equity-based crowdfunding; donation-based crowdfunding; P2P lending; and initial coin offering. P2P lending matches a multitude of lenders with borrowers who post loans through an online platform. P2P consumer lending is the most widespread form of alternative finance in Europe. This model accounted for 41% of all volume in 2017 (excluding P2P business lending, with 13.8% of the market share), amounting to €1.392 billion or a near doubling from €697 million in 2016.[2]

Scholars have examined how crowds make lending decisions and the consequences for listed loans' funding outcomes (for a review, see Morse, 2015). Information asymmetries and moral hazards are two challenges facing crowds when screening loans. To overcome resulting adverse selection issues, crowds can use quality signals and information disclosures (Iyer et al., 2016). Besides hard information, lenders seem to consider soft information, such as a description of a loan's purpose (an explanation for a poor credit grade that is voluntary and a typically unverifiable disclosure; Michels, 2012), identity claims, or judgments about the attraction or trustworthiness of faces from profile pictures. Information on what other investors do (information cascades) can also attract more funding (Herzenstein et al., 2011; Zhang & Liu, 2012).

Related literature has also tied local availability of credit to lending outcomes. Ramcharan and Crowe (2013) find that borrowers facing declines in home prices in their geographical locations during the recent housing crisis procured funding with higher interest rates compared with those of otherwise-matched borrowers. Butler et al. (2016) find that borrowers residing in areas with good access to bank finance request loans with lower interest rates—an effect that is more pronounced for borrowers seeking risky or small loans. Thus, both lenders and borrowers' geographical locations impact their decisions beyond the influence of home bias (Lin & Viswanathan, 2016), which describes lenders' preference to fund geographically proximate borrowers. Tang (2019) uses a shock to bank credit supply to find that P2P lending substitutes banks when serving infra-marginal borrowers and complements them for small loans. Overall, this study contributes to the growing interest among scholars who study the link between banks and P2P lending, with a special emphasis on the supply side of the market (lenders).

Crowdfunders' Motivation

Scholars have investigated backers' motivations in crowdfunding. Backers could be motivated extrinsically or intrinsically to participate. Extrinsic motivation describes external factors that encourage individuals to contribute in hopes of earning money, avoiding punishment, or complying with social norms (Deci & Ryan, 2010). In the context of crowdfunding, examples of extrinsic motivation could include receipt of tangible rewards for campaigns that involve pre-purchasing a product (Cholakova & Clarysse, 2015) or the collection of interest payments. Pierrakis and Collins (2013) surveyed P2P lenders and showed that financial returns are lenders' most important motivation. Additionally, backers might pursue direct reciprocity (Colombo et al., 2015).

A range of intrinsic motivations is enumerated for crowdfunders. Backers might act prosocially (Giudici et al., 2018) and enjoy helping others realize certain projects' success (Cholakova & Clarysse, 2015), especially when they like, sympathize, or identify with the cause or the campaign's goals (Boudreau et al., 2015). Backers might also want to belong to a community (Gerber & Hui, 2013), to be liked, or to be well-regarded by others. Finally, Daskalakis and Yue (2017) surveyed crowdfunders on their motivations and report that "interest and excitement" comes second to financial returns in reasons to participate in P2P lending. Demir et al. (2019) find that sensation seeking is a motivating factor behind the decision to lend on Prosper.com. Our research examines whether distrust in banks constitutes a relevant driver of P2P lending.

Distrust in Financial Institutions and Banks

Trust in institutions is impersonal, that is, individuals who trust institutions believe that the collective entities that describe institutions are perceived to be legitimate, technically competent, and able to fulfil their assigned duties and obligations efficiently. Distrust in banks represents consumers' reluctance to put themselves in a vulnerable position with respect to banks because they perceive banks to be incapable, exhibit opportunistic behavior, violate or breach obligations, act against consumers' interests, or even intentionally take advantage of consumers (Kramer, 1999; Lewicki et al., 1998; Sitkin & Roth, 1993).

A few surveys have assessed the U.S. general public's trust in banks. Sapienza and Zingales (2012) find that only 27% of Americans trust financial institutions. Gallup polls in 2012 also indicate that less than 30% of Europeans trusted banks or other financial institutions.[3] Overall, in the wake of the financial crisis of 2008–2009, several economists expressed concerns about a "trust crisis" in banking (e.g., Ziegler et al., 2019; Guiso et al., 2009; Knell & Stix, 2015; Sapienza & Zingales, 2012). Understanding the factors associated with trust in financial institutions is important to policymakers because distrust in banks can undermine financial stability by increasing the likelihood of bank runs (Guiso, 2010) or influencing the public's decisions about how to save (Stix, 2013).

What drives distrust in banks? Guiso (2010) uses several surveys to suggest that fraud, such as the Madoff case, which received heavy media attention, may be a reason for the collapse of trust in U.S. banks. Stevenson and Wolfers (2011) study trust in public institutions across business cycles in the U.S. and document how trust in several institutions, including banks, decreased during the Great Recession. Their study associates this development with rising unemployment, suggesting that trust fluctuations entail cyclical responses. Knell and Stix (2015) use Austrian survey data to find that the extension of deposit insurance coverage and the lack of bank collapses had a cushioning effect on trust in banks. van der Cruijsen et al. (2016) survey Dutch households and find respondents' personal adverse financial-crisis experiences reduce their trust in banks. The financial crisis brought to light banks' pervasive opportunistic behaviors (Guiso, 2010). Banks failed to act in investors' best interests. For instance, an important factor that precipitated the financial crisis was financial institutions' moral hazard in loan securitization, as they had limited skin in the game (Keys et al., 2010).

Trust in financial institutions, including banks, is necessary for financial markets to function efficiently. Such trust has played a historically deep-rooted role in the emergence of banking, especially vis-à-vis banks' safekeeping and depository functions (Thakor & Merton, 2018; Zucker, 1986). Consistent with this observation, distrust in banks reduces ownership of savings deposits (but drives cash preferences; Coupé, 2011; Stix, 2013). Guiso et al. (2013) find that less trust in banks makes it more likely that borrowers strategically default on their mortgage debts. This study suggests and investigates another consequence of distrust in banks: inflows into P2P lending.

Information Processing Under Distrust

Information-processing strategies differ under a distrust mindset compared with a trust mindset (for a review, see Mayo, 2015). Trust appears to be the default state of mind; thus, people in situations with a trust mindset typically rely on routine information-processing strategies and on uncritical acceptance of default positions. Routine strategies are decision frames that, more or less, are executed effortlessly (e.g., the decision maker provides a flimsy initial response based on heuristics) and are typically found to be the most useful in normal or well-known environments (Schul & Peri, 2015). Thus, routine strategies are more likely to be activated by default (Schul et al., 2008) because situations, people, and institutions are as they appear on the surface (i.e., they can be taken at face value), and careful and critical processing is unnecessary. Conversely, a state of distrust indicates that something in the environment is amiss or potentially misleading, fostering the use of non-routine information-processing strategies that involve close scrutiny and careful consideration of alternatives to one's initial default choices (e.g., Kleiman et al., 2015; Mayer & Mussweiler, 2011; Mayo et al., 2014; Schul et al., 2004, 2008). Extant research has highlighted specific patterns of thought and action patterns that these information-processing strategies generate under trust and distrust mindsets (Schul et al., 2004).

Under distrust, individuals engage in questioning their default positions (Mayer & Mussweiler, 2011; Posten & Mussweiler, 2013; Schul et al., 2008). For example, Mayo et al. (2014) suggest that individuals under a distrust mindset tend to use disconfirmatory hypothesis testing, allowing for falsification of their initial hypotheses. Under distrust, individuals consider events from multiple perspectives and interpret information in multiple frames (Schul et al., 1996), apply and activate multiple information categories (Friesen & Sinclair, 2011), encode incoming information as if it is both true and false (Schul et al., 1996), increase the chances of arriving at creative solutions to problem-solving tasks (Mayer & Mussweiler, 2011), attentively look for unusual contingencies (Schul et al., 2008), and rely less on stereotypes in favor of individuating information (Posten & Mussweiler, 2013). In sum, the distrust mindset promotes critically assessing default positions and fosters consideration of alternative responses and interpretations.

The stream of literature that focused on the distrust mindset has examined further how decisions are made while considering alternatives, finding that the distrust mindset fosters dissimilarity-focus comparisons (Posten & Mussweiler, 2013). To elaborate, it is helpful to note that one characteristic of all judgments is their essential relativity. When judging other objects or people, we tend to compare them with comparison standards that are easily accessible (Dunning & Hayes, 1996; Gilbert et al., 1995; Mussweiler, 2003). In comparison judgments, scholars have identified two patterns, depending on whether the invoked focus of the judgment in a given situation concerns similar or dissimilar aspects of the comparison standards. Dissimilarity-focused comparisons involve contrasting the target to a greater extent from the standard, whereas similarity-focused comparisons direct attention toward similarities between the target and the standard by selectively activating dimensions of interest that are consistent with such assimilation (Mussweiler, 2001, 2003). Posten and Mussweiler (2013) find that a (dis-)similarity-focus is more likely to be used under (dis-)trust. Overall, extant literature on the distrust mindset offers concrete information-processing mechanisms that can help us understand what dimensions of alternatives individuals are likely to rely on for comparison tasks.

Hypothesis Development

We propose that distrust in banks can motivate contributions to P2P lending on the supply side. The core argument is based on how the distrust mindset cognitively attunes people toward carefully considering alternatives (Kleiman et al., 2015; Schul et al., 2004). In the case of distrust in banks, regardless of its underlying source, it triggers a thought process that increases the salience of relevant alternative possibilities, including P2P lending, which competes directly with banks in its lending function, albeit with some operational differences. P2P lending opens direct access to the asset class of consumer loans to individual lenders who are wary of banks' motivations, intentions, or past opportunistic behaviors. P2P lending removes the need for banks, as a financial intermediary, to hold deposits and offer loans on their balance sheets. Therefore, we hypothesize that distrust in banks is associated with contributions to P2P lending and away from banks:

Hypothesis 1: *Greater distrust in banks is associated with higher participation in funding P2P loans.*

The following hypotheses raise the possibility that distrust in banks increases the lending flow to P2P loans (from the supply side) whose borrowers are dissimilar to what traditional banks typically serve. To support this argument, we draw on extant literature suggesting that individuals under a distrust mindset tend to focus on dissimilarities when making comparisons (Posten &

Mussweiler, 2013). Dissimilarity-focused comparisons involve contrasting the target (P2P loans) away from the standard (loans offered by banks). Accordingly, lenders with distrust in banks selectively engage in seeking information that highlights dissimilarities between P2P lending and banks. That is, in addition to considering P2P lending as an alternative option, lenders also compare and contrast features of P2P lending with those of banks. Here we highlight two observable (and testable) dimensions that can be of interest concerning contrast-based comparison judgments in this context: (i) loans from borrowers with less access to bank branches and (ii) loan size.

We first suggest that distrust in banks increases funding to P2P loan applications whose borrowers have limited physical access to traditional banks. While there is extensive research documenting why borrowers under-served by banks would seek funding on P2P, we underline that on the supply side, the role of a distrust-in-banks mindset among lenders responding to such under-served borrowers should not be overlooked. Accordingly, we hypothesize that the link between distrust in banks and inflows to P2P are stronger for marginal borrowers. This is so because the mindset associated with distrust-in-banks triggers comparing banks with P2P lending platforms on distinctive dimensions that include the geographic reach to borrowers and the underlying costs in doing so. P2P platforms can cost-effectively reach under-served and infra-marginal borrowers, who define a market segment well-differentiated with respect to customers served by traditional banks. This is possible thanks to technology advances that facilitate credit scoring of prospective borrowers, servicing, monitoring, and credit-history reporting of loan performances. P2P lending platforms create searchable databases of borrowers for all lenders without the need for relationship lending. P2P lenders have digitized most operations (including loan-origination processes), and as such, they do not need investment in a network of physical branch distributions. If distrust in banks is among the driving factors for contributions to P2P lending and that the distrust mindset fosters dissimilarity-focus comparisons between the customers served by banks and those of P2P lenders, then we would expect that distrust in banks fosters lending to a market segment that traditional banks are less likely to serve.

> ***Hypothesis 2:*** *Greater distrust in banks is associated with higher lender participation in funding P2P loan applications whose borrowers have lower access to banks.*

Following the same logic that individuals with distrust mindset tend to focus on dissimilarities in their comparisons, we next propose that under distrust in banks market participants selectively focus on another distinguishing feature of customers served by banks and P2P lenders, namely the lower bound of loan sizes P2P lenders can serve. P2P lenders differ from traditional banks in terms of loan sizes they can offer owing to lower search costs (explained previously) and reduced transaction costs involving bargaining, policing, or obtaining verified creditworthiness data in transactions.[4] While small borrowers are the most likely to benefit from the expansion of P2P lending (Tang, 2019), our arguments highlight how lenders with distrust in banks might also favor this set of borrowers. Given that a distinguishing feature of P2P platforms is the ability to serve customers whose loan sizes are perhaps too small for traditional banks, we expect that distrust-in-banks can trigger lenders' attention to this dissimilarity in the size of loans borrowers request. This is a similar argument to hypothesis 2 and proposes that on the supply-side, the relationship between participating in P2P loan funding owing to distrust in banks is stronger when bank offerings are deficient or fully lacking. Thus, if distrust in banks is among the driving factors for contributions to P2P lending and the distrust mindset fosters dissimilarity-focus comparisons between the type of loans that banks and P2P lenders can economically fund, then we would expect that distrust in banks encourages lending to borrowers with smaller loan sizes.

Hypothesis 3: *Greater distrust in banks is associated with higher lender participation in funding P2P loans that are smaller.*

Data

Peer-to-Peer Lending Data

Our sample comprises all bids made on Prosper.com from February 5, 2006 (the day the marketplace publicly opened) to October 19, 2008. By the end of our sample period, US$444 million had been bid on Prosper.com, of which US$288 million became successful bids. Our sample contains data on 181,889 listings and 5,973,771 bids. Given that our unit of analysis considers listing-state bidding possibilities, we transformed our data, yielding 7,275,560 observations. The choice of level of analyses at the state level is driven by data availability on bidders' location; we only have data on bidders' states of residence. Below, we explain why we restrict our main analyses to a sample of bids on listings until October 19, 2008.

First, between October 19, 2008 and July 13, 2009, Prosper.com was temporarily shut down, and Prosper suspended new lending. Prior to this hiatus, lenders from all states were allowed to participate in loans, but afterwards the Securities and Exchange Commission required Prosper to obtain each state's approval for lending to comply with state-mandated investor-protection regulations. After the shutdown, given the gradual nature of Prosper's ability to obtain operating licenses in various states, total bidding amounts increased, but as of the end of 2011, they had not yet reached their heights prior to the closure.

Second, as the market has grown, institutional investors have begun to engage in P2P lending (Lin et al., 2017; Mohammadi & Shafi, 2017). Lin et al. (2017) show that institutional investors invested less than 5% of all investments in Prosper prior to October 2008, but this grew after the shutdown and peaked in 2012. As we focus on determinants of participation of individuals (and not institutions) within the P2P online market, our chosen period is suitable for analysis.

Finally, limiting the sample to prior to October 2008 helps us avoid confounding factors associated with the U.S. financial crisis (the collapse of the investment bank Lehman Brothers was on September 15, 2008).

Dependent Variables

The main dependent variable is the total dollar amount of bids into each loan listing by bidders from each state (*Participation Amount*). This variable is natural log-transformed, and measures participation in funding P2P loans. The average of this variable is $58.1. Alternatively, we use a dummy variable equal to one if at least one bidder from a state (regardless of the amount) participates in a loan, and zero otherwise (*Participation Indicator*). This alternative variable assesses the likelihood of participating in P2P loans. The average of this variable is 18.4%. We also test whether, conditional on participation in a P2P loan (*Participation Indicator* = 1), the total amount increases with distrust in banks. The average of this variable is equal to $315.5.[5]

Distrust in Banks

The data originates from the General Social Survey (GSS), obtained from the U.S. National Opinion Research Council (NORC) at the University of Chicago, which biennially surveys nearly 2,500 individuals regarding their level of confidence in various institutions. This survey contains information on respondents' location, income, age, gender, race, education, political orientation, and religion (in certain years). We obtained confidential geo-identifiers for respondents to this survey, which also contain state-of-residence data.[6] The survey asks: "As far as the people running these institutions (namely banks and financial institutions) are concerned, would you say you have a great deal of confidence, only some confidence, or hardly any confidence at all in them?" Possible answers to the institutional-confidence questions were (a) a great deal, (b) only some, (c) hardly any, or (d) don't know. We defined a respondent distrust-in-banks dummy variable as being equal to 1 if the response was (c) and 0 if the response was (a) or (b); we exclude those responding with (d).[7] By averaging the dummy variable across respondents residing in a state, we obtain the average level of prevailing *distrust in banks* sentiment in that state.[8]

Being limited by our P2P data time frame, we utilize trust data in the 2006 and 2008 survey waves. For 2007, we utilize average values corresponding to 2006 and 2008.[9] Not all 50 U.S. states, plus D.C., are surveyed in each biennial survey wave. We include all states surveyed in both the 2006 and 2008 survey waves, which totaled 40 states. The lowest levels of distrust in banks is in Kentucky (0%), Connecticut (7.1%), Wyoming (9.0%), Wisconsin (9.3%), and Indiana (9.9%). The five states exhibiting the highest levels of distrust in banks are Delaware (75%), the District of Columbia (37.5%), New Mexico (32.3%), Iowa (26.1%), and Arizona (27.4%).[10] For robustness, we winsorized the distrust in bank variable at 5% to ensure that outliers (e.g., Kentucky and Delaware) do not drive our results. The results are robust and available upon request.

Moderators

Borrower bank density is defined as the number of bank branches in the borrower's state per state population. *Listing size* is defined as the natural logarithm of the total dollar amount that the borrower has requested for a given listing.

Control Variables

We collect an extensive list of additional state-related (of lenders) variables to control for possible confounding factors, including technological development, economic conditions, demographics, and access to banking.

To ensure that our distrust in banks is not merely capturing a general component of distrust, we also include the variable *Trust in Others* in our specifications. To build this variable, we use data from another question from the same survey, phrased as follows: "Do you think most people can be trusted?" Possible answers are (a) Most people can be trusted, (b) You can't be too careful, (c) It depends, or (d) I don't know. The *Trust in Others* variable is constructed as a share of state residents responding (a) Most people can be trusted (we exclude those who responded [d] I don't know). Furthermore, we include *Distrust in Government* to capture a general dimension of anti-establishment distrust. Possible answers to the trust in government question were (a) a great deal, (b) only some, (c) hardly any, or (d) don't know. The *Distrust in Government* variable is constructed as a share of state residents responding (c) hardly any to the question of trust in the U.S. federal government (we exclude those who responded [d] don't know).

Prior literature has shown that geographical distance plays an important role in P2P lending behavior (Lin & Viswanathan, 2016). Thus, we include a variable that measures the geographical distance between the borrower and lender. To control for a state's general economic condition, we include annual gross domestic product (GDP) growth and GDP per capita. We also control for population, population density, and each state's working-age population. Another set of controls captures tech-savviness among state's residents, namely level of Internet use at home, percentage of science and engineering graduate study enrollments, and per capita cyber-crime perpetrators.

We additionally control for P2P demand in the borrower's state to separate the direct relationship between distrust in banks and P2P lending from increases in local demand for P2P funding. We also control for financial literacy as an explanatory factor distinct from lenders' distrust in banks. We add a control for entrepreneurial activities within a state by including a variable to capture the per-capita annual change in net total number of firms in a state compared with the prior year. Furthermore, we control for banking density to capture to what extent lending on P2P platforms is driven by scarcity of banking services or investment advice. Finally, we include several variables to capture states' demographic characteristics: religion (Protestant, Jewish), race (White, Hispanic), political views (Republicans), and gender (Male). Supplemental Appendix 1 (2) provides variable descriptions and data sources (including a correlation table). Table 1 summarizes descriptive statistics of all variables included in the main analysis.[11]

Empirical Strategy

We exploit geographical variation in participation in peer-to-peer loans and distrust in banks to test our theoretical predications. The analysis is conducted at the level of U.S. states and loans. For each loan, we have 40 observations that corresponds to the number of U.S. states in the GSS survey. Thus, we aggregate all bids (pertaining to a listing) from lenders in a state into one observation. We repeat this for all states and listings. This leads to 7,275,560 (40 × 181,889) observations from 181,889 listings.

Denoting lender states by i, peer-to-peer loans by j, and time by t, the main regression specification is as follows:

$$P2P\ Participation_{ij} = \beta_1 \times Distrust\ in\ Banks_{it} + \gamma X_{it} + \alpha Y_{ij} + lj + \varepsilon_{ij} \tag{1}$$

The explanatory variable of interest is the state-averaged level of distrust in banks. The main dependent variable is the log of the total amount of bids into a given loan listing by bidders from each state (*Participation Amount*). The vector X_{it} includes controls for state-level economic and demographic characteristics that may affect participation level in peer-to-peer markets. The vector Y_{ij} includes *Lending Distance*, which varies across the bidder's state (i), and loans (j). The data are unlikely to capture all sources of heterogeneity. Participation can be driven by factors on both the demand and supply sides. On the demand side, borrowers' characteristics also can affect lenders' participation. We include loan fixed effects (lj) that control for unobserved demand-side heterogeneity by calculating within-loan estimates (Wooldridge, 2010). As the loans are usually open for a short period of time (between seven and 14 days), it is less likely for demand-side characteristics to vary across time for each loan. To isolate the *Distrust in Banks* effect from other supply-side characteristics, we control for an extensive list of economic and demographic characteristics (X_{it}) that may affect the state level of participation in peer-to-peer markets and can be correlated with *Distrust in Banks*. We also cluster standard errors for each listing.

Results

Our main analysis focuses on associations between distrust in banks and participation in P2P lending. Table 2 reports estimates based on specification (1), which includes control variables and loan-fixed effects, with the level of analysis at listing-state of bidder.

Table 1. Data Summary Statistics (N = 7,275,560).

Variable name	Mean	SD	Median	Min	Max
Dependent variables					
Participation indicator	0.184	0.387	0	0	1
Participation amount	58.066	316.81	0	0	33056.02
State trust measures					
Distrust in banks	0.195	0.134	0.176	0	0.75
Lister or listing characteristics					
Borrower banking density	0.311	0.078	0.305	0.191	0.677
Listing size (log)	8.606	0.847	8.517	6.908	10.127
High risk listings	0.793	0.405	1	0	1
Debt to income ratio	0.415	1.14	0.22	0	10.01
Home ownership	0.377	0.485	0	0	1
Control variables					
Trust in others	0.407	0.156	0.4	0	0.778
Distrust in government	0.419	0.124	0.412	0	0.789
Lending distance (log)	7.127	1.346	7.335	0	9.015
Internet access	0.674	0.063	0.683	0.521	0.79
GDP per capita	49.511	20.235	44.900	30.500	168.200
GDP growth	0.039	0.033	0.036	−0.043	0.19
Population	7,146,038	6,937,427	5,412,337	522,667	36,604,337
State P2P demand	1.05	0.48	0.977	0	7.308
Financial literacy	3.001	0.107	3.017	2.75	3.276
New firms	0.071	0.438	0.055	−0.887	1.629
Science and engineering specialization	0.179	0.048	0.179	0.061	0.324
Cybercriminality	0.421	0.201	0.455	0.112	0.907
Banking density	0.35	0.077	0.351	0.191	0.554
Population density	0.17	0.564	0.049	0.002	3.672

(Continued)

Table 1. Continued

Variable name	Mean	SD	Median	Min	Max
Working age population	0.531	0.013	0.53	0.503	0.568
Male	0.491	0.006	0.491	0.472	0.509
White	0.798	0.134	0.832	0.294	0.965
Hispanic	0.105	0.1	0.074	0.011	0.452
Republican	0.441	0.116	0.440	0.034	0.666
Protestant	0.527	0.131	0.517	0.269	0.758
Jewish	0.015	0.018	0.009	0.001	0.085

Table 2. Determinant of Participation in P2P Loans.

	Participation indicator		Participation Amount[a]			
Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)
Distrust in banks (H1)	0.034***	0.169***	0.275***	0.211***	0.307***	1.129***
	(0.001)	(0.012)	(0.006)	(0.010)	(0.015)	(0.032)
Distrust in banks x borrower bank density (H2)					−0.100*	
					(0.042)	
Distrust in banks x listing size (H3)						−0.099***
						(0.004)
Trust in others	0.057***	0.866***	0.237***	0.041***	0.237***	0.238***
	(0.001)	(0.015)	(0.006)	(0.008)	(0.006)	(0.006)
Distrust in government	0.002**	0.038***	0.027***	−0.027***	0.027***	0.025***
	(0.001)	(0.008)	(0.004)	(0.007)	(0.004)	(0.004)
Lending distance (log)	−0.003***	−0.002**	−0.021***	−0.008***	−0.021***	−0.021***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Internet access	0.117***	3.141***	0.868***	2.714***	0.868***	0.872***
	(0.005)	(0.045)	(0.024)	(0.032)	(0.024)	(0.024)
GDP per capita (log)	0.048***	0.268***	0.235***	0.181***	0.235***	0.236***
	(0.001)	(0.012)	(0.005)	(0.009)	(0.005)	(0.005)
GDP growth	−0.099***	−0.736***	−0.366***	1.224***	−0.366***	−0.364***
	(0.006)	(0.049)	(0.031)	(0.040)	(0.031)	(0.031)
Population (log)	0.087***	0.646***	0.508***	0.605***	0.508***	0.508***
	(0.000)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
P2P loan demand	0.016***	0.077***	0.089***	0.153***	0.089***	0.089***
	(0.000)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
Financial literacy	−0.046***	−0.401***	−0.293***	−0.188***	−0.293***	−0.292***
	(0.002)	(0.017)	(0.007)	(0.011)	(0.007)	(0.007)
New firm creation density	0.018***	0.072***	0.059***	−0.041***	0.059***	0.057***

(Continued)

Table 2. Continued

	Participation indicator		Participation Amount[a]			
Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)
	(0.000)	(0.005)	(0.002)	(0.004)	(0.002)	(0.002)
Science and engineering specialization	0.173***	0.385***	1.110***	0.443***	1.110***	1.108***
	(0.003)	(0.029)	(0.014)	(0.021)	(0.014)	(0.014)
Cybercriminality	0.034***	0.133***	0.209***	0.099***	0.209***	0.208***
	(0.001)	(0.016)	(0.005)	(0.007)	(0.005)	(0.005)
Banking density	−0.238***	−1.307***	−1.202***	−0.455***	−1.202***	−1.206***
	(0.002)	(0.022)	(0.012)	(0.018)	(0.012)	(0.012)
Population density	−0.010***	−0.074***	0.011***	0.092***	0.011***	0.010***
	(0.001)	(0.006)	(0.003)	(0.004)	(0.003)	(0.003)
Working age population	−0.751***	−7.835***	−2.348***	1.557***	−2.346***	−2.364***
	(0.015)	(0.138)	(0.071)	(0.111)	(0.071)	(0.071)
Male	3.671***	2.163***	23.195***	8.721***	23.193***	23.157***
	(0.038)	(0.347)	(0.174)	(0.283)	(0.174)	(0.174)
White	−0.031***	−0.791***	−0.089***	−0.338***	−0.089***	−0.089***
	(0.001)	(0.010)	(0.005)	(0.009)	(0.005)	(0.005)
Hispanic	0.031***	0.686***	0.390***	1.202***	0.390***	0.392***
	(0.002)	(0.015)	(0.009)	(0.013)	(0.009)	(0.009)
Republican	−0.221***	−1.431***	−1.075***	−0.716***	−1.075***	−1.074***
	(0.001)	(0.014)	(0.007)	(0.011)	(0.007)	(0.007)
Protestant	0.154***	0.943***	0.835***	0.420***	0.835***	0.837***
	(0.002)	(0.018)	(0.009)	(0.016)	(0.009)	(0.009)
Jewish	2.143***	4.346***	10.264***	−0.098	10.264***	10.269***
	(0.015)	(0.117)	(0.068)	(0.086)	(0.068)	(0.068)
Constant	−2.663***	−9.908***	−17.720***	−11.609***	−17.720***	−17.693***
	(0.021)	(0.195)	(0.102)	(0.152)	(0.102)	(0.102)

(Continued)

Table 2. Continued

	Participation indicator		Participation Amount[a]			
Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)
Listing FE	Yes	Yes	Yes	Yes	Yes	Yes
Specification	OLS	Logit	OLS	OLS	OLS	OLS
Observations	7,275,560	7,275,560	7,275,560	1,272,927	7,275,560	7,275,560
Adjusted *R*-squared	0.467		0.537	0.537	0.537	0.537
Number of listings	181,889	181,889	181,889	110,772	181,889	181,889

Notes. Clustered standard errors are reported in parentheses. The symbols ***, **, *, + mean that the reported coefficients are statistically different from zero, respectively, at the 0.1%, 1, 5% and 10% level.
[a]This variable is in natural logarithmic form.

Model 1 of Table 2 is a linear probability model, in which the dependent variable is a dichotomous variable indicating whether a bidder from a state has bid on a listing or not. The coefficient on distrust in banks is positive and statistically significant (0.034, p < .001). One standard-deviation increase in distrust in banks is associated with a 0.4% increase in probability of participation in P2P listings. We find similar results using a logistic regression (Table 2, Model 2).

Models 3 and 4 of Table 2 use OLS specifications to predict *Participation Amount* as a dependent variable. The coefficient of the distrust in banks variable in Model 3 (0.275, p < .001) suggests that greater distrust in banks is associated with higher amounts of participation by bidders, in support of Hypothesis 1. The coefficient implies that a one standard-deviation increase in distrust in banks is associated with a 3.7-percentage-point increase in the amount of money invested in a loan. In Model 4 of Table 2, we restrict our analysis to states that participate in bidding on P2P loans and exclude zero-participation amounts. Thus, the number of observations is reduced to 1,272,927. This is the intensive margin of participation in P2P loan listings. The positive and significant magnitude (0.211, p < 0.001) of distrust in banks is consistent with our expectations. Overall, based on results from Models 1 to 4, distrust in banks is associated with a higher probability of participation and a higher dollar amount of participation in funding P2P loans.

Beyond our main results described above, we note that "trust in others" is positively correlated with participation in P2P lending across all models. To understand the magnitude of the effect of distrust in bank on participation, we compare its effect with "trust in others." The economic magnitude of "distrust in bank" relative to "trust in others" in Models 1 and 3 is 59.6% and 116%, respectively. Supplemental Appendix 5 shows the marginal effect of a one-unit change in "distrust in bank", "trust in others," and "distrust in government."

Heterogeneity in Effects of Distrust in Banks on Participation in P2P Lending

In this section, we test Hypothesis 2 (the less accessible banks are for a borrower, the stronger the association between distrust in banks and participation in funding P2P loans) and Hypothesis 3 (the lower the listing size, the stronger the association between distrust in banks and participation in funding P2P loans). Model 3 in Table 2 forms our baseline regression for testing cross-sectional variations in the effect of distrust in banks on participation in P2P loans. In Model 5 of Table 2, the coefficient of interaction term (distrust in banks and borrower bank density) is negative and statistically significant (beta = −0.100, p < .05). The coefficient implies that at the average value of distrust in banks (0.195), a change in borrower bank density equivalent to that from its maximum value (0.677) to its minimum value (0.191) corresponds to a 20.3% increase in the effect of distrust in banks on participation in P2P loans. This implies that the lower the bank density in a borrower's state (worse local access to financing), the larger the effect of lenders' distrust in banks on participation in P2P loans. The results provide empirical evidence that supports Hypothesis 2.

We then test Hypothesis 3. In Model 6 of Table 2, the coefficient of the interaction term (distrust in banks and listing size) is negative and statistically significant (beta = −0.099, p < .001). The coefficient implies that at the average value of distrust in banks (0.195), change in listing size from its maximum value (10.127) to its minimum value (6.908) corresponds to a 252.1% increase in the effect of distrust in banks on participation in P2P loans. This implies that the smaller the loan, the larger the effect of distrust in banks on lenders' P2P loan participation. The results provide empirical evidence supporting Hypothesis 3.

Additional Analyses and Robustness Check

This section investigates our construct's validity, endogeneity issues, alternative explanations, and external validity through additional analyses and robustness checks. For the sake of brevity, we report some of the results in the Supplemental Appendix, including definitions and descriptive statistics for variables used in this section.[12]

Construct Validity

The main independent variable (distrust in banks) is extracted from the GSS survey. The construct's validity can be a concern, as this measure might be noisy and not merely capture distrust in banks. To alleviate this concern, we conduct an additional analysis.[13]

We investigate whether events related to banks and financial institutions determine distrust in banks. *Construct validity* refers to what extent a measure reflects the theoretical construct (Cronbach & Meehl, 1955)—in this case, distrust in banks. Distrust originates from breaches to expectations of the trustee's goodwill or technical competence (Dimoka, 2010). Consequently, events such as bank fraud, in which expectations of banks' benevolence are not met (Guiso, 2010), or bank failures, in which expectations, vis-a-vis banks' competence, are damaged, should engender societal distrust in banks and other financial institutions. To test the validity of our survey-based construct of distrust in banks, we test the effect of such events on it.

Using an extensive database of all cases of fraud committed by listed financial firms and commercial bank failures in the U.S. from 1978 to 2012, we investigate whether distrust in banks in states is associated with the revelation of financial institution frauds and banking failures.

We proxy for the severity of bank failures in a state using the FDIC's estimation of losses of failed banks, and for the severity of frauds using the log of monetary penalties imposed by regulators on firms and employees, or the log of duration of prison sentences served by convicted employees. To control for the size of each state's banking system, we standardize our failure measures by dividing them by total commercial bank domestic deposits in states. We lag our bank failure and financial firm fraud measures by one period to determine their effect on engendering distrust in banks.

Table 3 presents regression results for our analyses. In Model 1, we regress distrust in banks on the frequency of bank failures in a state. The coefficient is positive and statistically significant (beta = 0.068, $p < .05$). A standard-deviation increase in exposure to bank failures in a state corresponds to 1.5% in additional distrust in banks. In Model 2 of Table 3, we use our first proxy for the severity of financial firm fraud, comprising penalties on firms and employees. Our coefficient is positive and statistically significant (beta = 0.011, $p < .01$). A standard-deviation ($161 million) increase in such penalties from the mean of $8 million to $173 million is associated with a 14.1% increase in our distrust variable. In Models 4–6, we use alternative variables for bank failures and frauds, and results are very similar, showing that there is positive correlation between bank failures and frauds with distrust in banks. Fraud's economic impact on distrust in banks seems to be larger than bank failures' impact on distrust in banks.

Endogeneity Issues

Estimates of the main coefficient can be biased due to two sources of unobserved heterogeneity: demand and supply side factors. We control for unobserved heterogeneity from the demand side by including listing fixed effects. To attenuate concerns about supply-side heterogeneity, we included an extensive list of economic and demographic characteristics that may affect the regional level of participation in peer-to-peer markets. While this reduces concerns over unobserved supply-side heterogeneity, it is not able to address the issue completely. In this subsection, we address this issue in a few steps.

Table 3. Determinant of Distrust in Banks.

	Distrust in Banks					
	(1)	(2)	(3)	(4)	(5)	(6)
Bank failures	0.068*		0.065*			
	(0.030)		(0.030)			
FDIC Est. losses of bank failures				0.748*	0.720*	0.723*
				(0.297)	(0.303)	(0.301)
Penalties for financial firm frauds		0.011**	0.010*		0.010**	
		(0.004)	(0.004)		(0.004)	
Frauds' prison sentences						0.010*
						(0.005)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes	Yes	Yes
Sample period	1978–2012	1978–2012	1978–2012	1978–2012	1978–2012	1978–2012
Observations	810	810	810	810	810	810
Adjusted *R*-squared	0.444	0.440	0.446	0.441	0.444	0.442

Notes. All regressions include all controls: Trust in others, distrust in government, age, years of education, male, high income, White, Hispanic, Republican, Protestant, Jewish, employed, GDP growth. The symbols ***, **, *, + mean that the reported coefficients are statistically different from zero, respectively, at the 0.1%, 1, 5% and 10% level. The level of analyses is state-year.

First, we use a longer time period from 2006 to 2012 (the main analyses only went through October 2008). This longer period (due to greater variations in distrust) allows us to improve our identification strategy. We repeat all analyses on the new sample (Table 4, Models 1 and 2). The results remain similar to the main findings.

Second, we include the state (of the lender) fixed effects in the model, allowing us to reduce concerns about time-invariant heterogeneities across states (Table 4, Models 3 and 4). Again, the results support our main hypotheses.

Third, we use an instrumental variable approach to alleviate endogeneity concerns. In the previous section, we showed that at the state level, fraud committed by listed financial firms and commercial bank failures are correlated positively with distrust in banks. We argue that while these variables are correlated with distrust in banks (relevance criteria), they are not correlated strongly with unobserved state-level characteristics (exclusion restriction). The exclusion restriction is more valid for frauds that listed financial firms committed. The decision to commit fraud is made by a handful of individuals working in financial institutions and is less likely to affect general state-level economic and demographic characteristics. To implement this method, we use a two stage instrumental variable approach at the state-listing level (Table 4, Models 5–7). In the first stage, we estimate distrust in banks by including fraud that listed financial firms committed, commercial bank failures, and all control variables (Model 5). Cragg-Donald Wald F-statistics of the first-stage regression (1400) is larger than the critical value of 10. This indicates that our instrumental variables are not weak (Stock & Yogo, 2005). The R-squared of the first stage is also 0.651. The preceding statistics reassure us about the relevance and validity of the instrumental variables. In the second stage, we use estimated distrust in banks (from the first stage) and repeat Models 1 and 3 from Table 2 (Table 4, Models 2, 3, and 5). The results support our hypothesis that distrust in banks is associated with greater participation in funding P2P loans.

Alternative Explanations

A possible concern is that our results are driven by a common time pattern of the growth of P2P lending and distrust in banks (e.g., due to the U.S. financial crisis of 2008–2009). The financial crisis also impacted interest rates strongly. This is especially alarming, as our sample includes observations from 2008 (our sample ends on October 19, 2008). To alleviate this concern, we restrict our analysis to 2006 only, as well as to 2006 and 2007. This should alleviate such a concern, as Lehman Brothers collapsed in September 2008, which is considered to be the epicenter of the financial collapse (Gertler & Gilchrist, 2018). Interest rates that the Federal Reserve set also were quite stable during 2006 and 2007. The results (Supplemental Appendix 7) lend support to our hypothesis that distrust in banks is associated with greater participation in funding P2P loans.

Types of Distrust

Distrust in banks, as a driver of participation in P2P lending, can be related to sources of distrust. On the one hand, a fear of losing money invested by banks, and on the other, a more general and ideologically oriented distrust in banks as institutions. Depending on which source is the more important driver, our results' implications clearly differ. If fear of losing money is the prevalent driver of resource allocation, banks and states' actions to alleviate such concerns could be expected to impact participation in P2P lending directly. Alternatively, if ideologically oriented types of distrust in banks drive our results, adopting P2P lending reflects motives other than strictly financial considerations.

To investigate the mechanism underlying fear of losing money, we examine whether increased participation in P2P lending (that seemingly is associated with distrust in banks) can be associated with loss-aversion behavior. We argue that if distrust in banks is driven by a fear of losing

Table 4. Determinant of Participation in P2P Loans Using Time Period 2006–2012.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Participation indicator	Participation amount	Participation indicator	Participation amount	Distrust in banks	Participation indicator	Participation amount
					First stage	Second stage	Second stage
Distrust in banks	0.090***	0.598***	0.075***	0.446***		0.315***	1.190***
	(0.001)	(0.006)	(0.002)	(0.009)		(0.007)	(0.031)
FDIC Est. losses of bank failures (t minus 1)					0.520*** (0.003)		
Financial institution frauds' prison sentences (log; t minus 1)					0.010*** (0.000)		
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Listing FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	No	Yes	Yes	No	No	No
Observations	8,214,309	8,214,309	8,214,309	8,214,309	8,214,309	8,214,309	8,214,309
Adjusted R-squared	0.505	0.575	0.510	0.587	0.651	0.140	0.200
Number of listings	232,645	232,645	232,645	232,645	232,645	232,645	232,645

Notes. Models 1 and 2 replicate the results of main models in Table 2. In models 3 and 4, we include state of borrower fixed effect. Model 5 reports the first stage of the instrumental variable model. Models 6 and 7 show the second stage of instrumental variable models. All regressions include all controls including trust in others, distrust in government, lending distance, internet access, GDP per capita, GDP growth, population, P2P demand, financial literacy, new firms, science & engineering specialization, cybercriminality, banking density, population density, working age population, male, White, Hispanic, Republican, Protestant, Jewish. Clustered standard errors are reported in parentheses. The symbols ***, **, *, + mean that the reported coefficients are statistically different from zero, respectively, at the 0.1%, 1, 5% and 10% level.

[a]This variable is in natural logarithm.

Table 5. Heterogeneity of Participation in P2P Loans Based on Riskiness of Loans and Borrowers.

	Participation amount[a]		
	(1)	(2)	(3)
Distrust in banks × high-risk listings	0.547***		
	(0.010)		
Distrust in banks × debt to income ratio		0.043***	
		(0.002)	
Distrust in banks × borrower homeownership			−0.208***
			(0.007)
Distrust in banks	−0.144***	0.260***	0.358***
	(0.011)	(0.006)	(0.006)
Controls	Yes	Yes	Yes
Listing FEs	Yes	Yes	Yes
Observations	7,275,560	7,275,560	7,275,560
Adjusted R-squared	0.538	0.537	0.537
Number of listings	181,889	181,889	181,889

Notes. All regressions include all controls including trust in others, distrust in government, lending distance, internet access, GDP per capita, GDP growth, population, P2P demand, financial literacy, new firms, science & engineering specialization, cybercriminality, banking density, population density, working age population, male, White, Hispanic, Republican, Protestant, Jewish. Clustered standard errors are reported in parentheses. The symbols ***, **, *, + mean that the reported coefficients are statistically different from zero, respectively, at the 0.1%, 1, 5% and 10% level.
[a]This variable is in natural logarithm.

money, lenders should be less-inclined to invest in riskier loans, which have a greater chance of default, thereby providing lenders with a higher probability of losing their money.[14] We measure the riskiness of the loan and borrowers using three different variables. First, we include a dummy variable, *High-Risk Listing*, representing listings by borrowers with credit categories of C or lower (i.e., D, E, and HR). Second, we include the borrower's debt-to-income ratio. Finally, we consider whether the borrower is a homeowner. Borrowers with higher debt-to-income ratios have a higher probability of default, but borrowers who are homeowners are deemed less risky, as their home can be used as collateral.

Table 5 reports the results from introducing interactions between distrust in banks and our risk variables. In Model 1, we interact distrust in banks with the dummy variable *High-Risk Listings*. The result shows that the effect of distrust in banks on participation in P2P loans is larger for borrowers with higher risks (worse credit ratings). We cannot include credit categories separately in our specification, as they are correlated perfectly with listing fixed effects. Model 2 (3) shows that the effect of distrust in banks on participation in P2P loans is larger (smaller) for borrowers with higher debt-to-income ratios (homeownership). Generally, the results show that the effect of distrust in banks on participation in P2P loans is larger for riskier loans and borrowers. These results suggest that the form of distrust in banks that is driven by fear of losing money seemingly would not be the main driver of participation among crowdfunders with greater distrust in banks.

External Validity

Another concern is whether our result is only valid for the Prosper.com context and the institutional environment in the U.S. For further robustness tests, we repeat all analyses using a sample of all P2P loans active between 2010 and 2013 in the United Kingdom and measure distrust in banks from the European Bank for Reconstruction and Development's Life in Transition Survey (LiTS) II. Details on the data and variables are explained in Panel D of Supplemental Appendix 8. Generally, the results (Supplemental Appendix 8, Table A6i) are similar to those of Table 2 and show that increases in distrust in banks are correlated positively with the likelihood and level of participation in P2P loans. Using different surveys and samples increases confidence in our main findings' external validity.

Effect of Distrust in Banks on Bank Deposits

Our theoretical argument was that individuals with higher distrust in banks are likely to allocate a portion of their assets to alternative assets (e.g., crowdfunding) instead of holding them with banks. Thus, we should also observe that distrust in banks would decrease assets held with banks. While this hypothesis is not new and has been reported in prior studies (Guiso, 2010; Sapienza & Zingales, 2012), we repeat the analyses by regressing the aggregated deposits of each single-state bank on our distrust in banks variable. Thus, the level of analysis is at a single-state bank-year. We extract bank deposits and balance sheets from the Federal Deposit Insurance Corporation's (FDIC) branch-level data. Our sample covers the 2001–2016 period. The sign and magnitude of our distrust in banks variable (Supplemental Appendix 9) indicate that increases in distrust in banks decrease (increase) deposits (other liabilities) in single-state banks.

Conclusion and Discussion

This study leverages insights from the literature on the distrust mindset to argue that distrust in banks boosts the use of P2P lending. We use data from Prosper.com and find that residents of states with higher levels of distrust in banks are more likely to participate in P2P loans and allocate greater sums toward P2P loans. Given negative correlations between distrust in banks and bank deposits reported in prior studies (e.g., Sapienza & Zingales, 2012) and also verified in this study, our findings imply that distrust in banks drives the adoption of peer-to-peer lending as an alternative to banks. Additionally, the relationship between distrust in banks and inflows to P2P lending is stronger for borrowers who seek small loans and those who live in areas with lower access to physical bank branches.

We discuss the potential origins of distrust in banks in the context of our study. Distrust in banks can reflect two sets of distinctive judgments. The first concerns the expectation that a generic bank will fail to repay depositors and violate its commitments. This situation represents heightened fears that investors or depositors will lose all or part of their money, for example, due to the possibility of bank failure. Such pessimistic perceptions were especially widespread during the recent financial crisis after Lehman Brothers collapsed in 2008. The second source of distrust concerns a diffused belief that actors at financial institutions (e.g., brokers, bankers, financial advisors, etc.,) may act opportunistically and take advantage of their investors. For instance, bank managers might charge non-transparent commissions, hide relevant information, commit fraud, misuse funds, or undertake risky and speculative investment bets that benefit themselves at the cost of customers and investors. This second source of distrust in banks can take the form of social or ideological perspectives. In fact, protest movements such as Occupy Wall Street in 2011, were partially motivated by such negative sentiment toward banks, as evidenced by the publication of a book titled *Occupy Finance*, which the group "Occupy Wall Street Alternative Banking Group" distributed to discuss misconduct in the financial industry leading up to the financial crisis and the ways in which the financial industry skirted prosecution.[15] We presented some preliminary and indirect evidence in our context that favors ideologically oriented distrust in banks over distrust in banks' abilities to live up to their direct obligations toward their clientele. In particular, we find that the relationship between distrust in banks and P2P participation is stronger for high-risk and high-default borrowers. This evidence likely weakens the idea that P2P lenders are primarily concerned with a fear of losing money when distrusting banks (Had this been the case, the effect of distrust in banks would be expected to correlate with a preference for low risk borrowers).

Another discussion point from our study relates to the role of generalized trust (trust in strangers) and inflows to P2P lending. Prior research has reported a positive relationship between generalized trust and several financial and economic outcomes, including economic performance (Knack & Keefer, 1997), flow of trade (Guiso et al., 2009). van der Cruijsen et al. (2019) find that trust in other people has a statistically and economically significant positive effect on participation in a wide range of peer platform markets, where goods or services are exchanged between peers through online platforms. We find similar evidence investigating a particular type of such markets, that is, loan-based crowdfunding models. Generalized trust appears to lubricate economic activity in the form of sharing financial resources, particularly substituting for heavy reliance on informal borrowing or more established ways of accessing financial services.

This study makes two theoretical contributions. We contribute to extant research that explore P2P lenders' motivations (Demir et al., 2019; Shafi & Mohammadi, 2019). Crowdfunding literature has highlighted both intrinsic and extrinsic motivations, including earlier access to innovative products and ideas, making an impact, sympathy, a desire to help others, feeling good about oneself, recognition from others, image promotion and social reputation, and sensation seeking (Boudreau et al., 2015; Cholakova & Clarysse, 2015; Colombo et al., 2015; Demir et al., 2019; Galak et al., 2011). We are able to offer a new motivation and further delineate the moderating conditions associated with this new motivation by choosing a crowdfunding type that offers (lending) functions comparable to those of banks and by employing geographic variations on expressed distrust in banks. Our broader contribution to extant literature on investors in crowdfunding draws on theories first developed in social psychology about information processing under the distrust mindset (Mayo, 2015). Moreover, we applied these theories to observational data instead of laboratory experiments, which have frequently been used to develop and test such theories, with certain methodological caveats, including limited room for external validity assessments.

We also contribute to an emerging stream of literature interested in the relationship between technology and financial intermediaries (e.g., Balyuk, 2019; Chava et al., 2017; Fuster et al., 2019; Saiedi et al., 2020; Thakor, 2020). In particular, we add to the conversation about the advantages of firms that exploit financial technology (fintech firms) over incumbents—whether P2P lending is a substitute for or complement to bank lending. Whereas most studies focus on the substitute role between banks and fintech lenders from the demand side (Buchak et al., 2018; De Roure et al., 2019; Tang, 2019), we examine the supply side, which new theoretical papers, such as Thakor and Merton (2018), are beginning to investigate further.

Our findings have several practical implications, including for policymakers concerned with seed and early-stage gaps in markets for entrepreneurial finance, as well as for individuals such as entrepreneurs who aim to succeed in fundraising. With this growth in the volume of crowdfunding transactions during the past decade, scholars initially focused on examining demand-driven factors—such as campaign characteristics, the product, and the management team—which all correlate with campaign success. Subsequently, scholars have investigated crowdfunders' motivations as another important growth driver. One overlooked impetus for crowdfunders' contributions is negative sentiments toward established institutions. Such distrust-in-bank motivated contributions, in particular, have the potential to address gaps in funding from current institutions (e.g., limited access to bank branches). Note that policymakers are concerned with negative effects associated with distrust in the banking sector, including financial instability and bank runs, lower demand for financial products, and investors' adverse portfolio choices, discounting of advice, and reduced reliance on financial intermediaries when making financial decisions. Accordingly, policymakers might pursue regulatory interventions and oversight, but these concerns might be overstated, as distrust in banks may have helped with the emergence of alternatives (especially when these alternatives fill a market gap and have not yet suffered from major failures). Whereas failures to maintain consumer trust may have adverse impacts on incumbents (e.g., banks), they can lend an advantage to new and emerging fintech competitors. Therefore, policymakers can heed our evidence, which provides a dynamic perspective on disruption.

This paper contains certain limitations that offer opportunities for future research. First, while we used two different samples in different countries, our identification strategy remains malleable to unobserved heterogeneity. While we cannot exogenously manipulate levels of distrust in banks to study contributions to crowdfunding, we performed several analyses to increase our findings' reliability. Future research can examine the effect of institutional differences on the presented results despite our efforts in using samples from two countries. Also, we assume that P2P lenders in our sample share the same beliefs about trust in banks as the average person living in that state at the time of survey measurements. Finally, future research can investigate whether our results can be extended to other forms of crowdfunding. Such analyses also would require identifying corresponding institutions that provide services similar to those of different crowdfunding forms.

We conclude this paper by highlighting the role of negative trust sentiment toward banks in propelling P2P lending' growth. Whereas distrust in financial institutions traditionally is viewed as detrimental for financial stability, we propose a silver lining: Distrust in banks fuels growth of P2P lenders, which increases the diversity of available funding options, especially in dimensions that are dissimilar to banks. By embracing new developments for fintech lenders, we hope that this study inspires further research into factors that propel this new industry.

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Notes

1. Cambridge Center for Alternative Finance (CCAF); See Ziegler et al. (2019)
2. -See Ziegler et al. (2019)
3. Available here: https://news.gallup.com/poll/162602/european-countries-lead-world-distrust-banks.aspx
4. For instance, platforms provide a standard contract and enforcement that make negotiations unnecessary and obviate the need for individual collections activity. P2P lenders also automate the loan-origination process (Buchak et al., 2018; Fuster et al., 2019), lowering the fees associated with loan applications and approval. The decrease in costs makes it economical for lenders to provide smaller loans (on which less information is available), especially when existing options are not suitable or available.
5. One concern with this aggregated amount is that we are not able to differentiate between investments that originate from just a few bidders and those from a large number of bidders. Thus, in robustness checks, we also include number of bids per capita (bids per capita) and the number of unique bidders per capita (bidders per capita) as alternative dependent variables. The results show that distrust in banks is associated with a larger number of bidders and bids. Results are available upon request.
6. The authors signed a non-disclosure agreement with the NORC. Some of the data used in this analysis are derived from Sensitive Data Files of the GSS, obtained under special contractual arrangements designed to protect the anonymity of respondents. These data are not available from the authors. Persons interested in obtaining GSS Sensitive Data Files should contact the GSS at GSS@NORC.org
7. Less than 1.5% of respondents answered (d) don't know (1.1% in 2006 and 1.4% in 2008).
8. Survey-based, state-level trust variables have been taken to be representative in prior studies in economics (e.g., Aghion et al., 2010; Giannetti & Wang, 2016).
9. We repeated our analysis by excluding 2007 and the results are very similar and are available upon request. We also assumed that the distrust variable did not change in 1 year, so we replace the distrust variable for 2007 with values from 2006. Again, the results are very similar and available upon request.
10. The extreme values in Kentucky and Delaware can be attributed to the small number of respondents in the survey because changing one answer will have a significant effect on distrust in bank. To verify robustness, we defined a lower limit of 20 to and 50 respondents per state as a minimum cut-off for survey respondents. This also led to exclusion of outlier states Kentucky and Delaware. The results are highly similar and available upon request. Finally, we created a three (two)-year trailing average of three (two) waves of surveys. Again, the results are very similar and are available upon request.
11. For the sake of brevity, description and summary statistics for the rest of the variables included in the following sections are reported in Appendices 3 and 4.
12. Variable definitions and descriptive statistics can be found respectively in Supplemental Appendices 3 and 4.
13. We also check how much our variable (distrust in banks) overlaps with the Gallup Analytics surveys on "Confidence in Institutions," which examines a random sample of approximately 1,000 individuals across the U.S. Supplemental Appendix 6 shows distrust in banks from both surveys (GSS and Gallup) across time. Measures derived from the surveys are highly correlated (92.5%). This shows that both surveys (which are conducted independent of each other) measure the same construct and, thus, can increase our construct validity.
14. For example, Iyer et al. (2016) show that the default rate is 14.7% in the lowest risk-category level (AA) and reaches 51.6% in the highest credit-category level (HR). In addition, in case of default, lenders lose only 9% of their principals in credit category AA, but lose 38.5% of their principals in credit category HR.
15. http://altbanking.net/projects/our_book/

Supplemental Material

Supplemental material for this article is available online.

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