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The Role of Trust in Online Lending*

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Abstract

We study the impact of trust on the expansion of online lending in the U.S. over the 2008-2016 period. Using data from the largest platform, we demonstrate that a misconduct-driven decline of trust in traditional banking is associated with a statistically and economically significant increase in online lending at the state level. To the contrary, increased social trust strengthens in-person, bank-based borrowing and informal borrowing, reducing the demand for impersonal online lending. Both of these effects operate primarily through borrowers. We also use a shock that affects only investors to demonstrate that distrust in traditional finance increases participation in online lending.

Keywords: financial development, consumer loans, bank misconduct, FinTech
JEL Classification: A13, G00, G21, K00

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1 Introduction

Trustworthiness matters in financial transactions.[1] Hence, the expansion of new financial services, such online lending, may be constrained by the level of trust among prospective market participants. Similarly, a decline in faith in traditional forms of finance could generate growth in online lending by driving borrowers away from banks. Such considerations are especially relevant in the aftermath of the Great Recession, where widespread misconduct in the financial sector gave rise to the concern that "fraud has become a feature and not a bug" (Zingales (2015), p.19). By eliminating the middleman, online lending platforms are able to reduce investor apprehension about opportunistic behavior that is often associated with traditional financial intermediaries. From a borrower's perspective, online lending is relatively impersonal, which suggests that increased interpersonal trust will primarily benefit bank-based borrowing, where personal interactions with bank employees remain common.

Using nearly-complete loan and application histories from the two largest and oldest U.S. platforms, LendingClub.com and Prosper.com, we measure the impact of time and geographic variation in trust on state-level online lending. Our measures of trust are divided into three groups: 1) interpersonal trust; 2) trust in traditional banking; and 3) trust in traditional finance. Following the literature (e.g., Gambetta (2000); Guiso et al. (2008)), we define a borrower's interpersonal trust as the subjective probability she assigns to the chance of being cheated by others, and use survey responses from the General Social Survey (GSS) to measure it. Similarly, borrower trust in the traditional banking sector is defined as an individual's subjective probability of being cheated by banks. We construct a proxy for trust in banks using financial misconduct data from the Consumer Financial Protection Bureau (CFPB). Finally, we use an analogous definition for investor trust in the traditional financial sector more generally, and measure this using the geographic distribution of Madoff scandal victims, as in Guiso (2010).

We first examine how borrower trust in traditional banks affects online lending at the state level. Controlling for local macroeconomic conditions, loan-borrower characteristics, and geographic and time fixed effects, we show that lower trust in traditional banking is associated with a higher level of online lending. In particular, an increase of one complaint

[1] E.g. see Guiso et al. (2004, 2008, 2013), Giannetti and Wang (2016), and Rau (2017).

per bank branch is associated with a 6% increase in the ratio of online debt to total debt[2] for the median state. This finding also appears to be borrower-related, which indicates that bank misconduct may drive existing customers away from traditional banking to online platforms.

In contrast to our results for trust in traditional banks, we find that higher interpersonal trust weakens online lending growth, since online lending is perceived to be impersonal relative to bank-based borrowing. In particular, a one standard deviation increase in personal trust is associated with a -11% decline in the online debt to total debt ratio for the median state. We also show that interpersonal trust operates in the same direction on credit card debt, which is also impersonal, but in the opposite direction on mortgage debt, which often requires interaction with bank staff. Furthermore, this result holds when our measure of trust in traditional banking is included as a control, which suggests that the two measures have distinct effects on borrowing. It also holds in both application and loan data.

In addition to these findings, we also identify which borrower segments are most sensitive to variation in trust levels. The 2015 FDIC National Survey of Unbanked and Underbanked Households shows that a low level of trust in banks is a significant impediment for underserved borrowers seeking financial services. Macro-level evidence points to a positive association between unemployment and distrust in institutions–and, in particular, banks (Stevenson and Wolfers 2011)–which suggests that a low level of trust in financial institutions is likely to be particularly important for underbanked households who often lack stable employment and have low credit ratings. In fact, we find that a lower level of trust in banks and a lower level of interpersonal trust are both positively associated with a higher share of online lending in the low credit rating segment.

Finally, turning to the supply side, we test whether a decline of investor trust in traditional finance increases online lending. We use the locations of the Madoff scandal victims to capture geographic variation in this category of trust. Since the scandal largely pre-dates our sample, there is no time variation to exploit. We find that investment in online lending platforms is affected positively by exposure to the Madoff scandal, which is consistent with the conjecture that it shattered the confidence of wealthy investors, shifting interest to

[2] We refer to all household debt not channeled through online lending as "total debt" or "bank debt."

alternative financial investments, such as online lending.

Our analysis complements the extensive literature on trust by exploring its role in the financial development of online lending. Generalized trust–that is, interpersonal trust and trust in institutions–has been shown to be positively associated with financial development (e.g., Guiso et al. (2004)) and appears to be an important determinant of the crowdfunding boom at the international level, as shown in a key contribution by Rau (2017). Our paper is the first to study how different dimensions of trust affect online online lending. It also advances the literature by expanding our understanding of the scope of financial disintermediation that has occurred under FinTech.

The rest of the paper proceeds as follows. Section 2 reviews the related literature. Section 3 presents the theoretical framework and develops hypotheses. Section 4 provides background information on the online lending market and describes the data. The empirical results are presented in section 5. Finally, section 6 concludes. All tables are located in the Appendix.

2 Related literature

Our paper relates to three distinct strands of literature. First, it builds on the existing empirical research on social trust, connecting to the literatures on both interpersonal trust and trust in institutions. Second, our paper contributes to the literature on financial development and growth with a focus on financial innovation. And third, we complement the emerging literature on consumer credit and online lending that studies the micro- and macro-determinants of investor financing, as well as borrower behavior.

Trust. The literature proposes different definitions for the concept of trust. We use the one proposed in Gambetta (2000), which is tightly connected to beliefs.[3] For online lending, Duarte et al. (2012) demonstrate that having a trustworthy appearance matters, and that it affects both investor and borrower behavior. This was shown using data from Prosper.com, a U.S.-based online lending platform, for the years in which investors were able to access borrowers' pictures. Several papers also document trust as an important determinant of

[3]See Fehr (2009) for a review of the "Economics and Biology of Trust."

stock market participation.[4] For credit markets, trust appears to be even more important, since debt claims are characterized by a limited upside for investors. Consequently, investors have more to fear from being cheated by borrowers. However, trust in lenders and the perception of fair treatment also play an important role for borrowers. Guiso et al. (2013) find that lower trust in banks makes it more likely that borrowers strategically default on their mortgage debt. Moreover, there is an extensive literature documenting the response to perceived unfair treatment in various areas (e.g., Xia et al. (2004)), suggesting that it also influences borrowers' willingness to switch to online lending platforms.

Financial innovation. Guiso et al. (2004) document the important role played by trust and social capital, more generally, in financial development. Financial development, in turn, has been demonstrated to be a facilitator of economic growth, as argued, e.g. by Rajan and Zingales (1998). Rau (2017) suggests that the international expansion of crowdfunding is positively related to interpersonal trust, as well as the quality of regulation, the degree of financial development, and internet access.

In light of the existing literature, the deterioration of trust in the traditional banking industry after the Great Recession (e.g., Corsetti et al. (2010)) may have lowered the barriers to entry for new players from the FinTech sphere, fueling disintermediation in some market segments targeted by online lending platforms (FSB 2017). Since the widespread financial misconduct before and after the crisis involves many of the largest banks (Sakalauskait 2016), our measure of distrust in banks is based on misconduct, which should be particularly relevant for the sample period under consideration.

Online lending. Crowdfunding platforms have enjoyed rapid growth in recent years and have received increased attention in the literature.[5] We focus on online lending, which is the dominant worldwide form of crowdfunding (Rau 2017).[6] Within online lending, consumer credit is the largest market segment and tends to attract high-risk borrowers who want small

[4]See Guiso et al. (2008) for the effect of a lack of generalized trust and interpersonal trust, and Giannetti and Wang (2016) for the effect of a deterioration of trust due to corporate fraud.

[5]For a recent review of the literature on crowdfunding, see Belleflamme et al. (2015). Specific to crowdlending (or online lending), see Morse (2015).

[6]For an in-depth overview see the Cambridge Center for Alternative Finance (CCAF) Benchmarking Reports referenced in Rau (2017).

loans, a slice of the market that is underserved by traditional banks (De Roure et al. 2016). Many borrowers in this segment also use online platforms to increase their total borrowing capacity (Demyanyk et al. 2017). Online consumer credit is often uncollateralized and can be seen as a substitute for credit cards and other forms of consumer credit. Lending platforms operate with significantly lower costs than traditional banks and specialize in automated credit scoring. This can give FinTech lenders an advantage in screening high-risk borrowers (Einav et al. 2013), which may allow them to extend more generous loans to medium-risk borrowers. The expansion of online lending appears to be highest in regions where traditional banks are absent or capital constrained.[7]

A number of papers employ the peer-to-peer (P2P) online lending market as a laboratory to study different micro aspects of lending, such as the role of informational frictions, using U.S. data from the Prosper.com[8] and LendingClub.com[9] consumer credit platforms. However, macroeconomic developments have also been shown to play an important role.[10] From an investor's perspective, Lin and Viswanathan (2016) document substantial home bias in online lending, which resonates with the extensive home bias literature in economics and finance. The implication for our paper is that shifts in investor attitudes in a region are likely to have measurable implications for regional online lending volumes.

3 Theoretical framework and hypothesis development

We reviewed an extensive literature that documents the historical role of trust in financial markets. With the emergence of online lending, different varieties of trust have surfaced

[7]See, e.g., Havrylchyk et al. (2017).

[8]Papers using data from Prosper.com study the role of soft information, such as the appearance of borrowers (Duarte et al. 2012; Pope and Sydnor 2011; Ravina 2012; Gonzales and Komarova Loureiro 2014), the importance of screening in lending decisions (Iyer et al. 2015; Hildebrand et al. 2016; Balyuk 2016), the herding of lenders (Zhang and Liu 2012), the importance of geography-based informational frictions (Lin and Viswanathan 2016; Senney 2016), the auction pricing mechanism that existed prior to 2011 (Chen et al. 2014; Wei and Lin 2015), and the ability of marginal borrowers to substitute between financing sources (Butler et al. 2015).

[9]There are papers using data from LendingClub.com to study adverse selection (Hertzberg et al. 2015) and retail investor risk-aversion (Paravisini et al. 2016).

[10]Crowe and Ramcharan (2013) study the effect of home prices on borrowing conditions. Bertsch et al. (2017) study monetary normalization and online lending.

as links in the chain that connect FinTech to traditional banking. The dominant forms of consumer credit, traditional bank loans and credit card debt, have faced growing competition from online lending platforms, especially in the segment for uncollateralized, high-risk credit debt for underbanked households.

3.1 Theoretical framework

From a conceptual viewpoint, we propose a stylized theoretical model that emphasizes the borrower perspective. This allows us to gain insights into how different dimensions of trust could affect the development of the online lending market. We allow borrowers in the model to choose between different sources of funding and assign them a payoff that depends negatively on the borrowing costs and on the probability of being cheated or treated unfairly. This might entail unfair contractual terms, opaque or unpredictable fees, or deliberate missales. We assume that personal interaction can help borrowers to build trust with lenders, and lenders to build trust with borrowers. The empirical literature suggests that this is especially true for repeated interactions in borrower-bank relationships. In a lending context, it can help to convey soft information during an interaction with a loan officer. This personal, relationship-specific component of lending favors traditional banks.[11]

On the other hand, online lending platforms have a clear cost advantage over traditional banks: credit scoring is automated and there is no need to maintain a branch network. We assume that online platforms can leverage FinTech to offer cheaper loans based on hard information to the borrower segments they target, as long as there is no important soft information or relationship component that can be captured by traditional banks.

Formally, we consider a simultaneous-move, one-shot game with a continuum of borrowers of mass $m > 0$, indexed by i with interest in obtaining a long-term, uncollateralized loan of fixed size, $L = 1$. The credit market is competitive and uncollateralized. On the supply side, there is a large number of traditional banks and online lending platforms that compete

[11] We acknowledge that an appearance-based trust measure is likely to be positively associated with the chances of individual borrowers to obtain a loan from a bank or from an online lending platform, where borrowers were able to post pictures in the initial years (see Duarte et al. (2012)). The survey-based interpersonal trust measure elicits, however, a different dimension of trust that is independent of person-specific traits.

by setting lending rates. For simplicity, all agents are risk-neutral. The cost of traditional banks to issue one loan is f_B and the cost of online lenders to issue one loan is $f_O \in (1, f_B)$.

We aim to capture the heterogeneous ability of borrowers to take advantage of an in-person relationship with a traditional bank that allows them to convey soft information and to improve monitoring via repeated interaction.[12] To do this in a stylized way, we assume that borrowers have a baseline repayment probability of $0 < p < 1$ and face an idiosyncratic cost $c_i \in U[0, \bar{c}]$ to further increase the repayment probability to q if they decide to incur the cost and take out an in-person loan from a traditional bank, where $\bar{c} > 0$ and $p < q < 1$.

Let $\bar{r}$ denote borrowers' reservation interest rate. We assume that borrowers have a lack of trust in both types of lenders, since they believe they may be cheated or treated unfairly with a certain probability. For simplicity, the expected utility cost of being cheated by banks is given by $\tau_B > 0$, while the expected cost of being cheated by online lenders is $\tau_O > 0$.

The timing is as follows. First, borrowers decide whether to incur a cost that allows them to increase their repayment probability with traditional banks. Second, lenders simultaneously offer rates to borrowers who then decide which offer to accept. In effect, banks compete by offering one rate to borrowers who are known to have an increased repayment probability when taking an in-person laon and a different rate to all remaining borrowers, while online lending platforms compete by offering a single interest rate to all borrowers.

Result 1 below describes the credit market equilibrium and summarizes the key comparative statics that guide our development of hypotheses.

Result 1 *A sufficient condition for the existence of a credit market equilibrium with participation of all borrowers is given by:*

$$\min\{f_B/q + \tau_B + \bar{c}, f_B/p + \tau_B, f_O/p + \tau_O\} \leq \bar{r}. \tag{1}$$

All loans are issued by traditional banks if the relative trust in banks is high:

$$\min\{f_B/q + \bar{c}, f_B/p\} < f_O/p + (\tau_O - \tau_B), \tag{2}$$

[12]We emphasize the benefits from relationship banking and repeated interaction, which we capture in a reduced from. We acknowledge the extensive literature on signaling. Important screening tools that have been discussed include collateral and loan quantities (Bester 1985).

which is the case if $(\tau_O - \tau_B)$ *is high. If inequality (2) is violated and* $f_B/q < f_O/p + (\tau_O - \tau_B)$*, then a fraction* $\hat{c}/\bar{c}$ *of borrowers incur the cost for the relationship investment and accept a loan from traditional banks, while all others do not incur the cost for the relationship investment and accept a loan from online lending platforms, where:*

$$\hat{c} \equiv f_O/p - f_B/q + (\tau_O - \tau_B). \tag{3}$$

The total online lending volume, $m(1 - \hat{c}/\bar{c})$*, is increasing in* τ_B*,* f_B *and* $\bar{c}$*, while it is decreasing in* τ_O *and* f_O*. Finally, if inequality (2) is violated and* $f_B/q \geq f_O/p + (\tau_O - \tau_B)$*, then all borrowers do not incur the cost and exclusively accept loans from online platforms.*

3.2 Hypothesis development

Guided by the literature and the theoretical framework above, we design empirical tests to measure the relationship between interpersonal trust, trust in traditional banking, trust in traditional finance, and the expansion of online lending. We first introduce the hypothesis tests and, thereafter, present the corresponding econometric models.

Hypothesis 1: trust in traditional banking (borrowers)

H0: Deterioration of trust in traditional banking, caused by bank misconduct, is positively correlated with the expansion of online lending at the state level in the US.

One implication of Result 1 is that the entry and expansion of online lending platforms in the consumer credit market should depend on the level of trust in banks. Result 1 predicts that the deterioration of trust in traditional banks after the financial crisis, captured by an increase in τ_B relative to τ_O, reduces the barrier to entry for online lending platforms and is associated with an increase in the market share of online lending.

We relate the measure of state-level online lending development to CFPB-reported bank misconduct using the following empirical model:

$$Y_{i,t} = \beta_1 \text{CFPB complaints}_{i,t} + \gamma X_{i,t} + (A_i + B_t) + \epsilon_{i,t}. \tag{4}$$

The dependent variable is the ratio of P2P debt (millions) to total debt (tens of billions) in state i in month t.[13] The bank misconduct variable is computed as the number of consumer complaints filed to the CFPB in the same month. Our specification also includes state fixed effects, A_i, and time fixed effects, B_t. We estimate the model with OLS.

Since online lending platforms operate with significantly lower costs than traditional banks and specialize in automated credit scoring, FinTech lenders have an inherent advantage in screening high-risk borrowers (Einav et al. 2013). Thus, we might expect that the deterioration of trust in banks has a disproportionately large impact on the high-risk borrower segment. In fact, Result 1 suggests that a cost advantage for platforms screening high-risk borrowers, i.e. an increase in $f_B - f_O$, is associated with a larger share of online lending in this segment.

Hypothesis 2: interpersonal trust (borrowers)

H0: States with higher interpersonal trust should experience less credit demand in the online lending market, since online platforms are perceived to be impersonal relative to traditional banking and informal lending from friends and family.

Another implication of our theoretical framework is that borrowers will find loans from banks more attractive if it is less costly for them to take advantage of in-person relationships with traditional banks. Result 1 predicts that a lower cost-to-invest in a borrower-bank relationship, captured as a reduction in $\bar{c}$, is associated with a higher lending volume for traditional banks relative to online lending. Furthermore, higher interpersonal trust may also give borrowers better access to alternative sources of funding, such as informal credit from family and friends. Such credit is often strictly preferred by borrowers and easier to obtain. In the context of our model, it amounts to a lower m, which is associated with a reduction in online lending. Either way, *H0* follows.

To test our hypothesis, we regress the online lending development measure on the social trust measures, computed using the GSS survey question on interpersonal trust. The

[13]Note that we use millions for P2P debt and tens of billions for total debt to deal with scaling issues, since the P2P market is small relative to the financial sector for much of our sample. Importantly, however, we will show that the effect of trust on the P2P market itself is economically significant.

regression is specified as follows:

$$Y_{i,t} = \beta_1 \text{Interpersonal trust}_i + \gamma X_{i,t} + (B_t) + \epsilon_{i,t}. \tag{5}$$

We use a cross-sectional measure of social trust that is computed as the average of the GSS's social trust question over the period 1973-2006 (Algan and Cahuc 2014). This captures the slow moving component of social trust, which the literature suggests is most salient.

Hypothesis 3: trust in traditional finance (investors)

H0: Investor trust in traditional banking is negatively correlated with investor participation in online lending. Thus, negative shocks to investor trust will lead to faster growth in online lending.

We treat the impact of the Madoff investment scandal in late 2008 as a negative shock to trust in traditional finance. We argue that the discovery of large scale fraud may have caused investor attitudes to shift, increasing interest in alternative investments, such as online lending. While traditional finance was tarnished by the former Nasdaq Chairman's scandal, online lending platforms, which offer a high level of transparency and information provision, may have actually gained. Thus, we would expect the supply of funds to the online market to increase, lowering borrowers' funding costs on online lending platforms.

In the context of our theoretical framework, such a shift in relative funding conditions can be captured as a decrease in $f_O - f_B$. Hence, Result 1 predicts an increase in total online lending. The econometric model is set up as follows:

$$Y_{i,t} = \beta_1 \text{Madoff victims}_i + \gamma X_{i,t} + (B_t) + \epsilon_{i,t}. \tag{6}$$

The Madoff victim measure is given by the number of investors who suffered losses in the scandal at the state level, as in Guiso (2010). We include only time fixed effects in the specification because the Madoff scandal data is cross-sectional.

In addition to the state-level regressions, we also investigate the relationship between trust measures and subgroup differences in applicant credit quality. We also use loan application level regressions to measure the impact of trust in traditional banking on the extensive and intensive borrowing margins.

4 Data and descriptive statistics

Peer-to-peer (P2P) online lending first emerged in the U.S. in 2005 in the form of crowdfunding. *Prosper.com* was the first U.S.-based platform, followed by *LendingClub.com*, which has been the market leader for several years. According to a Federal Reserve Bank of Cleveland study, U.S. P2P lending grew by an average of 84% per quarter between 2007 and 2014 (Demyanyk 2014). More recently, online lenders have started to transition from crowdfunding, which entails raising small amounts of funds from multiple lenders, to a mix of crowdfunding and marketplace lending, which involves securing wholesale funding from institutional investors. The accounting firm PricewaterhouseCoopers expects online lending platforms to reach 10% of revolving US consumer debt by 2025.[14]

Our primary dataset consists of a panel of 1.7 million loan-borrower observations from LendingClub, which operates the largest online platform for consumer credit in the US and was founded in 2006.[15] As of October of 2017, LendingClub has more than 1.5 million customers, including both investors and borrowers, and has originated loans in excess of $28 billion. While LendingClub's base of institutional investors has grown strongly since 2014, retail investors participation remains significant. Since LendingClub only recently expanded to the small business loan and auto refinancing segment, we focus exclusively on personal uncollateralized loans. Borrowers request loans ranging from $500 to $40,000 with a maturity of 3 to 5 years. The median borrower has a loan size of $13,000, an interest rate of 13%, a yearly income of $65,000, an employment duration of 6 years, and a low proprietary credit rating. The personal loans issued by LendingClub are used for a variety of purposes, including debt consolidation, large durable good purchases, and unexpected expense financing. The highest rated borrowers may have normal access to traditional sources of credit from banks and credit cards, but the lowest rated borrowers are likely to be underserved.

[14]See market study by PricewaterhouseCoopers (2015).

[15]We use LendingClub as our primary subject of study because Prosper SEC filings are incomplete over the first four years of our sample.

After a prospective borrower submits an application, the platform collects self-reported and publicly available information, including the borrower's credit history. LendingClub uses a credit model to decide on the borrower's qualification for the loan, to assign a credit score, and to set a fixed interest rate and repayment schedule. The process is fast and qualified borrowers can expect to receive an offer within 24 hours. The platform provides a large set of loan-borrower characteristics to investors and divides the market into two distinct segments: fractional and whole. The fractional loan market is where a crowd of investors screens loans posted on the platform and funds individual borrowers in $25 increments. The whole loan market is where individual borrowers are matched with large investors who purchase entire loans. While the former market is dominated by retail investors, the latter market is dominated by institutional investors. Individual loan applications are allocated to the fractional or whole loan market by the platform and have no influence on it. We observe whether individual loan applicants successfully obtain funding and from which market segment. Provided borrowers accept the loan, the total funding volume (net of an origination fee) is disbursed. LendingClub offloads the risk to lenders and then services the loan throughout its duration, which includes monthly installment transfers from borrowers to lenders.

LendingClub (as well as Prosper) generates fee income that is growing in transaction volume. Specifically, LendingClub's fee structure for fractional loans consists of the following: 1) an origination fee of 1-6%, paid by borrowers at loan disbursement; 2) a servicing fee of 1% on the payments transferred to lenders; and 3) a set of collection fees imposed for late payment and default. The servicing fee differs for the whole loan market.

In addition to our primary dataset for LendingClub, we also have a secondary dataset with application data for Prosper, which spans the 2012-2017 period. Prosper's platform design is very similar to LendingClub's. Our application data for both LendingClub and Prosper comes from 424B3 filings, which we retrieved from the SEC's Edgar database. Our loan data for LendingClub comes from LendingClub's loan book, retrieved from their website. The SEC filings contain all application data, including loan and borrower characteristics. The loan book contains the set of loans originated, as well as loan characteristics, borrower characteristics, and repayment status updates. See Table I for the list of variable definitions and Table II for the associated summary statistics of our primary dataset.

We also collect information on variables related to the core hypotheses we test in the paper: 1) a survey-based measure of interpersonal trust; 2) factors that affect trust in traditional banking, such as instances of bank misconduct; 3) debt origination data from the Federal Reserve Bank of New York; 4) FDIC bank branch data; and 5) state-level economic and demographic controls. The period we study begins with the earliest available data on P2P lending in the U.S. in 2008 and continues until 2016. Data sources (3) and (4) are used primarily to normalize our variables of interest.

The survey-based measure of trust was obtained from the General Social Survey (GSS), which is conducted biennially by the National Opinion Research Center (NORC) at the University of Chicago. This contains a measure of interpersonal trust, is available for the 1973-2016 period, and includes both the region of residence and region of residence at age 16 for each respondent. We focus on interpersonal trust for the current region of residence and average over all observations in a given state-year. This yields a measure with a scale of 0 to 1, which varies between 0.18 and 0.62 in our sample.

We also collect data on several factors that affect trust, including exposure to financial misconduct. We use the following data for financial misconduct: 1) the Consumer Financial Protection Bureau's (CFPB) Consumer Complaint Database; and 2) the list of Bernie Madoff's victims. The CFPB data contains the name of the bank, the time of the complaint, and the location of the customer. We compute the total number of complaints per state. We then normalize this by the number of bank branches in the state, which we take from the Federal Deposit Insurance Corporation's (FDIC) database. The average state has 0.20 complaints per branch. We hand collected the list of Bernie Madoff's victims' identities and locations from the New York Times's website. We then computed the number of victims per state.

5 Empirical results

We test our hypotheses listed in Section 3 and present the results. We also include robustness checks to further nuance our empirical test results. All tests conducted using our primary dataset, but are robust to the inclusion of secondary data from Prosper.

5.1 Borrower trust in traditional banking

The first hypothesis claims that a lack of trust in financial institutions drives borrowers from traditional banks to online lenders. To measure trust, we use consumer complaints filed to the U.S. Consumer Financial Protection Bureau (CFPB). The underlying assumption is that borrowers in states that experience a high number of complaints per bank branch–an indication of bank misconduct or customer mistreatment–will tend to have lower levels of trust in traditional banks.

In Table III, we test Hypothesis 1 by regressing the ratio of online debt (m$) to total debt (10b$) on the average number of consumer complaints per bank branch at the state level. We use complaints per bank branch to measure distrust in traditional financial institutions. In total, we have 2839 state-month observations. In the even-numbered columns, we use a specification that controls for the following variables at the state-level: population density, GDP, the unemployment rate, and the population size. We also control for borrower characteristics by including the state-level averages for the interest rates charged on loans, the gross income levels of borrowers, and the number of years employed. In columns 3 and 4, we include fixed effects to control for time-invariant state level characteristics. Columns 5 and 6 include both state and year fixed effects to control for time-invariant, state-level characteristics and other common sources of time series variation that may have contributed to growth. In columns 7 and 8, we replace year fixed effects with year-month fixed effects, along with state fixed effects. This imposes more rigorous control on the time trend and the business cycle component to capture any shocks that occurred in a particular month.

Our estimate of the impact of borrower trust in traditional banking on P2P borrowing is positive and statistically significant at the 1% level. Column 8 contains our preferred regression specification. We find that increasing the number of complaints by 1 per bank branch is associated with a 0.009 increase in the online debt ratio. Stated differently, a one complaint increase per bank branch is associated with an increase in the ratio of online debt to total debt by 6% for the median state. This suggests that distrust in traditional financial institutions has an economically significant impact on the growth of online lending.

We also analyze the impact of CFPB complaints on the extensive and intensive margins using loan application-level information. We compute the impact on the extensive margin by regressing the fraction of P2P borrowers in the state's population on the average borrower pool quality variables and on state level controls. The intensive margin is measured using a regression that links the loan application size to borrower-loan characteristics. From Table IV and V, we find that the results for the CFPB are mostly driven by the extensive margin, rather than the intensive margin. Equivalently, CFPB complaints at the state level motivate higher online lending growth, but do not affect borrowers' decisions about the loan amount.

These results align well with intuition. Namely, a higher level of distrust in banks is associated with a higher number of borrowers deciding to switch to online lending. Conversely, there is no compelling reason to expect that the typical borrower who switches would request more funds. Thus, it seems plausible that state-level gains would be driven by extensive margin gains. This is also consistent with our theoretical framework, which makes predictions about the extensive margin.

5.2 Interpersonal trust

To test Hypothesis 2, we regress the fraction of P2P debt on a cross-sectional measure of trust–namely, the average of positive responses to the interpersonal trust question from the General Social Survey (GSS) over the period 1973-2006, which pre-dates our sample (See Algan and Cahuc (2014)). Previous work in the literature argues that interpersonal trust is a slow-moving variable within a given society, which suggests that regional variation is likely to be most meaningful.[16] As predicted, the relationship between interpersonal trust and P2P debt is negative, which suggests that higher levels of interpersonal trust are associated with less online lending at the state-level. Both measures yield similar results and are robust.

In Table VI, the cross sectional variable from the GSS is used as the measure of interpersonal trust. Note that the cross-state variation of trust in other people is a weight between zero and one. In total, we have 4297 observations at the state-month level, although the GSS trust measure is kept constant over time. In even-numbered columns, we add a list of additional controls, including the state-level population density, GDP, the unemployment rate, and the population size. As in Table III, we control for other borrower characteristics

[16] Trust is rooted in history and social norms (Tabellini 2008). See, e.g., Algan and Cahuc (2010) and Dohmen et al. (2012) on inter-generational transmission of trust.

by including state-level averages for the interest rate charged on the loans, the gross income level of the borrowers, and the number of years employed. Since the measure of interpersonal trust is time-invariant for each state, we cannot include state fixed effects to absorb the unobserved variables that might drive the result. We include year fixed effects in columns 3 and 4, and year-month fixed effects in column 5 and 6. This captures the time-varying business cycle component and anything that occurred systematically to the economy. The coefficient estimate does not change substantially across specification, and is roughly -0.15 and statistically significant at the 1% level. This suggests that a one standard deviation increase in interpersonal trust is associated with -11% reduction in online lending's share for the median state.

At least two factors can plausibly explain our results. First, online lending provides a marketplace where lenders and borrowers do not have to interact personally. This differs from traditional banking-based borrowing, which often requires interaction between the borrower and a bank employee. In this respect, the disintermediation facilitated by online lending reduces the importance of interpersonal trust. Lending decisions are made using algorithms, rather than with hard and soft information elicited through human interaction. Second, borrowing from friends and family members constitutes an important channel for inexpensive credit, especially in the event of an unexpected expense or crisis. In states with high interpersonal trust, we expect individuals to have closer ties that enable informal borrowing through this channel. Even though online borrowing is a convenient and direct way of obtaining credit, informal lending will be preferred for more borrowers in states with higher interpersonal trust. We will examine this more formally below.

To test whether interpersonal trust is the relevant channel, we repeat the exercise from Table VI, but replace P2P's debt share with credit card borrowing (Table VII) and mortgage borrowing (Table VIII). We find a negative relationship between interpersonal trust and credit card borrowing, indicating that our findings for the online lending market also hold for credit card debt. This is what we would expect, since credit card borrowing is similar to online lending in that it is an impersonal process with no interviews required. It is also similar to online lending and informal lending in that it may be used to handle budgetary shocks (e.g. medical bills, car repairs, etc.), since it is unsecured and may be used with short notice. To the contrary, none of this is true for mortgage debt, which is secured by the value of the home, often requires a personal interaction with a bank employee, and has a larger principle amount and a longer maturity. In line with this explanation, we find a positive, rather than negative, relationship between interpersonal trust and mortgage borrowing. This supports our claim that in-person borrowing and informal lending gain from higher interpersonal trust, but online borrowing and credit card borrowing do not.

5.3 Investor trust in traditional finance

Thus far, we have exclusively focused on the demand side of P2P credit by using loan application data. To capture how investor preferences shaped platform growth, we examine the Madoff investment scandal, which arguably influenced only investor attitudes towards risky investments. In Table IX, we regress the originated loan volume that was funded by both investor types as a share of total borrowing on the number of Madoff victims in the same state, a dummy indicating whether the loan was wholesale or retail, and the interaction of both terms. In total, there are 4653 observations at the state-month level. The specifications are similar to those in Table VI. In even-numbered columns, we add a list of state-level controls, including population density, GDP, the unemployment rate, and population size. We also control for other borrower characters at the state level that may drive results, including the average interest rate charged on the loans, the average gross income level of the borrowers, and the average number of years employed. We include year fixed effects in columns 3 and 4, and year-month fixed effects in columns 5 and 6. The coefficient from the last column indicates that increasing the Madoff victim count by 1000 in a state is associated with a 0.006ppt increase in the online-to-total lending share. This is equivalent to a 4.7% increase in the ratio of online debt to total debt in the median state. While this effect is somewhat smaller relative to our findings for borrowers, it is likely to be biased downward, since it relies on investor home bias, which may be relatively weak.

5.4 Robustness checks

Above, we discussed the empirical tests for the hypotheses presented in Section 3. We found support for the hypothesis that reduced borrower trust, driven by bank misconduct, increases participation in the online lending market. We also found that social trust, measured by interpersonal trust, hinders the expansion of online lending. In the following section, we will analyze subgroups with heterogenous borrower characteristics. We will then consider a regression specification that includes both bank misconduct and interpersonal trust.

5.4.1 Borrower subgroups

To identify which borrower quality group is more sensitive to bank misconduct and other trust measures, we repeat the exercises from Table III, Table VI, and Table IX, but for borrowers with high and low credit ratings. Fourty percent of the borrowers have a rating of either "A" or "B." We consider these borrowers to be high quality and assign a value of one to them for the dummy variable "highrating." The rest of the borrowers have ratings ranging from "C" to "E," and have a highrating variable equal to zero.

We include the highrating dummy, the CFPB consumer complaint measure, and their interaction term in the regression presented in Table X. Following the same specification as in Table III, we find that the positive relationship between distrust in traditional banks and P2P borrowing is driven by the low rated borrowers.

We continue our analysis with the specification from Table VI, but now try to identify which credit quality group is more sensitive to changes in interpersonal trust. We include the highrating dummy, the interpersonal trust measure, and their interaction term in the regression presented in Table XI. The coefficients from last column indicate that the negative relationship between higher interpersonal trust and P2P borrowing comes mostly from the low rated borrowers.

5.4.2 Joint impact of bank distrust, interpersonal trust, and Madoff scandal

To test whether bank misconduct and interpersonal trust are jointly influencing P2P borrowing, we include both regressors in the same specification, which yields the results presented in Table XII. The specifications are identical to those in Table III. We observe that both regressors remain statistically significant at the 1% level and the signs remain unchanged. Hence, each measure constitutes a substantial influence over the borrower's decision to obtain credit from an online platform. We also test whether interpersonal trust and Madoff victims in the state influence the online lending origination jointly, and then add the CFPB complaint measure. We find that the results from bank distrust, interpersonal trust and Madoff scandal are stable in Table XIII and Table XIV.

Overall, our empirical analysis indicates that trust in financial intermediation and interpersonal trust have shaped the development of online lending markets in the United States. The relationship is primarily driven by borrowers, rather than investors, and is most strongly influenced by borrowers with poor credit characteristics.

6 Conclusion

Trust has historically played a central role in the development of financial markets. In the absence of trust, borrower and investor apprehension prevents individuals from entering into mutually-beneficial contracts. Consequently, high trust societies benefit from greater financial depth and lower transaction costs. And low trust societies lack financial services and rely heavily on informal borrowing. This relationship between trust and financial markets may be especially relevant in the wake of the great financial crisis, which has given rise to the notion that "fraud has become a feature and not a bug" (Zingales (2015), p.19).

The existing literature focuses primarily on trust in traditional lending markets. Following Rau (2017), we examine evidence on the role of trust in online lending, which has grown rapidly in the U.S. since 2005; and consider multiple measures: interpersonal trust, trust in traditional banking, and trust in traditional finance. The first two operate primarily through borrowers. The last operates through investors.

To measure the expansion of U.S. online lending, we use loan book data and SEC filings. We also use 1) a survey-based measure of interpersonal trust from the GSS; 2) a measure of bank misconduct with both geographic and time variation, computed using the CFPB's database of consumer financial complaints; and 3) a general measure of distrust in traditional finance, captured by the geographic distribution of Madoff scandal victims. Our main regressions use data from LendingClub, which is the largest platform and has better data availability; however, our results are robust to the inclusion of Prosper data.

We first identify the impact of trust in traditional banking on the ratio of P2P debt to total debt. Our measure of trust is derived from consumer financial complaints submitted to the CFPB. We show that an increase of one complaint per bank branch is associated with a 6% increase in the ratio of online-to-total debt for the median state.

We also show that an increase in interpersonal trust is associated with a reduction in P2P debt relative to other debt. In particular, a one standard deviation increase in survey-reported interpersonal trust is associated with a -11% decrease in the online-to-total debt ratio for the median state. This suggests that in-person, bank-based borrowing and informal borrowing benefit from improvements in interpersonal trust; whereas online borrowing is largely perceived to be impersonal. We also show that interpersonal trust operates in the same direction on credit card debt, but in the opposite direction on mortgage debt. This aligns well with the observation that credit card debt is largely impersonal; whereas mortgage debt often requires personal interactions with bank employees.

In addition to our results for borrowers, we also consider a shock that affects only investors–namely, the number of Madoff scandal victims in a state–to discern the impact of an decline of trust in traditional finance. We find that investment in online lending is positively affected, which is consistent with the conjecture that the scandal shattered the confidence of wealthy investors, spurring interest in alternative investments outside the traditional finance sphere, such as online lending.

Overall, we find evidence that trust played a statistically and economically significant role in the expansion of online lending. Additionally, trust and factors that affect trust tended to push online lending and bank-based lending in opposite directions. Events that erode trust in bank-based borrowing, such as financial misconduct, increased online borrowing. Similarly, increases in interpersonal trust appear to benefit in-person, bank-based borrowing at the expense of online borrowing. Going forward, we expect that the dimensions of trust explored in this paper will remain important determinants of online lending growth and, more generally, FinTech development.

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Table I: Variable definitions

Variable	Description	Source
State level		
CFPB complaints	Total number of consumer complaints regarding banking services	Consumer Financial Protection Bureau (CFPB)
Interpersonal trust	A survey-based measure of general trust in other people	General Social Survey (GSS)
Madoff	Number of investors that suffered losses due to the Madoff Scandal	New York Times
Total debt	Total dollar amount of household debt; state level	NY Fed Consumer Panel
Credit card debt	Total dollar amount of credit card debt; state level	NY Fed Consumer Panel
P2P debt	Total dollar amount of P2P debt; state level	Platforms, computed by authors
GDP	Gross Domestic production in the past 12 months	US Census Bureau
Population	Total number of population registered in the state in the past 12 months	Bureau of Labor Statistics
Total Area	Total land area of the state	US Census Bureau
Branch No.	Total number of bank branches in the state	FDIC SoD data
Loan-Borrower level		
Maturity	Maturity that is recorded under the loan identification number	Platforms
Loan size	Dollar Amount of loan that is applied for	Platforms
Loan interest rate	Interest rate that is assigned to the loan	Platforms
Credit rating	Credit rating	Platforms
Loan purpose	The purpose for the online lending loans	Borrowers
Income	Annual income	Borrowers reported, verified by platforms
Employment	Length of employment history	Borrowers reported, verified by platforms

Table II: Summary statistics

	Mean	SD	P25	Median	P75	N
State-level variables (by state)						
Interpersonal trust	0.40	0.11	0.33	0.39	0.46	49
Madoff in thousands	0.86	1.15	0.17	0.40	1.30	51
State-level variables (by state and year)						
Credit card debt (10b$)	1.53	1.83	0.38	0.91	1.94	459
Total debt (10b$)	24.35	33.20	6.04	15.19	32.06	459
population density	0.11	0.43	0.02	0.03	0.07	459
Log GDP	12.21	1.01	11.43	12.29	12.94	459
Log population	14.94	1.03	14.20	15.08	15.64	459
Unemployment rate	6.76	2.12	5.10	6.60	8.10	459
Number of bank branches (k)	1.82	1.73	0.47	1.46	2.38	459
State-level variables (by state and month)						
CFPB complaints per branch	0.20	0.66	0.06	0.10	0.16	2839
P2P debt (m$)	5.83	11.41	0.31	1.59	6.32	4653
P2P debt/Total debt	0.24	0.25	0.02	0.15	0.41	4653
Average DTI ratio	0.17	0.06	0.13	0.17	0.19	4653
Average interest rate	0.13	0.01	0.13	0.13	0.14	4653
Average annual income (k$)	75.08	26.41	65.78	73.16	81.56	4653
Average employment duration	5.30	1.11	4.95	5.50	5.82	4653
Loan-borrower level variables						
Credit card debt (per cap)	2947.62	566.29	2515.00	2880.00	3350.00	459
Total debt (per cap)	46358.24	12645.88	36595.00	43295.00	54255.00	459
Loan size	14961.15	8791.76	8000.00	13000.00	20000.00	1745948
Interest rate	0.14	0.05	0.10	0.13	0.16	1745948
High rating	0.37	0.48	0.00	0.00	1.00	1745948
Annual income (k$)	79.72	180.73	45.00	65.00	90.00	1745948
Employment	5.56	3.79	2.00	5.00	10.00	1745948

Notes: This table shows the summary statistics for all variables used in the empirical analysis. The sample covers the largest P2P platform, LendingClub, between 2008 and 2016. Where possible, we use state-level variables with monthly frequencies, while the loan-borrower level variables contain individual-specific information. The CFPB data extends back to 2012. Thus, the observation number is smaller than for other variables. It also means that the loan level regression with the CFPB complaints measure will use a fraction of the whole application sample. The variable *interpersonal trust* is computed as the state-level average of positive responses to the General Social Survey's (GSS) question about interpersonal trust over the 1973-2006 period, however there are only 49 states in our sample. Note that the Madoff victim count is 51 because we do not include U.S. territories. The variable *Credit card debt* is the state-level total credit card debt, and *total debt* is the state total household debt not channeled through online lending. Both are in 10-Billion dollar terms, provided by New York Fed consumer panel dataset.

Table III: Online lending and CFPB consumer complaints

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CFPB	0.017**	0.021***	0.023***	0.012***	0.009***	0.008***	0.009***	0.009***
	(0.007)	(0.005)	(0.007)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
DTI		0.669*		0.408*		0.284*		0.113***
		(0.366)		(0.216)		(0.150)		(0.038)
interest rate		-4.054***		-2.493**		-0.814		1.300*
		(1.413)		(1.091)		(1.078)		(0.712)
income		0.003***		0.001**		0.000		-0.000
		(0.001)		(0.001)		(0.000)		(0.000)
employment		-0.000		-0.001		0.004		0.013*
		(0.013)		(0.009)		(0.009)		(0.007)
pop. density		0.007		-1.299***		-1.195***		-1.141***
		(0.012)		(0.185)		(0.164)		(0.163)
log GDP		-0.049**		-0.546***		-0.404***		-0.442***
		(0.020)		(0.140)		(0.138)		(0.139)
log population		0.076***		1.746***		-0.293*		-0.213
		(0.018)		(0.564)		(0.156)		(0.145)
unemployment rate		-0.052***		-0.129***		-0.024***		-0.024***
		(0.007)		(0.010)		(0.003)		(0.003)
Year FE	NO	NO	NO	NO	YES	YES	NO	NO
State FE	NO	NO	YES	YES	YES	YES	YES	YES
Year-Month FE	NO	NO	NO	NO	NO	NO	YES	YES
Controls	NO	YES	NO	YES	NO	YES	NO	YES
No. of observations	2839	2839	2839	2839	2839	2839	2839	2839
Adj. R-square	0.002	0.270	0.111	0.567	0.684	0.692	0.874	0.881

Notes: This table reports the results of regression equation

$$Y_{i,t} = \beta_1 \text{CFPB complaints}_{i,t} + \gamma X_{i,t} + (A_i + B_t) + \epsilon_{i,t}$$

using the CFPB consumer complaints as the key explanatory variable to measure consumers' distrust in traditional banking. The dependent variable is the fraction of online lending demand compared to the household total debt at the monthly frequency. *CFPB* is the number of consumer complaints per branch in state i in month t. We include a number of independent variables to control for the average quality of loans. *DTI* is the simple average debt-to-income ratio of all the loans from state i at month t. *Interest rate* is the average value of interest rates for loans in the state at month t. *Income* and *Employment* measure the average annual income and years of employment for the borrowers in state i in month t. We also control for state level variables such as population density ($1000/km^2$), the logarithm of GDP, the logarithm of population and state unemployment rate. The different columns present different combinations of state fixed effects and time fixed effects. Standard errors, in parentheses, are corrected for clustering of observations by year-month. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table IV: Extensive margin: number of applicants/population and CFPB complaints

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CFPB	0.071***	0.079***	0.063***	0.030***	0.020***	0.020***	0.020***	0.019***
	(0.022)	(0.016)	(0.019)	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)
DTI		1.527*		1.055*		0.720*		0.218**
		(0.903)		(0.561)		(0.390)		(0.105)
interest rate		-12.974***		-7.828**		-3.360		1.267
		(4.053)		(3.081)		(3.070)		(1.863)
income		0.008***		0.002		-0.000		-0.001
		(0.002)		(0.001)		(0.001)		(0.001)
employment		0.002		0.003		0.015		0.038**
		(0.039)		(0.024)		(0.022)		(0.017)
pop. density		-0.058		-1.516***		-1.235***		-1.155***
		(0.041)		(0.471)		(0.404)		(0.378)
log GDP		0.517***		-1.508***		-1.168***		-1.273***
		(0.064)		(0.380)		(0.364)		(0.368)
log population		-0.420***		7.300***		1.869***		2.078***
		(0.062)		(1.687)		(0.416)		(0.437)
unemployment rate		-0.150***		-0.371***		-0.100***		-0.100***
		(0.018)		(0.028)		(0.009)		(0.009)
Year FE	NO	NO	NO	NO	YES	YES	NO	NO
State FE	NO	NO	YES	YES	YES	YES	YES	YES
Year-Month FE	NO	NO	NO	NO	NO	NO	YES	YES
Controls	NO	YES	NO	YES	NO	YES	NO	YES
No. of observations	2839	2839	2839	2839	2839	2839	2839	2839
Adj. R-square	0.005	0.324	0.119	0.627	0.722	0.730	0.891	0.896

Notes: This table reports the extensive margin regression:

$$Y_{i,t} = \beta_1 \text{CFPB complaints}_{i,t} + \gamma X_{i,t} + (A_i + B_t) + \epsilon_{i,t}$$

using the CFPB consumer complaints as the key explanatory variable to measure consumers' distrust in traditional banking. The dependent variable is the fraction (basis points) of online lending applicants in the state population at month t. *CFPB* is the number of consumer complaints per branch in state i in month t. We include a number of independent variables to control for the average quality of loans. *DTI* is the simple average debt-to-income ratio of all the loans in state i in month t. *Interest rate* is the average value of interest rates for loans in state i in month t. *Income* and *Employment* measure the average annual income and years of employment for the borrowers in state i in month t. We also control for state level variables such as population density ($1000/km^2$), the logarithm of GDP, the logarithm of population and state unemployment rate. The different columns present different combinations of state fixed effects and time fixed effects. Standard errors, in parentheses, are corrected for clustering of observations by year-month. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table V: Intensive margin: size of loan request and CFPB complaints

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CFPB	0.003	0.005	0.000	0.000	-0.001*	-0.000	-0.000	-0.000
	(0.007)	(0.007)	(0.002)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
homeowner		0.047***		0.019***		0.019***		0.019***
		(0.005)		(0.003)		(0.003)		(0.003)
has mortgage		0.034***		0.037***		0.037***		0.037***
		(0.003)		(0.002)		(0.002)		(0.002)
employment		0.003***		0.004***		0.004***		0.004***
		(0.000)		(0.000)		(0.000)		(0.000)
annual income		0.000***		0.000***		0.000***		0.000***
		(0.000)		(0.000)		(0.000)		(0.000)
interest rate		0.316***		0.280***		0.290***		0.304***
		(0.025)		(0.020)		(0.017)		(0.017)
maturity		0.074***		0.074***		0.074***		0.073***
		(0.004)		(0.004)		(0.004)		(0.004)
Year FE	NO	NO	NO	NO	YES	YES	NO	NO
State FE	NO	NO	YES	YES	YES	YES	YES	YES
Year-Month FE	NO	NO	NO	NO	NO	NO	YES	YES
Controls	NO	YES	NO	YES	NO	YES	NO	YES
No. of observations	1680778	1680778	1680778	1680778	1680778	1680778	1680778	1680778
Adj. R-square	0.000	0.236	0.138	0.306	0.140	0.306	0.142	0.309

Notes: This table reports the extensive margin regression:

$$Y_{i,j,t} = \beta_1 \text{CFPB complaints}_{i,t} + \gamma X_{i,j,t} + (A_i + B_t) + \epsilon_{i,j,t}$$

using the CFPB consumer complaints as the key explanatory variable to measure consumers' distrust in traditional banking. The dependent variable is the fraction of applicant j's online loan request amount compared to the per capita household total debt in state i in month t. *CFPB* is the number of consumer complaints per branch in state i in month t. We include a number of independent variables to control for the individual borrower's characteristics. *homeowner* and *has mortgage* are dummy variables about the applicant's homeownership status. *employment* and *annual income* indicate the applicant's job and income situation. We also control for applicants' FICO score and loan request characteristics like the interest rate and the maturity. The different columns here present different combinations of state fixed effects and time fixed effects. Standard errors, in parentheses, are corrected for clustering of observations by state. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table VI: Online lending and interpersonal trust

	(1)	(2)	(3)	(4)	(5)	(6)
interpersonal trust	-0.103***	-0.346***	-0.133***	-0.154***	-0.134***	-0.150***
	(0.024)	(0.057)	(0.024)	(0.025)	(0.024)	(0.024)
DTI		1.125**		0.194		0.074
		(0.436)		(0.127)		(0.047)
interest rate		0.080		-0.121		0.570
		(0.697)		(0.523)		(0.437)
income		0.000*		0.000		-0.000
		(0.000)		(0.000)		(0.000)
employment		0.021***		0.001		0.003
		(0.004)		(0.003)		(0.003)
pop. density		0.020**		-0.045***		-0.042***
		(0.010)		(0.007)		(0.006)
log GDP		0.054***		0.027***		0.022***
		(0.019)		(0.007)		(0.007)
log population		0.012		-0.030***		-0.026***
		(0.020)		(0.007)		(0.006)
unemployment rate		-0.063***		0.004***		0.003***
		(0.007)		(0.001)		(0.001)
Branch		-0.014***		0.003**		0.003**
		(0.002)		(0.001)		(0.001)
Year FE	NO	NO	YES	YES	NO	NO
State FE	NO	NO	NO	NO	NO	NO
Year-Month FE	NO	NO	NO	NO	YES	YES
Controls	NO	YES	NO	YES	NO	YES
No. of observations	4297	4297	4297	4297	4297	4297
Adj. R-square	0.002	0.466	0.760	0.765	0.866	0.870

Notes: This table reports the regression on:

$$Y_{i,t} = \beta_1 \text{Interpersonal trust}_i + \gamma X_{i,t} + (B_t) + \epsilon_{i,t}.$$

$Y_{i,t}$ is the total amount of online lending demand in state i in month t normalized by total bank debt. *Interpersonal trust* is the average of the social trust question responses in the General Social Survey (GSS) over the period 1973-2006. We include a number of independent variable to control for the average quality of loans. *DTI* is the simple average debt-to-income ratio of all the loans from in state i in month t. *Interest rate* is the average value of interest rates for loans in state i in month t. *Income* and *Employment* measure the average annual income and years of employment for the borrowers in state i in month t. We also control for state level variables such as population density ($1000/km^2$), the logarithm of GDP, the logarithm of population, state unemployment rate, and the number of bank branches in thousands. Standard errors, in parentheses, are corrected for clustering of observations by year-month. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table VII: Credit card debt and interpersonal trust

	(1)	(2)	(3)	(4)
interpersonal trust	-0.004***	-0.010**	-0.004***	-0.014***
	(0.001)	(0.004)	(0.001)	(0.002)
pop. density		-0.002		-0.003***
		(0.002)		(0.001)
log GDP		-0.018**		-0.013***
		(0.005)		(0.003)
log population		0.013**		0.009***
		(0.004)		(0.002)
unemployment rate		-0.000		-0.001***
		(0.001)		(0.000)
Branch		0.003***		0.002***
		(0.001)		(0.001)
Year FE	NO	NO	YES	YES
State FE	NO	NO	NO	NO
Year-Month FE	NO	NO	NO	NO
Controls	NO	YES	NO	YES
No. of observations	441	441	441	441
Adj. R-square	0.001	0.254	0.238	0.431

Notes: This table reports the robustness regression as:

$$Y_{i,t} = \beta_1 \text{Interpersonal trust}_i + \gamma X_{i,t} + (B_t) + \epsilon_{i,t}.$$

$Y_{i,t}$ is the fraction of aggregate outstanding credit card debt in the total outstanding bank debt to households in state i in year t. *Interpersonal trust* is the average of the social trust answers in the General Social Survey (GSS) over the period 1973-2006. We also control for state level variables such as population density ($1000/km^2$), the logarithm of GDP, the logarithm of population, the state unemployment rate, and the number of bank branches in thousands. Standard errors, in parentheses, are corrected for clustering of observations by year. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table VIII: Mortgage lending and interpersonal trust

	(1)	(2)	(3)	(4)
interpersonal trust	0.126***	0.185***	0.126***	0.168***
	(0.009)	(0.014)	(0.009)	(0.004)
pop. density		-0.022*		-0.029***
		(0.011)		(0.002)
log GDP		0.127***		0.151***
		(0.020)		(0.006)
log population		-0.115***		-0.132***
		(0.023)		(0.008)
unemployment rate		0.013***		0.010***
		(0.004)		(0.001)
Branch		-0.007**		-0.010***
		(0.002)		(0.002)
Year FE	NO	NO	YES	YES
State FE	NO	NO	NO	NO
Year-Month FE	NO	NO	NO	NO
Controls	NO	YES	NO	YES
No. of observations	441	441	441	441
Adj. R-square	0.047	0.334	0.179	0.454

Notes: This table reports the robustness regression as:

$$Y_{i,t} = \beta_1 \text{Interpersonal trust}_i + \gamma X_{i,t} + (B_t) + \epsilon_{i,t}.$$

$Y_{i,t}$ is the fraction of aggregate outstanding mortgage debt in the total outstanding bank debt to households in state i in year t. *Interpersonal trust* is the average of the social trust question responses in the General Social Survey (GSS) over the period 1973-2006. We also control for state level variables such as population density ($1000/km^2$), the logarithm of GDP, the logarithm of population, the state unemployment rate, and the number of bank branches in thousands. Standard errors, in parentheses, are corrected for clustering of observations by year. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table IX: Online lending and Madoff scandal victims

	(1)	(2)	(3)	(4)	(5)	(6)
Madoff victims	0.001	-0.005***	0.004***	0.006***	0.004***	0.006***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
DTI		0.969***		0.068		0.016
		(0.262)		(0.056)		(0.030)
interest rate		-0.087		-0.119		0.232***
		(0.496)		(0.261)		(0.086)
income		0.001***		0.000		0.000*
		(0.000)		(0.000)		(0.000)
employment		0.143***		0.010**		0.004
		(0.021)		(0.004)		(0.003)
pop. density		0.024***		-0.023***		-0.022***
		(0.008)		(0.003)		(0.003)
log GDP		0.037**		-0.003		-0.006
		(0.018)		(0.005)		(0.005)
log population		0.013		-0.005		-0.003
		(0.019)		(0.005)		(0.005)
unemployment rate		-0.042***		0.006***		0.006***
		(0.005)		(0.001)		(0.001)
Branch		-0.016***		0.002**		0.002**
		(0.002)		(0.001)		(0.001)
Year FE	NO	NO	YES	YES	NO	NO
State FE	NO	NO	NO	NO	NO	NO
Year-Month FE	NO	NO	NO	NO	YES	YES
Controls	NO	YES	NO	YES	NO	YES
No. of observations	4653	4653	4653	4653	4653	4653
Adj. R-square	0.000	0.434	0.826	0.829	0.930	0.933

Notes: This table reports the results of regression equation:

$$Y_{i,t} = \beta_1 \text{Madoff victims}_i + \gamma X_{i,t} + (B_t) + \epsilon_{i,t}.$$

The dependent variable is the total amount of originated online lending in state i in month t normalized by total bank debt. *Madoff victims* is the number (in thousands) of investors who suffered losses in the scandal at the state level. We include a number of independent variables to control for the average quality of loans. *DTI* is the simple average debt-to-income ratio of all the loans from in state i in month t. *Interest rate* is the average value of interest rates of loans in state i in month t. *Income* and *Employment* measure the average annual income and years of employment for the borrowers in state i in month t. We also control for state level variables such as population density ($1000/km^2$), the logarithm of GDP, the logarithm of population, state unemployment rate, and the number of bank branches in thousands. Standard errors, in parentheses, are corrected for clustering of observations by year-month. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table X: Online lending and CFPB complaints: by loan quality

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CFPB	0.010**	0.012***	0.014***	0.008***	0.007***	0.007***	0.007***	0.007***
	(0.004)	(0.003)	(0.004)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
highrating=1	-0.073***	-0.078***	-0.073***	-0.078***	-0.073***	-0.075***	-0.073***	-0.075***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
highrating=1 x CFPB	-0.005***	-0.004**	-0.005***	-0.004**	-0.005***	-0.005***	-0.005***	-0.005***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
interest rate		-0.144***		-0.122***		-0.061**		-0.035*
		(0.041)		(0.033)		(0.026)		(0.018)
income		0.000		-0.000		-0.000		0.000
		(0.000)		(0.000)		(0.000)		(0.000)
employment		-0.000		0.000		0.000		-0.000
		(0.000)		(0.000)		(0.000)		(0.000)
pop. density		0.014***		-0.605***		-0.587***		-0.587***
		(0.004)		(0.090)		(0.081)		(0.081)
log GDP		-0.019***		-0.272***		-0.195***		-0.199***
		(0.006)		(0.070)		(0.066)		(0.066)
log population		0.036***		1.026***		-0.150**		-0.144**
		(0.007)		(0.308)		(0.071)		(0.070)
unemployment rate		-0.035***		-0.070***		-0.012***		-0.012***
		(0.004)		(0.005)		(0.001)		(0.001)
Year FE	NO	NO	NO	NO	YES	YES	NO	NO
State FE	NO	NO	YES	YES	YES	YES	YES	YES
Year-Month FE	NO	NO	NO	NO	NO	NO	YES	YES
Controls	NO	YES	NO	YES	NO	YES	NO	YES
No. of observations	5644	5644	5644	5644	5644	5644	5644	5644
Adj. R-square	0.085	0.272	0.176	0.558	0.678	0.682	0.843	0.847

Notes: This table reports the regression of the online lending amount by borrower credit quality in a certain state for a given month, normalized by the total bank debt in the same state, on the credit rating dummy, CFPB consumer complaints, and their interactions. *highrating=1* means the borrowers have a credit rating of either "A" or "B". *CFPB* is the number of consumer complaints per branch in state i in month t. We include a number of independent variables to control for the average quality of loans. DTI is the simple average debt-to-income ratio of all the loans from state i in month t. *Interest rate* is the average value of interest rates for loans in state i in month t. *Income* and *Employment* measure the average annual income and years of employment for the borrowers in state i in month t. We also control for state level variables such as population density ($1000/km^2$), the logarithm of GDP, the logarithm of population and state unemployment rate. The different columns present different combinations of state fixed effects and time fixed effects. Standard errors, in parentheses, are corrected for clustering of observations by year-month. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table XI: Online lending and interpersonal trust: by loan quality

	(1)	(2)	(3)	(4)	(5)	(6)
interpersonal trust	-0.069***	-0.232***	-0.081***	-0.094***	-0.081***	-0.094***
	(0.015)	(0.028)	(0.015)	(0.015)	(0.015)	(0.015)
highrating=1	-0.059***	-0.061***	-0.063***	-0.065***	-0.063***	-0.065***
	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)
highrating=1 x interpersonal trust	0.034***	0.037***	0.042***	0.043***	0.042***	0.043***
	(0.010)	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)
interest rate		0.007		-0.047**		-0.030
		(0.042)		(0.022)		(0.019)
income		-0.000		-0.000		-0.000
		(0.000)		(0.000)		(0.000)
employment		0.002***		0.000*		0.000**
		(0.000)		(0.000)		(0.000)
pop. density		0.007		-0.022***		-0.022***
		(0.006)		(0.003)		(0.003)
log GDP		0.020**		0.009***		0.009***
		(0.010)		(0.003)		(0.003)
log population		0.012		-0.012***		-0.012***
		(0.010)		(0.003)		(0.003)
unemployment rate		-0.041***		0.002***		0.001***
		(0.003)		(0.000)		(0.000)
branch		-0.000***		0.000***		0.000***
		(0.000)		(0.000)		(0.000)
Year FE	NO	NO	YES	YES	NO	NO
State FE	NO	NO	NO	NO	NO	NO
Year-Month FE	NO	NO	NO	NO	YES	YES
Controls	NO	YES	NO	YES	NO	YES
No. of observations	8406	8406	8406	8406	8406	8406
Adj. R-square	0.033	0.408	0.736	0.741	0.836	0.840

Notes: This table reports the regression of online lending amount by borrower credit quality in a certain state for a given month, normalized by the total debt in the same state, on the credit rating dummy, interpersonal trust, and their interactions. *highrating=1* means the borrowers have a credit rating of either "A' 'or "B". *Interpersonal trust* is the average of the social trust question responses in the General Social Survey (GSS) over the period 1973-2006. We include a number of independent variables to control for the average quality of loans. *DTI* is the simple average debt-to-income ratio of all the loans from state i in month t. *Interest rate* is the average value of interest rates for loans in state i in month t. *Income* and *Employment* measure the average annual income and years of employment for the borrowers in state i in month t. We also control for state level variables such as population density ($1000/km^2$), the logarithm of GDP, the logarithm of population, state unemployment rate, and the number of bank branches in thousands. Standard errors, in parentheses, are corrected for clustering of observations by year-month. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level.

Table XII: Online lending, interpersonal trust and CFPB complaints

	(1)	(2)	(3)	(4)	(5)	(6)
interpersonal trust	-0.179***	-0.583***	-0.196***	-0.230***	-0.197***	-0.208***
	(0.032)	(0.063)	(0.033)	(0.036)	(0.033)	(0.036)
CFPB	0.015**	0.021***	0.007***	0.007***	0.007***	0.008***
	(0.006)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
DTI		0.539*		0.224		0.081
		(0.294)		(0.153)		(0.051)
interest rate		-4.168***		-0.606		1.247
		(1.370)		(1.288)		(1.213)
income		0.002***		0.000		-0.000
		(0.001)		(0.001)		(0.000)
employment		0.007		0.007		0.015
		(0.013)		(0.012)		(0.011)
pop. density		-0.020		-0.068***		-0.060***
		(0.014)		(0.010)		(0.010)
log GDP		0.013		0.040***		0.036***
		(0.017)		(0.012)		(0.012)
log population		0.017		-0.039***		-0.034***
		(0.016)		(0.012)		(0.012)
unemployment rate		-0.069***		0.006***		0.006***
		(0.007)		(0.002)		(0.002)
Year FE	NO	NO	YES	YES	NO	NO
State FE	NO	NO	NO	NO	NO	NO
Year-Month FE	NO	NO	NO	NO	YES	YES
Controls	NO	YES	NO	YES	NO	YES
No. of observations	2751	2751	2751	2751	2751	2751
Adj. R-square	0.008	0.346	0.580	0.593	0.766	0.779

Notes: This table reports the results of regression equation:

$$Y_{i,t} = \beta_1 \text{CFPB complaints}_{i,t} + \beta_2 \text{Interpersonal trust}_i + \gamma X_{i,t} + (B_t) + \epsilon_{i,t}$$

using the CFPB consumer complaints as the key explanatory variable to measure consumers' distrust in traditional banking. The dependent variable is the fraction of online lending demand compared to the household total debt at the monthly frequency. *CFPB* is the number of consumer complaints per branch in state i in month t. *Interpersonal trust* is the measure of social trust from the General Social Survey (GSS) during 1973-2006. Variables *DTI*, *Interest rate*, *Income*, and *Employment* are the average measures for borrowers in state i in month t. We also control for state level variables such as population density ($1000/km^2$), the logarithm of GDP, the logarithm of population and state unemployment rate. Standard errors, in parentheses, are corrected for clustering of observations by year-month. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table XIII: Online lending, interpersonal trust and Madoff victims

	(1)	(2)	(3)	(4)	(5)	(6)
interpersonal trust	-0.027**	-0.195***	-0.031***	-0.035***	-0.032***	-0.034***
	(0.012)	(0.030)	(0.009)	(0.009)	(0.008)	(0.007)
Madoff victims	0.000	-0.008***	0.004***	0.005***	0.004***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
DTI		0.900***		0.054		0.009
		(0.246)		(0.051)		(0.027)
interest rate		-0.223		-0.136		0.214***
		(0.495)		(0.262)		(0.071)
income		0.001***		0.000		0.000*
		(0.000)		(0.000)		(0.000)
employment		0.146***		0.011***		0.005*
		(0.021)		(0.004)		(0.003)
pop. density		0.021***		-0.022***		-0.021***
		(0.008)		(0.003)		(0.003)
log GDP		0.041**		-0.002		-0.004
		(0.018)		(0.004)		(0.005)
log population		0.007		-0.006		-0.004
		(0.018)		(0.005)		(0.005)
unemployment rate		-0.048***		0.004***		0.003***
		(0.005)		(0.001)		(0.001)
Branch		-0.011***		0.003***		0.003***
		(0.002)		(0.001)		(0.001)
Year FE	NO	NO	YES	YES	NO	NO
State FE	NO	NO	NO	NO	NO	NO
Year-Month FE	NO	NO	NO	NO	YES	YES
Controls	NO	YES	NO	YES	NO	YES
No. of observations	4523	4523	4523	4523	4523	4523
Adj. R-square	0.001	0.455	0.829	0.832	0.936	0.938

Notes: This table reports the results of regression equation:

$$Y_{i,t} = \beta_1 \text{Interpersonal trust}_i + \beta_2 \text{Madoff victims}_i + \gamma X_{i,t} + (B_t) + \epsilon_{i,t}.$$

The dependent variable is the originated P2P debt amount in state i in month t normalized by total bank debt. *CFPB* is the number of consumer complaints per branch. *Interpersonal trust* is the measure of social trust from the General Social Survey (GSS) during 1973-2006. *Madoff victims* is the number (in thousands) of investors who suffered losses in the scandal. Variables *DTI*, *Interest rate*, *Income*, and *Employment* are the average measures for borrowers in state i in month t. We also control for state level variables such as population density ($1000/km^2$), the logarithm of GDP, the logarithm of population and state unemployment rate, and the number of bank branches in thousands. Standard errors, in parentheses, are corrected for clustering of observations by year-month. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level.

Table XIV: Online lending, CFPB complains, interpersonal trust and Madoff victims

	(1)	(2)	(3)	(4)	(5)	(6)
CFPB	0.012**	0.018***	0.003**	0.003**	0.002**	0.003**
	(0.005)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
interpersonal trust	-0.039**	-0.349***	-0.045***	-0.042**	-0.047***	-0.027**
	(0.016)	(0.034)	(0.013)	(0.018)	(0.013)	(0.012)
Madoff victims	0.004***	0.000	0.007***	0.009***	0.007***	0.009***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
DTI		0.384**		0.066		0.015
		(0.153)		(0.064)		(0.036)
interest rate		-4.617***		-0.693		0.687**
		(1.111)		(0.840)		(0.285)
income		0.004***		0.000		0.001***
		(0.001)		(0.000)		(0.000)
employment		0.176***		0.089***		0.041**
		(0.047)		(0.027)		(0.016)
pop. density		0.017		-0.030***		-0.029***
		(0.011)		(0.005)		(0.004)
log GDP		-0.071***		-0.008		-0.018*
		(0.017)		(0.013)		(0.010)
log population		0.089***		0.001		0.011
		(0.016)		(0.012)		(0.010)
unemployment rate		-0.062***		0.006***		0.006***
		(0.005)		(0.001)		(0.001)
Year FE	NO	NO	YES	YES	NO	NO
State FE	NO	NO	NO	NO	NO	NO
Year-Month FE	NO	NO	NO	NO	YES	YES
Controls	NO	YES	NO	YES	NO	YES
No. of observations	2739	2739	2739	2739	2739	2739
Adj. R-square	0.003	0.452	0.701	0.710	0.888	0.896

Notes: This table reports the results of regression equation:

$$Y_{i,t} = \beta_1 \text{CFPB complaints}_{i,t} + \beta_2 \text{Interpersonal trust}_i + \beta_3 \text{Madoff victims}_i + \gamma X_{i,t} + (B_t) + \epsilon_{i,t}.$$

The dependent variable is the originated P2P debt amount in state i in month t normalized by total debt. *CFPB* is the number of consumer complaints per branch in state i in month t. *Interpersonal trust* is the measure of social trust from the General Social Survey (GSS) during 1973-2006. *Madoff victims* is the number (in thousands) of investors who suffered losses in the scandal at the state level. Variables *DTI*, *Interest rate*, *Income*, and *Employment* are the average measures for borrowers in state i in month t. We also control for state level variables population density ($1000/km^2$), the logarithm of GDP, the logarithm of population and state unemployment rate. Standard errors, in parentheses, are corrected for clustering of observations by year-month. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level.

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