# Bank Misconduct, Trust, and Online Lending*

Christoph Bertsch
*Sveriges Riksbank*

Isaiah Hull
*Sveriges Riksbank*

Yingjie Qi
*Stockholm School of Economics*

Xin Zhang
*Sveriges Riksbank*

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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 nearly complete loan and application data from the online lending market, we demonstrate that a misconduct-driven decline of trust in traditional banking is associated with a statistically and economically significant increase in online lending demand at the state and county levels. Furthermore, we show that this effect is strongest for low rated borrowers and weakest in states with high levels of generalized trust. We also examine generalized trust in isolation and show that it strengthens in-person, bank-based borrowing, reducing the demand for impersonal online lending. Finally, we 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
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# 1 Introduction

Trustworthiness matters in financial transactions.[1] Hence, the expansion of new financial services, such as 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 role for a financial intermediary, online lending platforms are able to reduce investor apprehension about the type of opportunistic behavior that is often associated with traditional banking. From a borrower's perspective, online lending is relatively impersonal, which suggests that an increase in generalized trust–that is, the level of trust in other people in general–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 and county-level online lending. Our measures of trust are divided into three groups: 1) trust in traditional banking; 2) generalized trust; and 3) trust in traditional finance. Following the literature (Gambetta 2000; Guiso et al. 2008), we define trust as the subjective probability assigned to the chance of being cheated. We capture trust in traditional banking–that is, the subjective probability of being cheated by banks[2]– through shocks in financial misconduct complaints collected by the Consumer Financial Protection Bureau (CFPB). This complaint-based measure is indicative of perceived fraud, tracks bank scandals closely, and is often referenced in news articles. Roughly 25% of the consumer complaint narratives contain explicit references to acts of misconduct, criminality, cheating, theft, and deception. The remaining cases typically document alleged instances of borderline misconduct, where negligent customer service lead to material losses. Similarly, we measure generalized trust, the subjective probability of being cheated by other persons in general, through responses to the General Social Survey (GSS).[3] Finally, we capture a shock

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

[2] Cheating can, for example, entail unfair contractual terms, opaque or unpredictable fees, or missales.

[3] Generalized trust typically refers to trust across social groups, rather than trust within a group.

to trust in traditional finance using the geographic distribution of Madoff scandal victims, as in Guiso (2010).

Our main finding explores trust in traditional banking using bank misconduct complaints. In particular, we examine how borrower trust in traditional banks affects online lending at the state and county levels. Controlling for local macroeconomic conditions, loan-borrower characteristics, and geographic and time fixed effects, we document a positive conditional correlation between bank misconduct complaints and the demand for online lending. In particular, an increase of one complaint per bank branch is associated with a 6% increase in the ratio of online debt demand to total debt[4] for the median state. Additionally, the impact is larger on borrowers with lower credit ratings, which indicates that bank misconduct may drive existing customers away from traditional banking to online platforms. These findings also hold in county level regressions with state-time fixed effects and county-level controls. Furthermore, our results are robust to the use of lagged bank misconduct measures and to alternative specifications of the dependent variable that use loan originations, rather than measures of loan demand. In a separate robustness exercise, we use deep learning to classify the topic of each complaint. We then confirm that our main results remain significant, even if we exclusively use complaints about fraud.[5] Moreover, in a separate exercise, we find suggestive evidence that the positive association between bank misconduct and the expansion of online lending is least pronounced in regions with a high level of generalized trust.

In further analysis, we examine the role played by generalized trust in greater detail. In contrast to our findings for trust in traditional banks, we find that lagged generalized trust is negatively correlated with–and plausibly causes–a lower level of online lending growth. To the contrary, generalized trust is positively associated with bank based lending and informal borrowing. This is because generalized trust strengthens the in-person component of bank based and informal borrowing, while having less of an effect on impersonal online consumer credit. 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 generalized trust operates in the same direction on credit card debt, which is also

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

[5]Since CFPB consumer narratives are only available for a subset of our sample period, we do not use this approach in the main regression exercises; however, the results are available on request.

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 identify which borrower segments are most sensitive to variation in trust levels. The 2015 FDIC National Survey of Unbanked and Underbanked Households reveals 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 generalized 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 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 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, which is positively correlated with trust in institutions, is also positively associated with financial development (e.g., Guiso et al. (2004)). Our paper is the first to study how different dimensions of trust affect online lending. It also advances the literature by contributing to our understanding of how FinTech has driven financial disintermediation and relates to the literature on the interaction between banks and shadow banks. Moreover, our paper also relates to the recent online lending platforms literature, which shows that online lending is often a substitute for bank lending (Tang 2018), while online lending platforms can complement banks in the underserved borrowers segment. In both cases, online lenders achieve this by taking advantage of financial technology innovations (Balyuk 2018).

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 discusses identification challenges and measurement. Section 5 provides background information on the online lending market and section 6 describes the data. The empirical results are presented in section 7. Finally, section 8 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 generalized trust and trust in institutions, as well as the literature on financial misconduct. Second, our paper contributes to the literature on financial development and growth with a focus on financial innovation, as well as on the interaction between the incumbent banking system and the emerging non-bank competitors. 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 and define trust as the subjective probability assigned to the chance of being cheated.[6] 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 stock market participation.[7] 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

[6] See Fehr (2009) for a review of the "Economics and Biology of Trust." On the relationship between the subjective and actual probability of being cheated see Butler et al. (2016).

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

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.

In light of the existing literature, the deterioration of trust in traditional banking after the Great Recession (e.g., Corsetti et al. (2010)) may have lowered the barriers to entry for new FinTech players, 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 (Sakalauskaite 2016), our measure of distrust in banks is based on misconduct, which should be particularly relevant for the sample period considered. Specifically, we employ CFPB complaint data which has been used to study the quality of financial services (Begley and Purnanandam 2018). Different from the existing literature, our main focus is on high frequency variation in CFPB complaints attributed to bank misconduct, which tend to be related to bank scandals and perceived fraud.

Financial misconduct outside the banking industry has also received attention in the literature. Egan et al. (2017) study misconduct in the financial advisory industry and Gurun et al. (2018) demonstrate the detrimental effect of the Madoff scandal on the investment advisors. Moreover, Gurun et al. (2018) provide suggestive evidence for the transmission of trust shocks originating from the Madoff scam in social networks. Similarly, we study the Madoff shock to investor trust and measure its effect on the expansion of online lending.

**Financial innovation.** Guiso et al. (2004) document the important role that trust and, more generally, social capital play in financial development. Financial development, in turn, has been demonstrated to facilitate economic growth (e.g., Rajan and Zingales (1998)).

Our paper also speaks to the literature on the interaction between banks and shadow banks, such as the studies by Buchak et al. (2017) and Fuster et al. (2018), which evaluate the impact of FinTech on mortgage lending. In contrast, we study the market for uncollateralized online consumer credit and shed light on the role of trust in the context of financial disintermediation when new financial products and instruments become available to borrowers.

**Online lending.** Crowdfunding platforms have enjoyed rapid growth in recent years and have received increased attention in the literature.[8] We focus on peer-to-peer (P2P) online lending, which is the dominant worldwide form of crowdfunding (Rau 2017).[9] Within U.S. online lending, consumer credit is the largest market segment and tends to attract high-risk borrowers who want small 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 and to reduce discriminatory biases (Bartlett et al. 2017). The expansion of online lending appears to be highest in regions where traditional banks are absent or capital constrained.[10]

A number of papers employ the 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[11] and LendingClub.com[12] consumer credit platforms. 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 effects on regional online lending volumes.

[8] For literature reviews on crowdfunding and crowdlending, see Belleflamme et al. (2015) and Morse (2015).

[9] For an in-depth overview refer to the Cambridge Center for Alternative Finance Benchmarking Reports.

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

[11] 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 and of hard information in lending decisions (Iyer et al. 2015; Hildebrand et al. 2016; Balyuk 2018; Faia and Paiella 2017), 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. 2015a). There are also papers studying macroeconomic developments (Crowe and Ramcharan 2013; Bertsch et al. 2017).

[12] There are papers using data from LendingClub.com to study adverse selection (Hertzberg et al. 2015), retail investor risk-aversion (Paravisini et al. 2016) and P2P as a substitute for bank lending (Tang 2018).

# 3 Theoretical framework and hypothesis development

An extensive literature documents the historical role of trust in financial markets. With the emergence of online lending, different varieties of trust have surfaced as links that connect FinTech and traditional banking. The dominant forms of consumer credit, traditional bank loans and credit card debt, have faced growing competition from online platforms, especially in the segment for uncollateralized, high-risk credit for underbanked households.

We give a verbal description of the model and relegate the development of a formal theoretical framework to Appendix A. Since a large part of our empirical analysis focuses on borrower application data, we propose a stylized model for the uncollateralized consumer credit market that emphasizes the borrower perspective and funding choice. Thereby, we gain insights into how different dimensions of trust could affect the development of the online lending market. Consistent with the definition of trust as the subjective probability of being cheated, differences in trust are captured as differences in the expected cost of being cheated.

The model comprises a competitive traditional banking sector and online lending platforms. Borrowers choose whether to consolidate their existing debt, and if so, which alternative funding source to select: a term loan from a traditional bank or a loan from an online platform.[13] This borrower choice is motivated by the self-reporting of loan applicants. Around three quarters of applicants for online consumer credit state debt consolidation as the loan purpose. Applicants may, for instance, wish to obtain a cheaper term loan from a traditional bank or from an online lending platform to pay off revolving consumer credit stemming from credit cards, which are frequently issued by non-bank financial firms.

For borrowers, traditional banks are more familiar, but online lending platforms tend to be less expensive and offer a potentially more rewarding customer experience. We assume that online platforms have a significant cost advantage over traditional banks, since they specialize in automated credit scoring and do not have to maintain a costly branch network. In practice, this gives online platforms an edge, especially in screening high-risk borrowers (Einav et al. 2013). By leveraging FinTech, platforms can offer cheaper loans based on hard information to the borrower segments they target, as long as there is no important soft

[13]Notably, a simplified version of our model can also be applied to the alternative problem of how to fund new expenses, e.g. durable goods, with a term loan. The key insights are unaltered.

information or relationship component that can be captured by traditional banks.

We assign borrowers 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 and can be interpreted as a switching cost.[14]

First, we examine the role played by trust in traditional banking versus online lending. Consider a loss of faith in traditional banks triggered by a shock to bank misconduct that materializes in a spike of CFPB complaints. From the perspective of borrowers, the degradation of reputation and the loss of trust in traditional banks makes online lending platforms more appealing, because borrowers fear that banks will take advantage of them with unfair contractual terms or missales. As a result, borrowers move in larger numbers to online lending platforms and the effect is likely to be stronger for high-risk borrowers given the advantage of online lending platforms in screening the low quality segment. Hypotheses 1a and 1b follow.[15]

**Hypothesis 1a: borrower trust in traditional banking**

*H0: A deterioration of trust in traditional banking, caused by bank misconduct, is positively correlated with the expansion of online lending demand at the regional level in the US.*

**Hypothesis 1b: heterogeneous effects of trust in banking (across borrowers)**

*H0: The prediction of Hypothesis 1a is more pronounced for high-risk borrowers.*

[14]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 (Duarte et al. 2012). The survey-based generalized trust measure, however, elicits a different dimension of trust that is independent of person-specific traits.

[15]Formally, both predictions are derived in Result 1 in Appendix A. Result 1 states that the deterioration of trust in traditional banks after the financial crisis reduces the barrier to entry for online lending platforms and is associated with an increase in the market share of online lending. Moreover, Result 1 suggests that a cost advantage of online platforms at screening high-risk borrowers is associated with a larger share of online lending in this segment.

In relation to Hypothesis 1a, we might also expect that trust in traditional banks is less negatively affected by bank misconduct in regions with high levels of generalized trust. Here, optimism about trust is prevalent and not easily shattered.[16] Hypothesis 1c follows.

**Hypothesis 1c: heterogeneous effects of trust in banking (across regions)**

*H0: The prediction of Hypothesis 1a is less pronounced for regions with a high level of generalized trust.*

Second, we consider a positive shock to generalized trust. The GSS survey question used in our empirical study appears to be linked to expectations about other people's behavior (Sapienza et al. 2013), which, in our case, involves beliefs about borrower trustworthiness. In response to a positive personal trust shock, borrowers privilege traditional banks, where contracts are more personal and in-person interactions with a loan officer can help borrowers to utilize the belief of increased trustworthiness. Furthermore, higher generalized 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. Either way, Hypothesis 2 follows.[17]

**Hypothesis 2: generalized trust (borrowers)**

*H0: States with higher generalized trust should experience less credit demand in the online lending market, since online platforms are impersonal relative to traditional banking and to informal lending from friends and family, where borrower trustworthiness matters more.*

The opposite prediction can be obtained for the investor side. If a higher level of generalized trust favors anonymous transactions on online lending platforms, then more funds are channeled to such platforms, leading to a relative increase in credit vis-à-vis traditional banks, which makes borrowers more inclined to switch.

[16] We thank our discussant, Luigi Guiso, for suggesting we analyze this link.

[17] Result 1 predicts that an increase in borrower trustworthiness, captured as a lower cost-to-invest in a borrower-bank relationship is associated with a higher lending volume for banks relative to online lending.

From the outset, we would expect the effect underlying Hypothesis 2 to be dominant, meaning that a positive shock to generalized trust is negatively associated with the expansion of online lending. This is because the business model of online lending platforms is increasingly tailored towards wholesale investors and emphasizes its transparency of underwriting standards and borrower characteristics as a substitute for investor trust in banks.

Third, consider a negative shock to investor trust in traditional finance, triggered by the Madoff scandal. In response to the discovery of large scale fraud, investor attitudes shift towards alternative investments, such as online lending. While traditional finance was tarnished by the former Nasdaq Chairman's scandal, online platforms, which offer a high level of transparency and information provision, may have actually gained. Hypothesis 3 follows.[18]

**Hypothesis 3: trust in traditional finance (investors)**

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

# 4 Identification challenges and measurement of trust

## 4.1 Identification challenges

We encounter two major identification challenges that are common to work on trust in economics (e.g., Algan and Cahuc (2010) and Algan and Cahuc (2014)). The first is the potential endogeneity of trust: rather than trust affecting online lending, online lending may instead affect trust. The second is omitted variable bias: a confounding variable may jointly determine both trust and online lending. Reverse causality can be trivially ruled out, since the participants in online lending are a small fraction of the population and cannot plausibly influence trust on the county or state level. Nevertheless, we explain the identification and robustness checks in the following section. For the sake of clarity, we will discuss the

[18] In the context of our theoretical framework, this is captured by a shift in relative funding conditions. Hence, Result 1 predicts an increase in total online lending.

identification strategy for each category of trust separately.

We will start with trust in traditional banking, which is used to test Hypotheses 1a, 1b, and 1c. We first note that earlier attempts to measure the causal impact of trust on economic variables suffered from a lack of time variation in trust measures. This made it impossible to control for time invariant features, such as region-specific political, economic, and social factors. Algan and Cahuc (2010) overcame this by using a novel, time-varying measure of trust embodied in the country of origin of immigrants. Similarly, we approach this challenge by constructing a novel measure of trust with both time and granular geographic variation. Our measure of trust is derived from complaints filed to the Consumer Financial Protection Bureau (CFPB) about the local office or branch of a particular financial institution. We assume that an increase in complaints in a given county-month indicates a deterioration in how consumers were treated or perceived themselves to be treated by financial institutions. A reduction in this metric would indicate that consumers perceive an increase in the likelihood of being cheated, which would translate into a decrease in trust using the Gambetta (2000) definition, which we have adopted in this paper.

Using a trust measure with county-time variation enables us to use state-month-year fixed effects. This eliminates the possibility that a variable with state-month-year variation could be jointly determining trust and the county-level online lending share. The identification strategy relies on comparing two counties with similar characteristics, but different amounts of consumer complaints filed against traditional banks. In addition to this, we attempt to control for all plausible confounders with county-time variation, including average loan characteristics, income, employment, population size, population density, educational attainment, Internet penetration, and competition in the banking sector. We also run these regressions at the state level and find qualitatively similar results. The robustness of our results indicates that the results are unlikely to be driven by local economic conditions differences or other region specific factors. We further demonstrate that the relationship between online lending and the trust in traditional banks comes primarily through the extensive margin, which is measured as the number of online borrowing applicants divided by the population size. Given the small number of applications per state and the correspondingly small number of complaints about online lending in the CFPB database, it is not plausible that the number of applications could impact our measure of trust in any substantial way.

These findings jointly alleviate the concern of endogeneity for the measure of trust in banks. They also suggest that alternative theories based on supply-side effects and credit rationing are unlikely to offer a plausible explanation for our results.

Next, we consider the same two identification challenges for regressions involving our second measure of trust, which is constructed using responses to the General Social Survey (GSS). Recall that this measure was used in Hypothesis 2 (and 1c). Here, reverse causality is not possible, since we are using a static measure of trust that averages survey responses over the 1973-2006 period within each state. Note that we start with the first survey and include all additional waves prior to the Great Recession. This not only precludes reverse causality, but also eliminates an important source of omitted variable bias–namely, that the Great Recession or the recovery from it may have jointly determined trust and online lending. By using a pre-Great Recession trust measure, we rule out this possibility. We further attempt to rule out omitted variable bias by including a wide range of controls in the regression, including time fixed effects, average loan characteristics, income, employment, population density, GDP, population size, the unemployment rate, and the number of bank branches.

Finally, we consider the identification problem for the regressions that employ our final measure of trust, which is employed to test Hypothesis 3 by exploiting geographic variation in Madoff scandal victims (see Gurun et al. (2018)). Pairing our measure of trust with the investor home bias assumption for online lending (see, e.g., Lin and Viswanathan (2016)), we are able to identify an effect of the deterioration of trust in traditional finance on the geographic expansion of online lending. This approach, originally outlined by Guiso (2010), relies on the underlying assumption that victims experienced reduced trust in traditional finance, and that this trust reduction was likely to have diffused through their networks of high net worth individuals. In addition to this, it also increased the probability that local newspapers and television news programs would cover the story of a resident who had become the victim of a scam. Again, this measure is static and pre-dates our loan sample, reducing the likelihood that reverse causality could be an issue; however, it also limits our ability to control for regional economic developments and is only available at the state level.

## 4.2 New measure of trust

We will first discuss our measure of trust in traditional banking, which is novel to our paper and based on misconduct complaints. Existing survey-based measures of trust in banks have limitations. For instance, they are typically only available at an annual or biennial frequency and the low number of survey respondents does not allow for a study at the regional level. This contrasts with our granular measure of trust in traditional banking, based on the CFPB consumer complaint database, which is available at a high frequency for the county level.

There are few existing papers using CFPB complaint data. One example is Begley and Purnanandam (2018), who study bank service quality. We extend the existing literature by using CFPB complaint data to construct a bank misconduct measure that serves as a high-quality proxy for distrust in banks. Typical CFPB complaints include fees and contractual terms that are regarded as unjustified or unfair, dissatisfaction with services, or misselling of products. Often, the severity of such issues was allegedly sufficient to generate financial losses for the complainant.

Overall, CFPB complaints can be seen as allegations of either misconduct or borderline misconduct in the form of negligence and deception. Since borderline cases are sometimes quite mild, we performed a robustness check where we exclusively extracted complaints related to perceived fraud. We did this by training a deep learning model to identify descriptions of fraud. We then used the model to predict the probability that each narrative was discussing an incident of perceived fraud. From this, we used a version of the model for which out-of-sample performance was high (85% classification accuracy) to identify fraud-related comments and retain them for this exercise. Our findings align closely with our main results, but require us to discard most CFPB complaints, since they do not contain narratives, which is why we instead use the full sample in our main regressions.[19]

Despite containing some noise, our CFPB complaints-based measure is indicative of widespread customer perception of unfair treatment by banks that can be traced to specific regions with a high concentration of customer dissatisfaction.[20] Moreover, egregious misconduct is likely to be covered in local news outlets in areas with a high concentration of customer

[19]Additional results are available on request.

[20]Attenuation bias due the noisy CFPB complaint measure suggests that the effects we measure are a lower bound for the true effects.

dissatisfaction; and major bank scandals are arguably key factors in the deterioration of trust. The relationship between bank scandals and shocks to CFPB complaints suggests that our measure is likely to serve well as a proxy for distrust in traditional banking. Spikes in CFPB complaints about a particular institution tend to be associated with a critical media coverage that also sows distrust in the same institution. On the other hand, media reports regularly refer to the number of CFPB complaints to gauge the magnitude of bank scandals, which increases the publicity of CFPB complaints.

The 2013 Bank of America surge in customer complaints serves as an example of this phenomenon. Bank of America experienced a strong spike in CFPB complaints in January 2013, which took half a year to ebb off. Customer complaints centered around mortgage loan modifications and loan servicing, which was especially pronounced for loans in delinquency or foreclosure–a business area that has been contentious to BoA before, reflected in a 2.8bn penalty by the Office of the Comptroller of the Currency related to earlier mortgage abuses.[21] Notably, the surge in CFPB complaints acted as a catalyst for wide-spread news coverage of Bank of America's financial misconduct.[22]

# 5 The P2P online lending market

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.[23]

Our primary data set is from LendingClub, which operates the largest online platform for

[21] See `https://violationtracker.goodjobsfirst.org/violation-tracker/-bank-of-america-0`.
[22] See, e.g., `https://www.wsj.com/articles/SB10001424127887323361804578388791087793804`.
[23] See market study by PricewaterhouseCoopers (2015).

consumer credit in the US and was founded in 2006. As of August of 2018, LendingClub has more than 2.5 million customers, including both investors and borrowers, and has originated loans in excess of $38 billion. LendingClub's base of institutional investors has grown strongly since 2014; and retail investors have become a minority, representing less than 10% of the investment volume in 2018. 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.

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.

The highest rated borrowers in online lending markets may have good access to traditional sources of credit from banks and credit cards. For them, online lending could be a substitute to traditional forms of lending. In contrast, the lowest rated borrowers are likely to be underserved by traditional banks. In our primary dataset, 60% of borrowers have a FICO score below 700. This compares with 46% in the U.S. population in 2012. The platforms make lending decisions based on algorithms that use hard information like the FICO score and detailed borrower characteristics as an input. Investors can closely monitor platforms' lending standards and loan performance in different market segments over time.[24]

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.

# 6 Data and descriptive statistics

Our primary dataset consists of a panel of 1.7 million loan-borrower observations from LendingClub. 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.[25] Prosper's platform design is 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 C.2 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 generalized 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; 5) state-level and county-level eco-

[24]Notably there was a LendingClub scandal in April 2016 when the founding CEO Renaud LaPlanche resigned amidst the discovery of an improper sale of loans to an institutional client that deviated from investor instructions. While this incident had a marked effect on inflows from institutional investors, it was arguably unrelated to borrower trust and is taken care of by our regression specification.

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

nomic and demographic controls; 6) regional bank concentration data from the FDIC; and 7) Internet access data from the Current Population Survey (CPS). The period we study begins with the earliest available data on P2P lending 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 generalized trust, which 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 generalized 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 county or state. We then normalize this by the number of bank branches in the county or state, which we take from the Federal Deposit Insurance Corporation's (FDIC) database. The average state has 0.20 complaints per branch and month. The CFPB complaint database covers several categories of complaints. When constructing our baseline measure for shocks to bank misconduct, we include all complaints about traditional banking service categories (e.g. bank account services, credit reporting, debt collection, etc.). Typical complaints include dissatisfaction with services, the misselling of products, as well as fees and contractual terms that are regarded as unjustified or unfair. We 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.

# 7 Empirical results

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

## 7.1 Bank misconduct and borrower trust in traditional banking

To test Hypotheses 1a-c, we use the following empirical model as a baseline to relate the measure of regional online lending development to our measure of shocks to bank misconduct:

$$Y_{i,t} = \beta_1 \text{CFPB complaints}_{i,t} + \gamma X_{i,t} + (A_{i,t} + B_t) + \epsilon_{i,t}. \tag{1}$$

The dependent variable, $Y_{it}$, is the ratio of demand for P2P debt (millions) to total debt (tens of billions) in county $i$ in month $t$. The P2P market is small relative to the traditional banking sector in our sample. We normalize the P2P loan demand with the household debt balance of the P2P borrowers in the state, computed using the New York Fed consumer credit panel data. As the state consumer credit report is updated annually, the main variation in our dependent variable comes from the changes of P2P loan demand. This normalization ensures that the dependent variable is stationary and bounded by one. It also provides an intuitive interpretation of the results. Importantly, however, we will show that the effect of trust on the P2P market itself is economically significant, meaning that the results continue to hold qualitatively when using P2P debt demand as left-hand side variable.

The bank misconduct variable is computed as the number of consumer complaints filed to the Consumer Financial Protection Bureau (CFPB) in the same month. Our underlying assumption is that borrowers who file complaints are likely to disseminate their dissatisfaction with a bank branch via their local networks. Moreover, CFPB complaints may indicate a wide-spread customer perception of unfair treatment by institutions in a particular region.[26]

Our specification includes state fixed effects, $A_i$, and time fixed effects, $B_t$. For the county-level regressions, we use state-time fixed effects, $A_{i,t}$. State or county level controls

[26] In section 4, we provide supporting evidence from major bank scandals. We describe the CFPB complaints measure in more detail in section 6.

and borrower characteristics are denoted with $X_{i,t}$. We estimate the model with OLS and report the regression results in sections 7.1.1 and 7.4.1, respectively. In section 7.1.1 we also use loan application level regressions to measure the impact of trust in traditional banking on the extensive and intensive borrowing margins. The county-level analysis can be found in section 7.4.1. In addition to the state-level and county-level regressions, we also investigate the relationship between trust measures and subgroup differences in applicant credit quality in section 7.1.2. Thereafter, section 7.1.3 explores how the relationship between bank misconduct and the expansion of online lending is affected by regional heterogeneity in the level of generalized trust.

#### 7.1.1 Testing Hypothesis 1a

Hypothesis 1a claims that a deterioration of trust in traditional banks drives borrowers from traditional banks to online lenders. To measure trust in traditional banking, we use consumer complaints filed to the U.S. Consumer Financial Protection Bureau. As explained in the data section, we construct a measure of regional consumer complaints and normalize by the number of bank branches. We capture geographic variation through the location of the complainant. Our 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. The reasoning is that the affected consumers may disseminate their dissatisfaction with a bank branch or service to their social network. Furthermore, instances of egregious misconduct will be more likely to be covered by local news outlets in areas were consumers are most affected.

In Table C.4, we test Hypothesis 1a by regressing the ratio of online lending demand (m$) to total household debt (10b$) 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 spanning from 2012 to 2016. 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 most conservative 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 lending demand 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, which we further corroborate in section 7.4.1. We also find that these results are robust to the inclusion of additional county-level controls or the use of lagged CFPB complaint values. We include the following as additional controls: a measure for banking competition,[27] educational attainment, and Internet penetration. The results are reported in Table D.1 in the Online Appendix. The coefficients of the CFPB complaint measure change only marginally and remain statistically significant. The county-level regressions with state-time fixed effects and county-level controls are shown in our robustness checks in section 7.4.1. We are able to explore the variation of online lending and CFPB complaint at the county level with a stricter empirical specification. All the results are consistent qualitatively with different specifications. Note that all key results are robust to the replacement of the dependent variable with the level of online lending demand or when using loan origination instead of application data. Since all of our results for the other trust measures are robust to the inclusion of the additional controls, we omit them in the other regressions.

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

[27] We use the HHI index to measure bank competition. Recall that the construction of the CFPB complaints measure incorporates the number of bank branches.

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 C.5 and C.6, 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 positive shock to bank misconduct is associated with a higher number of borrowers switching 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 primarily driven by the extensive margin. This is also consistent with our theoretical framework, which makes predictions about the extensive margin and reflects the finding in Tang (2018) that online lending is often a substitute for bank lending.

#### 7.1.2 Testing Hypothesis 1b

To identify which borrower quality group is more sensitive to bank misconduct and other trust measures, we repeat the exercises from Table C.4, but for borrowers with high and low credit ratings. Forty percent of the borrowers have a FICO score above 700. We consider these borrowers to be of high quality and assign a value of one to them for the dummy variable "highrating." The rest of the borrowers, roughly corresponding to sixty percent of the sample, get a highrating dummy equal to zero.

We include the highrating dummy, the CFPB consumer complaint measure, and their interaction term in the regression presented in Table C.7. Following the same specification as in Table C.4, we find that the positive relationship between distrust in traditional banks and P2P borrowing is driven by the low rated borrowers. In other words, lower quality borrowers are more likely to be picked up by online lending platforms ("bottom fishing") when they are exposed to misconduct or are unsatisfied with the service they get from traditional banking.

### 7.1.3 Testing Hypothesis 1c

We next examine the heterogeneous effect of trust in traditional banking across regions. We repeat the exercise from Table C.4, but group the states according to their level of generalized trust. The cross-sectional generalized trust measure is computed as the average of the GSS's generalized trust question over the period 1973-2006, which pre-dates our sample.

The results are presented in Table C.8, where we include the CFPB measure, the generalized trust measure, the full set of controls from Table C.4, and year-month fixed effects. In columns 1, 2, and 3, we split the sample into terciles along the generalized trust dimension: bottom, middle and top. We find that the the positive relationship between distrust in traditional banks and P2P borrowing is concentrated in the middle tercile, for which the CFPB coefficient remains both positive and highly significant. Next, we split the sample in two generalized trust subgroups: low and high. The results are presented in columns 4 and 5, respectively. Now the positive relationship between distrust in traditional banks and the P2P borrowing is concentrated in the low generalized trust subgroup.

Taken together, we find suggestive evidence that the positive association between bank misconduct and the P2P borrowing is less pronounced in regions with a high level of generalized trust. Hence, we cannot reject Hypothesis 1c. It appears that borrowers in regions with an intermediate level of generalized trust are most responsive to bank misconduct. This result is plausible, since the occurrence of bank misconduct is likely to confirm the prevalence of pessimistic trust beliefs when the level of generalized trust is very low. Instead, a high level of generalized trust is likely to mute borrowers' responsiveness to bank misconduct.

## 7.2 Generalized trust

To test hypothesis 2, we regress the ratio of demand for P2P debt to total debt on the social trust measure, computed using the GSS survey question on generalized trust. The regression is specified as follows:

$$Y_{i,t} = \beta_1 \text{generalized trust}_i + \gamma X_{i,t} + (B_t) + \epsilon_{i,t}. \tag{2}$$

As before, we use a cross-sectional measure of social trust that is computed as the average of the GSS's generalized trust question over the period 1973-2006, which pre-dates our sample (Algan and Cahuc 2014). The literature finds that the slow-moving component of generalized trust is most salient, which indicates that regional variation is likely to be most meaningful.[28]

The results are presented in Table C.9. 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, the population size, and the number of bank branches. As in Table C.4, we control for other borrower characteristics 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 generalized trust is time-invariant for each state, we cannot include state fixed effects to absorb the unobserved variables that might otherwise drive the results. 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 for generalized trust 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 generalized trust is associated with 11% reduction in the online lending demand share for the median state. The result is robust to the inclusion of additional controls. Hence, we cannot reject Hypothesis 2. The results suggest that borrower side channels may play a more important role than investor side channels.

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 interactions between the borrower and a bank employee. Online lending platforms make lending decisions using algorithms, rather than with hard and soft information elicited through human interaction. In this respect, the disintermediation facilitated by online lending reduces the importance of trust in a person by substituting it for transparency about borrower characteristics. Second,

[28] Trust is rooted in history and social norms (Tabellini 2008), with cultural and family backgrounds playing an important role (Butler et al. 2015b; Jiang and Lim 2016). See, e.g., Algan and Cahuc (2010) and Dohmen et al. (2012) on inter-generational transmission of trust.

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 generalized 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 generalized trust. We will examine this more formally below.

To test whether generalized trust is the relevant channel, we repeat the exercise from Table C.9, but replace P2P's debt share in Table C.10 with credit card borrowing and mortgage borrowing. We find a negative relationship between generalized 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 generalized trust and mortgage borrowing. This supports our claim that in-person borrowing and informal lending gain from higher generalized trust, but online borrowing and credit card borrowing do not.

Finally, we again consider sub-group effects. We try to identify which credit quality group is more sensitive to changes in generalized trust by including the highrating dummy, the GSS trust measure, and their interaction term in the regression presented in Table C.11. The coefficients from the last column indicate that the negative relationship between higher generalized trust and P2P borrowing in Table C.9 comes mostly from low rated borrowers.

## 7.3 Investor trust in traditional finance

Thus far, we have 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.

Gurun et al. (2018) demonstrate the detrimental effect of the Madoff scandal on investment advisors and provide suggestive evidence of the trust shock's transmission within local social networks. Based on the existence of home bias in online lending (Lin and Viswanathan, 2016), we study the implications of Madoff scandal induced shifts in regional investor attitudes on regional online lending volumes.

To test Hypothesis 3, we use the following econometric model:

$$Y_{i,t} = \beta_1 \text{Madoff victims}_i + \gamma X_{i,t} + (B_t) + \epsilon_{i,t}. \tag{3}$$

Contrary to the earlier hypotheses, we use P2P loan origination data, rather than application data, since we are interested in the supply side. 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 because the Madoff scandal data is cross-sectional.

In Table C.12, 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 C.9. 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. Unfortunately, there is no available investor portfolio allocation database that enables researchers to pin down switching to alternative investment opportunities, including to online lending. This exercise serves as a proximate test to study the impact of trust in traditional investment opportunities on the growth of online lending.

## 7.4 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 reported bank misconduct, increases participation in the online lending market. We also found that social trust, measured by generalized trust, hinders the expansion of online lending. In the following section, we extend the bank distrust results to the county level, which allows us to include state-time fixed effects. We also consider a regression specification that includes both bank misconduct and generalized trust.[29]

### 7.4.1 Bank misconduct and borrower trust in traditional banking: county level

For complaints made by customers between December 2011 and October 2014, the complainant's location can be identified using ZIP code data from the CFPB's database. We use this information to repeat the baseline test in Table C.4, but at the county level. We supplement the data with county-level information from the Bureau of Economic Analysis, which contains total area, population, total income, and number of jobs in each county. In total, we have 45,822 county-month observations (see Table C.3 for summary statistics).

We regress the ratio of online lending demand (m$) to total household debt (10b$) on the average number of consumer complaints per bank branch at the county level. The results are presented in Table C.13. In the even-numbered columns, we use a specification that controls for county-level variables: population density, the logarithm of total income, the number of jobs, the population size, banking competition, educational attainment, and Internet penetration. We also control for borrower characteristics by including the county-level averages for debt-to-income ratio, the interest rates charged on loans, the gross income levels of borrowers, and the number of years employed. In columns 1 and 2, state-year fixed effects are included to absorb changes that occurred in a specific state and year. In columns

[29] Beyond the reported robustness checks, we also repeat our main exercises on trust in traditional banks, but in an instrumental variables regression setting. We use lags of the CFPB measure of distrust in traditional banks. The coefficient estimates are quantitatively similar and statistically significant at the 1% level.

3 and 4, we include state-month fixed effects to control for potential seasonality within a year. Columns 5 and 6 include the strictest fixed effects that can be included–namely, state-by-year-month fixed effects–to absorb any shocks that might have happened in a given state and month in our sample. This conservative econometric specification helps to control for observable and unobservable variation at the state level over time.

Our estimate of the impact of borrower trust in traditional banking on P2P borrowing is positive and statistically significant at the 1% level. Column 6 contains our most conservative regression specification. We find that increasing the number of complaints by 1 per bank branch at the county level is associated with a 0.222ppt increase in the online debt ratio. The impact is larger than for the state-level regression result because the median number of CFPB complaints at the county level is quite small. This suggests that distrust in traditional banking has an economically significant impact on the online lending sector development at the county level.

We also conduct the same exercise for borrower subgroups at county level as we did in Table C.7. The corresponding county level regression results are presented in Table C.14. We find consistently negative and significant coefficients for the high credit rating group dummy and its interaction with CFPB complaints per branch. This implies that the relationship between distrust in traditional banking and the development of online lending is mainly driven by borrowers with lower credit scores. It confirms the conjecture that the online lending platforms are "bottom fishing"–that is, serving lower credit quality borrowers.

One of the concerns regarding our bank misconduct measure is that the complaints against bank misconduct could happen before switching is observed. We replace the CFPB complaint number per branch with 1 month lagged values in the aforementioned regressions. The results, shown in Tables D.2 and D.3 in the Online Appendix, indicate that the qualitative results still hold with statistical significance. The magnitude, however, is smaller than the regression results using contemporaneous CFPB complaints variable.

### 7.4.2 Joint impact of bank distrust, generalized trust, and Madoff scandal

To test whether bank misconduct and generalized trust are jointly influencing P2P borrowing, we include both regressors in the same specification and 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. The same holds when generalized trust and Madoff victims in the state influence the online lending origination jointly. In Table D.4 in the Online Appendix we jointly include generalized trust, Madoff victims and the CFPB complaint measure. Again the results are stable.

# 8 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 traditional lending markets. We examine evidence on the role of trust in the expansion of online lending, which has grown rapidly in the U.S. since 2005; and consider multiple measures: trust in tradtional banking, generalized trust, 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 measure of bank misconduct with both geographic and time variation, computed using the CFPB's database of consumer financial complaints; 2) a survey-based measure of generalized trust from the GSS; and 3) a general measure of distrust in traditional finance, captured by the geographic distribution of Madoff scandal victims. The 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.

Our main result explores trust in traditional banking using bank misconduct complaints. We first identify the impact of trust in traditional banking on the ratio of the demand for

P2P debt to household 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 online lending demand share for the median state. This conditional correlation is strongest for the high-risk borrower segment. Both results remain significant in county-level regressions. Moreover, we find suggestive evidence that the positive association between bank misconduct and the expansion of online lending is less pronounced in regions with a high level of generalized trust.

We also show that an increase in generalized trust is associated with a reduction in the demand for P2P debt relative to other debt. In particular, a one standard deviation increase in survey-reported generalized trust is associated with a 11% decrease in the online lending demand share for the median state. This suggests that in-person, bank-based borrowing and informal borrowing benefit from improvements in generalized trust; whereas borrowing from online platforms is largely perceived to be impersonal. Moreover, we show that generalized 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 also credit card debt is largely impersonal; whereas mortgage debt often requires personal interactions with bank employees.

In addition to our results for borrowers, we 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, 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 generalized 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 could remain important determinants of online lending growth and of the pathways for financial disintermediation. More generally, trust appears to play an important role when FinTech developments give rise to new financial products, services, or instruments.

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# A Formal model

Formally, we consider a simultaneous-move, one-shot game with a continuum of borrowers of mass $m > 0$, indexed by $i$ with an interest in potentially consolidating their debt by obtaining a long-term, uncollateralized loan of fixed size, $L = 1$. The credit market is competitive and uncollateralized. If borrowers decide to consolidate their debt, they may choose from a large number of traditional banks and online lending platforms that compete by setting lending rates. For simplicity, all agents are risk-neutral. The cost for traditional banks to issue one loan is $f_B > 1$ and the cost for online lenders to issue one loan is $f_O \in (1, f_B)$.

Let the random variable $r$ be the reservation interest rate of an individual borrower. It captures the cost they incur when deciding not to consolidate their debt. We assume that reservation interest rates are uniformly distributed $r \sim U[\underline{r}, \overline{r}]$, with $1 < \underline{r} < \overline{r}$. Furthermore, we aim to capture the heterogeneous trustworthiness or ability of borrowers to take advantage of in-person relationships with traditional banks that allow them to convey soft information and to improve monitoring via repeated interaction, reducing the likelihood that a traditional bank encounters an risky borrower.[30] To do this in a stylized way, we assume that borrowers have a perceived baseline repayment probability of $0 < p < 1$ and face an idiosyncratic cost $c_i \sim U[0, \overline{c}]$ to further increase the perceived repayment probability to $q$ if they decide to incur the cost and take out an in-person loan from a traditional bank, where $p < q < 1$ and $\overline{c} > 0$. For analytical convenience, $c_i$ and $r$ are independently distributed.

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 given 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 $\tau_O > 0$.[31] Both costs are uniform across borrowers and capture disutility from unfair fees or contractual terms in a stylized way.

The timing is as follows. First, borrowers decide whether to incur a cost that allows them to benefit from having built trust in personal interactions with the bank's loan officer,

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

[31] Borrowers only care about the lending policies and conduct of online lending platforms. For them, it is irrelevant by whom they are funded and they also have no influence over it.

which is captured by an increase in the perceived repayment probability. Second, lenders simultaneously offer rates to borrowers who then decide whether or not to consolidate their debt and which offer for alternative funding to accept. In effect, traditional banks compete by offering one rate to trusted borrowers who are perceived to have an increased repayment probability when taking an in-person loan and a different rate to all remaining borrowers, while lending platforms compete by offering a single interest rate to all borrowers.

We describe the credit market equilibrium and summarizes the key comparative statics.

**Result 1** *An individual borrower optimally decides to consolidate her debt if and only if:*

$$r > \min\{f_B/q + \tau_B + c_i, f_B/p + \tau_B, f_O/p + \tau_O\}. \tag{4}$$

*She chooses alternative funding from a traditional bank if the relative trust in banks is high:*

$$\min\{f_B/q + c_i, f_B/p\} < f_O/p + (\tau_O - \tau_B). \tag{5}$$

*Instead, if inequality (5) is violated, she chooses alternative funding from an online lending platform. There exists a credit market equilibrium characterized by a segmentation into borrowers who (a) do not consolidate their debt, (b) seek funding from banks, and (c) seek funding from online lenders. The corresponding lending volumes are derived in the Appendix. The online lending demand increases in $\tau_B$, $f_B$, $\bar{c}$ and $m$, while it decreases in $\tau_O$ and $f_O$. The bank lending demand decreases in $\tau_B$, $f_B$ and $\bar{c}$, while it increases in $\tau_O$, $f_O$ and $m$.*

The results guide the hypothesis development and derivations can be found in Appendix B. As expected, a higher level of distrust in traditional banks and less favorable borrowing conditions offered by banks are, at the margin, associated with an increase in the online lending demand and, hence, volume. The same holds for an increase in the cost-to-invest in a borrower-bank relationship. As stated earlier, a simplified version of our model can also be applied to the context of funding new expenses, as opposed to debt consolidation.[32]

[32] To do this, $r$ can be held fixed and treated as an outside option (i.e. opportunity cost of not making the expense). Importantly, the key predictions on the online lending demand are unaltered. Notice that all formal results are stated as "weak" increases or decreases and not "strict" increases or decreases. We have strict increases or decreases for cases when the solution is interior. Since there are a many cases to consider, we relegate the details to the Appendix.

# B Derivations

The volumes for no debt consolidation, bank lending and online lending ($\mathcal{N}$, $\mathcal{B}$ and $\mathcal{O}$) are:

$$\begin{aligned}
\mathcal{N} &\equiv m\int_{\underline{r}}^{\max\{\min\{f_B/p+\tau_B, f_O/p+\tau_O, \overline{r}\}, \underline{r}\}} \frac{1-\hat{c}_2(r)/\overline{c}}{\overline{r}-\underline{r}}dr \\
\mathcal{B} &\equiv m\Big(\int_{\underline{r}}^{\max\{\min\{f_B/p+\tau_B, f_O/p+\tau_O, \overline{r}\}, \underline{r}\}} \frac{\hat{c}_2(r)/\overline{c}}{\overline{r}-\underline{r}}dr + \int_{\max\{\min\{f_B/p+\tau_B, f_O/p+\tau_O, \overline{r}\}, \underline{r}\}}^{\overline{r}} \frac{\Phi_B(r)}{\overline{r}-\underline{r}}dr\Big) \\
\mathcal{O} &\equiv m\int_{\max\{\min\{f_O/p+\tau_O, \overline{r}\}, \underline{r}\}\}}^{\overline{r}} \frac{\Phi_O(r)}{\overline{r}-\underline{r}}dr,
\end{aligned}$$

where the integration bounds and the thresholds relate to equations (4) and (5), so that $\hat{c}_1 \equiv \min\{\max\{0, f_O/p - f_B/q + (\tau_O - \tau_B)\}, \overline{c}\}$, $\hat{c}_2(r) \equiv \min\{\max\{0, r - (f_B/q + \tau_B)\}, \overline{c}\}$ and:

$$\Phi_B \equiv \begin{cases} \hat{c}_1/\overline{c} \;\; if \;\; f_B/p < f_O/p + (\tau_O - \tau_B) \\ 1 \;\; otherwise \end{cases} \qquad\qquad \Phi_O \equiv 1 - \Phi_B.$$

Recall that both traditional banks and online lenders behave competitively and set rates equal to their risk adjusted funding cots. For $\hat{c}_2(\overline{r}) = 0$ no borrower decides to consolidate debt, $\mathcal{N} = m$, if $\overline{r} \leq f_O/p + \tau_O$, while all borrowers prefer funding from online lenders, $\mathcal{O} = m$, if $\underline{r} \geq f_O/p + \tau_O$. When $\hat{c}_2(\overline{r}) = 0$ and $f_O/p + \tau_O \in (\underline{r}, \overline{r})$, borrowers are split in a group that decides not to consolidate debt, $\mathcal{N} = m(f_O/p + \tau_O - \underline{r})/(\overline{r} - \underline{r})$, and a group that prefers funding form online lenders, $\mathcal{O} = m - \mathcal{N}$. Both scenarios require that distrust in banks, $(\tau_B - \tau_O)$, is high and are characterized by an online lending volume, $\mathcal{O}$, that is decreasing in $f_O$, $\tau_O$ and increasing in $\underline{r}, \overline{r}$ and $m$. Next, consider the case $\hat{c}_2(\overline{r}) > 0$ and $\hat{c}_1 = 0$. Here all borrowers consolidate debt and prefer funding from online lenders, $\mathcal{O} = m$, since relative distrust in banks is high. Finally, consider the case $\hat{c}_2(\overline{r}) > 0$ and $\hat{c}_1 > 0$. Here the lending volume by banks, $\mathcal{B}$, is strictly positive and increasing in $f_O$, $\tau_O$ and $m$, while it is decreasing in $f_B$, $\tau_B$ and $\overline{c}$. If $\hat{c}_1 < \overline{c}$ and $f_O/p + \tau_O < \overline{r}$, the online lending volume, $\mathcal{O}$, is strictly positive and increasing in $\tau_B$, $f_B$, $\overline{c}$ and $m$, while it is decreasing in $f_O$ and $\tau_O$. Conversely, it is zero, $\mathcal{O} = 0$, if either $\hat{c}_1 = \overline{c}$ or $f_O/p + \tau_O \geq \overline{r}$, which holds for high levels of distrust in online lending. All borrowers decide to consolidate debt, $\mathcal{N} = 0$ if $\hat{c}_2(\underline{r}) \geq \hat{c}_1$.

# C Main tables

Table C.1: Variable definitions

| Variable | Description | Source |
|---|---|---|
| *State level* | | |
| CFPB complaints | Total number of consumer complaints regarding banking services | Consumer Financial Protection Bureau (CFPB) |
| Generalized 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 | Total number of bank branches in the state | FDIC SoD data |
| College attainment rate | Percentage of population that have a college (or higher) degree | US Census Bureau |
| Bank competition | Herfindahl-Hirschman Index (HHI) calculated with each bank's market share in the state | Federal Deposite Insurance Corporation (FDIC) |
| Internet access | Percentage of population that has internet access from some location | Current Population Survey 2009 |
| *County level* | | |
| CFPB complaints | Total number of consumer complaints regarding banking services | CFPB |
| Total debt | Total dollar amount of household debt; county level | NY Fed Consumer Panel |
| 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 county | US Census Bureau |
| Branch | Total number of bank branches in the county | FDIC SoD data |
| College attainment rate | Percentage of population that have a college (or higher) degree | US Census Bureau |
| Bank competition | HHI calculated with each bank's market share in the county | FDIC |
| Internet access | Residential Fixed Connections over 200 kbps in at least one direction per 1,000 households | Current Population Survey |
| *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 C.2: Summary statistics

| | Mean | SD | P25 | Median | P75 | N |
|---|---|---|---|---|---|---|
| *State-level variables (by state)* | | | | | | |
| Generalized 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(1000/km2) | 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 |
| HHI | 0.11 | 0.09 | 0.06 | 0.09 | 0.12 | 459 |
| College+ attainment (in % ) | 27.15 | 5.44 | 23.60 | 26.00 | 29.80 | 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$) | 5.83 | 11.41 | 0.31 | 1.59 | 6.32 | 4653 |
| P2P debt (m$)/Bank debt (10 bn$) | 0.24 | 0.25 | 0.02 | 0.15 | 0.41 | 4653 |
| Average DTI ratio | 0.17 | 0.06 | 0.13 | 0.17 | 0.19 | 4653 |
| Average interest rate | 0.13 | 0.01 | 0.13 | 0.13 | 0.14 | 4653 |
| Average annual income (k$) | 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 *generalized trust* is computed as the state-level average of positive responses to the General Social Survey's (GSS) question about generalized 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 C.3: Summary statistics: county level

| | Mean | SD | P25 | Median | P75 | N |
|---|---|---|---|---|---|---|
| *County-level variables (by county and year)* | | | | | | |
| Pop. density (1000/km2) | 0.118 | 0.793 | 0.009 | 0.021 | 0.055 | 6645 |
| Log county income | 14.104 | 1.429 | 13.098 | 13.926 | 14.913 | 6645 |
| Log county population | 10.496 | 1.362 | 9.582 | 10.381 | 11.281 | 6645 |
| Log county jobs | 9.773 | 1.434 | 8.728 | 9.621 | 10.600 | 6645 |
| Internet | 0.003 | 0.001 | 0.003 | 0.003 | 0.004 | 6645 |
| college+ attainment rate (in %) | 0.187 | 0.084 | 0.128 | 0.166 | 0.224 | 6645 |
| HHI | 0.212 | 0.194 | 0.079 | 0.152 | 0.279 | 6645 |
| *County-level variables (by county and month)* | | | | | | |
| P2P debt (m$)/Bank debt (10 bn$) | 0.19 | 0.29 | 0.04 | 0.10 | 0.22 | 45822 |
| CFPB complaints per branch | 0.19 | 1.15 | 0.00 | 0.00 | 0.07 | 45822 |
| Average DTI ratio | 0.18 | 0.06 | 0.15 | 0.18 | 0.22 | 45822 |
| Average interest rate | 0.14 | 0.03 | 0.13 | 0.14 | 0.16 | 45822 |
| Average annual income (k$) | 71.05 | 110.39 | 49.99 | 62.97 | 78.06 | 45822 |
| Average employment duration | 5.84 | 2.74 | 4.25 | 5.80 | 7.75 | 45822 |

*Notes:* This table shows the summary statistics for all variables used in the county level regressions. The sample covers the largest P2P platform, LendingClub, between 2012 and 2016. Where possible, we use county-level variables with monthly frequencies, while the loan-borrower level variables contain individual-specific information. The CFPB data doesn't cover all counties in different months.

Table C.4: 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 for the period 2012-2016 using 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 over household total debt in state $i$ at the monthly frequency. *CFPB complaints* 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 C.5: 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 for the period 2012-2016:

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

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 complaints* 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 P2P 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 C.6: 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) |
| 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 for the period 2012-2016:

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

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 complaints* 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 C.7: Online lending and CFPB complaints: by borrower 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 fraction of online lending demand by borrower credit quality over household total debt in a certain state for a given month on the credit rating dummy, CFPB consumer complaints, and their interactions. *highrating=1* means the borrowers have a FICO score above 700. *CFPB complaints* 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 P2P 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 C.8: Online lending and CFPB complaints: by generalized trust

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| CFPB | 0.023 | 0.029*** | -0.001 | 0.021*** | -0.002 |
| | (0.015) | (0.006) | (0.004) | (0.006) | (0.004) |
| generalized trust | -0.394*** | -0.709*** | 0.019 | -0.406*** | -0.079 |
| | (0.114) | (0.141) | (0.134) | (0.072) | (0.066) |
| DTI | 0.221** | -0.019 | 0.051 | 0.134* | 0.042 |
| | (0.092) | (0.063) | (0.065) | (0.079) | (0.050) |
| interest rate | 1.540*** | -1.584** | 1.287** | 1.652*** | 0.799* |
| | (0.596) | (0.707) | (0.518) | (0.508) | (0.426) |
| income | 0.000 | -0.002*** | -0.000 | -0.000 | -0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| employment | 0.007 | 0.032*** | 0.012* | 0.009 | 0.018*** |
| | (0.007) | (0.006) | (0.007) | (0.006) | (0.005) |
| population density | -0.045*** | 0.156*** | -0.033 | -0.051*** | -0.069 |
| | (0.009) | (0.049) | (0.097) | (0.008) | (0.073) |
| log GDP | 0.020 | 0.046** | 0.134*** | 0.048*** | 0.134*** |
| | (0.020) | (0.022) | (0.033) | (0.016) | (0.024) |
| log population | 0.002 | -0.027 | -0.176*** | -0.016 | -0.161*** |
| | (0.018) | (0.023) | (0.034) | (0.015) | (0.026) |
| unemployment rate | -0.003 | 0.005 | 0.014*** | 0.005 | 0.018*** |
| | (0.004) | (0.004) | (0.005) | (0.003) | (0.004) |
| Subsample | Bottom | Middle | Top | Low | High |
| Year-Month FE | YES | YES | YES | YES | YES |
| Controls | YES | YES | YES | YES | YES |
| No. of observations | 874 | 986 | 891 | 1301 | 1450 |
| Adj. R-square | 0.008 | 0.346 | 0.580 | 0.593 | 0.729 |

*Notes:* This table reports the results of regression equation on subsamples:

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

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 over household total debt in state $i$ at the monthly frequency. *CFPB* is the number of consumer complaints per branch in state $i$ in month $t$. *Generalized trust* is the measure of social trust from the General Social Survey (GSS) during 1973-2006. We split the sample into bottom/middle/top according to the level of generalized trust. Later we look into the low/high generalized trust subgroups. Variables *DTI*, *Interest rate*, *Income*, and *Employment* and other state level variables such as population density ($1000/km^2$), the logarithm of GDP, the logarithm of population and state unemployment rate are defined as before. 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 C.9: Online lending and generalized trust

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| generalized 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) |
| branches | | -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 results for the period 2008-2016 using the regression:

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

The dependent variable is the fraction of online lending demand over household total debt in state $i$ at the monthly frequency. *Generalized 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 P2P 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 C.10: Credit card debt, mortgage lending and generalized trust

| | Dependent variable: credit card debt | | | | Dependent variable: mortgage lending | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| generalized trust | -0.004*** | -0.010** | -0.004*** | -0.014*** | 0.126*** | 0.185*** | 0.126*** | 0.168*** |
| | (0.001) | (0.004) | (0.001) | (0.002) | (0.009) | (0.014) | (0.009) | (0.004) |
| pop. density | | -0.002 | | -0.003*** | | -0.022* | | -0.029*** |
| | | (0.002) | | (0.001) | | (0.011) | | (0.002) |
| log GDP | | -0.018** | | -0.013*** | | 0.127*** | | 0.151*** |
| | | (0.005) | | (0.003) | | (0.020) | | (0.006) |
| log population | | 0.013** | | 0.009*** | | -0.115*** | | -0.132*** |
| | | (0.004) | | (0.002) | | (0.023) | | (0.008) |
| unemployment rate | | -0.000 | | -0.001*** | | 0.013*** | | 0.010*** |
| | | (0.001) | | (0.000) | | (0.004) | | (0.001) |
| branches | | 0.003*** | | 0.002*** | | -0.007** | | -0.010*** |
| | | (0.001) | | (0.001) | | (0.002) | | (0.002) |
| Year FE | NO | NO | YES | YES | NO | NO | YES | YES |
| Controls | NO | YES | NO | YES | MO | YES | NO | YES |
| No. of observations | 441 | 441 | 441 | 441 | 441 | 441 | 441 | 441 |
| Adj. R-square | 0.001 | 0.254 | 0.238 | 0.431 | 0.047 | 0.334 | 0.179 | 0.454 |

*Notes:* This table reports the robustness regression for the period 2008-2016 as:

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

For columns 1-4 the dependent variable is credit card debt in state $i$ in year $t$. For columns 5-8 the dependent variable is mortgage lending in state $i$ in year $t$. *Generalized 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 C.11: Online lending and generalized trust: by borrower quality

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| generalized 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 generalized 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) |
| branches | | -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 demand 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, generalized trust, and their interactions. *highrating=1* means the borrowers have a FICO score above 700. *Generalized 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 C.12: 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) |
| branches | | -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 for the period 2008-2016 using the regression:

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

The dependent variable is the total amount of originated P2P debt 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 P2P 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 C.13: Online lending and CFPB consumer complaints at the county level

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| CFPB | -0.008 | 0.222*** | 0.033 | 0.242*** | -0.010 | 0.222*** |
| | (0.040) | (0.042) | (0.040) | (0.044) | (0.041) | (0.043) |
| DTI | | -0.026 | | -0.009 | | -0.027 |
| | | (0.018) | | (0.021) | | (0.021) |
| interest rate | | 0.497*** | | 0.543*** | | 0.505*** |
| | | (0.044) | | (0.047) | | (0.047) |
| income | | 0.000*** | | 0.000*** | | 0.000*** |
| | | (0.000) | | (0.000) | | (0.000) |
| employment | | 0.003*** | | 0.003*** | | 0.003*** |
| | | (0.001) | | (0.001) | | (0.001) |
| pop. density (1000/km2) | | 0.017*** | | 0.017*** | | 0.017*** |
| | | (0.003) | | (0.003) | | (0.003) |
| log county income | | 0.191*** | | 0.203*** | | 0.190*** |
| | | (0.050) | | (0.050) | | (0.051) |
| log county population | | -0.326*** | | -0.342*** | | -0.324*** |
| | | (0.054) | | (0.054) | | (0.055) |
| log county jobs | | 0.049* | | 0.050* | | 0.048* |
| | | (0.026) | | (0.026) | | (0.027) |
| college | | 0.086 | | 0.068 | | 0.088 |
| | | (0.102) | | (0.102) | | (0.104) |
| internet | | 6.037 | | 4.592 | | 6.103 |
| | | (5.643) | | (5.658) | | (5.685) |
| HHI | | 0.539*** | | 0.538*** | | 0.537*** |
| | | (0.090) | | (0.090) | | (0.092) |
| State-Year FE | YES | YES | NO | NO | NO | NO |
| State-Month FE | NO | NO | YES | YES | NO | NO |
| State-Year-Month FE | NO | NO | NO | NO | YES | YES |
| Controls | NO | YES | NO | YES | NO | YES |
| No of observations | 45822 | 45822 | 45822 | 45822 | 45822 | 45822 |
| Adj. R-square | 0.160 | 0.404 | 0.134 | 0.397 | 0.153 | 0.399 |

*Notes:* This table reports the results of regression equation:

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

using the CFPB consumer complaints as the key explanatory variable. The dependent variable is the fraction of online lending demand over household total debt in county $j$ in state $i$ at the monthly frequency. *CFPB* is the number of consumer complaints per branch in county $j$ of 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 county $j$ at month $t$. *Interest rate* is the average value of interest rates for P2P loans in the county $j$ at month $t$. *Income* and *Employment* measure the average annual income and years of employment for the borrowers in county $j$ and month $t$. We also control for county level variables such as population density ($1000/km^2$), the logarithm of county average income, the logarithm of population, and logarithm of number of jobs. In addition, we control for HHI Index of bank competition, percentage of population with a college or above degree as proxy for financial literacy, and internet usage. 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 C.14: Online lending and CFPB complaints: by borrower quality at the county level

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| CFPB | 0.646*** | 0.559*** | 0.660*** | 0.559*** | 0.653*** | 0.563*** |
| | (0.196) | (0.132) | (0.195) | (0.132) | (0.199) | (0.133) |
| highrating=1 | -0.009*** | -0.003 | -0.009*** | -0.003 | -0.009*** | -0.003 |
| | (0.003) | (0.002) | (0.003) | (0.002) | (0.003) | (0.002) |
| highrating=1 x CFPB | -0.079** | -0.058* | -0.079** | -0.059** | -0.078** | -0.057* |
| | (0.030) | (0.029) | (0.030) | (0.029) | (0.030) | (0.029) |
| DTI | | -0.294*** | | -0.297*** | | -0.297*** |
| | | (0.027) | | (0.028) | | (0.028) |
| interest rate | | -0.532*** | | -0.515*** | | -0.537*** |
| | | (0.084) | | (0.079) | | (0.087) |
| income | | 0.000*** | | 0.000*** | | 0.000*** |
| | | (0.000) | | (0.000) | | (0.000) |
| employment | | -0.002*** | | -0.002*** | | -0.002*** |
| | | (0.000) | | (0.000) | | (0.000) |
| pop. density (1000/km2) | | 0.007*** | | 0.007*** | | 0.007*** |
| | | (0.002) | | (0.002) | | (0.002) |
| log county income | | 0.139*** | | 0.137*** | | 0.139*** |
| | | (0.036) | | (0.036) | | (0.036) |
| log county population | | -0.275*** | | -0.274*** | | -0.275*** |
| | | (0.043) | | (0.043) | | (0.044) |
| log county jobs | | 0.034* | | 0.035** | | 0.034* |
| | | (0.017) | | (0.017) | | (0.017) |
| college | | -0.086 | | -0.083 | | -0.087 |
| | | (0.064) | | (0.066) | | (0.065) |
| internet | | -5.051 | | -5.027 | | -4.988 |
| | | (4.598) | | (4.700) | | (4.655) |
| HHI | | 0.336*** | | 0.335*** | | 0.334*** |
| | | (0.057) | | (0.057) | | (0.057) |
| State-Year FE | YES | YES | NO | NO | NO | NO |
| State-Month FE | NO | NO | YES | YES | NO | NO |
| State-Year-Month FE | NO | NO | NO | NO | YES | YES |
| Controls | NO | YES | NO | YES | NO | YES |
| No of obs | 69773 | 69773 | 69773 | 69773 | 69773 | 69773 |
| Adj. R-square | 0.225 | 0.523 | 0.213 | 0.521 | 0.236 | 0.530 |

*Notes:* This table reports the regression of the online lending amount by borrower credit quality in a certain county for a given month, normalized by the total bank debt in the same state, on the credit rating dummy, CFPB, and their interactions. *highrating=1* means the borrowers have a FICO score above 700. *CFPB* is the number of consumer complaints per branch in county $j$ of 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 county $j$ in month $t$. *Interest rate* is the average value of interest rates for P2P loans in county $j$ in month $t$. *Income* and *Employment* measure the average annual income and years of employment for the borrowers in county $j$ in month $t$. We also control for county level variables such as population density ($1000/km^2$), the logarithm of county average income, the logarithm of population, and logarithm of number of jobs. In addition, we control for HHI Index as proxy for bank competition, percentage of population with a college or above degree as proxy for financial literacy. Standard errors, in parentheses, are corrected for clustering of observations by state. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

# D Online Appendix

Table D.1: Online lending and CFPB consumer complaints with additional controls

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| CFPB | 0.017** | 0.023*** | 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 | | 0.537* | | 0.408* | | 0.280* | | 0.108*** |
| | | (0.319) | | (0.216) | | (0.149) | | (0.038) |
| interest rate | | -4.225*** | | -2.487** | | -0.796 | | 1.324* |
| | | (1.397) | | (1.088) | | (1.083) | | (0.715) |
| income | | 0.003*** | | 0.001** | | 0.000 | | -0.000 |
| | | (0.001) | | (0.001) | | (0.000) | | (0.000) |
| employment | | 0.002 | | -0.001 | | 0.003 | | 0.013* |
| | | (0.013) | | (0.009) | | (0.009) | | (0.007) |
| population density | | 0.041** | | -1.298*** | | -1.196*** | | -1.141*** |
| | | (0.019) | | (0.184) | | (0.166) | | (0.164) |
| log GDP | | 0.106*** | | -0.552*** | | -0.381*** | | -0.415*** |
| | | (0.024) | | (0.142) | | (0.135) | | (0.135) |
| log population | | -0.066*** | | 1.757*** | | -0.374** | | -0.305** |
| | | (0.024) | | (0.585) | | (0.157) | | (0.147) |
| unemployment rate | | -0.056*** | | -0.129*** | | -0.021*** | | -0.021*** |
| | | (0.006) | | (0.011) | | (0.003) | | (0.002) |
| college | | -1.210*** | | 73.285** | | -39.587** | | -35.111** |
| | | (0.095) | | (35.339) | | (16.130) | | (15.174) |
| internet | | -0.210** | | -31.681* | | 18.940** | | 16.587** |
| | | (0.086) | | (16.440) | | (8.185) | | (7.658) |
| hhi | | 0.215*** | | -0.120 | | 0.453*** | | 0.515*** |
| | | (0.035) | | (0.262) | | (0.158) | | (0.137) |
| 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 | 0.326 | 0.111 | 0.567 | 0.684 | 0.693 | 0.874 | 0.882 |

*Notes:* We repeat the regression in Table C.4. In addition, we also control for the percentage of the population with a college degree, internet usage and the HHI Index of bank competition. 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 D.2: Online lending and lagged CFPB consumer complaints at the county level

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| CFPB | 0.024*** | 0.021*** | 0.024*** | 0.021*** | 0.024*** | 0.021*** |
| | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) |
| DTI | | -0.056*** | | -0.035 | | -0.061*** |
| | | (0.020) | | (0.022) | | (0.022) |
| interest rate | | 0.393*** | | 0.435*** | | 0.398*** |
| | | (0.048) | | (0.047) | | (0.052) |
| income | | 0.000** | | 0.000** | | 0.000** |
| | | (0.000) | | (0.000) | | (0.000) |
| employment | | 0.003*** | | 0.003*** | | 0.003*** |
| | | (0.000) | | (0.000) | | (0.001) |
| pop. density (1000/km2) | | 0.015*** | | 0.015*** | | 0.015*** |
| | | (0.002) | | (0.002) | | (0.002) |
| log county income | | 0.146*** | | 0.159*** | | 0.144*** |
| | | (0.039) | | (0.038) | | (0.040) |
| log county population | | -0.224*** | | -0.240*** | | -0.222*** |
| | | (0.048) | | (0.048) | | (0.049) |
| log county jobs | | 0.015 | | 0.015 | | 0.014 |
| | | (0.031) | | (0.031) | | (0.032) |
| college | | 0.144* | | 0.125 | | 0.147* |
| | | (0.083) | | (0.083) | | (0.085) |
| internet | | -6.258 | | -8.292 | | -6.160 |
| | | (6.780) | | (6.856) | | (6.915) |
| HHI | | 0.520*** | | 0.520*** | | 0.520*** |
| | | (0.114) | | (0.114) | | (0.117) |
| State-Year FE | YES | YES | NO | NO | NO | NO |
| State-Month FE | NO | NO | YES | YES | NO | NO |
| State-Year-Month FE | NO | NO | NO | NO | YES | YES |
| Controls | NO | YES | NO | YES | NO | YES |
| No of obs | 41173 | 41173 | 41173 | 41173 | 41173 | 41173 |
| Adj. R-square | 0.145 | 0.326 | 0.116 | 0.316 | 0.134 | 0.318 |

*Notes:* This table reports the results of regression equation:

$$Y_{i,j,t} = \beta_1 \text{CFPB complaints}_{i,j,t-1} + \gamma X_{i,j,t} + (A_{i,t}) + \epsilon_{i,j,t}$$

using the lagged CFPB consumer complaints as the key explanatory variable. The dependent variable is the fraction of online lending demand over household total debt in county $j$ in state $i$ at the monthly frequency. *CFPB* is the number of consumer complaints per branch in county $j$ of state $i$ in month $t-1$. 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 county $j$ at month $t$. *Interest rate* is the average value of interest rates for P2P loans in the county $j$ at month $t$. *Income* and *Employment* measure the average annual income and years of employment for the borrowers in county $j$ and month $t$. We also control for county level variables such as population density ($1000/km^2$), the logarithm of county average income, the logarithm of population, and logarithm of number of jobs. In addition, we control for HHI Index of bank competition, percentage of population with a college or above degree as proxy for financial literacy, and internet usage. 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 D.3: Online lending and lagged CFPB: by borrower quality at the county level

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| CFPB | 0.016*** | 0.011*** | 0.016*** | 0.010*** | 0.017*** | 0.011*** |
| | (0.005) | (0.003) | (0.006) | (0.003) | (0.006) | (0.003) |
| highrating=1 | -0.010*** | -0.006*** | -0.010*** | -0.006*** | -0.010*** | -0.006*** |
| | (0.002) | (0.001) | (0.002) | (0.001) | (0.002) | (0.002) |
| highrating=1 x CFPB | -0.006*** | -0.001** | -0.006*** | -0.001** | -0.006*** | -0.001** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| DTI | | -0.356*** | | -0.357*** | | -0.358*** |
| | | (0.057) | | (0.059) | | (0.059) |
| interest rate | | -0.783*** | | -0.771*** | | -0.794*** |
| | | (0.157) | | (0.151) | | (0.164) |
| income | | -0.000 | | -0.000 | | -0.000 |
| | | (0.000) | | (0.000) | | (0.000) |
| employment | | -0.003*** | | -0.003*** | | -0.003*** |
| | | (0.001) | | (0.001) | | (0.001) |
| pop. density (1000/km2) | | 0.007*** | | 0.008*** | | 0.007*** |
| | | (0.001) | | (0.001) | | (0.001) |
| log county income | | 0.106*** | | 0.103*** | | 0.106*** |
| | | (0.027) | | (0.026) | | (0.027) |
| log county population | | -0.201*** | | -0.198*** | | -0.201*** |
| | | (0.035) | | (0.033) | | (0.036) |
| log county jobs | | 0.000 | | 0.001 | | -0.000 |
| | | (0.020) | | (0.020) | | (0.020) |
| college | | -0.007 | | -0.001 | | -0.008 |
| | | (0.054) | | (0.057) | | (0.055) |
| internet | | -14.311** | | -14.558** | | -14.130** |
| | | (6.435) | | (6.381) | | (6.502) |
| HHI | | 0.354*** | | 0.353*** | | 0.353*** |
| | | (0.073) | | (0.073) | | (0.073) |
| State-Year FE | YES | YES | NO | NO | NO | NO |
| State-Month FE | NO | NO | YES | YES | NO | NO |
| State-Year-Month FE | NO | NO | NO | NO | YES | YES |
| Controls | NO | YES | NO | YES | NO | YES |
| No of obs | 67700 | 67700 | 67700 | 67700 | 67700 | 67700 |
| Adj. R-square | 0.143 | 0.454 | 0.125 | 0.452 | 0.154 | 0.462 |

*Notes:* This table reports the regression of the online lending amount by borrower credit quality in a certain county for a given month, normalized by the total bank debt in the same state, on the credit rating dummy, lagged CFPB, and their interactions. *highrating=1* means the borrowers have a FICO score above 700. *CFPB* is the number of consumer complaints per branch in county $j$ of state $i$ in month $t-1$. 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 county $j$ in month $t$. *Interest rate* is the average value of interest rates for P2P loans in county $j$ in month $t$. *Income* and *Employment* measure the average annual income and years of employment for the borrowers in county $j$ in month $t$. We also control for county level variables such as population density ($1000/km^2$), the logarithm of county average income, the logarithm of population, and logarithm of number of jobs. In addition, we control for HHI Index as proxy for bank competition, percentage of population with a college or above degree as proxy for financial literacy. 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 D.4: Online lending, CFPB complains, generalized 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) |
| generalized 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:

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

The dependent variable is the total amount of originated P2P debt in state $i$ in month $t$ normalized by total bank debt.*CFPB* is the number of consumer complaints per branch in state $i$ in month $t$. *Generalized 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.