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The impact of public corruption on marketplace lending outcomes

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ABSTRACT

This study investigates the impact of public corruption on lending outcomes in the context of Marketplace Lending (MPL) platforms such as LendingClub. Utilizing data on over one million loans and state-level corruption metrics from the US Department of Justice, this research uniquely examines within-country variations in corruption. Our findings reveal a significant correlation between public corruption and loan defaults, with a 3 % increase in default rates per unit increase in corruption. Interest rates also rise by 9 basis points under similar conditions. These effects persist across various model specifications and robustness checks. We demonstrate that trust mediates the relationship between corruption and loan defaults, and that neither governance nor enforcement explains the observed impacts. This study contributes to the literature by linking corruption to individual financial behavior in fintech lending, highlighting the crucial role of trust in financial transactions.

1. Introduction

Public corruption is one of the most pervasive and damaging issues afflicting societies worldwide. It involves the misuse of public office for personal gain (Shleifer and Vishny, 1993), leading to a profound breach of trust placed by the public in their institutions. Trust provides the essential basis for economic interactions and transactions; it is not an inherent quality, but a delicate balance nurtured by transparency, accountability, and integrity (Park and Blenkinsopp, 2011). By eroding trust, corruption damages economic performance since it undermines the smooth functioning of financial markets (Gulino and Masera, 2022).

The relationship between public corruption and financial outcomes has long intrigued scholars and policymakers alike. While public corruption's destructive effects on economic growth and institutional stability are well-documented (Chang and Chu, 2006), its implications for individual financial transactions remain less explored. And, to the best of our knowledge, the effects on financial outcomes intermediated by marketplace lending (MPL) platforms, are yet to be uncovered. This research gap is the focus of our study.

Unlike traditional bank loans, MPL operates through peer-to-peer (P2P) platforms, where individual investors lend directly to borrowers, thereby bypassing the intermediation of traditional financial institutions (Balyuk, 2023; Chava et al., 2021; Cornelli et al., 2023). MPL offers a uniquely valuable setting, since unlike institutionalized banking systems with established regulatory frameworks and risk management practices, MPL platforms offer little or no scope for direct, face-to-face, impacts of corruption on lending outcomes, Instead, public corruption is likely to affect those outcomes indirectly, by influencing the quality of the borrower pool.

These considerations motivate the present article, which analyses public access data on over 1 million loans obtained from LendingClub's website. We combine these data with annual information on state-level corruption obtained from public reports on the activities and operations of the public integrity section compiled by the US Department of Justice (Chourou et al., 2024; El Ghoul et al., 2023; Hossain et al., 2021; Smith, 2016). To the best of our knowledge, this is the first study that links within-country variations in corruption to individual loan outcomes – specifically, defaults and interest rates. Recent research on MPLs has explored loan outcomes at the individual level (Croux et al., 2020; Chava et al., 2021; Wang and Overby, 2022; Pursiainen, 2023); but it has yet to explore the impact of public corruption on these outcomes. Defaults carry implications for individual welfare as well as the financial

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health of borrowers; and interest rates register the affordability of credit which is known to affect borrowers' welfare too (Edelberg, 2006; Smith et al., 2013). Our empirical analysis controls for a wide range of individual and loan characteristics, as well as state-level economic conditions.

The results of our empirical analysis are striking. We find that public corruption – measured as the number of annual convictions of public officials per 100,000 individuals within each state – is significantly and substantially related to individual loan defaults. Specifically, loans are 3 % more likely to default for every 1 unit increase in the public corruption measure, such that moving from the median corrupt state (Arizona) to the third most corrupt state (Louisiana) increases the default rate from 19.6 % to 22.6 %. Our estimates of the effects of public corruption are statistically significant and stable across a variety of different model specifications. Furthermore, we find that the same 1 unit increase in public corruption increases interest rates on the LendingClub platform by 0.09 percentage points on average. Moving from the median to the most corrupt state increases the interest premium from 13.22 % to 13.31 %.

We go on to establish that the findings are robust to controlling for the interest rate, which seems to partially price in default risk. However, the effect of public corruption remains statistically and economically significant, suggesting that the pricing of MPL loans does not fully impound information about, and hence price in the risks entailed by, public corruption. This finding is indicative of possible loan mispricing on LendingClub's MPL platform (Li et al., 2023; Pursiainen, 2023; Wei and Lin, 2017).

A well-known limitation of exploiting cross-state variation is the possibility of confounds associated with unobservable regional characteristics. Hence, we re-run the analysis using several alternative research designs. The first exploits individual differences in corruption exposure, enabling state-level fixed effects to be included. While this controls for time-invariant unobservables, it is still correlational and relies on state-level corruption data. A second alternative research design is difference-in-differences (DiD), which exploits an exogenous shock to corruption based on a US Supreme Court decision in 2010. While this approach is quasi-causal, the DiD analysis does not utilize variations in treatments across states, and is subject to the usual identifying assumptions. The third research design exploits a subset of data on the zip codes of borrowers to measure local corruption at the judicial district level. The limitation here is that the data are incomplete. Yet, despite limitations with each of these approaches, a remarkably consistent picture emerges, suggesting that our results are robust.

We go onto explore three candidate channels for the indirect transmission of public corruption to defaults. One channel is that perceptions of public corruption in a given state reduces trust in that state (Villoria et al., 2013) – which increases the risk of strategic defaults. We explore this possibility both by including measures of general trust as an additional covariate and by conducting a mediation analysis. Empirical support is found for this channel. We also investigate two alternative channels through which public corruption might affect loan outcomes. These channels, suggested by prior literature, are governance and contract enforcement. We obtain measures of governance and enforcement at the state level; but we find that neither of these channels can explain the findings.

This article makes the following contributions to the literature. First, it generates several novel findings that extend the literature on how local characteristics affect lending and financial performance outcomes. Some prior research has argued that asymmetric information and transaction costs make physical distance relevant to understanding financial transactions (Petersen and Rajan, 2002). For example, it has been suggested that local banks find it easier to collect soft information about borrowers, leading to better-informed lending decisions and superior loan performance (Agarwal and Hauswald, 2010). Moreover, local entrepreneurs can benefit from a 'home bias' of investors located in their region (Parwada, 2008). Local banks improve SME access to bank credit, reduce the cost of finance, and spur venture growth (Fafchamps and Schündlein, 2013; Hasan et al., 2017). In contrast, we study a setting where physical distance is flattened by the Internet, yet where local factors still remain relevant. Our results suggest the reason is the effect of local corruption on loan repayment rates. Hence, our findings extend our knowledge about the importance of local factors for the operation of financial markets.

Second, this article contributes to the literature on how social capital and trust affect lending in general and P2P lending in particular. Prior research has linked social interactions within local communities in general, as well as high-trust environments specifically, with greater willingness by individuals to invest in risky assets (Hong et al., 2004; Guisoet al., 2004; El-Attar and Poschke, 2011), and with more favorable financial outcomes (Hasan et al., 2017). Yet research which has explored effects of social capital on P2P lending outcomes specifically, has yielded a mixed picture of positive (Lu et al., 2020; Hasan et al., 2022) and insignificant (Chen et al., 2016) results. It is unclear the extent to which institutional quality, e.g., the absence of corruption, can explain these heterogeneous findings. In contrast, we break new ground by exploring how public corruption can reduce generalized trust which worsens financial outcomes. We do so while controlling for regional social capital, to disentangle the effects of trust from those of social capital.

Third, we contribute to the literature on finance and corruption by exploring public corruption's impacts on lending outcomes. Whereas prior research has studied the effects of corruption on firms, and on broad aggregate outcomes (e.g., Chen et al., 2023; Chourou et al., 2024; El Ghoul et al., 2023; Ellis et al., 2020; Hossain et al., 2021; Huang et al., 2023; Smith, 2016), we analyze this issue at the individual level. We are the first to establish that better governance and stricter default collection laws operate independently of corruption itself, rather than being manifestations of it. This is a new and surprising addition to the literature.

Finally, this paper also adds to the burgeoning literature treating lending outcomes on MPL platforms (Danisewicz and Elard, 2023; Kräussl et al., 2024; Lin et al., 2013; Tang, 2019; Wei and Lin, 2017). This literature has explored several aspects of the borrower pool and loan terms but has not yet investigated whether and how public corruption affects lending outcomes on these platforms. In view of the growing importance of fintech (Cornelli et al., 2023), it is interesting to learn more about whether it offers an escape route from corruption or is just the latest conduit through which corruption can operate. The next section provides a brief conceptual discussion to set the stage for the empirical analysis that follows.

2. Corruption and finance: A conceptual discussion

2.1. Corruption and traditional finance

At the outset, it is helpful to define precisely what we mean by 'public corruption'. As in Shleifer and Vishny (1993), we define public corruption as the sale by government officials of public property for personal gain. For example, corrupt officials may collect bribes in return for granting permits and licenses (Bliss and Di Tella, 1997). Public corruption may have direct effects on economic financial outcomes, as we go on to explain below; but it might also have indirect effects if its very presence influences people's financial responsibility. We start by briefly discussing the direct effects of corruption, in the context of traditional bank credit. Later, we will discuss indirect channels.

Firms located in areas where public corruption is strong tend to reduce the risk of expropriation by corrupt local officials by holding less cash, paying out more to shareholders, and relying on greater leverage (Smith, 2016; Hossain et al., 2021). Banks respond by charging these firms higher interest rates (Hossain et al., 2020), while auditors find these firms harder to audit and consequently charge higher audit fees (Jha et al., 2021). Possible exposure to corruption also increases CEO compensation costs (Chen et al., 2023). Evidence also suggests that

state-level corruption entails an innovation penalty (Ellis et al., 2020), and is associated with lower firm value (Dass et al., 2016).

The banking sector also pays a price for direct exposure to public corruption, in the form of an adverse risk profile of loan portfolios and a buildup of bad loans. That induces traditional banks to restrict loan coverage and credit extension (Kebede et al., 2023). Corruption can also undermine the soundness of the banking sector as a whole, and is a potential cause of banking crises (Ben Ali et al., 2020), as well as reduced macroeconomic growth (Park, 2012; Son et al., 2020). By increasing the information asymmetries that banks face due to higher uncertainty regarding clients' cash-flows and ability to repay loans, corruption also reduces lending activity by US banks. This problem is accentuated in more corrupt areas (Bermpei et al., 2021).

2.2. Corruption and P2P lending via MPL platforms

MPL platforms such as LendingClub and Prosper compete with traditional financial intermediaries such as banks (Kräussl et al., 2024). MPL platforms match lenders and borrowers, eliminating financial intermediaries. Unlike traditional banks, MPL platforms rely heavily on data-driven technology to price loans and inform lenders about loan prospects (Cornelli et al., 2023; Iyer et al., 2016; Valle and Zeng, 2019). MPL platforms publish repayment histories of borrowers online and incorporate them in future lending decisions, which can exert discipline on borrowers (Einav et al., 2016; Xin, 2020). Greater competition, the collective information production by MPL platforms and their investors, and the use of reputation- based systems by MPL platforms, all challenge the traditional banking model.

Prior research has analyzed P2P lending data from MPL platforms and established several findings that will inform our own analysis. For example, consumers who borrow from MPL platforms have on average lower credit scores and higher long-term default rates relative to observably similar applicants for bank loans (Chava et al., 2021). This seems to reflect MPL lenders facing greater information asymmetries with respect to borrowers than traditional banks. Yet, it appears that the higher interest rates charged on higher-risk borrowers do not fully compensate for their higher probability of loan default. Other work (e.g., Croux et al., 2020) has identified a robust set of contractual loan characteristics, borrower characteristics and macro-economic variables that affect the likelihood of default.

However, none of this research has investigated whether and how public corruption might affect financial outcomes on P2P MPL platforms. The remainder of this section will explore three, *indirect*, channels that might explain impacts on P2P lending outcomes. We would not expect direct effects of corruption on P2P lending outcomes for at least two reasons. First, unlike traditional banks which mainly operate in one state and can leverage connections to local politicians to gain regulatory forbearance (Munshi, 1999; Park, 2012), MPL platforms like LendingClub would have to do this in all the states in which they operate. Second, while companies or high net wealth clients might seek to bribe politicians or bank officials to influence traditional banks and obtain credit or more favorable loan terms (Beck et al., 2006; Zheng et al., 2013), loan pricing decisions are automated on MPL platforms. Hence, lending decisions are made by decentralized private investors. Loan sizes are typically small on these platforms in any case.

The three indirect channels we discuss next are Governance, Enforcement, and Trust. What they all have in common is that public corruption reduces the quality of the borrower pool on MPL platforms – consistent with independent evidence of a preponderance of infra-marginal and over-extended borrowers on MPL P2P platforms (Tang, 2019; Wang and Overby, 2022). For each channel, we first explain how the mechanism might work, before deriving testable hypotheses that are subsequently confronted with the data.

2.2.1. Governance as a mechanism connecting corruption with P2P lending outcomes

The idea behind the governance mechanism is that good governance is an antidote to corruption, making it harder to conceal and perpetuate. That is why efforts to improve the quality of governance, which entails greater adherence to the rule of law and more effective government (Gilley, 2006), are closely connected to anti-corruption policies (Holmberg et al., 2009). According to the UNODC (2022), "violations of the principles of transparency, accountability and rule of law appear to be most closely associated with corruption." The World Bank in particular has taken a leading role in promoting good governance in efforts to combat corruption (Andersson et al., 2009). In the absence of such efforts, one might expect corrupt officials to actively weaken governance standards, removing the transparency and accountability that they are supposed to uphold.

If more corrupt states have weaker governance, how does this affect the performance of financial markets? Evidence that exploits cross-country variations in world governance indictors (Kauffman et al., 2007), suggests that better governance is associated with a range of favorable *traditional* banking and credit outcomes. These include lower risk of banking crises, greater bank stability, aggregate credit growth, high loan-to-asset ratios, and high private equity returns (Byström, 2004; Fratzscher et al., 2016; Demetriades and Fielding, 2012; Cumming et al., 2010). However, extant research does not tell us whether better governance is associated with favorable *P2P* financial outcomes – and if so, what the mechanism is.

We can posit an indirect mechanism based on social norms that influence the average financial responsibility of borrowers in a given jurisdiction, or state. We focus on one form of financial responsibility: taking the hard and virtuous road of repaying loans rather than the easy but immoral road of strategic default. Stringent governance standards in a state may send a powerful signal to convince citizens that strategic default is socially unacceptable because it imposes high social costs on a community. These costs include higher interest rates for every borrower in the locality, regardless of their hidden moral 'type' (Clemenz, 2012). Given evidence that people do enforce social norms by sanctioning others who deliberately violate them (e.g., Fehr and Fischbacher, 2004; De Quervain et al., 2004), even immoral borrowers might be reluctant to default, to avoid incurring social sanctions and stigma (Fay et al., 2002; Gross and Souleles, 2002). Hence, stringent governance standards might reduce defaults and interest rates through the indirect channel of social norms.

Hence, high levels of public corruption in a state weaken governance standards, thereby undermining social norms, so encouraging strategic default and increasing interest rates in that state. Note that this indirect mechanism applies to loans issued via MPL P2P platforms just as well as to loans originating from more traditional lenders. Thus:

Hypothesis A [Governance]. Corruption weakens governance standards in a state, leading to higher defaults and interest rates.

2.2.2. Contract enforcement as a mechanism connecting corruption with P2P lending outcomes

Even if states pass laws which enhance governance standards, their effectiveness depends on the extent to which they are enforced (Smith, 2016). In general, corruption can be expected to weaken enforcement standards. Weak enforcement standards can be encoded in the regulations pertaining to financial markets: as Djankov et al. (2008) pointed out, the willingness of lenders to extend credit depends on enforcement mechanisms that allow creditors to pursue a defaulting borrower's income and assets.

For example, in the United States, the Fair Debt Collection Practices Act of 1977 (FDCPA) – a federal law regulating the activities of third-party debt collectors in the US – prohibits certain types of 'abusive and deceptive' conduct by third-party debt collectors and creditors seeking to collect debts they have purchased from creditors. To date, 43 states have adopted their own laws that surpass the FDCPA in terms of

the restrictions they place on third-party debt collectors. Evidence shows that lenders operating in states with stricter laws about third-party debt collection enjoy lower recovery rates on delinquent credit card loans and extend less new credit as a result (Fedaseyeu, 2020).

More generally, one can argue that weak enforcement of governance standards socializes borrowers to believe that, just like politicians, they too can 'get away' with immoral actions like strategic default. The weaker contract enforcement relating to defaults in a state, the stronger this belief might be. Hence, high levels of public corruption in a state may weaken enforcement standards, thereby encouraging strategic default, resulting in high interest rates in that state. As with governance, this indirect mechanism applies naturally to loans issued over a MPL platform. We therefore have:

Hypothesis B [Contract Enforcement]. Corruption weakens contract enforcement in a state, leading to higher defaults and interest rates.

2.2.3. Generalized trust as a mechanism connecting corruption with P2P lending outcomes

Generalized trust can be defined as belief in the honesty of potential trading partners (Colquitt et al., 2007). Prior empirical research has highlighted the importance of generalized trust in the context of financial transactions made under conditions of asymmetric information (Hasan et al., 2017). Evidence shows that perceptions of political corruption erode social and institutional trust, normalize rule-breaking behavior, and increase people's willingness to break rules (Bardhan, 2004; Villoria et al., 2013). This erosion of trust also reduces citizens' willingness to cooperate with government officials and institutions (Park and Blenkinsopp, 2011) and diminishes incentives for honesty, leading to a cycle of distrust and rule breaking. Erosion of trust is further exacerbated by political scandals, which widen the trust gap between citizens and the government (Seligson, 2002).

One specific type of rule-breaking behavior is of course strategic default. This is reflected in evidence of a negative correlation between trustworthiness proxies and default outcomes (Duarte et al., 2012). Hence, high levels of public corruption in a state weaken generalized trust, thereby encouraging strategic default, resulting in high interest rates in that state. As before, this indirect mechanism applies naturally to loans issued over a MPL platform. We therefore have:

Hypothesis C. [Generalized Trust]. Corruption weakens generalized trust in a state, leading to higher defaults and interest rates.

3. Data and summary statistics

3.1. Data and sample

The data on peer-to-peer loans come from *LendingClub*, an online fintech platform. They span the period 2007—2018 and were downloaded from *LendingClub*'s website. Until it ceased P2P operations in December 2020, *LendingClub* was the largest P2P lending site and the first to issue an IPO on the NYSE in December 2014. Its services covered all states.

We obtained data on 1,345,350 loans of which 19.96 % were either charged off or defaulted (268,599 loans), with the rest having been paid in full (1076,751 loans). We dropped from the sample all loans with no clear end results, i.e., loans still being repaid at the end of the sample period, as well as rejected loan requests. Although the data covers 12 years, the number of loans registered in the first 6 years (2007 – 2012) was small (93,153 loans) and only started to increase dramatically from 2013 onward (see Table A.1 in Appendix A). The sample covers a total of $19.4 billion loans disbursed by the platform. The term of these loans was either 36 or 60 months with 75.87 % having 36-month terms.

3.2. Variables

3.2.1. Dependent variables

There are two dependent variables in this study. The first is *Default*, a dummy variable equal to one if the applicant defaulted or had a charge-off on the loan, and equal to zero if the loan was fully paid off within the observation period. The second dependent variable is the *Interest rate* on loans. Interest rates are determined by the platform using an algorithm which is conditioned on borrower credit information and loan characteristics, including loan size requested.

3.2.2. Independent variable

The main independent variable is public corruption in the state where the borrower was resident. This was measured using annual data on all public integrity convictions from the US Department of Justice (DOJ) Public Integrity Section within each state. This entity supervises all governmental integrity related crimes, including bribery of public officials, crimes related to elections, etc. The data are contained in a report that the DOJ sends to Congress entitled "*Report to Congress on the Activities and Operations of the Public Integrity Section*". We collected this information annually at the state level and scaled it by US Census Bureau population data per state before matching it with the loan data by address state of the loan holder and year. Our preferred corruption variable – *Convictions per 100,000 people* – has been widely used in previous research as a measure of local corruption (Brown et al., 2021; Butler et al., 2009; Ellis et al., 2020; Fisman and Gatti, 2002; Glaeser and Saks, 2006; Hossain et al., 2020; Smith, 2016).[1]

As in previous research, we assume the Federal Department of Justice identifies and prosecutes crimes uniformly across states, so that areas with more corruption would yield a greater number of convictions (Glaeser and Saks, 2006). Since this assumption might not be warranted, we will later conduct robustness checks by analyzing two alternative survey-based measures of corruption. Finally, since our chosen corruption variable is measured at the state level, we cannot include state fixed effects in our regressions. We will address this issue below by adopting alternative estimation strategies.

3.2.3. Variables measuring the mechanisms

Next, we discuss the variables associated with the three mechanisms and hypotheses discussed in the previous section. First, following previous authors (e.g., Andrews and Brewer, 2013; Bearfield and Bowman, 2017; Heckman, 2015; Knack, 2002; Lee and Liu, 2022), data on *Governance* are taken from the State Management Report card developed by the Government Performance Project (GPP). This yields four variables measuring the governance performance of state governments. This report, last issued in 2008, was based on survey responses from the states, public documents, and interviews with state officials. Its aim was to assess the quality of management in state government. Each state was given a grade from A to D, for each field of 4 fields: People (human resources management and retention), Infrastructure Management, Money (capital and budgeting management), and Information (performance management and transparency). See Appendix B for a list of components of these measures. We first recoded grades to numerical values from 1 to 10, where 1 is the worst (D) and 10 is the best (A), before generating four variables corresponding to each of the four fields above: *GPP People, GPP Infrastructure, GPP Money*, and *GPP Information*.

Second, we used Fedaseyeu's (2020) index of strictness of third-party debt collection laws to measure *Enforcement*. This index counts the number of state-level restrictions on third-party debt collectors. These restrictions range from licensing and/or bonding requirements imposed on third-party debt collection firms to declaring certain debt collection practices unlawful and/or making violations of debt collection laws a criminal offense. They are designed to protect customers from collection harassment. This index proxies the degree to which formal institutions enforce debt contracts robustly and fairly. It is available for the years

[1] It would be interesting to explore whether corruption in a lender's state also affects P2P lending outcomes. Unfortunately, the platform does not provide the necessary data to investigate this question.

1999 and 2014: we interpolated and extrapolated the values for other years.

Third, we measured *Trust* by taking responses to the General Social Survey[2] question: "Would you say that most people can be trusted or that you can't be too careful in dealing with people?" The 3-point Likert-scale-based answers indicate how much citizens generally trust their society. Possible answers are: "Can trust" = 1; "Depends" = 0; and "Can't be too careful" = −1. The measure is the annual average response at the state level. Survey responses are available in even-numbered years only, so we interpolated odd-numbered year values.

3.2.4. Control variables

First, although trust and social capital are related constructs, they represent distinct dimensions of social relationships and interactions. States differ in terms of cultural norms about corruption (Fisman and Miguel, 2007; Parsons et al., 2018). States with less social capital are likely to have more defaults and to be more prone to corruption. To avoid possible confounds between trust and social capital, we measured Social Capital using an index proposed by Lin and Pursiainen (2022).[3]

Second, poorer states tend to be exposed to both higher levels of corruption (Glaeser and Saks, 2006) and financial stress – factors known also to affect creditworthiness and default outcomes. It is therefore necessary to control for state-level *Unemployment rates, Population size*, and *Per capita income*. These data were obtained from the US Census Bureau.

Third, since research in economics has linked sex and ethnicity to financial risk, we control for *Female* (the percentages of females in the population). Also, following Glaeser and Saks (2006), who found that politicians are more likely to be corrupt in ethnically diverse areas, we control for ethnic *Fragmentation* in each state. Ethnic fragmentation is the chance that any two individuals from the same state are from different ethnic groups.[4]

Fourth, we include several loan level variables which might also affect default outcomes. These include a dummy variable indicating whether the loan is wholly (rather than partially) funded by an investor: *Funded by investor (W/P)*. We also add borrower-level credit-related variables, including the *Annual self-reported income* of the borrower, as well as their *Debt-to-income ratio*. The latter is a popular indicator which measures the solvency of borrowers and their capacity to pay back their debt. We further add two dummy variables to indicate whether the borrower owns a *Home* (Y/N) or has a *Mortgage* (Y/N), since these variables signal a stable financial situation. We also include a dummy variable to control for whether the borrower is *Applying alone* or with a partner (Y/N), as well as a variable to control for the *Number of open credit lines* i.e., approved loans and credit cards (regardless of whether they are used or not). To complement the previous variable, we also add a variable to control for the *Percentage of revolving line used*.

Finally, we measure the number of times borrowers were >30 days late in paying their loan instalments in the last two years (*Delinquency*). In addition, we add two variables to control for credit history. These are the number of *Credit inquiries* in the past 6 months, which represents how many times a lender checked the borrower credit score when the borrower applied for a loan excluding asset backed loans, and the *Number of derogatory public records* which reflects either a bankruptcy filing or a collection record.

3.3. Descriptive statistics

Table A.2 in Appendix A provides a detailed definition of each variable used in the study. Table 1 presents descriptive statistics for the variables described above. 20 % of loans in our sample defaulted. The average loan amount is $14,420, the average interest rate is 13.22 %, and convictions per 100,00 people varies from 0 at the 1st percentile to 1.08 at the 99th percentile. See Fig. 1 for a map of the geographical distribution of median public convictions per 100,000 across US states. Tables A.1 and A.3 in Appendix A provide additional data on the distribution of this variable across time and space. The corruption level spikes in Washington DC, but our results do not depend on dropping this location from the sample due to the small number of loans disbursed there.

All continuous variables are winsorized at the 1 % and 99 % level except for the variables Annual Income, Population per state, and Per capita income, which were transformed using the natural log function. Figs. 2 and 3 show the distributions of interest rates and loan amounts; Table A.4 in Appendix A displays the correlation matrix of the variables used in the analysis.

4. Results

The first part of this section analyzes the relationship between public corruption and the probability that loans default. The second part investigates the roles of three possible mechanisms: governance, contract enforcement, and generalized trust – thereby testing Hypotheses A, B, and C. The third part analyzes the relationship between public corruption and interest rates on loans.

4.1. Corruption and loan defaults

We use logistic regression to regress defaults on public corruption. Since the latter is measured at the state level and so is identical for all individuals *i* residing in the same state, *s* we follow Cameron and Miller (2015) and cluster standard errors at the state and year levels. Letting x_i include loan, borrower, and state-level control variables, we estimate:

$$Probability\ (default_i) = a + \beta\ Public\ Corruption_s + \gamma\ x_i + e_i \quad (1)$$

Table 2 reports the logit estimation results. Column (1) includes loan and borrower level control variables; column (2) adds the interest rate as a control variable; and, following Wang and Overby (2022), column (3) adds a control for whether loans were taken out for business purposes. Column (4) adds controls for geographical factors that might affect corruption, including Income per capita, State population, the State unemployment rate, and Social Capital. All coefficient estimates come with marginal effects to aid interpretation.

The marginal effects in column (1) indicate that loans are 4 % more likely to default for every one unit increase in the corruption measure. This estimate is statistically significant and remains fairly stable across the different specifications. This suggests that the results are not overly sensitive to the inclusion of controls variables. The effects of the controls are nevertheless interesting and intuitive: for example, a 1 % increase in annual income decreases the probability of default by 3.4 % in column (4), the most comprehensive specification. Also, an increase of one unit in the debt-to-income ratio of a borrower increases their probability of default by 0.2 % – 0.3 %. The number of open credit lines, the percentage of a revolving line utilized, delinquency in the last 2 years prior to the loan, the number of credit inquiries in the past 6 months before

[2] The General Social Survey 2022 Release 1 was obtained from NORC at the University of Chicago.

[3] Components of this index include: 1) the number of social associations per capita in each state (data retrieved from County Business Patterns); 2) the number of registered charitable organizations per capita in each state (data obtained from the National Centre for Charitable Statistics); and 3) the percentage of voters in each state who voted in recent presidential elections. The Social Capital index is available at the county level, but we aggregated it to the state level to match the data on corruption, which is unavailable at a lower level of aggregation than the state. These three components proxy for the strength of social norms and the development of social networks in society. The index is created by running principal component analysis with these variables. The first principal component is interpreted as the index of social capital.

[4] See Table A.2 in Appendix A for a formal definition. Results are similar if proportions of ethnic minority populations (e.g., African-American, Latinx) are used instead.

Table 1
Summary statistics
Summary statistics.

	N	Mean	Median	SD	1st Perc.	99th Perc.
Default (Y/N)	1345,350	.20	0.00	.4	0	1
Convictions per 100,000	1345,350	.28	0.25	.57	0	1.08
Interest rate on loan	1345,350	13.22	12.74	4.7	5.32	26.3
GPP Money	1341,875	5.45	6.00	2.1	2	9
GPP People	1341,875	5.33	5.00	2.03	3	10
GPP Infrastructure	1341,875	6.27	6.00	1.62	2	9
GPP Information	1341,875	6.19	6.00	1.93	3	10
Enforcement	1341,875	3.59	3.93	1.91	0	7.4
Trust	1345,350	−0.32	−0.27	.11	−0.57	−0.07
Annual self-reported income	1345,350	76,247.57	65,000.00	69,924.85	18,000	250,000
Debt-to-income ratio	1345,350	18.15	17.61	8.5	1.75	38.47
Loan amount	1345,350	14,419.97	12,000.00	8717.1	1500	35,000
Number of open credit lines	1345,350	11.56	11.00	5.29	3	29
Percentage of revolving line used	1345,350	51.76	52.10	24.47	.9	98.1
Delinquency	1345,350	.3	0.00	.73	0	4
Credit inquiries	1345,350	.65	0.00	.92	0	4
Applying alone (Y/N)	1345,350	.02	0.00	.14	0	1
Number of derogatory public records	1345,350	.2	0.00	.46	0	2
Funded by investor (W/P)	1345,350	.58	1.00	.49	0	1
Home (Y/N)	1345,350	.11	0.00	.31	0	1
Mortgage (Y/N)	1345,350	.49	0.00	.5	0	1
Social capital	1345,350	−0.91	−0.92	1.01	−2.29	1.24
Per capita income	1345,350	49,560.58	48,549.00	7480.6	36,005	67,761
Population size	1345,350	15,439,451	10,275,758.00	11,979,318	756,755	39,337,785
Unemployment rate	1345,350	5.41	5.10	1.45	2.8	9.9
Public integrity	1341,875	22.62	23.00	14.34	2	50
Corruption exposure	1345,350	2.65	2.36	1.8	.52	8.38
Cumulative corruption	1345,350	1.51	1.32	1.31	.27	4.35
Exposure years	1345,350	8.63	9	1.83	3	12
Female	1345,350	0.51	0.51	0.01	0.50	0.52
Fragmentation	1345,350	0.38	0.37	0.09	0.12	0.55

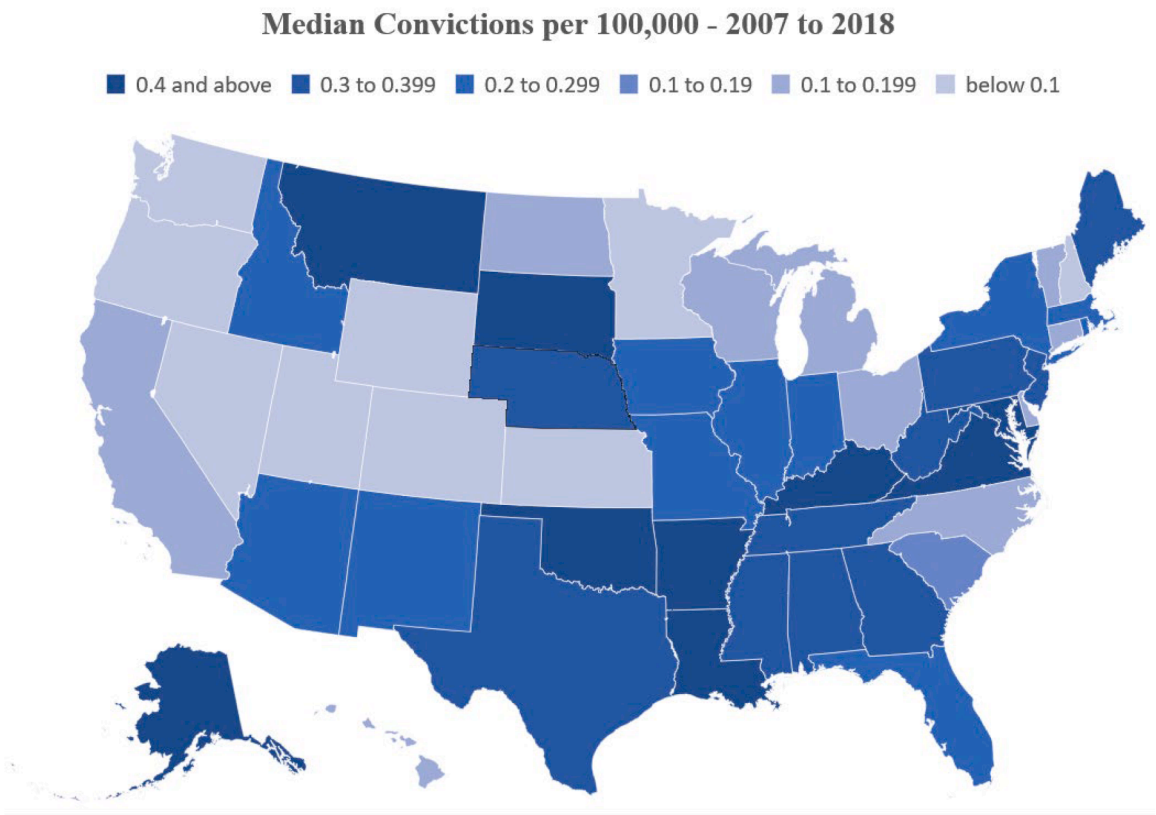

Fig. 1. The distribution of median convictions per 100,000 people across US states.

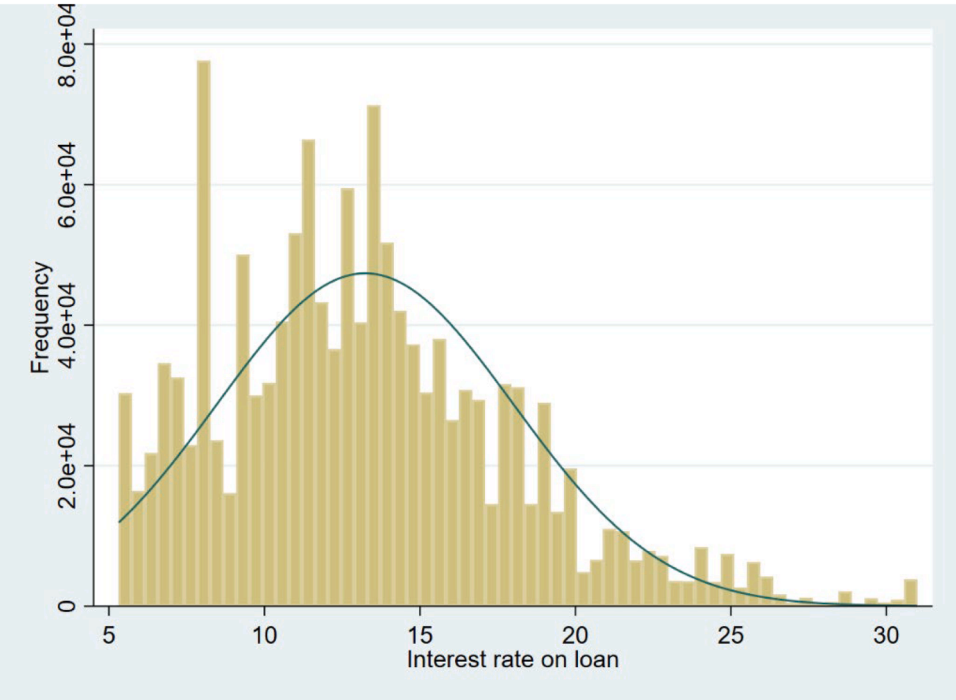

Fig. 2. The distribution of interest rates.

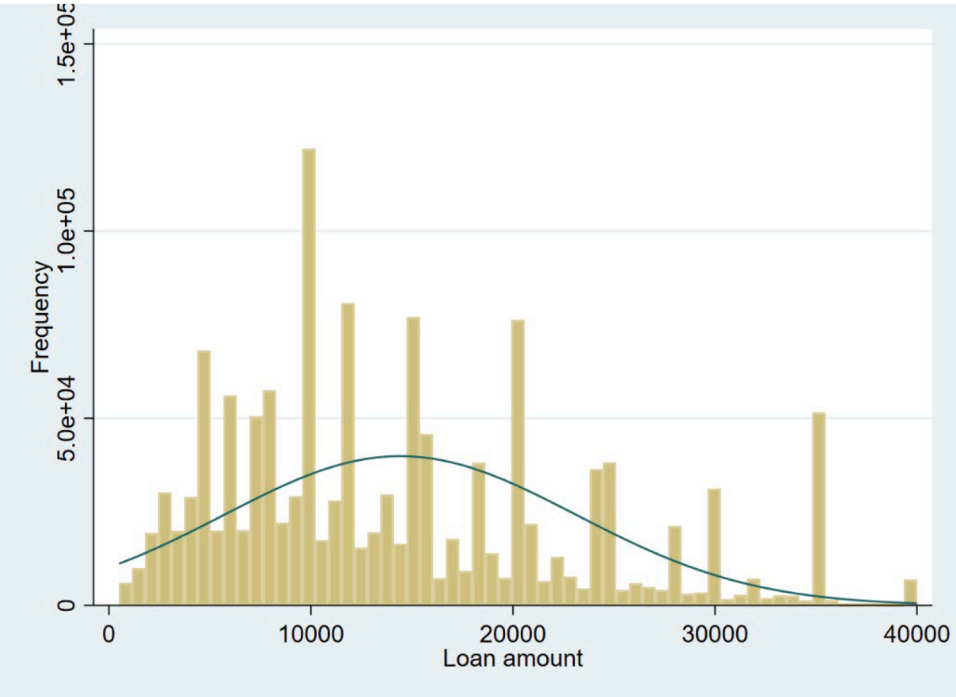

Fig. 3. The distribution of loan amounts.

the loan, and the number of derogatory public records, are also all positively associated with a higher probability of default on loans. On the other hand, owning a house or even having a mortgage negatively correlates with the probability of default.

Furthermore, a loan taken by an individual is 1.5 % – 2.3 % more likely to be repaid than a loan taken by two borrowers; and a loan funded wholly by an investor is more likely to be repaid than a loan funded partially by an investor. This suggests that when investors see good financial indicators of a borrower, they fund the whole loan but when they are unsure, they tend to diversify. Loans whose purpose is for business rather than individual reasons have a 7.1 % higher probability of default. Social capital in contrast slightly decreases the probability of default. Although the interest rate enters with a positive and significant coefficient, corruption remains significant with a slight decrease in its marginal effect which suggests that the pricing of these loans does not fully cover the risk of corruption.

It is possible, however, that the correlation between defaults and public corruption in a state could be driven by unobservable state-level

Table 2
Default and corruption
This table presents logistic regression results for loan default status (binary: Y/N). The sample comprises 1345,350 funded loans; the independent variable is State annual Convictions per 100,000. Columns (1) and (2) presents results with and without control variables. Column (2) includes the Interest rate on loans. Column (3) tests whether loans used for small businesses are prone to default more than individual loans due to corruption. Column (4) adds macro level control variables. Robust standard errors clustered by both year and state – in parentheses. *, **, and *** denotes significance at the 10 %, 5 %, and 1 % level, respectively.

	(1)		(2)		(3)		(4)	
Variables	Default (Y/N)	Marginal Effect	Default (Y/N)	Marginal Effect	Default (Y/N)	Marginal Effect	Default (Y/N)	Marginal Effect
Convictions per 100,000	0.272***	0.040***	0.259***	0.037***	0.261***	0.037***	0.209***	0.030***
	(0.055)	(0.008)	(0.054)	(0.008)	(0.054)	(0.008)	(0.053)	(0.008)
Interest rate on loan			0.098***	0.014***	0.099***	0.014***	0.098***	0.014***
			(0.002)	(0.000)	(0.001)	(0.000)	(0.002)	(0.000)
ln(Annual self-reported income)	−0.361***	−0.053***	−0.231***	−0.033***	−0.227***	−0.033***	−0.237***	−0.034***
	(0.012)	(0.002)	(0.012)	(0.002)	(0.012)	(0.002)	(0.012)	(0.002)
Debt-to-income ratio	0.017***	0.003***	0.013***	0.002***	0.013***	0.002***	0.013***	0.002***
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Number of open credit lines	0.013***	0.002***	0.013***	0.002***	0.012***	0.002***	0.012***	0.002***
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Percentage of revolving line utilized	0.008***	0.001***	0.004***	0.001***	0.003***	0.000***	0.004***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Delinquency	0.100***	0.015***	0.065***	0.009***	0.065***	0.009***	0.065***	0.009***
	(0.003)	(0.000)	(0.004)	(0.001)	(0.004)	(0.001)	(0.004)	(0.001)
Credit inquiries	0.204***	0.030***	0.097***	0.014***	0.097***	0.014***	0.100***	0.014***
	(0.004)	(0.001)	(0.004)	(0.001)	(0.004)	(0.001)	(0.004)	(0.001)
Number of derogatory public records	0.148***	0.022***	0.087***	0.013***	0.089***	0.013***	0.089***	0.013***
	(0.008)	(0.001)	(0.008)	(0.001)	(0.008)	(0.001)	(0.008)	(0.001)
Applying alone (Y/N)	−0.154***	−0.023***	−0.106***	−0.015***	−0.103***	−0.015***	−0.104***	−0.015***
	(0.023)	(0.003)	(0.023)	(0.003)	(0.023)	(0.003)	(0.022)	(0.003)
Funded by investor (W/P)	−0.163***	−0.024***	−0.008	−0.001	−0.008	−0.001	−0.008	−0.001
	(0.011)	(0.002)	(0.007)	(0.001)	(0.007)	(0.001)	(0.007)	(0.001)
Home (Y/N)	−0.232***	−0.034***	−0.209***	−0.030***	−0.206***	−0.030***	−0.205***	−0.029***
	(0.012)	(0.002)	(0.012)	(0.002)	(0.012)	(0.002)	(0.011)	(0.002)
Mortgage (Y/N)	−0.455***	−0.067***	−0.384***	−0.055***	−0.378***	−0.055***	−0.372***	−0.054***
	(0.020)	(0.003)	(0.020)	(0.003)	(0.020)	(0.003)	(0.020)	(0.003)
Female							5.765***	0.830***
							(1.187)	(0.170)
Fragmentation							0.237**	0.034**
							(0.102)	(0.015)
ln(Per capita income)							−0.145**	−0.021**
							(0.065)	(0.009)
ln(Population size)							0.022**	0.003**
							(0.010)	(0.001)
Social capital							−0.033***	−0.005***
							(0.009)	(0.001)
Unemployment rate							−0.015	−0.002
							(0.009)	(0.001)
Business = 1					0.465***	0.071***		
					(0.048)	(0.006)		
Business × Convictions per 100,000					−0.075			
					(0.122)			
Constant	0.206		−1.336***		−1.205***		−3.049***	
	(0.261)		(0.264)		(0.268)		(0.778)	
Year FE	Yes		Yes		Yes		Yes	
Purpose FE	Yes		Yes		Yes		Yes	
Employment length FE	Yes		Yes		Yes		Yes	
Term FE (36/60)	Yes		Yes		Yes		Yes	
Observations	1344,988	1344,988	1344,988	1344,988	1344,988	1344,988	1344,988	1344,988

factors. Thus, we next propose two alternative orthogonal sources of identifying variation in public corruption to uncover causal effects of corruption on loan performance. First, we exploit within-state cross-sectional differences in borrowers' experiences of public corruption. Second, we exploit an exogenous shock to the level of public corruption in the form of a 2010 Supreme Court ruling.

4.1.1. *Within-state difference in corruption exposure*

The foregoing analysis exploited changes in corruption levels across states over time. It did so by assigning identical corruption experiences to borrowers from the same state in a given year. However, past encounters with corruption may vary among individuals within the same state. To allow for this possibility, and to check whether the results using cross-state variation hold up, we next explore differential exposure to corruption among borrowers within a state. Specifically, older individuals might have encountered more instances of corruption compared to younger individuals. Therefore, inspired by Bu et al. (2022), we measure borrowers' exposure to corruption by computing a new variable, *Lifetime Corruption Exposure*, $LCE_{i,s,t-Ki}$, of adult borrower i in state s. This variable is defined as the number of convictions of public officials per 100,000 people that i experienced as of time t: i.e.,

$$LCE_{i,s,t-Ki} := \sum_{k=1}^{K_i} Corruption_{i,s,t-k},$$

where K_i denotes years of exposure for i.[5] To mitigate potential confounding effects related to age, we also control for K_i in the regressions. Note that this approach also enables state-year fixed effects to be included, thereby controlling for any unobserved state-level factors influencing both corruption levels and default rates.

Table 3 shows that within-state variation in borrowers' public corruption experience significantly and positively predicts loan defaults. This bears out the results in Table 2. A one-unit increase in a borrower's exposure to (local) corruption increases the borrower's probability of defaulting by 3.8 % percentage points (a 19 % increase relative to the sample mean). Since both state and year fixed effects are included, we infer that the effect of corruption is not driven by state-level conditions. The year fixed effects also absorb any time-varying factors that may affect default outcomes.

4.1.2. Difference-in-differences analysis

To further probe the robustness of our baseline regression findings, we analyze an exogenous shock stemming from the Supreme Court's (SCOTUS's) decision in January 2010 to overturn the McCain–Feingold Campaign Reform Act of 2002. The SCOTUS decision refers to the landmark case of *Citizens United* v. *Federal Election Commission*. This ruling fundamentally changed the landscape of campaign finance in the United States by allowing corporations, unions, and other organizations to spend unlimited amounts of money on political campaigns, as long as they did not directly coordinate with candidates or political parties. By permitting large financial contributions to political advocacy, the *Citizens United* decision may have opened the door to a range of corrupt behaviors, including *quid pro quo* arrangements, favoritism, and the prioritization of donor interests over public welfare. This created a risk that public officials prioritized the interests of their financial backers over the needs of their constituents (Hossain et al., 2020).

The hypothesized effect of deregulating campaign finance is to increase corruption in regions where such practices are already prevalent. We exploit this exogenous shock to corruption by using a Difference-in-Difference (DiD) design. Thus, define a dummy *Post* which equals 0 for all loans in the pre-shock period (12 months before the SCOTUS decision) and equals 1 for all loans in the post-shock period (12 months after the SCOTUS decision). Also, define a dummy *Treated* which equals 1 if the borrower is located in a high (above-median) corruption area, and 0 if not. Table 4 presents estimates of a series of DiD models. The baseline specification in Column (1) uses a logit model without macroeconomic controls. The interaction term, *Post* × *Treated*, is positive and significant at the 5 % level, suggesting that borrowers in high-corruption areas have significantly higher default rates in the post-SCOTUS period. This finding aligns with our hypothesis that deregulation in campaign finance worsens corruption-related impacts on financial stability in affected regions.

We next address threats to identification from missing macro factors that might have coincided with the exogenous shock in 2010, as well as the possibility that the two types of states were on different trajectories prior to the shock. The remaining columns of Table 4 explore the robustness of the results to the inclusion of state-level macroeconomic variables (column (2)) and OLS estimation (column (3)). Column (4) reports the results of a placebo test using a "false" post-treatment period one year after the SCOTUS decision. The interaction term in the placebo model is insignificant, confirming the temporal specificity of the SCOTUS effect. To test the parallel trends assumption, we conduct a second placebo test using data from one year prior to the SCOTUS decision. The estimates of the interaction term in column (5) are also insignificant, casting doubt on pre-existing trends in default rates between high- and low-corruption areas prior to the intervention. This supports the validity of the DiD model and indicates that the observed post-SCOTUS effect is attributable to the policy shift rather than to pre-existing differences.

The consistent negative sign of the *Post* coefficient across all specifications, including the placebo tests, suggests that the decline in default rates is part of a general downward trend over time, rather than being

Table 3
Default and corruption exposure
This table presents logistic regression results for loan default status (binary: Y/N). The sample comprises 1344,989 funded loans. The independent variable is borrower corruption exposure, and the main independent variable is Lifetime Corruption Exposure, defined in the text. Robust standard errors clustered by both year and state – in parentheses. *, **, and *** denotes significance at the 10 %, 5 %, and 1 % level, respectively.

Variables	(1) Default (Y/N)	(2) Marginal effects
Lifetime Corruption Exposure	0.038***	0.005***
	(0.011)	(0.002)
Interest rate on loan	0.097***	0.014***
	(0.002)	(0.000)
ln(Annual self-reported income)	−0.225***	−0.032***
	(0.012)	(0.002)
Debt-to-income ratio	0.013***	0.002***
	(0.001)	(0.000)
Number of open credit lines	0.013***	0.002***
	(0.001)	(0.000)
Percentage of revolving line utilized	0.004***	0.001***
	(0.000)	(0.000)
Delinquency	0.067***	0.010***
	(0.004)	(0.001)
Credit inquiries	0.099***	0.014***
	(0.004)	(0.001)
Number of derogatory public records	0.101***	0.014***
	(0.007)	(0.001)
Applying alone (Y/N)	−0.102***	−0.015***
	(0.023)	(0.003)
Funded by investor (W/P)	−0.008	−0.001
	(0.007)	(0.001)
Home (Y/N)	−0.212***	−0.030***
	(0.011)	(0.002)
Mortgage (Y/N)	−0.374***	−0.054***
	(0.020)	(0.003)
Female	−22.763*	−3.273*
	(12.420)	(1.786)
Fragmentation	−1.583	−0.228
	(1.759)	(0.253)
ln(Per capita income)	0.034	0.005
	(0.282)	(0.041)
ln(Population size)	−0.904**	−0.130**
	(0.444)	(0.064)
Social capital	0.046	0.007
	(0.047)	(0.007)
Unemployment rate	0.010	0.001
	(0.008)	(0.001)
Exposure years	−0.038***	−0.005***
	(0.004)	(0.001)
Constant	21.943***	
	(7.579)	
Year FE	Yes	
State FE	Yes	
Purpose FE	Yes	
Employment length FE	Yes	
Term FE (36/60)	Yes	
Observations	1344,988	

[5] K_i is defined as the minimum of (t - *earliest credit line* $_{i,t}$) and (t − 2006), where *earliest credit line* is the earliest date the borrower got a credit line. It is logical to assume that an individual's experience with the financial system starts then, so we use the same date to start calculating the first exposure to public corruption.

Table 4
Difference-in-differences estimates
The dependent variable is the default probability and the main independent variable is the interaction between *Post* and *Treated.* Here, *Post* equals 0 for all loans in the pre-shock period (12 months before the SCOTUS decision) and equals 1 for all loans in the post-shock period (12 months after the SCOTUS decision). *Treated* equals 1 if the borrower is located in a high-corruption (above-median) state and 0 otherwise. Column (1) displays results for the baseline logit model; column (2) adds controls for macroeconomic variables; and column (3) uses OLS regression instead of logit. Column (4) runs a placebo test one year after the actual SCOTUS date, and column (5) presents the result of another placebo test one year prior to the SCOTUS decision. Since all investors at that time were individuals, variables "Application type individual", and "Loan financing by investor (whole or fractional)", were omitted. Robust standard errors clustered at the state and year level in parentheses *** $p <$ 0.01, ** $p < 0.05$, * $p < 0.1$.

Dependent variable (Default Y/N)	(1) Logit	(2) Added macro variables	(3) OLS	(4) One year after	(5) One year before
Post × Treated	0.472**	0.441**	0.103**	0.172	−0.216
	(0.258)	(0.232)	(0.051)	(0.137)	(0.432)
Post = 1	−1.811***	−1.797***	−0.299***	−1.122***	−1.256***
	(0.144)	(0.137)	(0.033)	(0.105)	(0.294)
Treated = 1	−0.576*	−0.408*	−0.096*	−0.206	0.247
	(0.280)	(0.243)	(0.052)	(0.142)	(0.442)
Interest rate on loan	0.131***	0.129***	0.018***	0.085***	0.138***
	(0.012)	(0.012)	(0.002)	(0.008)	(0.021)
ln(Annual income self-reported)	−0.488***	−0.499***	−0.062***	−0.725***	−0.458***
	(0.065)	(0.063)	(0.009)	(0.052)	(0.087)
Borrower debt to income ratio	0.009	0.009	0.001	0.008**	0.004
	(0.006)	(0.006)	(0.001)	(0.004)	(0.008)
The number of open credit lines	0.016**	0.018***	0.002**	0.014***	0.021**
	(0.007)	(0.007)	(0.001)	(0.004)	(0.009)
Percentage of revolving line utilized	0.006***	0.006***	0.001***	0.010***	0.008***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.002)
Delinquency in 2 years prior to the loan	−0.033	−0.023	−0.007	0.039	−0.114
	(0.060)	(0.060)	(0.008)	(0.041)	(0.081)
Credit inquiries in past 6 months prior to the loan	0.174***	0.186***	0.024***	0.147***	0.139***
	(0.028)	(0.028)	(0.004)	(0.022)	(0.053)
Number of derogatory public records	0.407***	0.405***	0.070***	0.335***	0.273
	(0.111)	(0.108)	(0.019)	(0.085)	(0.177)
Home ownership owned(Y/N)	−0.166*	−0.154	−0.019	−0.077	−0.243*
	(0.096)	(0.099)	(0.013)	(0.059)	(0.145)
Home ownership mortgage (Y/N)	−0.027	−0.021	−0.002	−0.006	0.111
	(0.073)	(0.072)	(0.009)	(0.045)	(0.085)
Social capital		−0.069	−0.010*	−0.047	−0.199***
		(0.045)	(0.005)	(0.032)	(0.071)
ln(Per capita personal income state-year)		0.020	0.014	0.186	0.466
		(0.291)	(0.037)	(0.186)	(0.322)
ln(Population state-year)		−0.096***	−0.014***	0.003	−0.173***
		(0.036)	(0.005)	(0.032)	(0.055)
Unemployment rate state-year		0.075***	0.010***	0.050***	0.110***
		(0.016)	(0.002)	(0.015)	(0.035)
female		−7.565	−1.230**	3.371	−5.931
		(4.840)	(0.598)	(3.809)	(8.476)
fragmentation		0.835**	0.113**	0.218	0.927
		(0.383)	(0.049)	(0.270)	(0.468)
Constant	1.502**	5.593*	1.134***	1.014	−0.959
	(0.716)	(3.350)	(0.399)	(2.052)	(3.242)
Employment Length	Yes	Yes	Yes	Yes	Yes
Purpose	Yes	Yes	Yes	Yes	Yes
Term	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Observations	9500	9500	9500	19,391	3644
R-squared			0.120		

specifically associated with the SCOTUS decision. This trend can be attributed to the platform's ongoing improvements in its lending practices during the study period. The lending platform progressively enhanced its risk management and tightened credit criteria, which led to a systematic reduction in default rates across both high- and low-corruption areas. These improvements include stricter borrower screening, enhanced loan terms, and possibly better collections processes, all of which would contribute to a gradual, year-on-year decline in default rates (Freedman and Jin, 2011; Jagtiani and Lemieux, 2017).

4.2. Testing the mechanisms by which corruption affects loan defaults

We next test our three hypotheses to identify the underlying mechanisms for the results. First, we explore whether corruption affects loan default through bad governance. If so, we would expect that including variables capturing the quality of governance in states would reduce or eliminate the effect of corruption on defaults. Table 5 presents the results of separately adding to the regression model the components of the GPP State Management Report card: Capital and Budgeting, Infrastructure Management, HR and Retention, and Information. None of the four variables are statistically significant, suggesting that these aspects of governance cannot explain the results attributed above to corruption. Moreover, the corruption variable remains significant with similar coefficient sizes as reported in Table 2. Thus, we find no support for Hypothesis A, and rule out this mechanism.

Second, we explore whether controlling for enforcement soaks up the effects of public corruption. We do so by splitting the sample into two sets of states: those with high (above-median) and low (below-median) restrictions on debt collection practices using the median of the *Enforcement* index for each year. Columns (1) and (2) of Table 6 report

Table 5
Adding the Governance (GPP indices) variables
This table presents logistic regression results for loan default status (binary: Y/N). The independent variable is annual Convictions per 100,000. The model is augmented with measures of state management grading scales, namely the Capital and Budgeting Management item in column (1), the Infrastructure Management scale in column (2), the HR and Retention scale in column (3), and the Information scale in column (4). Robust standard errors clustered by both year and state and mentioned in parentheses. *, **, and *** denotes significance at the 10 %, 5 %, and 1 % level, respectively.

Variables	(1) Default (Y/N)	(2) Default (Y/N)	(3) Default (Y/N)	(4) Default (Y/N)
Convictions per 100,000	0.226***	0.222***	0.235***	0.237***
	(0.056)	(0.055)	(0.053)	(0.055)
Interest rate on loan	0.098***	0.098***	0.098***	0.098***
	(0.002)	(0.002)	(0.002)	(0.002)
GPP Money	0.002			
	(0.006)			
GPP Infrastructure		0.005		
		(0.005)		
GPP People			−0.008	
			(0.005)	
GPP Information				−0.004
				(0.005)
ln(Annual self-reported income)	−0.235***	−0.235***	−0.235***	−0.235***
	(0.012)	(0.012)	(0.012)	(0.012)
Debt-to-income ratio	0.013***	0.013***	0.013***	0.013***
	(0.001)	(0.001)	(0.001)	(0.001)
Number of open credit lines	0.012***	0.012***	0.012***	0.012***
	(0.001)	(0.001)	(0.001)	(0.001)
Percentage of revolving line utilized	0.004***	0.004***	0.004***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)
Delinquency	0.065***	0.065***	0.065***	0.065***
	(0.004)	(0.004)	(0.004)	(0.004)
Credit inquiries	0.100***	0.100***	0.100***	0.100***
	(0.004)	(0.004)	(0.004)	(0.004)
Number of derogatory public records	0.088***	0.088***	0.089***	0.088***
	(0.008)	(0.008)	(0.008)	(0.008)
Applying alone (Y/N)	−0.103***	−0.103***	−0.103***	−0.103***
	(0.023)	(0.023)	(0.022)	(0.022)
Funded by investor (W/P)	−0.008	−0.008	−0.008	−0.008
	(0.007)	(0.007)	(0.007)	(0.007)
Home (Y/N)	−0.206***	−0.205***	−0.205***	−0.205***
	(0.011)	(0.011)	(0.012)	(0.012)
Mortgage (Y/N)	−0.374***	−0.373***	−0.372***	−0.373***
	(0.020)	(0.020)	(0.020)	(0.020)
Female	5.538***	5.542***	5.044***	5.007***
	(1.152)	(1.183)	(1.247)	(1.245)
Fragmentation	0.258***	0.265***	0.334***	0.269***
	(0.098)	(0.099)	(0.095)	(0.099)
Social capital	−0.024**	−0.022**	−0.016	−0.020*
	(0.010)	(0.010)	(0.010)	(0.010)
ln(Per capita income)	−0.117*	−0.104	−0.152**	−0.146**
	(0.065)	(0.074)	(0.061)	(0.063)
ln(Population size)	0.024**	0.021*	0.025**	0.027**
	(0.011)	(0.011)	(0.011)	(0.012)
Unemployment rate	−0.009	−0.008	−0.014	−0.011
	(0.012)	(0.010)	(0.010)	(0.010)
Constant	−3.320***	−3.432***	−2.665***	−2.754***
	(0.757)	(0.836)	(0.844)	(0.832)
Year FE	Yes	Yes	Yes	Yes
Purpose FE	Yes	Yes	Yes	Yes
Employment length FE	Yes	Yes	Yes	Yes
Term FE (36/60)	Yes	Yes	Yes	Yes
Observations	1341,513	1341,513	1341,513	1341,513

the results for these sub-samples, respectively. As expected, public corruption is associated with a higher probability of default in states with lax laws (marginal effect = 4.3 %) relative to states with strict laws (marginal effect = 2.0 %). Column (5) further examines the moderating role of debt collection laws by including it as an independent variable. The results suggest that corruption and strict laws are both significant and work in different directions. Yet adding the *Enforcement* variable into the model makes little difference to the size or significance of the coefficient on the public corruption variable, while the size of the marginal effect from *Enforcement* is tiny.[6] Hence, we find no support for Hypothesis B, and rule out this mechanism. Interestingly, *Social Capital* is only statistically significant in the 'strict law states' specification, where it enters with a negative sign. This aligns with evidence that social capital is associated with greater transparency in environments where formal institutions are strong (Berman, 1997; Rodriguez et al., 2005; Rothstein and Kumlin, 2001).

Third, we investigate the role of generalized trust as a possible mechanism. We use a measure suggested by Bu et al. (2022), which is based on a question from the General Social Survey (GSS) conducted by NORC at the University of Chicago. The question is: "Would you say that most people can be trusted or that you can't be too careful in dealing with people?" The 3-point Likert-scale-based answers indicate how much citizens generally trust people in their society. Possible answers are: "Can trust" (coded as +1), "Depends" (coded as 0) and "Can't be too careful" (coded as −1). Values of *Trust* are obtained by taking the average response within each state. NORC obtains responses in even-number years, so we interpolate for odd-number years.

Table 7 presents the results. Column (1) adds *Trust* to the specification: we observe that although *Convictions* still negatively affects default on P2P loans, the magnitude of the marginal effect decreases dramatically, from 3.7 % in Table 2 to 2.1 % in Table 7. At the same time, the marginal effect of *Trust* on default is −4.6 %. Column (2) adds the interaction between *Trust* and *Convictions*, but this is statistically insignificant. Adding the *Enforcement* variable to the model in column (3) does not change the results, either. Moreover, a test of the linear restriction that the sum of coefficients on the corruption and general trust variables is zero – i.e., trust completely offsets public corruption – cannot be rejected: $\chi^2(1) = 1.70$, with a p-value of 0.19. This supports Hypothesis C, implying that local corruption increases defaults in areas where general trust is low – an effect that ceases to operate in places where general trust is high.

If a lack of trust is indeed the underlying mechanism that explains how corruption affects defaults, *Trust* should also mediate the impact of corruption on defaults. We test this notion using the two-step procedure proposed by Baron and Kenny (1986). Thus, consider the following relationships:

$$default_i = i_1 + c \times Public\ Corruption_s + \gamma\, x_i + e_i \quad (2)$$

$$Trust = i_2 + a \times Public\ Corruption_s + \gamma\, x_i + e_i \quad (3)$$

$$default_i = i_3 + \acute{c} \times Public\ Corruption_s + b \times Trust + \gamma\, x_i + e_i \quad (4)$$

The coefficient $\acute{c}$ captures the *direct effect* of public corruption on loan default. The product of a and b, i.e., $a \times b$, captures the *indirect (mediated) effect* of corruption on default, i.e., mediated by trust. The coefficient c, mathematically equal to $a \times b + \acute{c}$, captures the *total effect* of public corruption on loan default. If *Trust* is a mediator, we should expect a significant positive value for the indirect effect. To test whether the mediation is statistically significant, Baron and Kenny (1986)

[6] We tested the linear restriction that the sum of coefficients on the corruption and enforcement variables equals zero (i.e., these variables exactly offset each other). The test statistic was $\chi^2(1) = 13.84$ ($p < 0.001$), rejecting the null hypothesis.

Table 6
Adding the Enforcement variable
This table presents logistic regression results for loan default status (binary: Y/N). The independent variable is annual Convictions per 100,000. Columns (1) and (3) presents results for states with low ('lax') and high ('strict') restrictions on third party debt collectors, respectively. Column (5) adds Enforcement as a control variable. The high and low restrictions are created by dividing states by above- or below-median scores of the Enforcement variable. Robust standard errors are clustered by both year and state and mentioned in parentheses. *, **, and *** denotes significance at the 10 %, 5 %, and 1 % level, respectively.

Variables	(1) Default (Y/N) Lax laws	(2) Marginal effects	(3) Default (Y/N) Strict laws	(4) Marginal effects	(5) Default (Y/N)	(6) Marginal effects
Convictions per 100,000	0.299***	0.043***	0.140***	0.020***	0.215***	0.031***
	(0.107)	(0.016)	(0.053)	(0.008)	(0.055)	(0.008)
Enforcement					−0.011***	−0.002***
					(0.003)	(0.000)
Interest rate on loan	0.097***	0.014***	0.099***	0.014***	0.098***	0.014***
	(0.003)	(0.000)	(0.002)	(0.000)	(0.002)	(0.000)
ln(Annual self-reported income)	−0.243***	−0.035***	−0.228***	−0.033***	−0.235***	−0.034***
	(0.017)	(0.003)	(0.017)	(0.002)	(0.012)	(0.002)
Debt-to-income ratio	0.014***	0.002***	0.012***	0.002***	0.013***	0.002***
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Number of open credit lines	0.012***	0.002***	0.013***	0.002***	0.012***	0.002***
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Percentage of revolving line utilized	0.004***	0.001***	0.003***	0.000***	0.004***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Delinquency	0.060***	0.009***	0.069***	0.010***	0.064***	0.009***
	(0.005)	(0.001)	(0.005)	(0.001)	(0.004)	(0.001)
Credit inquiries	0.105***	0.015***	0.095***	0.014***	0.100***	0.014***
	(0.007)	(0.001)	(0.005)	(0.001)	(0.004)	(0.001)
Number of derogatory public records	0.103***	0.015***	0.076***	0.011***	0.088***	0.013***
	(0.010)	(0.001)	(0.010)	(0.001)	(0.008)	(0.001)
Applying alone (Y/N)	−0.072**	−0.011**	−0.129***	−0.018***	−0.104***	−0.015***
	(0.033)	(0.005)	(0.029)	(0.004)	(0.023)	(0.003)
Funded by investor (W/P)	−0.005	−0.001	−0.011	−0.002	−0.008	−0.001
	(0.011)	(0.002)	(0.008)	(0.001)	(0.007)	(0.001)
Home (Y/N)	−0.222***	−0.032***	−0.190***	−0.027***	−0.206***	−0.030***
	(0.016)	(0.002)	(0.014)	(0.002)	(0.011)	(0.002)
Mortgage (Y/N)	−0.388***	−0.056***	−0.355***	−0.051***	−0.373***	−0.054***
	(0.037)	(0.005)	(0.018)	(0.003)	(0.020)	(0.003)
Female	7.163***	1.041***	5.154***	0.736***	4.822***	0.695***
	(1.702)	(0.248)	(1.523)	(0.216)	(1.084)	(0.156)
Fragmentation	0.088	0.013	0.332***	0.047***	0.272***	0.039***
	(0.186)	(0.027)	(0.111)	(0.016)	(0.101)	(0.015)
Social capital	−0.001	−0.000	−0.029***	−0.004***	−0.021**	−0.003**
	(0.017)	(0.003)	(0.010)	(0.001)	(0.010)	(0.001)
ln(Per capita income)	0.160	0.023	−0.317***	−0.045***	−0.120*	−0.017*
	(0.112)	(0.016)	(0.069)	(0.010)	(0.063)	(0.009)
ln(Population size)	0.014	0.002	0.029*	0.004*	0.020*	0.003*
	(0.017)	(0.003)	(0.015)	(0.002)	(0.011)	(0.002)
Unemployment rate	0.013	0.002	−0.018	−0.003	−0.007	−0.001
	(0.014)	(0.002)	(0.013)	(0.002)	(0.009)	(0.001)
Constant	−6.897***		−1.096		−2.826***	
	(1.183)		(0.909)		(0.725)	
Year FE	Yes		Yes		Yes	
Purpose FE	Yes		Yes		Yes	
Employment length FE	Yes		Yes		Yes	
Term FE (36/60)	Yes		Yes		Yes	
Observations	640,504	640,504	704,484	704,484	1341,513	1341,513

recommend computing the Sobel z-test (1982) using the statistic

$$Z_{ab} = \frac{a \times b}{\sqrt{b^2 s_a^2 + a^2 s_b^2}}$$

where *a, b* and their squared standard errors come from Eqs. (3) and (4), respectively.

The empirical results are as follows. The total effect from corruption was estimated as 0.295*** (se = 0.007). This comprised a direct effect of 0.216*** (se = 0.008), and an indirect effect of 0.079*** (se = 0.003). Also, $Z_{ab} = 2.89$, with a p-value < 0.01. Hence, we conclude that trust is a partial mediator of corruption, consistent with Hypothesis C.

4.3. Corruption and loan pricing

To check whether corruption also affects loan pricing, we use OLS regression methods and cluster standard errors at the state and year level to estimate the model:

$$Interest\ rate_i = a + \beta\ Public\ Corruption_s + \gamma\ x_i + e_i \quad (5)$$

We use a similar set of control variables to those of model (1). Table 8 reports the regression results for three specifications. In all specifications, loans taken out in more corrupt areas are significantly more expensive than those in less corrupt areas. Depending on the specification, an increase of one unit in the corruption measure is associated with an increase of at least 0.09 %, or 9 basis points in the interest rate charged to the loan.

We see that all borrower level variables that increased the default probability in Table 2 also increase loan prices in Table 8. For instance, column (1) shows that a one-point increase in the number of credit inquiries in the past 6 months increases the interest rate by 1.12 % on average; a one-point increase in credit delinquency in the 2 years prior

Table 7
Investigating the General Trust variable
This table presents logistic regression results for loan default status (binary: Y/N). The independent variable is State annual Convictions per 100,000. Column (1) adds General Trust to the model; column (2) adds an interaction between Convictions and General Trust; and column (3) adds Enforcement to the model. Robust standard errors are clustered by both year and state and given in parentheses. *, **, and *** denotes significance at the 10 %, 5 %, and 1 % level, respectively.

	(1)		(2)		(3)	
Variables	Default (Y/N)	Marginal effect	Default (Y/N)	Default (Y/N)	Marginal effect	Default (Y/N)
Convictions per 100,000	0.147**	0.021**	0.320**	0.046**	0.145**	0.021**
	(0.057)	(0.008)	(0.142)	(0.020)	(0.058)	(0.008)
Trust	−0.322***	−0.046***	−0.487***	−0.070***	−0.388***	−0.056***
	(0.094)	(0.014)	(0.164)	(0.024)	(0.091)	(0.013)
Trust X Convictions per 100,000			0.500	0.072		
			(0.405)	(0.058)		
Enforcement					−0.012***	−0.002***
					(0.003)	(0.000)
Interest rate on loan	0.098***	0.014***	0.098***	0.014***	0.098***	0.014***
	(0.002)	(0.000)	(0.002)	(0.000)	(0.002)	(0.000)
ln(Annual self-reported income)	−0.237***	−0.034***	−0.237***	−0.034***	−0.236***	−0.034***
	(0.012)	(0.002)	(0.012)	(0.002)	(0.012)	(0.002)
Debt-to-income ratio	0.013***	0.002***	0.013***	0.002***	0.013***	0.002***
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Number of open credit lines	0.012***	0.002***	0.012***	0.002***	0.012***	0.002***
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Percentage of revolving line utilized	0.004***	0.001***	0.004***	0.001***	0.004***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Delinquency	0.065***	0.009***	0.065***	0.009***	0.064***	0.009***
	(0.004)	(0.001)	(0.004)	(0.001)	(0.004)	(0.001)
Credit inquiries	0.100***	0.014***	0.100***	0.014***	0.100***	0.014***
	(0.004)	(0.001)	(0.004)	(0.001)	(0.004)	(0.001)
Number of derogatory public records	0.091***	0.013***	0.091***	0.013***	0.090***	0.013***
	(0.008)	(0.001)	(0.007)	(0.001)	(0.008)	(0.001)
Applying alone (Y/N)	−0.103***	−0.015***	−0.104***	−0.015***	−0.103***	−0.015***
	(0.022)	(0.003)	(0.022)	(0.003)	(0.023)	(0.003)
Funded by investor (W/P)	−0.008	−0.001	−0.008	−0.001	−0.008	−0.001
	(0.007)	(0.001)	(0.007)	(0.001)	(0.007)	(0.001)
Home (Y/N)	−0.208***	−0.030***	−0.208***	−0.030***	−0.210***	−0.030***
	(0.011)	(0.002)	(0.011)	(0.002)	(0.011)	(0.002)
Mortgage (Y/N)	−0.374***	−0.054***	−0.374***	−0.054***	−0.375***	−0.054***
	(0.020)	(0.003)	(0.020)	(0.003)	(0.020)	(0.003)
Female	6.937***	0.999***	6.869***	0.989***	6.111***	0.881***
	(1.133)	(0.163)	(1.114)	(0.160)	(0.975)	(0.140)
Fragmentation	0.108	0.016	0.100	0.014	0.124	0.018
	(0.109)	(0.016)	(0.108)	(0.016)	(0.106)	(0.015)
Social capital	−0.035***	−0.005***	−0.036***	−0.005***	−0.021**	−0.003**
	(0.010)	(0.001)	(0.010)	(0.001)	(0.010)	(0.001)
ln(Per capita income)	0.019	0.003	0.038	0.006	0.084	0.012
	(0.088)	(0.013)	(0.089)	(0.013)	(0.084)	(0.012)
ln(Population size)	0.011	0.002	0.008	0.001	0.008	0.001
	(0.011)	(0.002)	(0.011)	(0.002)	(0.011)	(0.002)
Unemployment rate	−0.007	−0.001	−0.007	−0.001	0.004	0.001
	(0.009)	(0.001)	(0.009)	(0.001)	(0.009)	(0.001)
Constant	−5.275***		−5.447***		−5.525***	
	(1.047)		(1.045)		(0.968)	
Year FE	Yes		Yes		Yes	
Purpose FE	Yes		Yes		Yes	
Employment length FE	Yes		Yes		Yes	
Term FE (36/60)	Yes		Yes		Yes	
Observations	1344,988	1344,988	1344,988	1344,988	1341,513	1341,513
R-squared						

to the loan increases the interest rate by 0.45 % on average; and other credit score-related variables also increase the price of loans including the percentage of revolving line utilized, debt to income ratio, and the number of derogatory public records. On the other hand, owning a house outright or with a mortgage decreases the price of a loan. Similar effects are observed for annual income of borrowers, individual borrower profiles, and loans that are fully funded by an investor. Column (2) shows that loans taken for business purposes are charged a

Table 8
Corruption and the interest rate
Presents OLS regressions where the dependent variable is the interest rate on loans and the independent variable is State annual Convictions per 100,000. Column (1) present results with control variables. Column (2) tests whether loans used for small businesses face higher interest rates than individual loans due to corruption. Column (3) adds macro level control variables. Robust standard errors are clustered by both year and state and mentioned in parentheses. *, **, and *** denotes significance at the 10 %, 5 %, and 1 % level, respectively.

Variables	(1) Interest rate on loan	(2) Interest rate on loan	(3) Interest rate on loan
Convictions per 100,000	0.190***	0.243***	0.091***
	(0.061)	(0.068)	(0.034)
ln(Annual self-reported income)	−1.350***	−1.336***	−1.378***
	(0.023)	(0.023)	(0.022)
Debt-to-income ratio	0.047***	0.048***	0.048***
	(0.003)	(0.003)	(0.003)
Number of open credit lines	0.004*	−0.008***	0.004*
	(0.003)	(0.003)	(0.003)
Percentage of revolving line utilized	0.051***	0.047***	0.051***
	(0.001)	(0.001)	(0.001)
Delinquency	0.452***	0.492***	0.452***
	(0.016)	(0.016)	(0.016)
Credit inquiries	1.120***	1.147***	1.127***
	(0.011)	(0.011)	(0.011)
Number of derogatory public records	0.752***	0.780***	0.759***
	(0.019)	(0.019)	(0.019)
Applying alone (Y/N)	−0.314***	−0.304***	−0.315***
	(0.042)	(0.043)	(0.042)
Funded by investor (W/P)	−1.383***	−1.462***	−1.381***
	(0.069)	(0.070)	(0.069)
Home (Y/N)	−0.304***	−0.314***	−0.274***
	(0.022)	(0.023)	(0.022)
Mortgage (Y/N)	−0.857***	−0.879***	−0.806***
	(0.037)	(0.038)	(0.036)
Female			2.890
			(1.761)
Fragmentation			0.974***
			(0.116)
ln(Per capita income)			−0.049
			(0.075)
ln(Population size)			0.005
			(0.015)
Social capital			−0.091***
			(0.012)
Unemployment rate			−0.013
			(0.011)
business = 1		3.058***	
		(0.212)	
Business X conviction per 100,000		0.185	
		(0.511)	
Constant	15.958***	16.502***	14.909***
	(0.346)	(0.333)	(1.245)
Year FE	Yes	Yes	Yes
Purpose FE	Yes	Yes	Yes
Employment length FE	Yes	Yes	Yes
Term FE (36/60)	Yes	Yes	Yes
Observations	1344,988	1344,988	1344,988
R-squared	0.414	0.383	0.415

higher interest rate but business-related loans in more corrupt states do not get charged a premium. Finally, unlike the case of loan defaults (Table 2), the income and population state level macro level variables are not significantly correlated with interest rates. However, social capital is significantly negatively related to the price of loans.

4.4. Further robustness checks

To check the robustness of the results, we use three alternative corruption measures, and conduct two different matching approaches.

4.4.1. Alternative corruption measures

Table 9 presents the results of estimating Eq. (5) using alternative measures of corruption. First, Column (1) uses values of the Center for Public Integrity's survey-based index. This comprises >330 indicators of corruption risk factors, laws, and enforcement procedures, as assessed by 100 experts in the field of public integrity. We also report the marginal effects using this measure. Column (2) uses a binary variable equal to 1 if a state is in the top quintile of corruption and equal to 0 otherwise (cf. Butler et al., 2009; Ellis et al., 2020). Third, column (3) uses the rolling five-year *cumulative corruption* per state on an annual basis scaled by population size. All control variables used in the earlier model specifications are included as well. Table 10 reports the results of re-estimating the interest rate Eq. (2) using the same alternative measures of public corruption.

The results in Table 9 show that each of these alternative measures are positively and significantly associated with default, though with smaller marginal effects compared with Table 2. The results in Table 10 are also qualitatively similar to those reported in Table 8. Hence, we conclude that our earlier interpretation is robust: public corruption negatively affects the ability of debtors to pay back their loans and is not sensitive to the precise measure of corruption chosen.

Finally, we also measured corruption at a more granular local level, namely judicial districts. LendingClub provides the first three digits only of borrowers' zip codes. We matched these to corresponding counties, and then linked each county to its respective judicial district. Each borrower was then associated with a district, enabling us to calculate convictions per 100,000 people at the district level instead of the state level. The availability of only partial zip codes led to some 366,050 observations being dropped. We re-estimated (1) for this variable, and found similar results as before. See Appendix C for details.

4.4.2. Estimates from matching estimators

In a further check, we re-ran the models using both propensity score matching and coarsened exact matching. First, for propensity score matching, we created a treatment dummy by dividing the sample into two subsamples, comprising observations in states with above- and below-median values of the 'State annual Convictions per 100,000′ variable for each year. We included all control variables from the baseline model (1) and used the $K = 4$-nearest neighbor matching technique, which takes each treated observation and searches for comparison observations with the closest propensity scores. We then computed the difference in outcome between the treated and each control observation and averaged out these differences across treated units. Second, for coarsened exact matching, we temporarily coarsened the data, exact matched on these coarsened data, and then ran the difference tests using the 'un-coarsened', matched, data.[7]

Table 11 reports the results for both matching techniques. The results show that the 'average treatment effects of the treated' for both Default and the Interest rate are positive and significant. As before, loans to borrowers located in more corrupt states are more prone to default and

[7] We used the same binary treatment variable as above, but due to the size of the database and the number of variables, we followed Blackwell et al. (2010) by matching observations using dichotomic variables (employment length, Application type individual, Loan financing by investor (whole or fractional), Home ownership owned (Y/N), Home ownership mortgage (Y/N), purpose, Loan maturity, year), before adjusting for the remaining imbalance via a regression model. We controlled for the rest of the variables from model (1) to estimate the sample average treatment effect on the treated. Further details available from the authors on request.

Table 9
Default and alternative measures of corruption
This table presents logistic regression results for loan default status (binary: Y/N). The independent variables are alternative measures of corruption: The Public Integrity index in columns (1), a binary variable = 1 if the state is in the top quintile of corruption in columns (2) and rolling cumulative 5 years State Convictions (scaled to population) in columns (3). Robust standard errors are clustered by both year and state and mentioned in parentheses. *, **, and *** denotes significance at the 10 %, 5 %, and 1 % level, respectively.

	(1)		(2)		(3)	
Variables	Default (Y/N)	Marginal Effects	Default (Y/N)	Marginal Effects	Default (Y/N)	Marginal Effects
Public integrity	0.002***	0.001***				
	(0.001)	(0.000)				
Top quintile			0.053***	0.008***		
			(0.019)	(0.003)		
Cumulative corruption					0.020***	0.003***
					(0.007)	(0.001)
Interest rate on loan	0.098***	0.014***	0.098***	0.014***	0.098***	0.014***
	(0.002)	(0.000)	(0.002)	(0.000)	(0.002)	(0.000)
ln(Annual self-reported income)	−0.234***	−0.034***	−0.236***	−0.034***	−0.237***	−0.034***
	(0.012)	(0.002)	(0.012)	(0.002)	(0.012)	(0.002)
Debt-to-income ratio	0.013***	0.002***	0.013***	0.002***	0.013***	0.002***
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Number of open credit lines	0.012***	0.002***	0.012***	0.002***	0.012***	0.002***
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Percentage of revolving line utilized	0.004***	0.001***	0.004***	0.001***	0.004***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Delinquency	0.065***	0.009***	0.065***	0.009***	0.065***	0.009***
	(0.004)	(0.001)	(0.004)	(0.001)	(0.004)	(0.001)
Credit inquiries	0.100***	0.014***	0.100***	0.014***	0.100***	0.014***
	(0.004)	(0.001)	(0.004)	(0.001)	(0.004)	(0.001)
Number of derogatory public records	0.089***	0.013***	0.088***	0.013***	0.089***	0.013***
	(0.008)	(0.001)	(0.008)	(0.001)	(0.008)	(0.001)
Applying alone (Y/N)	−0.103***	−0.015***	−0.104***	−0.015***	−0.104***	−0.015***
	(0.023)	(0.003)	(0.022)	(0.003)	(0.022)	(0.003)
Funded by investor (W/P)	−0.008	−0.001	−0.008	−0.001	−0.008	−0.001
	(0.007)	(0.001)	(0.007)	(0.001)	(0.007)	(0.001)
Home (Y/N)	−0.205***	−0.030***	−0.203***	−0.029***	−0.203***	−0.029***
	(0.012)	(0.002)	(0.012)	(0.002)	(0.011)	(0.002)
Mortgage (Y/N)	−0.372***	−0.054***	−0.371***	−0.054***	−0.370***	−0.053***
	(0.020)	(0.003)	(0.020)	(0.003)	(0.020)	(0.003)
ln(Per capita income)	−0.107	−0.015	−0.147**	−0.021**	−0.179***	−0.026***
	(0.066)	(0.010)	(0.066)	(0.010)	(0.066)	(0.010)
ln(Population size)	0.026***	0.004***	0.023**	0.003**	0.023**	0.003**
	(0.009)	(0.001)	(0.010)	(0.001)	(0.010)	(0.001)
Unemployment rate	−0.006	−0.001	−0.014	−0.002	−0.020**	−0.003**
	(0.010)	(0.001)	(0.010)	(0.001)	(0.009)	(0.001)
Female	4.793***	0.691***	6.162***	0.888***	6.204***	0.894***
	(1.195)	(0.172)	(1.286)	(0.185)	(1.222)	(0.175)
Fragmentation	0.444***	0.064***	0.310***	0.045***	0.290***	0.042***
	(0.105)	(0.015)	(0.104)	(0.015)	(0.107)	(0.015)
Social capital	−0.017*	−0.002*	−0.029***	−0.004***	−0.038***	−0.006***
	(0.009)	(0.001)	(0.009)	(0.001)	(0.010)	(0.001)
Constant	−3.117***		−3.223***		−2.877***	
	(0.724)		(0.842)		(0.805)	
Year FE	Yes		Yes		Yes	
Purpose FE	Yes		Yes		Yes	
Employment length FE	Yes		Yes		Yes	
Term FE (36/60)	Yes		Yes		Yes	
Observations	1341,513	1341,513	1344,988	1344,988	1344,988	1344,988

bear higher interest rates, compared to loans extended to borrowers in less corrupt states. Moreover, the differences are economically significant, ranging from 1.6 %−2.38 % more probable to default and from 0.022–0.154 basis points in higher interest rates. Hence, we conclude that matching methods do not overturn our earlier results.

5. Conclusion

We examine how public corruption impacts loan defaults and interest rates charged to MPL platform borrowers. We exploit state level variations in corruption to assess these impacts using a large sample of data from a large P2P lender, LendingClub. We find that public corruption is associated with significantly and substantially higher default

Table 10
Interest rate and alternative measures of corruption
This table presents the results of the OLS regression where the dependent variable is the interest rate charged on the loan. The independent variables are alternative measures of corruption: The Public Integrity index in columns (1), a binary variable = 1 if the state is in the top quintile of corruption in column (2) and rolling cumulative 5 years State Convictions (scaled to population) in column (3). Robust standard errors are clustered by both year and state and mentioned in parentheses. *, **, and *** denotes significance at the 10 %, 5 %, and 1 % level, respectively.

Variables	(1) Interest rate on loan	(2) Interest rate on loan	(3) Interest rate on loan
Public integrity	0.003***		
	(0.001)		
Top quintile		0.036	
		(0.023)	
Cumulative corruption to population			0.023***
			(0.007)
ln(Annual self-reported income)	−1.378***	−1.378***	−1.379***
	(0.023)	(0.023)	(0.022)
Debt-to-income ratio	0.048***	0.048***	0.048***
	(0.003)	(0.003)	(0.003)
Number of open credit lines	0.004	0.004*	0.004*
	(0.003)	(0.003)	(0.003)
Percentage of revolving line utilized	0.051***	0.051***	0.051***
	(0.001)	(0.001)	(0.001)
Delinquency	0.451***	0.452***	0.452***
	(0.016)	(0.016)	(0.016)
Credit inquiries	1.127***	1.126***	1.127***
	(0.011)	(0.011)	(0.011)
Number of derogatory public records	0.761***	0.759***	0.760***
	(0.019)	(0.019)	(0.019)
Applying alone (Y/N)	−0.314***	−0.315***	−0.315***
	(0.042)	(0.042)	(0.042)
Funded by investor (W/P)	−1.381***	−1.381***	−1.381***
	(0.069)	(0.069)	(0.069)
Home (Y/N)	−0.278***	−0.274***	−0.274***
	(0.022)	(0.022)	(0.022)
Mortgage (Y/N)	−0.807***	−0.807***	−0.806***
	(0.036)	(0.036)	(0.036)
Female	1.851	3.021*	3.197*
	(1.549)	(1.781)	(1.692)
Fragmentation	1.044***	1.000***	0.932***
	(0.101)	(0.116)	(0.119)
ln(Per capita income)	0.013	−0.037	−0.055
	(0.078)	(0.076)	(0.075)
ln(Population size)	0.007	0.006	0.006
	(0.013)	(0.015)	(0.015)
Unemployment rate	−0.004	−0.011	−0.015
	(0.010)	(0.011)	(0.011)
Social capital	−0.094***	−0.086***	−0.099***
Constant	14.648***	14.695***	14.830***
	(1.174)	(1.276)	(1.220)
Year FE	Yes	Yes	Yes
Purpose FE	Yes	Yes	Yes
Employment length FE	Yes	Yes	Yes
Term FE (36/60)	Yes	Yes	Yes
Observations	1341,513	1344,988	1344,988
R-squared	0.415	0.415	0.415

Table 11
Propensity score matching and coarsened exact matching
This table presents results using Propensity Score Matching and Coarsened Exact Matching. Column (1) summarizes Average Treatment on the Treated (ATT) impacts using Nearest Neighbor and Coarsened Exact Matching methods, where the treatment variable is binary, obtained by dividing states into above- or below-median values of State annual Convictions per 100,000. The outcome variable is Default in column (1) and Interest rate in column (2). Standard errors mentioned in parentheses. *, **, and *** denotes significance at the 10 %, 5 %, and 1 % level, respectively.

Variables	(1) Default (Y/N)	(2) Interest rate on loan
Nearest Neighbor (4):		
ATT: Treatment assignment	0.01604***	0.15433***
	(0.00069)	(0.00946)
Coarsened Exact Matching:		
SATT: sample average treatment effect on the treated	0.02385***	0.02240***
	(0.00201)	(0.00035)
Loan-level effects	Yes	Yes
Borrower-level effects	Yes	Yes
Year FE	Yes	Yes
Purpose FE	Yes	Yes
Employment length FE	Yes	Yes
Term FE (36/60)	Yes	Yes
Observations	1344,989	1345,350

rates, and that while corruption also increases lending rates, the impact of corruption on defaults remains large and significant even after controlling for loan pricing.

The evidence suggests that corruption adversely affects lending outcomes intermediated through MPL platforms, even though the lending takes place virtually. This sheds light on a hitherto unresolved question about whether public corruption is associated with higher rates of default. Our findings reveal that governance and enforcement measures at the state level do not alleviate the impact of corruption on loan outcomes, unlike general trust, which plays a crucial role. Specifically, increased exposure to corruption correlates with higher default rates, with general trust acting as a mediating factor. The proposed mechanism is that perceptions of corruption contribute to a normalization of rule-breaking behaviors among citizens which results in strategic defaults.

Our analysis distinguishes between general trust on one hand, and social capital on the other. Higher social capital is associated with fewer defaults and lower interest rates; but it does not weaken corruption's impact on defaults. In contrast, high levels of general trust offset the impact of corruption. Strikingly, the effects of corruption on default rates persist even after controlling for lending rates, which might be expected to price in the higher default risk. This suggests potential loan mispricing by platforms like LendingClub. While we cannot be sure that LendingClub's decision to terminate its P2P activities was influenced by high default rates associated with corruption, our findings are consistent with this possibility.

Overall, our results underscore the adverse effects of public corruption on loan outcomes on MPL platforms. This complements existing knowledge about corruption's negative impacts on a variety of other social and economic outcomes. Perhaps surprisingly, we show that the virtual nature of lending does not mitigate the influence of corruption, raising questions about whether corruption affects fintech platforms differently from traditional credit channels – a fruitful topic for future research.

CRediT authorship contribution statement

Abdulkader Kaakeh: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Simon C. Parker:** Writing – review & editing, Writing – original draft, Supervision, Investigation, Conceptualization.

Appendix A

Table A.1
Descriptive statistics on loans and corruption by year.

Year	Number of loans	Mean Convictions per 100,000	Median	sd	min	max
2007	251	.3485	.3397	.2115	0	1.1128
2008	1562	.3837	.2525	.8178	0	11.3747
2009	4716	.3535	.2816	.4004	0	4.7279
2010	11,536	.3355	.2759	.5204	0	6.7737
2011	21,721	.3253	.2667	.4785	0	6.2874
2012	53,367	.324	.2912	.4334	0	7.393
2013	134,804	.3128	.2266	.2543	0	2.7626
2014	223,103	.297	.2483	.2215	0	2.6402
2015	375,546	.2742	.2593	.1541	0	1.1817
2016	293,105	.2541	.2444	.1955	0	2.4949
2017	169,321	.2496	.2348	.2382	0	1.8029
2018	56,318	.1992	.165	.1739	0	2.6983

Table A.2
Variable definitions
All continuous variables were winsorized at the 1 % and 99 % except for the variables Annual income, population per state, and per capita income, which were transferred using the natural log and due to that, we lost 361 observations with zero values.

Variable	Description
Default	A dummy = 1 if the applicant defaulted/charge-off on the loan, and = 0 if the loan is fully paid within the observation period
Interest rate on loan	Interest rate on the loan
Convictions per 100,000	Annual corruption convictions from the Department of Justice Public Integrity Section scaled by population scaled by US Census Bureau population data per state per year
Social Capital	Lin and Pursiainen's (2022) annual proxy of social capital by U.S. state.
Unemployment rate	The rate of unemployment in each state per year
Population size	The population of each state per year
Per capita income	The income that persons receive in return of their provision of work, land and capital used as well as other income divided by the resident population of that state in that year
Enforcement	Fedaseyeu's (2020) index counting state-level restrictions on third-party debt collectors. These restrictions range from licensing and/or bonding requirements imposed on third-party debt collection firms to declaring certain debt collection practices unlawful and/or making violations of debt collection laws a criminal offense.
GPP Money	A measure of governance performance of state governments in the field of capital and budgeting management
GPP People	A measure of governance performance of state governments in the field of human resources and retention
GPP Infrastructure	A measure of governance performance of state governments in the field of infrastructure management
GPP Information	A measure of governance performance of state governments in the field of performance management and transparency
Loan amount	The listed amount of the loan applied for by the borrower. If at some point in time, the credit department reduces the loan amount, then it will be reflected in this value.
Funded by investor (W/P)	The initial listing status of the loan. A dummay takes the value of 1 if the loan is wholly funded fully by an investor and 0 if it is partially funded by an investor
Annual self-reported income	The self-reported annual income provided by the borrower during registration.
Debt-to-income ratio	A ratio calculated using the borrower's total monthly debt payments on the total debt obligations, excluding mortgage and the requested LC loan, divided by the borrower's self-reported monthly income.
Home (Y/N)	a dummy that represents if the borrower owns a house. It is equal one if the applicant owns a house. Otherwise, the variable takes value zero.
Mortgage (Y/N)	a dummy that represents if the borrower has a mortgage. It is equal one if the applicant owns a house. Otherwise, the variable takes value zero.
Applying alone (Y/N)	Indicates whether the loan is an individual application or a joint application with two co-borrowers
Number of open credit lines	The number of open credit lines in the borrower's credit file.
Percentage of revolving line used	Revolving line utilization rate, or the amount of credit the borrower is using relative to all available revolving credit.
Delinquency	The number of 30+ days past-due incidences of delinquency in the borrower's credit file for the past 2 years
Credit inquiries	The number of inquiries in past 6 months (excluding auto and mortgage inquiries)
Number of derogatory public records	Number of public records of either a bankruptcy filing, or a 'collection record' (i.e., an item so seriously overdue that it was sent to a collection agency).
Employment Length	Employment length in years. Possible values are between 0 and 10 where 0 means less than one year and 10 means ten or more years.
Purpose	A category provided by the borrower for the loan request.
Term	The number of payments on the loan. Values are in months and can be either 36 or 60.
Business	A dummy variable that equals one if the purpose of the loan is small business and equals zero otherwise
Public Integrity	Grade on anti-corruption laws and institutions created in 2015 by the State Integrity Investigation

(*continued on next page*)

Table A.2 (*continued*)

Variable	Description
Trust	A measure derived from household survey responses indicating the level of societal trust, assessed on a 3-point Likert scale ranging from 'Can trust' (1) to 'Can't be too careful' (−1). This measure is aggregated at the state level, with surveys conducted biennially by the central authority. Interpolation is applied for odd-numbered years, providing annual data for each state
Ki (Exposure years).	The minimum between (t - earliest credit linei,t) and (t −2006)
Fragmentation	The probability that any 2 random individuals from a state are the same ethnicity; equal to $1-\sum_{i=1}^{I}\left(\frac{n_i}{N}\right)^2$, where N is the total population and ni is the population shares by state-year for (i): white, black, and Asian
Female	The percent of females in population of each state per year
Cumulative corruption	The rolling five-year cumulative corruption per state on an annual basis scaled by population size

Table A.3
Descriptive statistics on loans and corruption by state.

State	Number of loans	Mean Convictions per 100,000	Median	sd	min	max
AK	3190	.3795	.5387	.2067	0	1.2605
AL	16,613	.3456	.3923	.1028	.2055	1.1128
AR	10,047	.3718	.4363	.1469	.1036	.5818
AZ	32,697	.3037	.2634	.1485	.1152	.6029
CA	196,529	.1889	.1647	.0422	.0811	.2462
CO	29,671	.0404	.0374	.0417	0	.2816
CT	19,729	.1375	.1672	.1228	0	.482
DC	3475	2.2241	1.4346	1.7754	1.0181	11.3747
DE	3783	.1254	.1061	.1617	0	.792
FL	95,611	.3189	.2813	.0615	.2099	.4105
GA	43,376	.4328	.336	.1603	.0856	.7082
HI	6758	.1778	.1433	.1445	0	.3514
IA	7	.2542	.2983	.0997	.097	.3606
ID	1689	.2005	.2375	.116	.0581	.3995
IL	51,723	.2594	.266	.112	.1415	.5351
IN	21,716	.2336	.2577	.0726	.1344	.4894
KS	11,241	.0883	.0687	.0906	0	.412
KY	12,839	.4053	.4302	.1247	.2016	.9497
LA	15,499	.719	.6847	.2258	.4502	1.2102
MA	30,977	.2574	.249	.0429	.1598	.4509
MD	31,228	.6325	.5177	.2998	.2814	1.3271
ME	2030	.2396	.301	.161	0	.3753
MI	35,234	.2006	.1916	.1054	.0604	.3416
MN	23,968	.0797	.0905	.0259	0	.2462
MO	21,261	.25	.2291	.066	.1655	.5233
MS	6588	.3524	.3679	.1249	.2341	.602
MT	3823	1.5503	1.8029	.8975	.1992	2.6402
NC	37,785	.1417	.1673	.0464	.041	.2851
ND	1602	.1204	.1324	.1285	0	.3947
NE	3586	.3238	.3147	.1491	0	.7271
NH	6449	.027	0	.0367	0	.304
NJ	48,450	.3076	.3155	.0551	.2363	.7145
NM	7362	.3501	.2867	.1858	.0478	.5741
NV	20,267	.0669	.0336	.0869	0	.2607
NY	109,849	.2565	.2444	.0661	.1325	.3459
OH	43,844	.1804	.1723	.0725	.0856	.5633
OK	12,281	.4878	.5114	.1029	.3297	.6807
OR	16,410	.0601	.0747	.0407	0	.1808
PA	45,524	.3338	.3361	.0512	.2502	.4248
RI	5872	.2508	.2839	.2267	0	.7591
SC	15,993	.0915	.1049	.0507	0	.2354
SD	2767	.5869	.6823	.5214	.1158	1.7168
TN	20,385	.3743	.3007	.1065	.1921	.6801
TX	110,173	.3408	.3313	.1122	.0769	.6269
UT	10,036	.0441	.0657	.0358	0	.2695
VA	38,040	.506	.469	.1148	.188	.9447
VT	2652	.122	.1598	.1397	0	.8011
WA	29,189	.1132	.0992	.0553	.045	.2192
WI	17,732	.1452	.1215	.0362	.1064	.2447
WV	4878	.5706	.3769	.3809	.2165	1.1888
WY	2922	.0965	0	.2102	0	.8811

Appendix B

The criteria that the GPP used for each category are as follows:
Information

- The state actively focuses on making future policy and collecting information to support that policy direction.
- Elected officials, the state budget office and agency personnel have appropriate data on the relationship between costs and performance and use these data when making resource-allocation decisions.
- Agency managers have the appropriate information required to make program management decisions.
- The governor and agency managers have appropriate data that enable them to assess the actual performance of policies and programs.
- The public has appropriate access to information about the state, the performance of state programs and state services and is able to provide input to state policy makers.

People

- The state regularly conducts and updates a thorough analysis of its human-capital needs.
- The state acquires the employees it needs.
- The state retains a skilled workforce.
- The state develops its workforce.
- The state manages its workforce-performance programs effectively.

Money

- The state uses a long-term perspective to make budget decisions.
- The state's budget process is transparent, easy to follow and inclusive.
- The state's financial management activities support structural balance between ongoing revenues and expenditures.
- The state's procurement activities are conducted efficiently and supported with effective internal controls.
- The state systematically assesses the effectiveness of its financial operations and management.

Infrastructure

- The state regularly conducts a thorough analysis of its infrastructure needs and has a transparent process for selecting infrastructure projects.
- The state has an effective process for monitoring infrastructure projects throughout their design and construction.
- The state maintains its infrastructure according to generally recognized engineering practices.
- The state comprehensively manages its infrastructure.
- The state creates effective intergovernmental and interstate infrastructure coordination networks.he link to the GPP project is: https://www.pewtrusts.org/en/research-and-analysis/reports/2008/03/03/grading-the-states-2008-report

Appendix C. Measuring local corruption at the judicial district level

LendingClub only provides the borrower's state and the first three digits of their ZIP code (e.g., 123xx), without specific addresses. We matched each three-digit ZIP code to its corresponding county and then linked each county to its respective judicial district. This allowed us to associate each borrower with their district, enabling us to calculate convictions per 100,000 people at the district level instead of the state level.

Out of the 928 three-digit ZIP code areas in the LendingClub database, 213 areas were located in more than one district within the same state. For instance, the ZIP code 100xx falls within New York, covering both the Eastern District of New York and the Southern District of New York. Since these ambiguous ZIP codes could not be assigned to a specific district, we removed them from our analysis, resulting in a loss of 366,050 observations. Additionally, 27 states (AK, AZ, CO, CT, DE, DC, HI, ID, KS, ME, MD, MA, MN, MT, NE, NV, NH, NJ, NM, ND, OR, RI, SC, SD, UT, VT, and WY) have only one district, meaning the corruption measure for those districts is the same as their state. These limitations explain why the results of using this corruption measure appear as a robustness check, rather than being reported in the main analysis of the paper.

The results appear in Table C.1. As can be seen, the results are qualitatively the same as those reported in Table 2, confirming that our findings are not sensitive to the use of state-level data.

Table C.1
Judicial District Corruption measure
This table presents logistic regression results for loan default status (binary: Y/N). The sample comprises 979,300 funded loans; the independent variable is Judicial district annual Convictions per 100,000. Robust standard errors clustered by both year and state – in parentheses. *, **, and *** denotes significance at the 10 %, 5 %, and 1 % level, respectively.

Variables	(1) Default (Y/N)
District convictions per 100k	0.1439*** (0.035)
Interest rate on loan	0.0978*** (0.002)
ln(Annual income self-reported)	−0.2416*** (0.012)
Borrower debt to income ratio	0.0129*** (0.001)
The number of open credit lines	0.0124*** (0.001)

(*continued on next page*)

Table C.1 (*continued*)

Variables	(1) Default (Y/N)
Percentage of revolving line utilized	0.0037***
	(0.000)
Delinquency in 2 years prior to the loan	0.0621***
	(0.004)
Credit inquiries in past 6 months prior to the loan	0.1021***
	(0.004)
Number of derogatory public records	0.0944***
	(0.008)
Application type individual	−0.0900***
	(0.027)
Loan financing by investor (whole or fractional)	−0.0084
	(0.008)
Home ownership owned(Y/N)	−0.2033***
	(0.013)
Home ownership mortgage (Y/N)	−0.3678***
	(0.020)
ln(Per capita personal income state-year)	−0.1426**
	(0.064)
ln(Population state-year)	0.0260**
	(0.011)
Unemployment rate state-year	−0.0137
	(0.010)
Female	6.5223***
	(1.331)
Fragmentation	0.3502***
	(0.102)
Social capital	−0.0327***
	(0.010)
Constant	−3.4997***
	(0.815)
Employment Length	Yes
Purpose	Yes
Term	Yes
Year	Yes
Observations	979,300

Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Supplementary materials

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.jbankfin.2025.107472.

Data availability

The authors do not have permission to share data.

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