From Health to Wealth:
The Impact of Health Insurance on Peer-to-peer Lending

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October 2025

Abstract

We study how health insurance coverage affects loan outcomes in the U.S. peer-to-peer lending market. Exploring regional differences in insurance coverage, we find that borrowers from areas with higher uninsured rates are associated with higher loan default probabilities and interest rates. The incremental increase in interest rates suggests only partial pricing of the health-related default risk. We address endogeneity issues using instrumental variable approach and quasi-natural experiment. Our findings imply that government health policy has direct spillover effects on household financial resilience.

JEL Classification: G21, D14, I13, I18

Keywords: health insurance, credit risk, peer-to-peer lending, Affordable Care Act

* We thank seminar participants at Deakin University for helpful comments. All errors are our own.

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Abstract

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1. Introduction

Health insurance plays a critical role in shielding individuals from the financial consequences of adverse health shocks. In the absence of coverage, individuals face heightened economic vulnerability from medical debt or disruptions to income and the ability to meet other financial obligations, such as loan repayments. Despite growing policy interest in the financial implications of being uninsured (e.g., Dobkin et al., 2018; Finkelstein et al., 2012; Hu et al., 2018), empirical evidence linking health insurance coverage to credit market outcomes remains limited. This paper addresses the gap by examining how geographic variation in health insurance coverage affects individual borrowing outcomes in the peer-to-peer (P2P) lending market.

The U.S. health insurance system combines employer-sponsored plans and public programs such as Medicaid and Medicare. However, millions of non-elderly adults remain uninsured, with significant regional disparities driven by demographic, economic, and policy factors. The implementation of the Affordable Care Act (ACA) in 2014 marked a turning point, reducing uninsured rates across states with uneven effects.[1] These disparities provide a natural setting to explore how insurance coverage influences financial behaviour.

P2P lending platforms, such as LendingClub, offer a unique lens through which to study this relationship. As an alternative to traditional credit channels, P2P platforms connect borrowers and investors directly.[2][3] The transparency of borrower-level data and the decentralized nature of pricing make P2P lending an ideal environment to isolate the effects of health insurance coverage on personal credit outcomes. We

[1] One contributing factor is the difference in state-level decisions on Medicaid expansion.
[2] P2P lending acts as a substitute for traditional bank loans and credit cards, especially for near-prime borrowers. (Tang, 2019)
[3] According to FEDS Notes (2023), P2P lending had already reached 35% of the U.S. market for unsecured personal loans by 2023. https://www.federalreserve.gov/econres/notes/feds-notes/fintech-issued-personal-loans-in-the-us-20230830.html

hypothesize that borrowers from regions with higher uninsured rates are more financially vulnerable and thus more likely to default on loans. Furthermore, we expect that P2P lenders, recognizing this elevated risk, will charge higher interest rates to borrowers from less-insured areas.

We test the hypotheses using a comprehensive dataset of over 900,000 LendingClub loans issued between 2010 and 2016. We match borrower location data with state-level uninsured rates, controlling for borrower and loan characteristics as well as macroeconomic conditions. The baseline tests show results confirming both hypotheses: a one-percentage-point increase in the uninsured rate raises the default probability by 0.03 percentage points and the interest rate by 0.01 percentage points. The latter magnitude suggests partial pricing of the impact due to insurance coverage.

We conduct several robustness checks. First, we show that the orthogonalized uninsured rates relative to GDP and unemployment rates continue to be significantly associated with loan default and pricing outcomes, indicating that our results are not driven by confounding factors due to local economic conditions. Second, we use Political Balance, defined as the fraction of a state's U.S. House of Representatives members belonging to the Democratic Party, as an instrumental variable (IV) for uninsured rates (Cummins, 2011; Rigby & Haselswerdt, 2013).[4] We find a strong correlation between the instrument and uninsured rates and document consistent results using the instrumented uninsured rates.

Third, we implement a difference-in-differences (DID) framework to examine how changes in health insurance coverage around the ACA, affect loan default probabilities and pricing. We group loans into those from the 15 states that experienced

[4] Though political preferences might correlate with broader economic or social conditions, it is unlikely that they directly affect P2P loan outcomes.

the largest (smallest) changes in uninsured rate from 2011 to 2016 to form the treated (control) group. The results show that the treated group exhibits more lowered default probability by 0.6% than the control group, though changes in loan pricing between the two groups do not differ significantly. Last, we redo the tests using an alternative measure based on estimated county-level uninsured rates from the County Health Rankings & Roadmaps database which allows us to capture finer geographic variation in insurance coverage. The results remain robust. The within-state comparisons demonstrate that our estimates are not caused by state-level omitted variables.

Our study contributes to several strands of literature. First, we complement the extensive research linking health shocks to household financial distress and credit outcomes. Prior work shows that health insurance has been shown to reduce credit delinquency, debt burdens, and bankruptcy risk (Finkelstein et al., 2012; Hu et al., 2018; Shupe, 2023). While the existing literature largely examines the effects of health risks in traditional credit settings such as mortgages and credit cards, our study is among the first to explore their impact on borrower risk and pricing in the peer-to-peer lending market.

Second, we contribute to the literature on credit risk assessment and loan pricing in alternative lending markets. The literature has shown that non-traditional signals, such as facial trustworthiness (Duarte et al., 2012), homophilous intensity (Li et al., 2023), gender (Chen et al., 2020), and social connections (Lin et al., 2013), can influence loan approval, interest rates, and default outcomes on peer-to-peer lending platforms. Our findings suggest that borrower' local environment carries important information for marketplace lending outcomes (Kaakeh & Parker, 2025)[5]. By

[5] See also Danisewicz and Elard (2023) on the role of marketplace lending. The study uses an exogenous shock to marketplace credit supply and documents that marketplace lending negatively affects personal bankruptcies.

documenting that uninsurance-related financial risk is partially priced into interest rates, our findings reveal a potential mispricing of borrower vulnerability by fintech credit algorithms (Chen et al., 2025) [6]. This highlights a novel informational inefficiency in P2P lending platforms. Traditional health-related risks are not fully incorporated into loan pricing, despite their predictive power for default.

Third, our paper contributes to the literature on the real effects of the Affordable Care Act (ACA). Previous studies focus on household consumption, labor market behavior, or general financial strain following ACA implementation (Caswell & Waidmann, 2019; Kuroki, 2021; Mazumder & Miller, 2016). We build on this literature by exploiting the ACA treatment effect as a quasi-natural experiment and using a difference-in-differences (DID) framework to identify the impact of insurance covereage on borrower default risk and loan pricing. We construct treatment and control groups based on realized reductions in uninsured rates, capturing heterogeneous policy exposure across states. This approach enables us to provide causal evidence on how large-scale health policy interventions affect credit risk and lending behavior in emerging financial markets.

The rest of the paper is organized as follows: Section 2 reviews the related literature and develops the hypotheses. Section 3 describes the data and methodology. Section 4 presents the empirical results. We conclude in Section 5.

2. Background and hypotheses

2.1 Health insurance

[6] The study documents reduced interest rate sensitivity to credit risk after a shift from auctions to posted prices.

The U.S. health insurance system relies primarily on employer-based coverage for working families, supplemented by public programs like Medicaid and Medicare.[7] Health insurance facilitates access to healthcare and protects against high medical costs (U.S. Centers for Medicare & Medicaid Services, 2025). In 2022, approximately 25.6 million non-elderly U.S. residents were uninsured, predominantly adults, with higher uninsured rates in the South and West (Finegold, 2021). The absence of health insurance creates significant challenges, as uninsured individuals are less likely to maintain their health or seek treatment for illnesses and injuries due to the high, unexpected costs they face compared to insured individuals (Wagstaff & Magnus, 2008). Moreover, uninsured patients often struggle to schedule medical appointments, as many providers require full payment at the time of service (Asplin et al., 2005).

Geographic differences in health insurance coverage occur due to demographic factors (such as differences in the age distribution across states), variations in state-level economic conditions, and policy changes that impact coverage rates (Conway & Branch, 2022; Pickle & Su, 2002). The Patient Protection and Affordable Care Act (ACA), implemented in 2014, significantly reduced uninsured rates across states. Simpson (2020) projects that full Medicaid expansion in the 15 non-participating states in 2020, ceteris paribus, would have reduced the uninsured population by 3.9 million, a 28% decrease. Because the ACA allowed states to choose whether to expand Medicaid, significant differences emerged across states in terms of implementation timing and coverage gains.

[7] The U.S. health insurance system includes both private and public sectors. Medicare covers nearly all elderly Americans, while Medicaid and the State Children's Health Insurance Program (SCHIP) cover approximately 40% of the poor and 25% of the near-poor nonelderly (Hoffman and Paradise, 2008). Employer-based coverage, the primary source for working-age adults, has eroded due to rising health insurance premiums outpacing inflation and wage growth.

As uninsured individuals lack a financial safety net that health insurance provides against high medical costs, they face higher financial risk associated with unexpected healthcare needs than insured individuals. In addition, uninsured individuals often delay or forgo necessary medical care due to cost concerns, which can impair daily functioning and increase the risk of income loss from health-related issues (Goetzel et al., 2004). Therefore, we expect those uninsured to be associated with higher financial risk as compared with those covered by health insurance.

2.2 Peer-to-peer lending

We use the peer-to-peer (P2P) lending market to gauge the economic impact of health insurance. P2P lending, initiated in the U.S. in 2005, has grown into a significant segment of the unsecured personal loan market, with LendingClub leading since its founding in 2006. By 2018, P2P lending accounted for approximately one-third of U.S. personal unsecured loans. As of June 2019, LendingClub had more than 3 million customers and had reached the $50 billion milestone of total loan originations (Bertsch et al., 2020).[8] P2P platforms streamline borrowing and lending through automated processes, reducing operational costs and connecting borrowers and lenders nationwide (Agrawal et al., 2013). Compared to traditional banks and credit card issuers, P2P platforms offer competitive interest rates and greater accessibility, particularly for near-prime borrowers underserved by conventional financial institutions.

P2P loans serve as an ideal venue to study the financial impact of health insurance. The disclosure of borrower and loan attributes by the platform allows us to control for

[8] P2P lending has evolved from a retail-driven model to one increasingly dominated by institutional investors, with retail investors accounting for less than 10% of funding volume by 2018 (Balyuk & Davydenko, 2024). The shift reflects broader market maturation and increases regulatory oversight following the 2008 financial crisis when the U.S. Securities and Exchange Commission began regulating P2P platforms as securities issuers.

other credit risk related factors and quantify the incremental effect due to insurance coverage. In addition, the nature of the platform as a third party to facilitate agreements between individual borrowers and lenders reduce the chance of monopoly pricing and render equilibrium prices. In the case of LendingClub, loan initiations start with a loan application. Once applicants meet certain eligibility criteria, they are offered a non-negotiable interest rate determined by the platform's proprietary algorithm, which incorporates inputs such as FICO scores, credit history, income, and debt-to-income ratios. The loan listing is then posted on the website and requires full funding from investors to proceed. Listings remain active for 30 days, during which the terms cannot be altered without cancelling and reposting the request. Applicants have the option to withdraw their request after listing but before loan issuance. A fully funded loan application, therefore, reflects that the pricing is an equilibrium agreement between the borrower and lenders.

2.3 Hypotheses

P2P borrowers are more financially vulnerable if not covered by health insurance. Unexpected medical expenses due to illness can lead to severe financial burden when the safety net from health insurance is not available. In addition, sickness presenteeism—where employees work despite illness due to financial pressures or fear of job loss—reduces productivity and contributes to potential earnings losses (Grinza & Rycx, 2020).[9] When faced with such health-related financial pressure due to urgent medical bills or an income loss, borrowers may prioritize immediate survival needs

[9] The financial vulnerability of uninsured workers can be exacerbated by the lack of mandated paid sick leave and limited job security under the Family and Medical Leave Act (Barron et al., 2000).

over loan repayments, which increases their default risk. Therefore, we expect a significant impact of health insurance on P2P loan default risk.

H1: Ceteris paribus, P2P loan default probability is positively related to uninsured rate.

Additionally, P2P lenders, in expectation of the financial risk impact due to borrowers' health insurance coverage, may require additional compensation in the form of higher interest rates from the borrowers located in higher uninsured rate regions.[10] LendingClub, operating in an environment of asymmetric information, may implicitly account for the elevated default risk of borrowers from states with higher uninsured rates by assigning a lower credit grade and a higher interest rate.

H2: Ceteris paribus, P2P loan interest rate is positively related to uninsured rate.

3. Data and methodology

3.1 Health insurance data

We use the health data from the US Census Bureau and define state-level uninsured rate as the percent uninsured among the non-elderly population in each state.[11] Figure 1 presents a heat map of average uninsured rates for all states during the period from 2010 to 2016. It demonstrates large variations of average uninsured rate across regions with the uninsured rate as high as 25% in Texas and that as low as 5% in Massachusetts and Hawaii. Southern and Western states generally show much higher average uninsured rates than Northeastern states.

[Figure 1 inserts here]

[10] This is similar to traditional banking practices that adjust loan terms for higher-risk borrowers (Bester, 1985).

[11] In the robustness check, we use the county level uninsured rate from County Health Rankings & Roadmaps (CHR&R).

State-level uninsured rates also vary over time. Figure 2 depicts the temporal evolution of uninsured rates in Massachusetts, Virginia, and Texas—representing the states with low, median, and high average uninsured rates, respectively—from 2010 to 2016. All three states exhibit a clear downward trend, with the most pronounced declines occurring between 2013 and 2014, likely reflecting the initial impact of the Patient Protection and Affordable Care Act (ACA). Texas consistently records the highest uninsured rates, peaking above 25% in 2010 and dropping to around 15% by 2016, while Massachusetts maintains the lowest, starting around 5% and falling to about 2%. The steepest declines of uninsured rate in Texas and Virginia occur around 2013, whereas Massachusetts, with a lower baseline, experiences a more gradual decline. Uninsured rates appear to stabilize from 2015. Despite the evolution of uninsured rates, persistent regional disparities among the three states continue to hold with the uninsured rate gap of around 15 percent between Texas and Massachusetts.

[Insert Figure 2 here]

3.2 P2P loan data

We use P2P loan-level data from LendingClub and restrict to 36-month loans (2010–2016) and 60-month loans (2010–2014). [12] The sample contains 903,860 observations. We collect detailed borrower and loan information provided by LendingClub which includes the borrower's state, first 3-digit zip code, Fico score range, debt-to-income ratio, annual income, home-owning and mortgage status, subgrade[13], the loan's purpose, amount, term, default status and interest rate.

[12] 60-month loans are restricted to those originated by 2014 as the post-2019 default data is unavailable.
[13] LendingClub assigns a credit grade ranging from A1 to G5 corresponding to borrowers from low to high credit risk levels.

We then match each P2P loan with the state-level uninsured rate based on the borrower's location (first 3-digit zip code) and the year of loan initiation. We merge the data with state-level gross domestic product and unemployment rate from the Bureau of Economic Analysis and the Bureau of Labor Statistics, respectively. In addition, we also use the corresponding county-level macro variables in a robustness test. We winsorize all continuous variables at the 1st and 99th percentiles.

3.3 Summary statistics

Table 1 reports the summary statistics. It shows that P2P loan borrowers have a median FICO score of 690[14] and a median annual income of $65,000. The median size of a loan is $12,000. The sample features more short-term than long-term loans (88% three-year loans and 12% five-year loans). We observe large heterogeneities in credit risk, demonstrated by a wide range of interest rates from 5% to 31% and that of subgrades from 1 to 35. The average uninsured rate based on the borrower's state location is around 12%.[15]

[Insert Table 1 here]

Table 2 compares borrower and loan characteristics between the highest ten and the lowest ten uninsured rate states. Loans from the states with high uninsured rates exhibit 1% higher default probability and 1% higher interest rate than those from the states with low uninsured rates. Borrowers from the states with high uninsured rates have slightly lower average Fico scores, higher debt ratios, but higher incomes. Notably,

[14] A higher FICO score indicates a lower credit risk, and a score in the range of 670 to 739 is generally considered good by most lenders. Most loan applicants in our dataset can be considered prime borrowers. The highest rated borrowers in P2P lending markets may have good access to traditional sources of credit from banks and credit cards (Bertsch et al., 2020).

[15] It likely reflects the average state-level uninsured rate in the later period as there are many more loans in the later period compared to the early years.

the states with higher uninsured rates exhibit higher average GDP and unemployment rates. These differences underscore the need to control for both borrower and loan characteristics as well as macro conditions in the analysis.

[Insert Table 2 here]

3.4 Methodology

In the baseline tests, we explore the effect of uninsured rate on P2P loan default and pricing. For the first, we apply both the OLS and the Logit regression models to facilitate comparison and interpretation. The dependent variable, $Default_{i,t}$, is defined to be 1 if a P2P loan *i* issued at year *t* is not fully paid off at maturity, and 0 otherwise. For the second, we use both $Interest\ Rate_{\ i,t}$ and $Subgrade_{i,t}$ to proxy for loan pricing. $Interest\ Rate_{\ i,t}$, is the interest rate corresponding to a P2P loan i issued in year *t*. $Subgrade_{i,t}$ is defined based on the loan grade assigned by LendingClub to indicate a borrower's risk profile. The models are as follows:

$$logit(Default_i) = \alpha_0 + \alpha_1 Uninsured_{s,t} + \alpha_2 X_{i,t} + \alpha_3 Z_{s,t} + \psi_t + \varepsilon_{i,t} \quad (1)$$

$$Interest\ Rate_{i,t}\ (Subgrade_{i,t}) = \alpha_0 + \alpha_1 Uninsured_{s,t} + \alpha_2 X_{i,t} + \alpha_3 Z_{s,t} + \psi_t + \varepsilon_{i,t} \quad (2)$$

where $Uninsured_{s,t}$, is the percentage of the non-elderly uninsured population in state *s* and in year *t*. The vector $X_{i,t}$ includes borrower and loan characteristics: the logarithm of the FICO credit score, the logarithm of the debt-to-income ratio, annual income, length of credit history, homeownership status, mortgage loan status, p2p loan amount, maturity, and interest rate[16]. The vector $Z_{s,t}$ includes state-level variables: the logarithm of GDP and the unemployment rate. We add year-fixed-effects to account for

[16] Interest rate is not used as a control variable in the regressions of loan pricing.

macroeconomic trends and time-specific shocks. Standard errors are clustered at the subgrade level to address potential correlations within a similar loan risk category.

4. Results

4.1 Baseline results

We begin by testing the effect of uninsured rate on the likelihood of loan default. Table 3 reports the coefficient estimates from both the OLS (in Columns 1 to 3) and the Logit models (in Columns 4 to 6). Across all specifications, the coefficients on uninsured rate are positive and statistically significant at the 1% level. According to the OLS estimate in the regression with all control variables, a one-percentage-point increase in the uninsured rate is associated with a 0.03 percentage point increase in default probability. Consistent with this, the marginal effect based on the Logit model shown in Column 7 indicates that a one-percentage-point increase in the uninsured rate raises the default probability by 0.03 percentage points. It implies there is a 3% chance higher of default triggered by high medical expenses for an average P2P borrower without health insurance compared to one with insurance. Given the average default rate of 5% in the dataset, the impact of uninsured rate on loan default is economically meaningful. For instance, a P2P loan borrower from Texas is more likely to default than one from Massachusetts by 0.64%, all else being equal. [17]

Coefficient signs on the control variables are as expected. FICO score, income, and the homeowner dummy are negatively associated with loan default, while debt-to-income ratio, loan amount, and interest rate positively affect default probability. Three-year loans have lower default probabilities than five-year loans, consistent with shorter

[17] The average uninsured rates in 2010 were 25% in Texas and 5% in Massachusetts. Based on the estimated marginal effect of 0.032, the implied difference in default probability is approximately 0.64 percentage points.

repayment periods reducing risk exposure. Both GDP and unemployment are positively associated with loan default, indicating regional differences across states. Our results are consistent with the findings that interest rates and unemployment rates are positively related to the default probability (Emekter et al., 2015; Foo et al., 2017), and income and FICO score are negatively related to the default probability (Cai et al., 2016; Herzenstein et al., 2011).

[Insert Table 3 about here]

We then test the effect of uninsured rate on loan pricing. Table 4 presents the results. Columns 1 to 3 use interest rate as the dependent variable, and Columns 4 to 6 use subgrade. The coefficient on the uninsured rate is positive and significant at the 1% level across all columns. The table shows that a one-percentage-point increase in the uninsured rate raises the interest rate by 0.01 percentage points (Column 3) and the subgrade by 1.36 percentage points (Column 6). Economically, it implies a 1% higher interest rate for an average P2P borrower without health insurance compared to one with insurance, all else being equal. Given that the average interest rate is 13%, the effect of uninsured rate on loan pricing is not trivial. In addition, combined with the finding in Table 3 that the default probability is 0.03% higher for a one-percentage-point increase in the uninsured rate, it suggests partial pricing of uninsured risk by LendingClub and P2P loan investors. The coefficients on the control variables align with the findings in the literature. Higher FICO scores and income reduce interest rates and subgrades, while debt-to-income ratios and loan amounts are positively associated with interest rates and subgrades. Three-year loans have lower average interest rates than five-year loans.

[Insert Table 4 about here]

Overall, these findings demonstrate a significant effect of health insurance on individuals' financial risk and support Hypotheses 1 and 2 that uninsured rates are positively associated with loan default risk and pricing.

4.2 Robustness checks

So far, the results are based on comparing loans from different states with different average uninsured rates. Since uninsured rates could correlate with other unobserved factors that potentially affect P2P loan risk and pricing, we now employ a battery of tests to verify the robustness of the findings.

4.2.1 Orthogonalized uninsured rate

Key reasons why people are insured include the financial subsidy from the local government and the access to coverage through a job. Therefore, our baseline findings could be subject to the concern that they just capture the impact of the macro environment where the P2P borrower is located. To mitigate this, we orthogonalize uninsured rate with local GDP and unemployment rate and then rerun the baseline regressions using the residual uninsured rate.

$$Uninsured_{s,t} = \beta_0 + \beta_1 Log(GDP)_{s,t} + \beta_2 Unemployment_{s,t} + \psi_t + \varepsilon_{i,t} \tag{3}$$

where $Uninsured_{s,t}$, $GDP_{s,t}$ and $Unemployment_{s,t}$ are state-level uninsured rate, GDP and unemployment respectively, and ψ_t is the year fixed effects. We verify that uninsured rate is positively associated with unemployment rate though the relationship between uninsured rate and local GDP is insignificant (untabulated).

Table 5 reports the findings using the orthogonalized uninsured rate. Consistent with the baseline findings, uninsured rate is positively associated with loan default (shown in Columns 1 and 2) as well as loan interest rate and subgrade (shown in Columns 3 and 4). The coefficient magnitudes are similar to those in Table 3 and Table 4, suggesting that the baseline findings do not merely capture the correlation between local macro factors and uninsured rate.

[Insert Table 5 about here]

4.2.2 Two-stage least squares (2SLS) regressions

To address the omitted variable bias that some excluded variables could be correlated with both uninsured rate and loan risk (/pricing), we employ the 2SLS regressions. We use political balance, defined as the fraction of a state's U.S. House of Representatives members belonging to the Democratic Party in a given year, as the instrument for uninsured rate. It satisfies both the relevance condition and the exclusion restriction. On the one hand, democratic control of state institutions is generally associated with lower uninsured rates. For instance, Cummins (2011) finds that states under Democratic control exhibit lower uninsured rates due to coverage-expanding reforms, reflecting partisan priorities in health policy. Rigby and Haselswerdt (2013) show that states with Democratic governors or legislatures were more proactive in establishing Affordable Care Act exchanges, facilitating greater insurance coverage. On the other hand, we argue that political balance in a borrower's location should not directly affect loan risk or pricing. First, the borrower's creditworthiness is fundamentally determined by individual-level characteristics such as income stability, debt-to-income ratio, payment history, that operate independently of the political composition of a state's House delegation. Second, while political control might be related to broader economic policies, these effects typically manifest through intermediary channels such as tax policies, rather than directly impacting an individual's ability to repay loans. Besides, typical lenders such as banks use credit risk models which are not directly influenced by a borrower's local political balance.

Specifically, we replace the uninsured rate with the predicted uninsured rate from the following first-stage regression and rerun the baseline tests.

$$Uninsured_{s,t} = \beta_0 + \beta_1 Political\ Balance_{s,t} + \beta_2 Log(GDP)_{s,t} + \beta_3 Unemployment_{s,t} + \psi_t + \varepsilon_{i,t} \quad (4)$$

where $Political\ Balance_{s,t}$ is the instrument and ψ_t denotes year fixed effects.

Table 6 reports the 2SLS regression results. The first-stage regression (Panel A) shows a significantly negative coefficient on *Political Balance*. A one-percentage-point increase in the Democratic share of a state's House delegation reduces the uninsured rate by 0.06 percentage points, consistent with Democratic-led states prioritizing coverage-expanding policies. In addition, uninsured rate is positively correlated with GDP and unemployment rate. The F-statistics of 61.95 demonstrates strong relevance of the instrument.

Panel B of Table 6 presents the replication of the baseline results using the instrumented uninsured rate. The coefficients of the uninsured rate are significantly positive in all regressions. Column 1 shows that a one-percentage-point increase in the uninsured rate raises the default probability by 0.25 percentage points. For loan pricing, Columns 3 and 4 imply that a one-percentage-point increase in the uninsured rate raises the interest rate by 0.03 percentage points and the subgrade by 0.05 units. Compared with the findings in Tables 3 and 4, the instrumented uninsured rate demonstrates a much stronger effect on both loan default and pricing. The evidence alleviates the concern that our findings are caused by omitted variables. Similar to the baseline results, higher FICO scores and income mean lower default probabilities and interest rates, while debt-to-income ratios and loan amounts are positively associated with loan default and interest rates. Notably, the coefficients of the unemployment rate become insignificant. As the unemployment rate is used as an exogenous variable in the first-stage regression and highly correlated with the uninsured rate, the instrumented uninsured rate could potentially capture its impact on P2P loan default and pricing.

[Insert Table 6 about here]

4.2.3 The difference-in differences test

To further validate our findings, we use the Patient Protection and Affordable Care Act (ACA) as a quasi-natural experiment that provides exogenous variation in the state-level uninsured rate. The ACA aims to regulate, overhaul, and expand Medicare and Medicaid coverage, with its major provisions coming into force in 2014. This legislation significantly reduced the number and percentage of people without health insurance. According to the National Center for Health Statistics, the percentage of uninsured individuals decreased from 16.0% in 2010 to 8.9% in the first half of 2016. Following the literature which documents that expansions in healthcare coverage mitigate financial strains by reducing debts, unpaid bills, and bankruptcy filings (Caswell & Waidmann, 2019; Kuroki, 2021; Mazumder & Miller, 2016), we hypothesize that increased insurance coverage around ACA implementation leads to lower probabilities of default and potentially lower interest rates in the P2P loan market. The pricing effect may not be evident if the lenders including the platform and the ultimate P2P loan investors do not timely incorporate changes to potential borrowers' insured status around the ACA.

As most states exhibit a reduction of uninsured rate during the period independent of the respective expansion status, we construct the treatment and the control groups based on the observed reductions in the percentage of non-elderly uninsured residents. Specifically, we define the treatment group (the control group) as the fifteen states with the largest (smallest) declines in the average uninsured rates from 2011 to 2016. Figure 3 illustrates the year-by-year average uninsured rates for the two groups. The treatment group had a 5% higher uninsured rate than the control group before 2012. The uninsured rates of both groups almost converged around 2016. Factors explaining the variations in uninsured rate between the two groups may include the ACA expansion, the initial uninsured level, and policy interventions. We argue that these factors do not directly affect default or pricing in the P2P loan market.

We then compare the evolution of loan default and pricing between the treatment and the control groups using a difference-in-differences (DID) specification:

$$Y_{i,t} = \alpha_0 + \alpha_1 Treatment_{i,t} + \alpha_2 Post_t + \alpha_3 Treatment_{i,t} * Post_t + \alpha_4 X_{i,t} + \alpha_5 Z_{s,t} + \psi_t + \varepsilon_{i,t} \quad (5)$$

Where the dependent variable is loan default, interest rate, or subgrade; $Treatment_{i,t}$ equals 1 (0) for the fifteen states that experienced the largest (smallest) changes in uninsured rate from the year 2011 to the year 2016; *Post* equals 1 if the loan was issued after 2013 and 0 otherwise; $X_{i,t}$ includes borrower and loan characteristics; $Z_{s,t}$ includes macro-level controls.

Table 7 reports the results. Columns 1 and 2 correspond to the default analysis. The coefficient of the *Treatment* dummy is insignificant, suggesting no difference between the treated and the control groups in the average default probabilities after controlling for loan and borrower characteristics. The coefficient of the *Post* dummy is significantly positive, implying a reduction of average loan quality accompanying a substantial growth of the P2P loan market during the period. Supporting our hypothesis, the coefficients on the interaction term of *Treatment* * *Post* are significantly negative. The coefficient in the OLS regression shows that loans from the states with higher reduction in uninsured rate exhibit lower default probability by 0.6%. The impact of uninsured rate dynamics is economically meaningful given that the treated group exhibits around 5% more reduction in uninsured rate than the control group over the period.

Columns 3 and 4 of Table 7 correspond to the loan pricing regressions. The positive coefficients of the *Treatment* dummy indicate higher interest rates for the treated group relative to the control group. This is consistent with the cross-sectional evidence that the treated group contains riskier loans with higher uninsured rate. However, the coefficients of the interaction term of *Treatment* * *Post* are insignificant, suggesting no significant pricing changes between the two groups of loans around the ACA enforcement. One explanation could be that investors (and lenders) do not timely and sufficiently account for the financial impact of insurance coverage expansion on loan borrowers. It reinforces the implication that the pricing of uninsured health risk in the P2P market is likely to be imperfect and involve learning.

Overall, the difference-in-differences test provides supporting evidence that an exogenous improvement in the uninsured rate is associated with enhanced financial safety in the P2P loan market though the impact on loan pricing is not evident.

[Insert Table 7 about here]

4.2.4 Alternative measure of uninsured rate

To enhance the geographic precision of our analysis, we employ an alternative measure of insurance coverage using county-level uninsured rates. The data are sourced from the County Health Rankings & Roadmaps database[18], which provides annual estimates of the percentage of non-elderly uninsured individuals at the county level as well as other variables. We aggregate the county-level figures of uninsured rate, GDP, and unemployment rate, to the 3-digit ZIP code levels to match the borrower location data in the LendingClub dataset. This finer granularity allows us to capture within-state variation in insurance coverage and conduct within-state comparisons.

Panel A of Table 8 presents the results of default analysis using the alternative uninsured rate measure. Note that we control for state-fixed-effects so that the coefficient estimates reflect within-state comparisons. Across both the OLS and Logit specifications, the coefficient on uninsured rate is positive and statistically significant at the 1% level. The marginal effect from the Logit model (Column 7) indicates that a one-percentage-point increase in the uninsured rate raises the default probability by 0.06 percentage points, doubling the estimate in Table 3 using the state-level uninsured rate. This suggests that within-state variations in insurance coverage can explain borrower financial vulnerability.

Panel B of Table 8 explores the impact on loan pricing, using both interest rate and subgrade as dependent variables. The uninsured rate is again positively and significantly associated with both pricing measured across all specifications. In Column 3, a one-percentage-point increase in the uninsured rate raises the interest rate by 0.01 percentage points, similar to the estimate in Table 4 using the state-level uninsured rate.

[18] It is constructed by the collaboration between the Robert Wood Johnson Foundation and the University of Wisconsin Population Health Institute.

Column 6 shows that the same increase leads to a 1.65 unit rise in subgrade, indicating assignment to a riskier credit category. Combined with the findings from default regressions, the evidence implies that the insurance-related financial risk is only partially priced by P2P loan investors.

The analysis based on county-level insurance coverage confirms and strengthens our baseline findings. The within-state comparisons mitigate the concern that state-level unobserved factors drive the findings.

[Insert Table 8 about here]

5. Conclusion

This study investigates how regional disparities in health insurance coverage affect loan outcomes in the U.S. peer-to-peer (P2P) lending market. Using a comprehensive dataset from LendingClub, we find that higher uninsured rates are significantly associated with increased loan default probabilities and elevated interest rates. We conduct multiple robustness checks using orthogonalization, instrumental variable, difference-in-differences, and granular county-level data.

Our findings underscore the critical role of health insurance in shaping household financial resilience. Borrowers from regions with higher uninsured rates face greater financial vulnerability in the form of P2P loan default. While the P2P platform and investors charge higher rates when the borrower is from an area with higher uninsured rate, the findings suggest only partial pricing adjustment.

Overall, our study contributes to the field exploring the intersection of health policy and financial outcomes, highlighting the impact of health infrastructure on economic behaviour. For lenders and investors, incorporating health-related variables into credit scoring models could improve risk assessment and pricing accuracy. For policy makers, expanding health insurance coverage can yield spillover benefits in the credit market by reducing default risk and enhancing financial stability.

Reference

Agrawal, A., Catalini, C., & Goldfarb, A. (2014) "Some simple economics of crowdfunding." *Innovation Policy and the Economy* 14.1 (2014): 63–97.

Asplin, B. R., K. V. Rhodes, H. Levy, N. Lurie, A. L. Crain, B. P. Carlin, and A. L. Kellermann. “Insurance Status and Access to Urgent Ambulatory Care Follow-Up Appointments.” *Journal of the American Medical Association*, 294 (2005), 1248–1254.

Balyuk, T., and S. Davydenko. “Reintermediation in FinTech: Evidence from Online Lending.” *Journal of Financial and Quantitative Analysis*, 59 (2024), 1997–2037.

Barron, J. M.; G. Elliehausen; and M. E. Staten. “Monitoring the Household Sector with Aggregate Credit Bureau Data: A New Source of Data Provides a Firmer Foundation for Credit Analysis and Decisions.” *Business Economics*, 35 (2000), 63–76.

Bartlett, R.; A. Morse; R. Stanton; and N. Wallace. “Consumer-Lending Discrimination in the FinTech Era.” *Journal of Financial Economics*, 143 (2022), 30–56.

Bester, H. “Screening vs. Rationing in Credit Markets with Imperfect Information.” *American Economic Review*, 75 (1985), 850–855.

Bertsch, C.; I. Hull; Y. Qi; and X. Zhang. “Bank Misconduct and Online Lending.” *Journal of Banking and Finance*, 116 (2020), 105822.

Cai, S.; X. Lin; D. Xu; and X. Fu. “Judging Online Peer-to-Peer Lending Behavior: A Comparison of First-Time and Repeated Borrowing Requests.” *Information and Management*, 53 (2016), 857–867.

Caswell, K. J., and T. A. Waidmann. “The Affordable Care Act Medicaid Expansions and Personal Finance.” *Medical Care Research and Review*, 76 (2019), 538–571.

Chen, J.; W. Huang; and X. Wang. “Peer-to-Peer Lending: Shift of Pricing Regime and Changes in Risk Sensitivity.” *Journal of Banking and Finance*, 176 (2025), 107459.

Chen, X.; B. Huang; and D. Ye. “Gender Gap in Peer-to-Peer Lending: Evidence from China.” *Journal of Banking and Finance*, 112 (2020), 105633.

Conway, D., and B. Branch. “Health Insurance Coverage Status and Type by Geography: 2019 and 2021.” *Washington, DC: US Census Bureau* (2022).

Cummins, J. “Party Control, Policy Reforms, and the Impact on Health Insurance Coverage in the U.S. States.” *Social Science Quarterly*, 92 (2011), 246–267.

Danisewicz, P.; and I. Elard. “The Real Effects of Financial Technology: Marketplace Lending and Personal Bankruptcy.” *Journal of Banking and Finance*, 155 (2023), 106986.

Demyanyk, Y.; E. Loutskina; and D. Kolliner. “The Taste of Peer-to-Peer Loans.” Working Paper No. 17-18, Federal Reserve Bank of Cleveland (2017).

De Roure, C.; L. Pelizzon; and P. Tasca. "How Does P2P Lending Fit into the Consumer Credit Market?" Discussion Paper No. 30/2016, Deutsche Bundesbank (2016).

Dobkin, C., Finkelstein, A., Kluender, R., & Notowidigdo, M. J. (2018). The economic consequences of hospital admissions. *American Economic Review*, *108*(2), 308-352.

Domowitz, I., and R. L. Sartain. "Determinants of the Consumer Bankruptcy Decision." *Journal of Finance*, 54 (1999), 403–420.

Duarte, J.; S. Siegel; and L. Young. "Trust and Credit: The Role of Appearance in Peer-to-Peer Lending." *Review of Financial Studies*, 25 (2012), 2455–2484.

Emekter, R.; Y. Tu; B. Jirasakuldech; and M. Lu. "Evaluating Credit Risk and Loan Performance in Online Peer-to-Peer (P2P) Lending." *Applied Economics*, 47 (2015), 54–70.

Finkelstein, A.; S. Taubman; B. Wright; M. Bernstein; J. Gruber; J. P. Newhouse; and Oregon Health Study Group. "The Oregon Health Insurance Experiment: Evidence from the First Year." *Quarterly Journal of Economics*, 127 (2012), 1057–1106.

Finegold, K. "Trends in the U.S. Uninsured Population, 2010–2020." Office of Health Policy, Assistant Secretary for Planning and Evaluation, U.S. Department of Health and Human Services (2021).

Foo, J.; L. H. Lim; and K. S. W. Wong. "Macroeconomics and FinTech: Uncovering Latent Macroeconomic Effects on Peer-to-Peer Lending." Working Paper, arXiv:1710.11283 (2017).

Gill, B. S. "Health Uninsurance Premium and Mortgage Interest Rates." *International Review of Financial Analysis*, 87 (2023), 102647.

Goetzel, R. Z.; S. R. Long; R. J. Ozminkowski; K. Hawkins; S. Wang; and W. Lynch. "Health, Absence, Disability, and Presenteeism Cost Estimates of Certain Physical and Mental Health Conditions Affecting U.S. Employers." *Journal of Occupational and Environmental Medicine*, 46 (2004), 398–412.

Grinza, E., and F. Rycx. "The Impact of Sickness Absenteeism on Firm Productivity: New Evidence from Belgian Matched Employer–Employee Panel Data." *Industrial Relations: A Journal of Economy and Society*, 59 (2020), 150–194.

Gross, T., and M. J. Notowidigdo. "Health Insurance and the Consumer Bankruptcy Decision: Evidence from Expansions of Medicaid." *Journal of Public Economics*, 95 (2011), 767–778.

Herzenstein, M.; S. Sonenshein; and U. M. Dholakia. "Tell Me a Good Story and I May Lend You Money: The Role of Narratives in Peer-to-Peer Lending Decisions." *Journal of Marketing Research*, 48 (2011), S138–S149.

Hoffman, C., and J. Paradise. “Health Insurance and Access to Health Care in the United States.” *Annals of the New York Academy of Sciences*, 1136 (2008), 149–160.

Hu, L.; R. Kaestner; B. Mazumder; S. Miller; and A. Wong. “The Effect of the Affordable Care Act Medicaid Expansions on Financial Wellbeing.” *Journal of Public Economics*, 163 (2018), 99–112.

Kaakeh, A.; and S. C. Parker. “The Impact of Public Corruption on Marketplace Lending Outcomes.” *Journal of Banking and Finance*, 177 (2025), 107472.

Kaiser Family Foundation. “Key Facts about the Uninsured Population.” Kaiser Family Foundation (2024).

Kuroki, M. “The Effect of Health Insurance Coverage on Personal Bankruptcy: Evidence from the Medicaid Expansion.” *Review of Economics of the Household*, 19 (2021), 429–451.

Li, J.; B. Zhang; M. Jiang; and J. Hu. “Homophilous Intensity in the Online Lending Market: Bidding Behavior and Economic Effects.” *Journal of Banking and Finance*, 152 (2023), 106876.

Lin, M.; N. R. Prabhala; and S. Viswanathan. “Judging Borrowers by the Company They Keep: Friendship Networks and Information Asymmetry in Online Peer-to-Peer Lending.” *Management Science*, 59 (2013), 17–35.

Mazumder, B., and S. Miller. “The Effects of the Massachusetts Health Reform on Household Financial Distress.” *American Economic Journal: Economic Policy*, 8 (2016), 284–313.

National Center for Health Statistics. “Health Insurance Coverage: Early Release of Estimates from the National Health Interview Survey, January–June 2016.” U.S. Centers for Disease Control and Prevention (2016).

Pickle, L. W., and Y. Su. “Within-State Geographic Patterns of Health Insurance Coverage and Health Risk Factors in the United States.” *American Journal of Preventive Medicine*, 22 (2002), 75–83.

Rigby, E., and J. Haselswerdt. “Hybrid Federalism, Partisan Politics, and Early Implementation of State Health Insurance Exchanges.” *Publius: The Journal of Federalism*, 43 (2013), 368–391.

Simpson, M. “The Implications of Medicaid Expansion in the Remaining States: 2020 Update.” *Washington, DC: Urban Institute*, 500 (2020).

Shupe, C. “Public Health Insurance and Medical Spending: The Incidence of the ACA Medicaid Expansion.” *Journal of Policy Analysis and Management*, 42 (2023), 137–165.

Tang, H. “Peer-to-Peer Lenders versus Banks: Substitutes or Complements?” *Review of Financial Studies*, 32 (2019), 1900–1938.

U.S. Centers for Medicare & Medicaid Services. “Why Coverage Is Important.” HealthCare.gov. (n.d.). Retrieved October 23, 2025, from https://www.healthcare.gov/why-coverage-is-important/

Wagstaff, A., and M. Lindelow. “Can Insurance Increase Financial Risk? The Curious Case of Health Insurance in China.” *Journal of Health Economics*, 27 (2008), 990–1005.

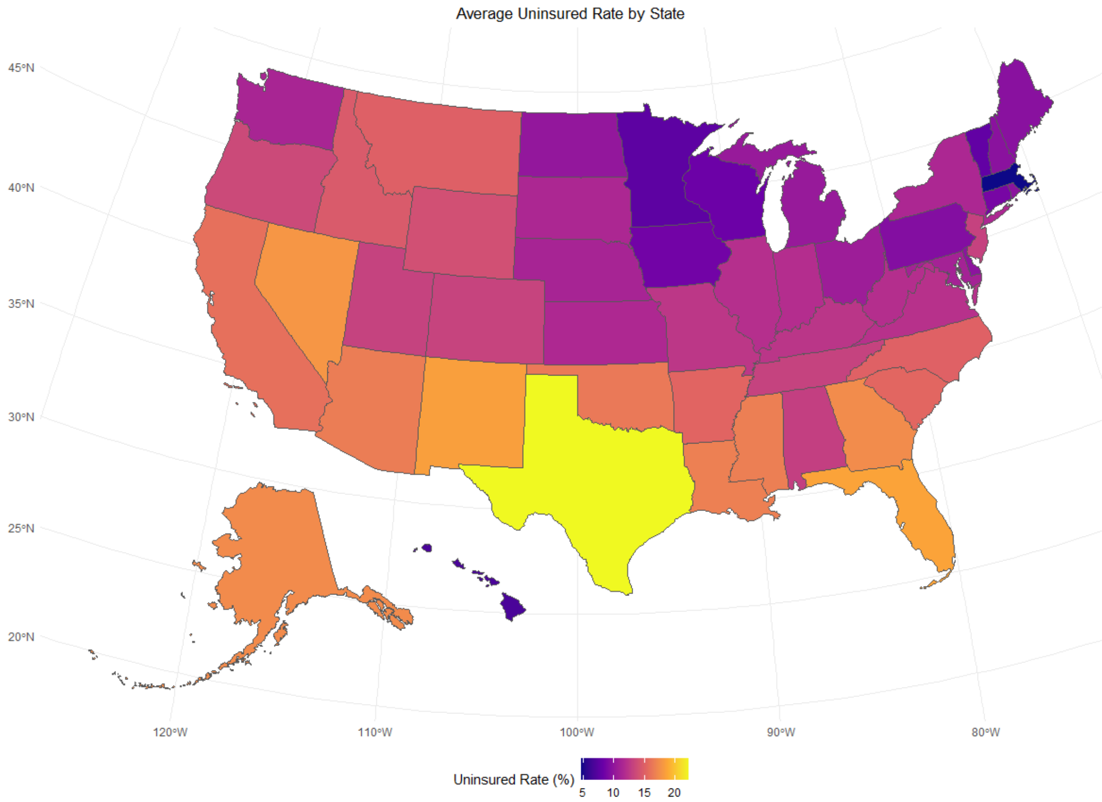

Figure 1. Uninsured Rates Across States.
This figure presents the heat map of average uninsured rates across states. The sample period is from 2010 to 2016.

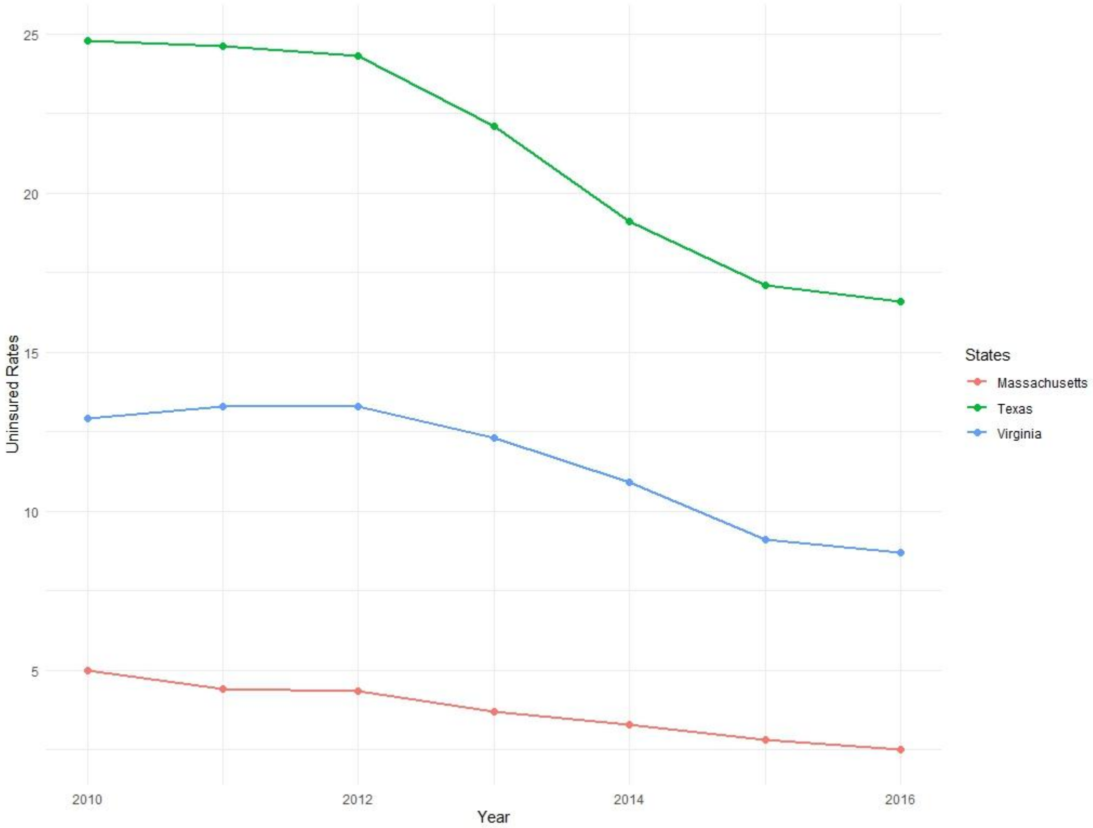

Figure 2. Dynamics of Uninsured Rates for Selected States.
This figure plots average uninsured rates for the selected states of Massachusetts, Virginia, Texas over the period of 2010 to 2016. Massachusetts and Texas correspond to the states with the lowest and the highest average uninsured rate in the sample, respectively.

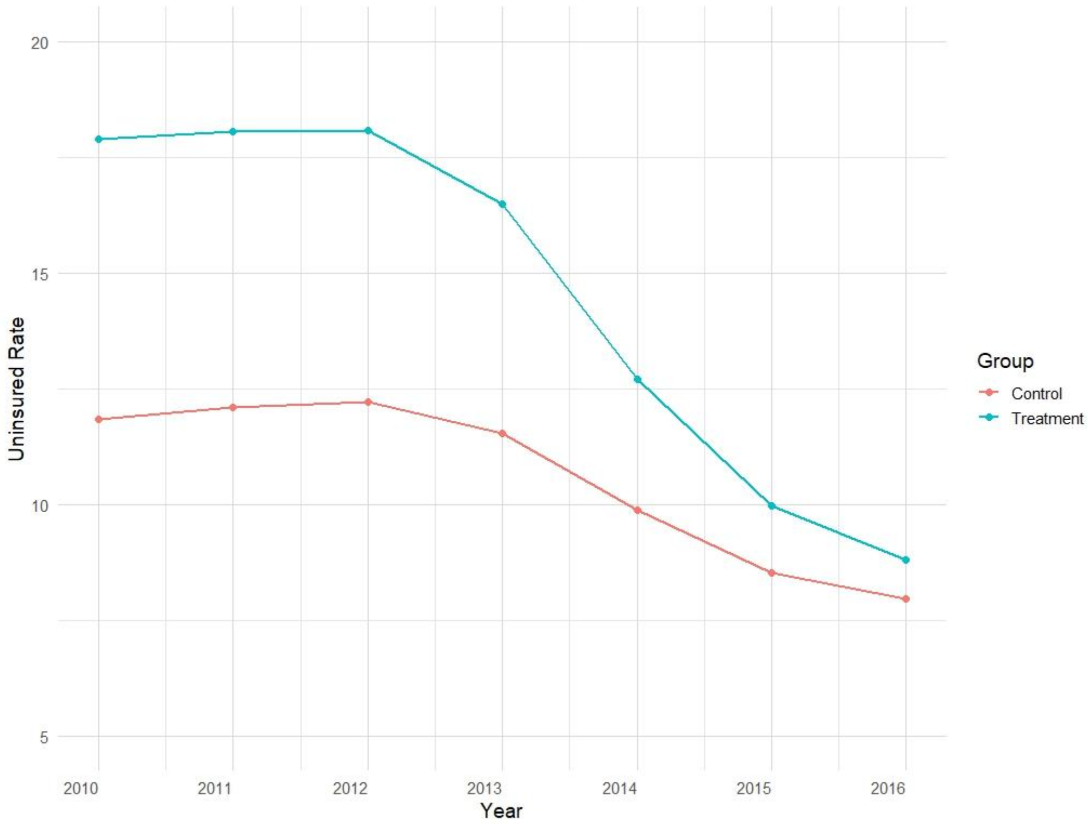

Figure 3. Uninsured Rates of the Treatment and the Control Groups.
This figure presents average uninsured rates over time for the treatment and the control groups in the difference-in-differences test. The treatment (control) group consists of 25 states that experienced the largest (smallest) changes in uninsured rate from the year 2011 to the year 2016.

Table 1. Summary statistics

Panel A reports descriptive statistics for both loan-level variables (borrower and loan characteristics) and other state-level variables. State-level variables correspond to characteristics of the respective state of the P2P loan borrower. The sample consists of all three-year loans from 2010 to 2016 and all five-year loans from 2010 to 2014 in LendingClub. Variable definitions are provided in Appendix A. Panel B presents pairwise Pearson correlation coefficients. ***, **, * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Descriptive statistics

	Mean	St. Dev.	Min	Median	Max
Borrower Characteristics					
Fico	694.98	30.63	660.00	690.00	845.00
Log (Debt / Income)	2.74	0.58	0.59	2.85	3.64
Income (000s)	74.50	42.30	20.00	65.00	260.00
Log (Credit Days)	8.56	0.46	7.24	8.57	9.54
Homeowner	0.10	0.30	0.00	0.00	1.00
Mortgage	0.48	0.50	0.00	0.00	1.00
Subgrade	10.90	6.08	1.00	10.00	35.00
Loan Characteristics					
Amount (000s)	13.60	8.31	1.60	12.00	35.00
Term36m	0.88	0.33	0.00	1.00	1.00
Default	0.17	0.37	0.00	0.00	1.00
Interest Rate	0.13	0.04	0.05	0.12	0.31
State-level variables					
Uninsured	0.12	0.04	0.02	0.12	0.25
Log (GDP)	12.20	1.03	10.20	12.10	14.70
Unemployment (%)	6.86	2.20	2.60	6.70	13.80
County-level variables					
Uninsured	0.17	0.05	0.04	0.17	0.47
Log (GDP)	15.65	1.73	11.91	15.44	20.35
Unemployment (%)	7.89	2.39	1.37	7.68	19.53

Panel B. Correlation matrix

	Default	Interest Rate	Subgrade	Fico	Log (Debt / Income)	Income	Log (Credit Days)	Homeowner	Mortgage	Amount	Term36m	Log (GDP)	Unemployment	Default
Uninsured	0.03***	0.12***	0.13***	0.07***	0.04***	-0.02***	-0.02***	-0.04***	-0.01***	0.05***	0.03***	-0.17***	0.19***	0.50***
Default		0.93***	0.23***	0.23***	-0.13***	0.08***	-0.07***	-0.05***	0.01***	-0.06***	0.03***	-0.12***	0.00	0.10***
Interest Rate			0.25***	0.25***	-0.02***	0.04***	0.01***	-0.03***	0.00	0.01**	0.09***	-0.18***	-0.02***	0.32***
Subgrade				0.98***	-0.43***	0.13***	-0.14***	-0.14***	0.00*	-0.08***	0.08***	-0.39***	-0.01***	0.14***
Fico					-0.45***	0.13***	-0.13***	-0.14***	0.01***	-0.09***	0.08***	-0.38***	-0.01***	0.08***
Log (Debt / Income)						-0.10***	0.12***	0.10***	0.01***	0.11***	0.12***	-0.01***	-0.00	0.07***
Income							-0.22***	0.06***	0.02***	0.01***	0.03***	-0.03***	-0.07***	-0.11***
Log (Credit Days)								0.27***	-0.04***	0.23***	0.48***	-0.04***	0.07***	-0.03***
Homeowner									0.03***	0.23***	0.21***	-0.04***	-0.03***	-0.06***
Mortgage										-0.32***	-0.02***	0.03***	-0.02***	-0.05***
Amount											0.18***	-0.09***	-0.14***	-0.03***
Term36m												-0.28***	0.02***	0.02***
Log (GDP)													0.03***	-0.23***
Unemployment														0.21***

Table 2 Comparisons between the high- and the low- uninsured groups
This table presents average characteristics of peer-to-peer (P2P) loans from the three selected states of Texas (TX), Virginia (VA), and Massachusetts (MA), as well as the high-uninsured and low-uninsured groups. TX, VA, and MA represent the states with the highest, the median, and the lowest average uninsured rate, respectively. The high- (low-) uninsured group consists of loans from the ten states with the highest (lowest) average uninsured rates. The t-stat column reports the univariate t-statistics for comparing the high- with the low-uninsured groups. The sample period is from 2010 to 2016. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	TX	VA	MA	High	Low	High- Low	t-stat
Uninsured	0.23	0.12	0.04	0.16	0.07	0.09	19.96
Default	0.16	0.16	0.16	0.17	0.16	0.01	10.48
Interest Rate	0.13	0.13	0.12	0.13	0.12	0.01	12.47
Subgrade	10.77	10.88	10.07	10.93	10.64	0.30	13.03
Fico	687.30	686.13	688.40	694.83	696.56	-1.73	-14.77
Log (Debt / Income)	2.80	2.75	2.66	2.78	2.74	0.04	17.57
Income	79.49	80.89	79.58	73.87	73.52	0.35	2.24
Log (Credit Days)	8.58	8.57	8.56	8.56	8.58	-0.02	-12.10
Homeowner	0.13	0.08	0.08	0.12	0.10	0.02	14.61
Mortgage	0.55	0.52	0.44	0.53	0.50	0.03	17.35
Amount	14.36	14.51	14.71	13.61	13.66	-0.06	-1.82
Term36m	0.89	0.85	0.87	0.88	0.87	0.02	12.27
Log (GDP)	14.16	13.00	12.99	12.36	12.01	0.35	2.66
Unemployment	6.63	5.96	6.74	6.73	5.53	1.20	4.17

Table 3. Probability of default

This table explores the effect of uninsured rate on loan default. Columns 1-3 present the results of the OLS regressions. Columns 4-6 present the results of the Logit regressions and Column 7 shows the average marginal effects based on the regression in Column 6. The dependent variable is loan default. The independent variable of interest is the uninsured rate, measured as the percentage of the nonelderly uninsured population in the state of the P2P loan borrower in the year the loan is issued. Variable definitions are in Appendix 1. The sample consists of all three-year loans from 2010 to 2016 and all five-year loans from 2010 to 2014 in LendingClub. Standard errors are clustered at the subgrade level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	OLS			Logit			
	1	2	3	4	5	6	7
Uninsured	0.054***	0.051***	0.030***	0.392***	0.416***	0.245***	0.032
	(0.011)	(0.010)	(0.011)	(0.092)	(0.080)	(0.088)	
Log (Fico)		-0.281***	-0.282***		-4.138***	-4.143***	-0.534
		(0.039)	(0.039)		(0.394)	(0.393)	
Log (Debt / Income)		0.024***	0.024***		0.209***	0.212***	0.027
		(0.002)	(0.002)		(0.008)	(0.008)	
Income		-0.000***	-0.000***		-0.003***	-0.003***	-0.000
		(0.000)	(0.000)		(0.000)	(0.000)	
Log (Credit Days)		-0.008***	-0.008***		-0.063***	-0.062***	-0.008
		(0.001)	(0.001)		(0.007)	(0.007)	
Homeowner		-0.017***	-0.016***		-0.120***	-0.113***	-0.015
		(0.002)	(0.002)		(0.010)	(0.010)	
Mortgage		-0.034***	-0.033***		-0.265***	-0.255***	-0.032
		(0.003)	(0.003)		(0.008)	(0.008)	
Amount		0.001***	0.001***		0.012***	0.012***	0.002
		(0.000)	(0.000)		(0.001)	(0.001)	
Term36m		-0.073***	-0.073***		-0.501***	-0.503***	-0.065
		(0.003)	(0.003)		(0.015)	(0.015)	
Interest Rate		1.639***	1.639***		10.995***	10.992***	1.416
		(0.000)	(0.000)		(0.412)	(0.412)	
Log (GDP)			0.002***			0.021***	0.003
			(0.001)			(0.003)	
Unemployment			0.002***			0.013***	0.002
			(0.000)			(0.002)	
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	
Observations	903,860	903,860	903,860	903,860	903,860	903,860	
R-squared/ Pseudo R2	0.003	0.067	0.067	0.003	0.075	0.075	

Table 4. Loan pricing

This table explores the effect of uninsured rate on loan pricing. The dependent variable is interest rate in Columns 1-3 and subgrade in Columns 4-6. The independent variable of interest is the uninsured rate, measured as the percentage of the nonelderly uninsured population in the state of the P2P loan borrower in the year the loan is issued. Variable definitions are in Appendix 1. The sample consists of all three-year loans from 2010 to 2016 and all five-year loans from 2010 to 2014 in LendingClub. Standard errors are clustered at the subgrade level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Interest Rate			Subgrade		
	1	2	3	4	5	6
Uninsured	0.011***	0.010***	0.010***	1.481***	1.476***	1.361***
	(0.003)	(0.002)	(0.002)	(0.499)	(0.227)	(0.224)
Log (Fico)		-42.369***	-42.365***		-61.347***	-61.340***
		(4.904)	(4.903)		(6.998)	(6.996)
Log (Debt / Income)		0.514***	0.516***		0.723***	0.726***
		(0.047)	(0.047)		(0.062)	(0.063)
Income		-0.009***	-0.009***		-0.013***	-0.013***
		(0.001)	(0.001)		(0.002)	(0.002)
Log (Credit Days)		-0.955***	-0.955***		-1.380***	-1.381***
		(0.127)	(0.127)		(0.175)	(0.176)
Homeowner		0.104***	0.108***		0.140***	0.145***
		(0.019)	(0.019)		(0.027)	(0.027)
Mortgage		-0.382***	-0.377***		-0.558***	-0.551***
		(0.051)	(0.050)		(0.072)	(0.071)
Amount		0.050***	0.050***		0.072***	0.072***
		(0.006)	(0.006)		(0.009)	(0.009)
Term36m		-4.318***	-4.319***		-6.679***	-6.681***
		(0.588)	(0.587)		(0.901)	(0.901)
Log (GDP)			0.001			0.000
			(0.005)			(0.007)
Unemployment			0.020***			0.034***
			(0.005)			(0.008)
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	903,860	903,860	903,860	903,860	903,860	903,860
R-squared	0.080	0.402	0.402	0.030	0.384	0.384

Table 5. Robustness check using orthogonalized uninsured rate

This table presents the robustness tests of the findings in Table 3 and Table 4 by using orthogonalized uninsured rate. The dependent variables are default in Columns 1-2, interest rate in Column 3, and subgrade in Column 4. The independent variable of interest is the orthogonalized uninsured rate calculated as the residual from the first-stage regression of uninsured rate on GDP and unemployment. Variable definitions are in Appendix 1. The sample consists of all three-year loans from 2010 to 2016 and all five-year loans from 2010 to 2014 in LendingClub. Standard errors are clustered at the subgrade level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Default		Interest Rate	Subgrade
	OLS	Logit		
	1	2	3	4
$Uninsured_{resid}$	0.030***	0.245***	0.010***	1.361***
	(0.011)	(0.088)	(0.001)	(0.224)
Log (Fico)	-0.282***	-4.143***	-0.424***	-61.340***
	(0.039)	(0.393)	(0.049)	(6.996)
Log (Debt / Income)	0.024***	0.212***	0.005***	0.726***
	(0.002)	(0.008)	(0.000)	(0.063)
Income	-0.000***	-0.003***	-0.000***	-0.013***
	(0.000)	(0.000)	(0.000)	(0.002)
Log (Credit Days)	-0.008***	-0.062***	-0.010***	-1.381***
	(0.001)	(0.007)	(0.001)	(0.176)
Homeowner	-0.016***	-0.113***	0.001***	0.145***
	(0.002)	(0.010)	(0.000)	(0.027)
Mortgage	-0.032***	-0.254***	-0.004***	-0.551***
	(0.003)	(0.008)	(0.001)	(0.071)
Amount	0.001***	0.012***	0.000***	0.072***
	(0.000)	(0.001)	(0.000)	(0.009)
Term36m	-0.073***	-0.503***	-0.043***	-6.681***
	(0.003)	(0.015)	(0.006)	(0.901)
Interest Rate	1.639***	10.992***		
	(0.025)	(0.412)		
Log (GDP)	0.002***	0.021***	0.000	0.002
	(0.000)	(0.003)	(0.000)	(0.007)
Unemployment	0.002***	0.014***	0.000***	0.044***
	(0.000)	(0.003)	(0.000)	(0.009)
Year Fixed Effect	Yes	Yes	Yes	Yes
Observations	903,860	903,860	903,860	903,860
R-squared/ Pseudo R2	0.067	0.075	0.402	0.384

Table 6. Robustness check using 2SLS

This table presents the robustness tests of the findings in Table 3 and Table 4 by using two-stage least squares (2SLS) regressions. Panel A shows the results of the first stage regression where political balance is the instrumental variable. Panel B shows the results of the second stage regressions where the independent variable of interest is the predicted uninsured rate based on the first stage estimates. The dependent variables are default in Columns 1-2, interest rate in Column 3, and subgrade in Column 4. Variable definitions are in Appendix 1. The sample consists of all three-year loans from 2010 to 2016 and all five-year loans from 2010 to 2014 in LendingClub. Standard errors are clustered at the subgrade level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A. First stage

	Uninsured
Political Balance	-0.055***
	(0.015)
Log (GDP)	0.003**
	(0.001)
Unemployment	0.007***
	(0.001)
Year Fixed Effect	Yes
F-stat	61.95
Observations	357
R-squared	0.592

Panel B. Second stage

	Default		Interest Rate	Subgrade
	OLS	Logit		
	1	2	3	4
Uninsured^	0.252***	2.079***	0.032***	4.530***
	(0.042)	(0.275)	(0.004)	(0.628)
Log (Fico)	-0.282***	-4.144***	-0.424***	-61.345***
	(0.039)	(0.392)	(0.049)	(6.996)
Log (Debt / Income)	0.024***	0.210***	0.005***	0.724***
	(0.002)	(0.008)	(0.000)	(0.062)
Income	-0.000***	-0.003***	-0.000***	-0.013***
	(0.000)	(0.000)	(0.000)	(0.002)
Log (Credit Days)	-0.008***	-0.062***	-0.010***	-1.382***
	(0.001)	(0.007)	(0.001)	(0.176)
Homeowner	-0.016***	-0.119***	0.001***	0.138***
	(0.002)	(0.010)	(0.000)	(0.027)
Mortgage	-0.033***	-0.262***	-0.004***	-0.559***
	(0.003)	(0.008)	(0.001)	(0.072)
Amount	0.001***	0.012***	0.000***	0.072***
	(0.000)	(0.001)	(0.000)	(0.009)
Term36m	-0.073***	-0.502***	-0.043***	-6.677***
	(0.003)	(0.015)	(0.006)	(0.901)
Interest Rate	1.638***	10.989***		
	(0.025)	(0.412)		
Log (GDP)	0.003***	0.024***	0.000**	0.013*
	(0.000)	(0.003)	(0.000)	(0.007)
Unemployment	0.000	0.002	0.000	0.013
	(0.000)	(0.003)	(0.000)	(0.008)
Year Fixed Effect	Yes	Yes	Yes	Yes
Observations	903,860	903,860	903,860	903,860
R-squared/ Pseudo R2	0.067	0.075	0.402	0.384

Table 7. Difference-in-differences test

This table presents the difference-in-differences (DID) regression results. The treatment (control) group consists of loans from the 25 states that experienced the largest (smallest) changes in uninsured rate from the year 2011 to the year 2016. Post is a dummy variable that equals 1 if the loan was issued after 2013 and 0 otherwise. The dependent variables are default in Columns 1-2, interest rate in Column 3, and subgrade in Column 4. Variable definitions are in Appendix 1. The sample consists of the corresponding three-year loans from 2011 to 2016 and five-year loans from 2011 to 2014 in LendingClub. Standard errors are clustered at the subgrade level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Loan Default		Interest Rate	Subgrade
	OLS	Logit		
	1	2	3	4
Treatment	0.011***	0.090***	0.001	0.214***
	(0.002)	(0.018)	(0.001)	(0.067)
Post	0.043***	0.309***	-0.013***	-0.188
	(0.005)	(0.026)	(0.001)	(0.209)
Treatment * Post	-0.005**	-0.034**	-0.000	-0.077
	(0.002)	(0.016)	(0.000)	(0.049)
Controls	Yes	Yes	Yes	Yes
Observations	560,809	560,809	560,809	560,809
R-squared/ Pseudo R2	0.063	0.071	0.388	0.379

Table 8: Robustness check using county-level uninsured rate

Panel A (Panel B) presents the robustness tests of the findings in Table 3 (Table 4) by using county-level uninsured rate. The dependent variables are default in Panel A, and interest rate and subgrade in Panel B. The independent variable of interest is the uninsured rate, measured as the percentage of the nonelderly uninsured population in the county of the P2P loan borrower in the year the loan is issued. Variable definitions are in Appendix 1. The sample consists of all three-year loans from 2010 to 2016 and all five-year loans from 2010 to 2014 in LendingClub. Standard errors are clustered at the subgrade level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Loan default

	OLS			Logit			
	1	2	3	4	5	6	7
Uninsured	0.192***	0.087***	0.057***	1.367***	0.691***	0.466***	0.060
	(0.024)	(0.017)	(0.019)	(0.205)	(0.142)	(0.151)	
Log (Fico)		-0.284***	-0.283***		-4.172***	-4.168***	-0.536
		(0.039)	(0.039)		(0.390)	(0.390)	
Log (Debt / Income)		0.024***	0.024***		0.212***	0.212***	0.027
		(0.002)	(0.002)		(0.008)	(0.008)	
Income		-0.000***	-0.000***		-0.003***	-0.003***	-0.000
		(0.000)	(0.000)		(0.000)	(0.000)	
Log (Credit Days)		-0.007***	-0.007***		-0.059***	-0.060***	-0.008
		(0.001)	(0.001)		(0.007)	(0.007)	
Homeowner		-0.018***	-0.018***		-0.129***	-0.133***	-0.017
		(0.002)	(0.002)		(0.010)	(0.009)	
Mortgage		-0.033***	-0.034***		-0.259***	-0.264***	-0.034
		(0.003)	(0.003)		(0.008)	(0.008)	
Amount		0.001***	0.001***		0.012***	0.012***	0.002
		(0.000)	(0.000)		(0.001)	(0.001)	
Term36m		-0.073***	-0.073***		-0.502***	-0.502***	-0.065
		(0.003)	(0.003)		(0.015)	(0.015)	
Interest Rate		1.631***	1.631***		10.963***	10.960***	1.409
		(0.025)	(0.025)		(0.409)	(0.409)	
Log (GDP)			-0.000			-0.002	-0.000
			(0.000)			(0.003)	
Unemployment			0.002***			0.015***	0.002
			(0.000)			(0.003)	
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	
State Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	
Observations	903,860	903,860	903,860	903,860	903,860	903,860	
R-squared/ Pseudo R2	0.005	0.068	0.068	0.006	0.076	0.077	

Panel B: Loan pricing

	Interest Rate			Subgrade		
	1	2	3	4	5	6
Uninsured	0.037***	0.015***	0.012***	5.113***	2.074***	1.650***
	(0.010)	(0.003)	(0.003)	(1.455)	(0.396)	(0.375)
Log (Fico)		-42.349***	-42.342***		-61.318***	-61.309***
		(4.888)	(4.887)		(6.976)	(6.974)
Log (Debt / Income)		0.516***	0.515***		0.727***	0.725***
		(0.047)	(0.047)		(0.062)	(0.062)
Income		-0.009***	-0.009***		-0.013***	-0.012***
		(0.001)	(0.001)		(0.002)	(0.002)
Log (Credit Days)		-0.953***	-0.954***		-1.378***	-1.379***
		(0.126)	(0.126)		(0.175)	(0.175)
Homeowner		0.092***	0.086***		0.123***	0.116***
		(0.018)	(0.019)		(0.026)	(0.026)
Mortgage		-0.375***	-0.382***		-0.548***	-0.556***
		(0.050)	(0.051)		(0.071)	(0.073)
Amount		0.050***	0.050***		0.072***	0.072***
		(0.006)	(0.006)		(0.009)	(0.009)
Term36m		-4.315***	-4.314***		-6.675***	-6.674***
		(0.587)	(0.586)		(0.900)	(0.900)
Log (GDP)			-0.003			-0.002
			(0.005)			(0.007)
Unemployment			0.021***			0.027***
			(0.005)			(0.006)
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	903,860	903,860	903,860	903,860	903,860	903,860
R-squared	0.082	0.403	0.403	0.032	0.385	0.385

Appendix 1. Variable definitions

Variables	Definition
Borrower Characteristics	
Fico	Lower boundary of the borrower's FICO credit score range at loan origination.
Debt / Income	Ratio of the borrower's total monthly debt payments (excluding mortgage and the requested LendingClub loan) to self-reported monthly income.
Income	Self-reported annual income (in thousands of dollars) provided by the borrower during registration.
Credit Days	Number of days between the opening of the borrower's earliest reported credit line and the peer-to-peer loan issuance date.
Homeowner	A dummy variable that equals 1 if the borrower owns a house, and 0 otherwise.
House Loan	A dummy variable that equals 1 if the borrower has a mortgage loan, and 0 otherwise.
Loan Characteristics	
Amount	Loan amount applied by the borrower.
Term36m	A dummy variable that equals 1 if the loan term is 36 months, and 0 otherwise.
Default	A dummy variable that equals 1 if the loan status is 'Charged Off', 'Default', or 'Does not meet the credit policy', and 0 otherwise.
Interest Rate	Interest rate charged to the borrower on the loan.
Subgrade	A numerical score based on the loan's subgrade, ranging from 1 (A1, highest) to 35 (G5, lowest).
Macro variables	
Uninsured	Percentage of the non-elderly population without health insurance, measured at the state and county levels. Source: U.S. Census Bureau, County Health Rankings & Roadmaps database.
GDP	Gross domestic product (in millions of U.S. dollars) over the past 12 months, measured at the state and county levels. Source: U.S. Census Bureau.
Unemployment	The number of unemployed individuals as a percentage of the total labor force, measured at the state and county levels. Source: U.S. Bureau of Labor Statistics.
Political Balance	Proportion of a state's U.S. House representatives from the Democratic Party, measured at the state level. Source: United States House of Representatives History, Art, and Archives.