Estimation of P2P Lending Rates and Lending Strategies

Review of Integrative Business & Economics Research

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ABSTRACT

This paper uses a quantile regression (QR) model to estimate the lending rates of peer-to-peer (P2P) lending and proposes several useful lending strategies for participants including borrowers, lenders, P2P platforms, and the government. Regarding the determinants of P2P lending rates, in addition to the traditional characteristic variables on loan contracts and borrowers, we particularly emphasize three crucial macroeconomic variables, namely, the S&P500 index return rate, the federal funds rate, and the real estate return rate. The estimation results identify the determinants of P2P lending rates and associated lending strategies. For each determinant, the marginal effects at different quantiles (i.e., quantile-varying marginal effects), especially the largest and smallest ones, provide crucial information for the lenders to earn higher returns, for the borrowers to incur lower loan costs, for the P2P platforms to maintain normal operations, and for the government to effectively monitor P2P lending and avoid disturbances to the financial and economic systems.

Keywords: Peer-to-peer (P2P) lending; Quantile regression; Quantile-varying marginal effect; Lending strategy.

Received 30 January 2021 | Revised 18 May 2021 | Accepted 20 June 2021.

1. INTRODUCTION

Financial technology (FinTech) is an emerging and extensive field that involves many different levels, including payment-related innovations (e.g., blockchain and some distributed ledger technologies) and technologies that promote personal and corporate payments (e.g., Venmo and Apple Pay) as well as online alternative lending. Online alternative lending has shown substantial growth since 2010. Peer-to-peer (P2P) lending (or, online lending, FinTech lending) has evolved from a platform connecting individual borrowers and lenders to a complex network that can characterize institutional investors,

ISSN: 2304-1013 (Online); 2304-1269 (CDROM); 2414-6722 (Print)

direct loans, and securitization transactions. The development of P2P lending and the use of big data have changed the financing methods for consumers and small businesses. There are some symptoms showing that these alternative lenders can benefit from cooperating with banks. For example, Lending Club secured a certain amount of loan through WebBank.

The rapid development of P2P lending has attracted the interest of researchers. Agrawal *et al*. (2013) illustrate how transaction costs, reputation, and market design explain the growth of P2P lending. A few studies analyze the role of P2P lenders in expanding credit availability and borrowers rejected by traditional banks. For example, Schweitzer and Barkley (2017) find that companies' loan applications rejected by banks had similar characteristics, and most of them turn to P2P lending. Other P2P lending surveys have shown that P2P lending platforms can increase the value of P2P lending (Desai and Meekings 2016). Some literature focuses on issues related to P2P lending, such as default rate (Emekter *et al*. 2015), herd behavior (Herzenstein *et al*. 2011), and social networks (Freedman and Jin 2017). However, most of these studies rely on survey data and are subject to sample selection bias and inconsistent response results.

A branch of research analyzes the determinants of P2P lending rates, and the main determinants include the characteristic variables of loan contracts and borrowers, such as loan amount, loan term, loan purpose, debt-to-income ratio (DTI), the years of employment, credit rating, and home ownership status (Demyanyk and Kolliner 2014; Mach *et al*. 2014; Emekter *et al*. 2015; Dietrich and Wernli 2016). Few studies emphasize the importance of macroeconomic conditions in determining P2P lending rates, such as the economic outlook and unemployment rate (Bertsch *et al*. 2016; Dietrich and Wernli 2016; Lin and Zaiyan 2016). In general, the conclusions in terms of the influence of the determinants on P2P lending rates are mixed.

Although previous studies have provided a good basis for estimating P2P lending rates, there are still at least three problems to be addressed. First, most of the past studies use the least squares approach to estimating P2P lending rates. This approach focuses more on the central tendency of a distribution. That is to say, it can only obtain the average marginal effect of an explanatory variable on the dependent variable and cannot predict the impact of the extreme values in the data. Second, most of the past studies consider only the impacts of loan contract terms and borrower's personal information on P2P lending rates and rarely consider the impacts of the macroeconomic environment variables on P2P lending rates. Third, most of the past studies do not provide P2P lending strategies, especially those based on the estimation results from a quantile regression performed in this study.

To address the above issues, this study applies the quantile regression approach and

ISSN: 2304-1013 (Online); 2304-1269 (CDROM); 2414-6722 (Print)

considers three important macroeconomic variables (federal funds rate, S&P500 index return rate, and real estate return rate) in estimatingP2P lending rates at various quantiles. The federal funds rate represents the direction of monetary policy, the real estate return rate proxies the stability of the economic system (Andrews *et al*. 2011),[1] while the S&P 500 index return rate proxies the non-permanent return to an investment in financial assets (Chava and Purnanandam 2010).[2] Due to the high correlation between the federal funds rate and unemployment rate, the latter is removed from this study avoid the collinearity problem (Bertsch *et al*. 2016; Dietrich and Wernli 2016), while the federal funds rate is retained to highlight the role of monetary policy in determining P2P lending rates. The estimation results from quantile regression at different quantiles provide useful information for borrowers, lenders, and P2P platforms to engage in and manage P2P lending.

In this study, 1,325,181 observations were collected from the database of the Lending Club online lending platform. The empirical findings achieve the following purposes: (1) The participants of P2P lending can more accurately estimate the effects of various determinants on P2P lending rates at different quantiles; (2) P2P lending platforms can effectively control their lending risks; and (3) P2P lenders and borrowers can understand in more detail the impacts of various determinants on P2P lending rates at different quantiles, and thereby reduce their P2P lending risks and attain more favorable lending rates.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature on the determinants of P2P lending rates as a basis for constructing an empirical model for this study. Section 3 introduces the quantile regression model used in this study to estimate the effects of various determinants on P2P lending rates at different quantiles. Section 4 describes the data sources, presents the empirical results, and proposes several P2P lending strategies for participants and regulators of P2P lending platforms. Section 5 concludes this article.

2. LITERATURE REVIEW

Most empirical studies on P2P lending rates use data from Lending Club and Prosper to conduct relevant estimations, and generally find that the determinants of P2P lending rates include loan characteristic factors, borrower-specific factors, and macroeconomic factors. The loan characteristic factors are mainly the loan amount and loan term, while the borrower-specific factors refer to all variables that affect credit rating. Regarding the

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[1]Greater house price volatility can reduce macroeconomic stability and income certainty for households.
[2]Chava and Purnanandam (2010) use the implied cost of capital as a measure of the expected return and find evidence in support of a positive relationship between default risk and stock returns.

ISSN: 2304-1013 (Online); 2304-1269 (CDROM); 2414-6722 (Print)

macroeconomic factors, P2P lending rates are generally influenced by changes in monetary policy and business cycles. Generally, a rise in risk-free interest rates increases the interest rates of newly signed loans. A change in economic cycle measured by unemployment rate or GDP growth also affects loan interest rates (Kiyotaki and Moore 1997).

In terms of loan contract factors and borrower-specific factors, empirical results from Demyanyk and Kolliner (2014) show that borrowers with good credit ratings can obtain lower interest rates through P2P lending rather than through credit card loans. Mach *et al*. (2014) show that P2P lending rates vary with loan purposes. Emekter *et al*. (2015) find that borrowers with low debt-to-income (DTI) ratios have lower default risks and that charging riskier borrowers higher lending rates cannot reduce the default rate. Chemiakin (2016) finds evidence showing that the P2P lending rate decreases by 0.654% if the the borrower's credit rating increases by one level, and that the loan purpose insignificantly affect the lending rate. Dietrich and Wernli (2016) use 665 observations from the loan data of Cashare, i.e., the largest platform in the Swiss P2P lending market, to estimate the lending rate, and find that borrowers with larger loan amounts and/or house ownership enjoy significantly lower lending rates, while those with a higher DTI need to pay higher lending rates.

Jagtiani and Lemieux (2017) use loan data from Lending Club to explore the difference between P2P lending platforms and traditional banks in terms of providing similar loans. Their empirical results show that under the same FICO score, borrowers of Lending Club are in general riskier than those of traditional banks. Moreover, under the same default risk, Lending Club's borrowers pay a lower loan spread than traditional banks' borrowers do. Zhang (2019) uses multiple regression and quantile regression to explore the factors influencing Lending Club's expansion to small business loans. His empirical evidence supports that small business loans provided by traditional banks and Lending Club are substitutes.

In terms of macroeconomic factors, Doms *et al*. (2007) indicate that changes in housing prices are expected to have an impact on mortgage delinquencies. Borrowing interest rates are usually high in states where subprime mortgage activities are interest rates are at high levels. After controlling for the current rise in housing prices, housing price deceleration measures are important predictors of changes in the default rate of subprime mortgages. In addition, in local markets where the unemployment rate is rising, borrowers may need to sell their houses to repay mortgage loans.

Bertsch *et al*. (2016) use Prosper and Lending Club data to study the influences of macroeconomic variables on default probability and lending rates. Their empirical results indicate that after controlling for the borrower and loan contract characteristics, states

ISSN: 2304-1013 (Online); 2304-1269 (CDROM); 2414-6722 (Print)

with a higher unemployment rate usually has higher P2P lending rates. In addition, an expected improvement in future economic conditions (measured by changes in the yield curve) leads to a fall in P2P lending rates.

Lian (2017) evaluates the impact of FED's interest rate adjustments during 2008-2016 on the Lending Club lending rates. His empirical evidence suggests that the interest rate cuts in 2008 significantly increased P2P lending rates especially for high-risk borrowers. However, the interest rate increases in 2015 did not cause P2P lending rates to fall significantly, while the lending rate of high-risk borrowers rose even after the rate increases. Thus, interest rate adjustments by FED had asymmetric effects on P2P lending rate.

Chen (2020) uses data from Lending Club and applies a regression model to estimate the impacts of FinTech indices, borrower risk characteristics, and macroeconomic conditions on FinTech lending rates. His empirical results show that the longer the loan term, a higher unemployment rate, a higher debt-to-income ratio, a lower credit rating, a higher federal funds rate, and/or a greater loan risk will increase FinTech lending rate. In addition, services provided by traditional banks and Lending Club are complementary. Furthermore, the loan purpose of repaying credit card debt has the lowest P2P lending rate among all loan purposes.

In sum, past studies do not consider two potential problems when estimating P2P lending rates. First, they ignore the differential effects of each individual variable on P2P lending rates. That is to say, each variable should have different impacts on P2P lending rates at different quantiles. Second, most of the past studies do not consider the impacts of crucial macroeconomic variables on P2P lending rates, leading to biased estimates especially under the framework of quantile regression. To address these potential issues, the present study formulates quantile regression models with independent variables including contract-specific factors, borrower-specific factors, and macroeconomic factors, and estimates the impacts of these variables on P2P lending rates. The quantile regression approach not only captures the differential impacts of the independent variables on P2P lending rates at different quantiles, but also provides important and detailed information for borrowers, lenders, and P2P lending platform (e.g., Lending Club) to adopt appropriate lending strategies aiming to reduce lending risks (or costs) and increase lending returns.

3. EMPIRICAL MODEL

3.1 Quantile regression

ISSN: 2304-1013 (Online); 2304-1269 (CDROM); 2414-6722 (Print)

The traditional regression approach can only observe the conditional distribution of the population mean. That is, the regression coefficient represents the average marginal distribution effect of the explanatory variable on the dependent variable, focusing on the estimation results when the central trend of the distribution is concentrated. Once the conditional distribution of the explanatory variable to the dependent variable does not lie in the population mean, the result may be insignificant. The quantile regression (QR), proposed by Koenker and Bassett (1978), is a statistical method used to estimate, infer, and process the conditional quantile function. By minimizing the linear objective function of the residuals, the best regression coefficient is estimated, that is, the regression coefficient is a measure of the marginal distribution effect of the explanatory variable on the dependent variable at a specific quantile. QR can overcome the shortcomings of the least squares estimation method and can predict the generation of extreme values of the data, thereby obtaining more accurate estimates and providing the characteristics of data distribution and redistribution.

Let Y be a real valued random variable with cumulative distribution function $F_Y = P(Y \le y)$. The θ*-th* quantile of Y is given by $Q_\theta(Y)$, where $\theta \sim (0,1)$. Let $Q_\theta(Y)$ be equal to a specific value q_θ, this means that θ of them will be less than or equal to q_θ, and $(1-\theta)$ of them will be greater than or equal to q_θ. Thus, q_θ can be solved by the following conditional equation:

$$q_\theta = arg \;\; M\,in \left[\theta \int_{y \ge q_\theta} |y - q_\theta|\, dF_Y(y) + (1-\theta)\int_{y<q_\theta} |y - q_\theta|\, dF_Y(y)\right] \tag{1}$$

Assume a linear model is as follows:

$$y_t = x_t\beta + \varepsilon_t,\; t = 1,\ldots,T \tag{2}$$

The regression at the θ*-th* quantile can be expressed as follows:

$$y_t = x_t\beta_\theta + \varepsilon_{\theta t},\; q_\theta\left(\frac{y_t}{x_t}\right) = x_t\beta_\theta \tag{3}$$

where $q_\theta(y_t/x_t) = x_t\beta_\theta$ represents the mean regression equation of the θ*-th* quantile of y under the condition of regressors vector x_t. The estimator of regression coefficients β_θ can be expressed as follows:

$$\beta_\theta = \underset{\beta}{\mathrm{Min}}\left\{\sum_{y \ge x_t\beta} \theta|y_t - x_t\beta| + \sum_{y<x_t\beta}(1-\theta)|y_t - x_t\beta|\right\} \tag{4}$$

Eq. (4) means that as long as the weight θ is given, the minimum weighted average of the absolute values of the error terms can be used to obtain the regression estimator under different quantiles. That is, if the observed value y is greater than or equal to the estimated value $x_t\beta_\theta$, the weight is θ, and the observed value y is less than the estimated value $x_t\beta_\theta$, the weight is $(1-\theta)$, then the parameter β_θ can be found. When θ=0.5, Eq. (4) is

ISSN: 2304-1013 (Online); 2304-1269 (CDROM); 2414-6722 (Print)

multiplied by 2 to become $\sum_{t=1}^{T}|y_t - x_t\beta|$. This is the estimator of LAD (least absolute deviation), which is also called median regression. Thus, median regression is just a special case of quantile regression. In addition, $\hat{\beta}_\theta$ means that x_t changes by one unit, y_t at the θ-th quantile will change by $\hat{\beta}_\theta$ units.

3.2 Estimation model of P2P lending rate

This study chooses the characteristic variables of loan contracts and borrowers, mentioned in the section of Literature Review, and adds key macroeconomic variables as the independent variables to construct the quantile regression model for estimating P2P lending rate as follows:

$$\begin{aligned} LOANR = \alpha + \beta_1 LOANA + \beta_{2.} DTI + \beta_{3.} GRADE + \beta_{4.} PAI + \beta_{5.} EMLEN + \\ \beta_{6.} H1 + \beta_{7.} TERM + \beta_{8.} P1 + \beta_{9.} P2 + \beta_{10.} SP500 + \beta_{11.} FFR + \beta_{12} RER + \mu \end{aligned} \tag{5}$$

where *LOANR*, *LOANA*, *DTI*, *GRADE, PAI*, *EMLEN*, *SP500*, *FFR*, *and RER* denote loan interest rate (%), loan amount, debt-to-income ratio (%), credit rating (from A to H), personal annual income, the years of employment, S&P500 index return rate (%), federal funds rate (%), and real estate return rate (%), respectively. *H1*, *TERM*, *P1*, and *P2* are dummy variables. *TERM* is the loan term, *TERM*=0 means a 36-month loan, and *TERM*=1 means a 60-month loan. P1 and P2 represent loan purposes. P1=P2=0 means loans for credit cards; P1=1 and P2=0 mean loans for debt consolidation, and P2=1 and P1=0 mean loans for other purposes. *H1* denotes the home ownership status of P2P borrowers. *H1*=1 means the borrowers already have a mortgage loan; *H1*=0 represents the borrowers belong to other home ownership status. Through the quantile regression mentioned above, the parameters β_θ at different quantiles can be estimated.

4. EMPIRICAL RESULTS AND LENDING STRATEGIES

4.1 Data description

Empirically, a total of 1,373,228 observations from the database of the Lending Club during Q1:2007-Q4:2018 is used for estimation. The data sources and measurements of variable used in this study are shown in Table 1.

Currently, there are two mechanisms for determining the interest rates that borrowers must pay from a P2P lending platform, i.e., *reverse auction process* and *published prices process*. The reverse auction system is similar to bond auctions where supply and demand determine interest rates. Potential borrowers post their loan applications on the platform, and investors bid at the corresponding minimum interest rate during the auction. Major players in the largest P2P lending market in the US and the UK use this pricing process, such as Lending Club and Prosper. The platform sets the interest rate of each loan list

ISSN: 2304-1013 (Online); 2304-1269 (CDROM); 2414-6722 (Print)

based on the information available to the borrower, which simplifies and shortens the process of borrowers and lenders (Chen *et al*. 2014).

Table 1 Data source and measure

Variable	Meaning	Measurement	Source
LOANR	Loan rate		Lending Club
LOANA	Loan amount		Lending Club
GRADE	Credit rating	The ranking from best to worst is A to G, A is set to 1, and so on, G is set to 7.	Lending Club
EMLEN	Years of employment	It ranges from 0.5 to 10 years, of which less than 1 year is set to 0.5 years, and more than 10 years to 10 years.	Lending Club
DTI	Debt-to-income ratio		Lending Club
TERM	Loan term, a dummy variable	TERM=0 means the loan term is 36 months, and TERM=1 means the loan term is 60	Lending Club
H1	Home ownership status, a dummy variable	*H1*=1 means borrowers already have a mortgage loan; *H1*=0 represents the borrowers belong to other home ownership status (including own, rent, and other).	Lending Club
P1, *P2*	Loan purpose, dummy variables	P1=P2=0 means loans for credit cards; P1=1 and P2=0 means loans for debt consolidation; and P2=1 and P1=0 means loans for other purposes.	Lending Club
RER	Real estate return rate		US Statistics Bureau
FFR	Federal funds rate		US Statistics Bureau
SP500	S&P500 index return rate		US Statistics Bureau

To understand the basic characteristics of each variable, a descriptive statistical analysis is performed, and the results are shown in Table 2. Regarding the variables capturing the loan contracts' and the borrowers' characteristics (Panel A), personal annual income (PAI) has the largest mean (80,007), and credit rating has the smallest one (2.5767). Personal annual income (PAI) has the largest (134,938) standard deviation, and the credit rating

ISSN: 2304-1013 (Online); 2304-1269 (CDROM); 2414-6722 (Print)

has the smallest one (1.2136). Obviously, PAI has the largest fluctuation magnitude among the six variables. Only the years of employment (EMLEN) have a negative skewness coefficient (-0.0558), showing a left-skewed distribution. Other variables have positive skewness coefficients, implying a right-skewed distribution. The amount of loan and the years of employment have kurtosis coefficients less than 3, which shows a platykurtic distribution. The kurtosis coefficients of the remaining variables are all greater than 3, revealing that these variables belong to a leptokurtic distribution. In addition, at the 5% significance level, the test statistics for normal distribution (Jarque-Bera) show that all these six variables are not a normal distribution.

Regarding the macroeconomic variables (Panel B), the unemployment rate (%) has the largest mean (4.3408), and S&P500 return rate (%) has the smallest one (-0.0076). Federal funds rate (%) has the largest (0.6336) standard deviation, and real estate return has the smallest one (0.0020). Moreover, all four variables have positive skewness coefficients and display a right-skewed distribution. For federal funds rate and unemployment rate, the kurtosis coefficients are less than 3, showing a platykurtic distribution, and for S&P500 return rate and real estate return, the kurtosis coefficients are greater than 3, belonging to a leptokurtic distribution. Finally, at the 5% significance level, the test statistics for normal distribution support that all these four variables are not a normal distribution.

Table 2 Descriptive statistics

Panel A. Loan contracts' and borrowers' characteristics

	LOANR	*LOANA*	*DTI*	*GRADE*	*PAI*	*EMLEN*
Mean	12.993	15230	19.270	2.5767	80007	5.4493
Max.	30.990	40000	999.00	7.0000	1.10E+8	10.000
Min.	5.3100	1000.0	0.0000	1.0000	0.3600	0.0000
Std. Dev.	5.0983	9639.3	16.883	1.2136	134938	3.9259
Skewness	0.9152	0.8004	28.246	0.6607	471.01	-0.0558
Kurtosis	3.8139	2.8448	1429.3	3.3387	351851	1.4021
J-B statistic	229339	147835	1.16E+11	106338	7.07E+15	146632
P-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	1373228	1373228	1373228	1373228	1373228	1373228

Panel B. Macroeconomic variables

	SP500	*FFR*	*UR*	*RER*
Mean	-0.0076	1.1199	4.3408	0.0050
Max.	0.0656	2.2700	5.0000	0.0111
Min.	-0.0617	0.3400	3.7000	0.0007
Std. Dev.	0.0267	0.6336	0.4292	0.0020
Skewness	0.6926	0.2739	0.1502	0.5621
Kurtosis	3.8623	1.7602	1.6047	4.0711

ISSN: 2304-1013 (Online); 2304-1269 (CDROM); 2414-6722 (Print)

J-B statistic	152137	104990	116413	137787
P-value	0.0000	0.0000	0.0000	0.0000
Observations	1373228	1373228	1373228	1373228

Notes: The meaning of each variable is as shown in Table 1. J-B statistic a test statistic to investigate the null hypothesis of a series with a normal distribution. Dummy variables are not included in the descriptive statistical analysis.

Table 3 Correlation test result

Correlation coefficient	*LOANR*	*DTI*	*GRADE*	*PAI*	*EMLEN*	*SP500*	*FFR*	*UR*	*RER*
LOANR	1								
DTI	0.044	1							
GRADE	0.073	0.115	1						
PAI	0.168	-0.069	-0.045	1					
EMLEN	0.093	-0.021	-0.018	0.062	1				
SP500	0.022	0.007	-0.033	0.008	-0.017	1			
FFR	0.054	0.022	-0.106	0.003	-0.044	0.313	1		
UR	-0.050	-0.022	0.100	-0.002	0.043	-0.232	-0.956	1	
RER	-0.012	-0.003	0.022	-0.001	0.001	-0.098	-0.181	0.140	1

Notes: The meaning of each variable is as shown in Table 1. Dummy variables are not included in the correlation test. Except for the correlation coefficient between RER and PAI, the remainder is significantly different from zero at the 5% significance level.

4.2 Empirical result

The estimation results of quantile regressions are shown in Table 4. This study estimates P2P lending rates at five important quantiles, i.e., θ=0.1, 0.25, 0.5, 0.75, and 0.9), while θ=0.25, 0.5, and 0.75 are the three quantiles corresponding to the quartile, and θ=0.1 and 0.9 represent two extreme quantiles.

At all the five quantiles, the variables that have a positive marginal effect on the lending rate include debt-to-income ratio (DTI), credit rating (GRADE), housing status (H1), and federal funds rate (FFR). In other words, the increase in the values of these four variables will increase the P2P lending rate. First, an increase in debt-to-income ratio or credit rating (that is, a deterioration in credit rating) indicates that the borrower's solvency becomes weaker, and the risk of default increases. To ensure the lender's rights, the lender of funds will compensate by raising the lending rate. Second, the debt burden of P2P borrowers with mortgages is heavier than that of borrowers without mortgages, and the risk of default is also higher, so the loan rate is higher. In addition, under normal circumstances, the increase in the federal funds rate will drive the increase in the

ISSN: 2304-1013 (Online); 2304-1269 (CDROM); 2414-6722 (Print)

traditional bank lending rate. If the P2P lending rate also rises at this time, it means that the two parties are in the same direction in adjusting the lending rate. They are complementary to each other.

Although the above variables have positive effects on the P2P lending rate, there are still some obvious differences in the marginal effects at different quantiles (i.e., *quantile-varying marginal effects*). First, for the debt-to-income ratio and housing status, the greatest marginal effect appears at the 0.5 quantile, and for the credit rating and federal funds rate, the largest marginal effect appears at the 0.9 quantile and 0.1 quantile, respectively. As for the smallest marginal effect, for the debt-to-income ratio and credit rating, it appears at the 0.1 quantile, and for the housing status and federal funds rate, it appears at the 0.9 and 0.75 quantiles, respectively. In other words, the median quantile and the two extreme quantiles (0.1 and 0.9 quantiles) play an extremely important role in the estimation results. More importantly, once the OLS method is used for estimation, it will cause a biased estimation result and provide no more detailed information for risk management in the P2P lending platform.

At all the five quantiles, the variables that have a negative marginal effect on the lending rate include personal annual income (PAI), the years of employment (EMLEN), loan term (TERM), loan purpose (P1 and P2), and S&P500 index return rate (SP500). The higher the YAI is or the longer the EMLEN is, the lower the default probability and lending rate would be. The increase in the SP500 that represents a booming economy or an increase in the financial investment return of P2P borrowers results in a reduction in default risk and then a lower required lending rate. The interest rates of P2P lending are lower for borrowers to repay the debts of credit cards and the other spending than borrowers to perform debt consolidation. The probable reason is that debt consolidation itself represents a complex debt repayment problem and may extend as persistent debt or debt behavior. However, P2P lending for other purposes (such as marriage, travel, etc.) is relatively simple and may be limited to a one-time expenditure. In addition, to actively expand the market share of 5-year small loans, Lending Club provides preferential borrowing rates, compared to 3-year small loans.

As mentioned above, the marginal effects of individual variables on the lending rates vary with the estimation results at different quantiles. That is, the marginal effects are *quantile-varying*.

For the readers to easily judge the difference in significance and symbol of the estimated coefficients in Table 4, we summarize these results in Table 5. Evidently, the sign and significance of the estimated coefficients display quite different. Moreover, the largest and smallest marginal effects of independent variables on the loan rates mostly appear at 0.1, 0.5, and 0.9 quantiles.

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Table 4 Estimation result of P2P lending rate

	Estimation model		
	Least square	Quantile regression (θ=0.1)	Quantile regression (θ=0.25)
Variable	Coefficient	Coefficient	Coefficient
C	2.4293(0.000)	1.3837(0.000)	1.9768(0.000)
LOANA	-0.0048(0.010)	-0.0080(0.000)	-0.0080(0.000)
DTI	0.0015(0.000)	0.0007(0.000)	0.0017(0.000)
GRADE	4.0571(0.000)	3.8068(0.000)	3.8712(0.000)
PAI	-0.0473(0.000)	-0.0531(0.000)	-0.0563(0.000)
EMLEN	-0.0002(0.479)	-0.0010(0.004)	-0.0006(0.000)
H1	0.0560(0.000)	0.0449(0.000)	0.0481(0.000)
TERM	-0.1526(0.000)	-0.0819(0.000)	-0.1498(0.000)
P1	-0.1035(0.000)	-0.0884(0.000)	-0.0860(0.000)
P2	-0.0012(0.679)	-0.0105(0.003)	-0.0088(0.000)
SP500	-0.0073(0.000)	-0.0114(0.000)	-0.0017(0.000)
FFR	0.6534(0.000)	0.7742(0.000)	0.6627(0.000)
RER	0.0472(0.000)	0.0656(0.000)	0.0892(0.000)
R-squared	0.9372		
F-statistic	1.88E+7(0.000)		
Pseudo R-squared		0.7117	0.7265
Quasi-LR statistic		2.83E+7(0.000)	4.57E+7(0.000)

	Estimation model		
	Quantile regression (θ=0.5)	Quantile regression (θ=0.75)	Quantile regression (θ=0.9)
Variable	Coefficient	Coefficient	Coefficient
C	3.4604(0.000)	3.5728(0.000)	2.8436(0.000)
LOANA	-0.0193(0.000)	-0.0107(0.000)	0.0086(0.000)
DTI	0.0032(0.000)	0.0024(0.000)	0.0018(0.000)
GRADE	3.9126(0.000)	4.1304(0.000)	4.2662(0.000)
PAI	-0.0777(0.000)	-0.0466(0.000)	0.0002(0.941)
EMLEN	-0.0002(0.615)	-0.0004(0.239)	-0.0007(0.024)
H1	0.0849(0.000)	0.0564(0.000)	0.0158(0.000)
TERM	-0.1937(0.000)	-0.1674(0.000)	-0.1528(0.000)
P1	-0.1702(0.000)	-0.0960(0.000)	-0.0282(0.000)
P2	-0.0170(0.000)	-0.0076(0.023)	0.0004(0.906)
SP500	-0.0053(0.000)	0.0002(0.789)	-0.0018(0.000)
FFR	0.4580 (0.000)	0.4571(0.000)	0.6515(0.000)
RER	0.1292(0.000)	0.0070(0.139)	-0.0353(0.000)
Pseudo R-squared	0.7319	0.7690	0.8044

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Quasi-LR statistic	3.81E+7(0.000)	4.46E+7(0.000)	5.21E+7(0.000)

Notes: The meaning of each variable is as shown in Table 1. The digits in ( ) after the estimated coefficients are p-values.

Table 5 Summarization of the significance and symbol of the estimated coefficients

Variable	*OLS*	θ=0.1	θ=0.25	θ=0.5	θ=0.75	θ=0.9
LOANA	-	$-^{m}$	-	$-^{M}$	-	+
DTI	+	$+^{m}$	+	$+^{M}$	+	+
GRADE	+	$+^{m}$	+	+	+	$+^{M}$
PAI	-	-	-	$-^{M}$	$-^{m}$	?
EMLEN	?	$-^{M}$	-	?	?	-
H1	+	+	+	$+^{M}$	+	$+^{m}$
TERM	-	$-^{m}$	-	$-^{M}$	-	-
P1	-	-	-	$-^{M}$	-	$-^{m}$
P2	?	-	-	$-^{M}$	$-^{m}$	?
SP500	-	$-^{M}$	$-^{m}$	-	?	-
FFR	+	$+^{M}$	+	+	$+^{m}$	+
RER	+	$+^{m}$	+	$+^{M}$	?	-
Frequency of maximum (M) and minimum (m) marginal effects		M=3 m=5	M=0 m=1	M=8 m=1	M=0 m=3	M=1 m=2

Notes: The symbols '+', '-', and '?', taken from Table 4, denote that the corresponding estimated coefficients are significantly positive, significantly negative, and insignificant, respectively. The meaning of each variable is as shown in Table 1.

Table 6 lists the heterogeneity test results of the estimation coefficients of quantile regression at different quantiles. The test takes the median quantile (θ=0.5) as the benchmark and examines whether the estimated coefficients at the 0.1, 0.5, and 0.9 quantiles are different. The reason to use these three quantiles is that the largest and smallest marginal effects of independent variables (see Table 5) on the loan rates mostly appear at 0.1, 0.5, and 0.9 quantiles. Once the test results confirm that there is a significant difference between the estimated coefficients, it strongly supports the need to use the quantile regression for estimation. The null hypothesis is that there is no significant difference in the estimated coefficients under different quantiles, that is, $\beta_k^{0.1} = \beta_k^{0.5}$ and $\beta_k^{0.5} = \beta_k^{0.9}$, k=1,…,12. Except for EMLEN, there are significant differences in the estimated coefficients of the remaining variables under three different quantiles. Thus, it is appropriate to use quantile regression for estimation, and it can provide more accurate estimation results and more diverse information content.

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Table 6 Heterogeneity test for the coefficients of quantile regression

Variable	Null hypothesis	F-statistic	p-value
LOANA	$\beta_1^{0.1} = \beta_1^{0.5}$ & $\beta_1^{0.5} = \beta_1^{0.9}$	44.17	0.000
DTI	$\beta_2^{0.1} = \beta_2^{0.5}$ & $\beta_2^{0.5} = \beta_2^{0.9}$	93.92	0.029
GRADE	$\beta_3^{0.1} = \beta_3^{0.5}$ & $\beta_3^{0.5} = \beta_3^{0.9}$	22851.3	0.000
PAI	$\beta_4^{0.1} = \beta_4^{0.5}$ & $\beta_4^{0.5} = \beta_4^{0.9}$	290.40	0.000
EMLEN	$\beta_5^{0.1} = \beta_5^{0.5}$ & $\beta_5^{0.5} = \beta_5^{0.9}$	0.95	0.387
H1	$\beta_6^{0.1} = \beta_6^{0.5}$ & $\beta_6^{0.5} = \beta_6^{0.9}$	153.23	0.000
TERM	$\beta_7^{0.1} = \beta_7^{0.5}$ & $\beta_7^{0.5} = \beta_7^{0.9}$	341.62	0.000
P1	$\beta_8^{0.1} = \beta_8^{0.5}$ & $\beta_8^{0.5} = \beta_8^{0.9}$	442.30	0.000
P2	$\beta_9^{0.1} = \beta_9^{0.5}$ & $\beta_9^{0.5} = \beta_9^{0.9}$	17.19	0.000
SP500	$\beta_{10}^{0.1} = \beta_{10}^{0.5}$ & $\beta_{10}^{0.5} = \beta_{10}^{0.9}$	192.26	0.000
FFR	$\beta_{11}^{0.1} = \beta_{11}^{0.5}$ & $\beta_{11}^{0.5} = \beta_{11}^{0.9}$	3564.2	0.000
RER	$\beta_{12}^{0.1} = \beta_{12}^{0.5}$ & $\beta_{12}^{0.5} = \beta_{12}^{0.9}$	117.31	0.000

Note: The meaning of each variable is as shown in Table 1. $\beta_k^{\theta}, k = 1,...,12$ $\theta = 0.1, 0.5, 0.9$ represents the estimated coefficient of explanatory variable k at the θ-*th* quantile.

According to the results in Table 4 through Table 6, several empirical results of this study support the necessity of using quantile regression to estimate P2P lending rates. First, under each quantile, the marginal effects of variables on the P2P lending rates are different, including the size and reversal of the effects, and the significance of the estimated coefficients. Second, the largest and smallest marginal effects of the independent variables on the P2P lending rates appear 3 times and 5 times for borrowers' loan rates at the 0.1 quantile, 8 times and 1 time for borrowers' loan rates at the 0.5 quantile, and 1 time and 2 times for borrowers' loan rates at the 0.9 quantile. Third, for borrowers with high loan interest rates (θ=0.75 and 0.9 quantiles), the marginal effect of specific variables (e.g., loan amount and real estate return) on the P2P lending rate will generate a reversal in sign, or produce insignificant marginal effects, such as PAI and P2 at the 0.9 quantile, and EMLEN, SP500, and real estate return at the 0.75 quantile.

In fact, the marginal effect of a specific regressor on the loan rate can describe the change in equilibrium loan rate. Thus, lenders and borrowers can adjust their lending behaviors according to the equilibrium shift. However, facing different quantiles of borrowers, lenders will make differential adjustments in loan rates. For example, leaders would increase the loan rate by 0.0007% for borrowers at the 0.1 quantile and by 0.0017% for borrowers at the 0.25 quantile as DTI increases by 1%. Similarly, borrowers at the 0.25 quantile would expect an increase of 0.0017% in the loan rate as DTI raises by 1%. The impacts of changes in other regressors on lending behavior can be similarly deduced.

4.3 Lending strategy suggestions

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According to the above results, this study provides the following suggestions in terms of the P2P lending strategies for the borrowers and lenders.

First, when estimating the P2P lending rate, it is more appropriate to use the quantile regression model due to its provision of richer information content, which provides a reference for investing in P2P lending. Regarding the choice of independent variables, in addition to the characteristics of the loan contracts and borrowers, the consideration of macroeconomic variables is also important; otherwise, it will produce biased estimation results and policy recommendations.

Second, if safety or low risk is the first consideration, during the periods of the rise of FFR and RER, the lenders of P2P lending should choose borrowers at the 0.1 quantile as the lending object because the marginal effect of the increase in loan interest rate is the largest. For borrowers with shorter working years, the lenders should also choose borrowers at the 0.1 quantile as the lending object to get the largest marginal benefit in the loan rates. Regarding the loan purpose, P2P borrowers at the 0.5 quantile that already have mortgage loans are the preferred objects for the lenders to obtain the highest lending returns.

Third, for the borrowers of P2P lending, choosing the following statuses for P2P lending is conducive to the decline in interest rates of P2P loans: (1) lower debt-to-income ratio; (2) improvement in credit rating; (3) the periods of stock markets boom, the federal funds rate fall, and the real estate price decline; (4) choice a 5-year loan, and (5) increase in the amount of loan. Specifically, it is most beneficial to get lower loan rates for borrowers at low quantile (θ=0.1) to choose lending during the periods of stock markets boom and FFR decline; for borrowers at median quantile (θ=0.5) to lower DTI, choose 5-year loans, and increase loan amounts, and for borrowers at high quantile (θ=0.9) to improve credit rating.

Fourth, the managers of the P2P lending platform need to carefully check and identify the correctness of the P2P borrowers' information in order to classify them into proper quantiles and reasonably reflect the marginal effects of each independent variable for the P2P lenders and borrowers to conduct the lending. Platform managers can even use the estimation model used in this paper to estimate the P2P lending rate and provide information about the estimated results for the borrowers and lenders. For example, using the estimation model in Table 4, platform managers can announce to borrowers and lenders about by how much the loan interest rate at each quantile will increase if FFR rises by 0.25%, so that the borrowers and lenders can prepare in advance to reduce the default risk. Specifically, the loan rate would increase by 0.1934% for borrowers at the 0.1 quantile and by 0.1629% for those at the 0.9 quantile. Moreover, a fall in the stock

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market (measured by SP500) also leads to a differential rise in the loan rates for borrowers at different quantiles. However, through an information announcement by platforms based on the results in Table 4, lenders will expect that the loan rate increase is largest for borrowers at the 0.1 quantile.

Finally, the stock market decline will pull up the P2P lending rates at most quantiles. Thus, the U.S. government should pay attention and take appropriate policies to avoid the collapse of the P2P lending market originated from stock index fall, which in turn hurts the financial system.

5. CONCLUSION

This study uses the quantile regression approach to estimating the P2P lending rates of the Lending Club platform. In addition to the traditional characteristic variables of loan contracts and borrowers, we particularly consider three important macroeconomic variables (federal funds rate and the return rates of S&P500 index and real estate) as explanatory variables and explore their roles in P2P lending rates.

This study provides strong empirical evidence for using the quantile regression approach to the estimation of P2P lending rates, and estimate the differential marginal effects (in scale, sign, and significance) of each determinant on P2P lending rates at various quantiles. Moreover, the largest and smallest marginal effects of each independent variable at different quantiles provide crucial information for P2P lenders to choose preferred borrowers to earn the highest returns, for P2P borrowers to select a correct timing to engage in lending and methods to improve their lending conditions and reduce their loan costs, and for the government to monitor the operation of P2P lending to avoid its potentially destabilizing effect on the financial system. We also offer several suggestions in terms of P2P lending strategies based on the empirical results from this study.

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