# The Impact of FinTech Index on P2P Lending Rate

Review of Integrative Business & Economics Research

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**ABSTRACT**

This study constructs an empirical model to investigate the impact of the financial technology index (FinTech index) on the interest rate spreads of FinTech lending. 1,201,658 observations from the Lending Club platform over the period of 2007 to 2018 were selected for our empirical analysis. The empirical results show that: (1) the higher the degree of financial technology development, the more conducive it is to reducing the loan interest rate of FinTech lending; (2) the longer the loan term is, the worse the credit rating is; and the higher the unemployment rate, income-to-debt ratio, and federal funds rate are, the greater the loan risk and the higher the interest rate spreads are; (3) services provided by traditional banks and FinTech lending platforms are mutually complementary; and (4) Borrowers borrow from FinTech to repay their credit card debts and their borrowing interest rate is the lowest among all borrowers; FinTech lends to borrowers who have mortgaged loans and charge them the lowest borrowing rate among all housing conditions. Several policy suggestions are provided.

Keywords: P2P lending; lending rate spreads; financial technology index; borrower's risk characteristics.

Received 9 February 2021 | Revised 6 June 2021 | Accepted 22 August 2021.

## 1. INTRODUCTION

Financial technology (FinTech) is an emerging field that involves many different levels, including payment-related innovations (e.g., blockchain and some distributed account


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

technologies), technologies promoting personal and corporate payments (e.g., Venmo, Apple Pay, and Square), online alternative lending, and etc. Since 2010, online alternative lending has shown substantial growth. Online lenders have evolved from a platform that connects individual borrowers with individual lenders to a complex network that can characterize institutional investors, direct loans, and securitization transactions. The advancement of FinTech lending and the use of big data have changed the way that consumers and small businesses secure financing. There are some signs that it is beneficial for these alternative lenders to cooperate with banks. For example, Lending Club obtains some loans through WebBank.

Some studies focus on issues related to FinTech lending, such as default rate (Emekter *et al*., 2015), herd behavior (Herzenstein *et al*., 2011), trust (Duarte *et al*., 2012), and social networks (Freemdan and Jin, 2014). Agrawal *et al*. (2013) illustrate how transaction costs, reputation, and market design explain the growth of FinTech lending from an economic point of view. A few studies discuss the role of FinTech lenders in expanding the availability of credit and allowing borrowers rejected by traditional banks to obtain the funds they need. For example, Schweitzer and Barkley (2017) find that companies whose loans are rejected by banks have similar characteristics, and most of them turn to FinTech lending. Other FinTech surveys show that the value of FinTech lenders can be enhanced through FinTech lending platforms.[1] However, most of these documents rely on survey data and are subject to sample selection biases and inconsistent response results. In addition, only a small number of FinTech lenders make loan ratings public, which prevents researchers from drawing more general and broader conclusions on the development of the FinTech industry.

Recently, an emerging research topic is the interest rate setting mechanism of FinTech lending. There are currently two mechanisms for determining the interest rate that a borrower must pay from a P2P (peer-to-peer) lending platform, including the reverse auction process and the posted prices process. The reverse auction system is similar to bond auctions where supply and demand determine interest rates. Potential borrowers publish their loan applications on the platform, and investors bid at the corresponding lowest interest rate during the auction. The Swiss P2P lending platform Cashare has been using this auction process since its launch in 2008. Major participants in the largest P2P lending markets in the U.S. and the U.K. also use the published price process. In these models, the platform sets the interest rate for each loan list based on the information available to the borrowers, which simplifies and shortens the process

[1] For example, Desai and Meekings' (2016) survey of Funding Circle finds that once the platform does not exist, 20% of borrowers will not be able to obtain external financing. A study by Ahmed *et al*. (2016) shows that nearly 35% of PayPal's loans of working capital go to low-and-moderate-income businesses, while the retailed bank has only 21%.


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

between the borrowers and the lenders (Chen *et al*., 2014).

With the use of alternative data sources, big data, and mechanized learning technologies and algorithms and the application of artificial intelligence models, FinTech companies seem to be able to reduce credit decision-making, credit monitoring costs and operating costs, thereby affecting the pricing of FinTech lending (measured by interest rate spread). The financial technology index (FTI) developed by Hieminga and Lande (2016) is to describe the environment and condition of a country's financial technology development. It contains three different levels (i.e., demand, supply, and risk) and thirteen component indicators and can be used to evaluate its impact on the FinTech lending rate.

Other studies emphasize the importance of macroeconomic conditions in determining the interest rates of FinTech loans (e. g., Bertsch *et al*., 2016; Lin and Wei, 2016). Bertsch *et al*. (2016) confirm that the unemployment rate has a positive effect on borrowers' loan rates, and if the future economic conditions improve, it will lead to a decline in the FinTech loan rates. However, these studies ignore the stationarity of macroeconomic variables, which may lead to biased estimation results (Wu *et al*., 2016).

The main purpose of this study is to construct a pricing model of FinTech lending to estimate the impacts of the FinTech environment (measured by FTI), macroeconomic variables (including stock return, federal funds rate, and unemployment rate), borrower risk characteristics (including credit rating scores, years of employment, and debt-to-income ratio (DTI)), and specific dummy variables (including borrower's housing status, loan term, loan purpose, and time dummy variables) on the interest rates of FinTech lending. Empirically, we select 1,201,658 observations from the Lending Club platform during 2007-2018 for estimation. There are three reasons for this. First, Lending Club is one of the few platforms that disclose its lending information. Second, Lending Club is a larger and more mature platform in this field, so there will be more reference value for the empirical results. In addition, Lending Club provides loan-level data that covers detail information about loans and borrowers instead of survey data.

The rest of this study is organized as follows. Section 2 briefly reviews relevant literature, including the impact of FinTech on obtaining credit and credit prices, as the basis for establishing the empirical model of this study. Section 3 constructs the pricing model of FinTech lending, including three types of explanatory variables: borrower's characteristic variables, macroeconomic variables, and dummy variables, and the dependent variable of FinTech loan rate spreads. Section 4 introduces the related tests to ensure the availability and the soundness of the empirical results, including correlation analysis to avoid the collinearity problem and unit root test to avoid the spurious regression problem. Section 5 reports the data source and empirical results, and the final section concludes the study and provides several policy suggestions.


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

## 2. LITERATURE REVIEW

Since the development time of financial technology lending is relatively short, there are few quantitative estimation studies involved. In light of this, this section mainly reviews the literature in terms of the impact of FinTech on credit access and credit pricing as the basis for establishing an empirical model.

### *2.1. FinTech and Lending*

Online FinTech lenders often use protective non-traditional information that is not used in traditional bank's loan decision-making and apply their own developed algorithms for lending. For example, develop online lending platforms and use big data to assess the credit risk of borrowers. Using this new method of credit risk assessment, some consumers can potentially increase the probability of the approval of credit applications. For example, some consumers with short credit history may not be able to meet the loan requirements of traditional banks, but they can use alternative data sources (such as mobile phone data, rent payment records, electronic payments, insurance claims, bank account transaction records, and social network records, etc.) to establish credit records and increase credit information to obtain online loans. Frame *et al*. (2001) use telephone survey data of the top 200 large banks in the U.S. to examine the impact of emerging small business credit scores on lending behavior. The estimation results show that small business credit scores result in an increase in small business loans due to lower information costs and information asymmetry between borrowers and lenders. In addition, the new algorithm of FinTech lenders expands lending activities to improve services to consumers who previously received low loans.

Online FinTech lenders rely more on other sources of information, such as sales information from Amazon, eBay, and other markets, shipping data from postal services, cash flow analysis and payment processors from business transaction checking accounts, and profitability analysis and prediction from social media. Crosman (2016) indicates that SoFi no longer uses FICO's scoring criteria as loan review conditions. Kabbage argues that FICO scores are not part of its credit review. The Prosper lending platform obtains 500 pieces of information from each borrower as a basis for credit evaluation; however, the FICO score responds just one piece of the information (i.e., borrowers need to obtain at least 640 points to enter the loan consideration list). In addition, Mills and McCarthy (2014) find that Fundbox and Bluevine evaluate the borrower's information on QuickBooks, Xero, or FreshBooks when making loans. The evaluation additionally uses an application program interface (API) to quickly obtain


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

several financial records authorized by the borrower within a few seconds. Wack (2015) points out that PayPal and Square began to provide credit to some businesses based on the sales data they obtained, and they are able to repay the loans directly from the income of these businesses.

Duarte *et al*. (2012), Gonzalez and Loureiro (2014), and Iyer *et al*. (2014) use Prosper's lending data to examine whether the characteristics of borrowers (e.g., borrower's appearance and verifiable network relationships) can affect loan success and loan rates. Iyer *et al*. (2014) find that lenders in the P2P lending market use soft information to estimate borrower's credit capability. Compared with credit scores, this method can predict the default rate more accurately, especially for borrowers with lower credit ratings.

### *2.2. FinTech lending and loan rates*

In addition to making consumers feel more convenient and faster, online alternative lending technology has provided better efficiency by reducing operating costs. Thus, it is important to examine whether FinTech lenders reflect lower lending costs on consumers' loan costs, and whether loan pricing reflects the risks taken. Some studies have tried to compare the interest rates of P2P lending platforms and traditional loans, but they have been limited by significant data, and the results are ambiguous.

Mach *et al*. (2014) use Lending Club's consumer loan data to explore loan rates for small businesses. It turns out that loan rates vary with the purpose of the loan, and these business loans are still subject to higher interest rates (consumer loans are used for small business purposes) even after controlling loan application conditions. In addition, comparing the loan rates of Lending Club and the National Federation of Independent Business members, it is found that P2P small business loans will pay about twice the interest rate of traditional borrowing channels. However, the small business loans in Lending Club's consumer loan data do not represent traditional small business loans because these loans have a very small initial amount, are unsecured, and are underwritten by consumers on the lending platform. Demyanyk and Kolliner (2014) use bankrate.com data and Lending Club's consumer loan rate to analyze the difference in the interest rates of credit cards. The results of the study find that consumers with good credit can obtain preferential interest rates through FinTech lending than credit cards. However, these data cannot be directly compared in terms of loan levels. Emekter *et al*. (2015) use Lending Club data to discuss credit risk and loan rates. As generally expected, borrowers with low debt-to-income ratios have a lower risk of default. Charging higher interest rates for high-risk borrowers does not reduce the default probability of loans.


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

De Roure *et al*. (2016) compare the loan rates of the German P2P lending platform (Auxmoney) and Deutsche Bundesbank. It is found that after controlling the risk characteristics of borrowers, the loan rates of the P2P lending platform and traditional bank are comparable. In addition, Buchak *et al*. (2017) study the rise of FinTech lenders and non-FinTech shadow banks in the housing loan market. Empirical data shows that FinTech borrowers are among the borrowers who value fast and convenient services, while FinTech lenders require interest rate premiums for their services. Dietrich and Wernli (2015) use data from Cashare (the largest participant in the Swiss P2P lending market with a market share of nearly 98%) to analyze borrowers' interest rates. The empirical results find that borrowers have larger loan amounts or belong to homeowners have significantly lower loan rates, while female borrowers and those with higher debt-to-income ratios have higher loan rates.

Bertsch *et al*. (2016) use Prosper and Lending Club data to assess the impact of macroeconomic factors on cognitive default probability and personal loan interest rates. The empirical results show that even after controlling the characteristics of borrowers and loans, states with higher unemployment rates have higher loan rates. In addition, it is expected that future improvements in economic conditions (measured by changes in the real yield curve) will lead to a decline in loan rates in the P2P lending market. Lin and Wei (2016) use the Prosper platform to compare the auction-based model used by Prosper before December 2010 with the posted-price model currently used. It turns out that the interest rates allocated by the posted-price model are approximately 100 basis points higher than those obtained by the auction-based model. In addition, loans generated by the posted-price model have a higher probability of default.

In summary, the literature rarely estimates the determination of the FinTech lending rates, especially the lack of assessing the impact of the FinTech development environment on the lending rates. Moreover, most of the previous studies ignore the impact of macroeconomic variables on the lending rates, leading to biased estimation results. In view of this, this study establishes a FinTech lending pricing model that includes variables such as FinTech index, borrower's risk characteristics, and macroeconomic conditions. This model not only highlights the role of FinTech index and macroeconomic variables in FinTech lending rates but also provides important information for FinTech borrowers, lenders, and the government to make relevant decisions.

## 3. EMPIRICAL MODEL

According to the literature above-mentioned, when evaluating FinTech lending rates, factors such as the development environment of financial technology, the risk


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

characteristics of borrowers, and the macroeconomic environment should be considered simultaneously. Since Lending Club is not a traditional financial firm, it is unable to obtain complete financial information. In addition, considering its publicly available information, this study establishes the following estimation equations to assess the impact of macroeconomic environmental variables, borrower's risk characteristics, and specific dummy variables on the credit price of FinTech lending.

$$IRS_{it} = \alpha_i + \beta_1 DTI_{it} + \beta_2 YOE_{it} + \beta_3 GTADE_{it} + \beta_4 SR_t + \beta_5 FFR_t + \beta_6 U_t + \beta_7 FTI_t + h_1 H1 + h_2 H2 + h_3 H3 + d_{term} TERM + p_1 P1 + p_2 P2 + \varepsilon_{it} \quad (1)$$

The dependent variable ( $IRS_{it}$ ) represents the interest rate spread or the risk premium of the FinTech lending rate, which is the difference between the FinTech lending rate and the risk-free interest rate measured by the interest rate of US Treasury bonds with the same maturity date.

Regarding borrower's risk characteristics, the debt-to-income ratio of the borrower ( $DTI_{it}$ ) is used to measure the ability to repay; the length of borrower's employment ( $YOE_{it}$ ) is used to evaluate of borrower's work stability and the repayment ability, and $GTADE_{it}$ represents the credit rating of borrowers from the best rating A to the worst rating G. Generally speaking, the lower the $DTI_{it}$ is, the stronger the borrower's tolerance would be; the longer the $YOE_{it}$ is, the lower the interest rate spread would be, and the better the $GTADE_{it}$ is, the lower the interest rate spread would be.

In Eq. (1), the control factors that excessively influence credit demand, variables such as stock return ( $SR_t$ ), federal funds rate ( $FFR_t$ ), unemployment rate ( $U_t$ ), financial technology index ( $FTI_t$ ), and dummy variables are considered. Stock return represents the prosperity and decline of the capital market, which in turn affects the wealth and repayment behavior of borrowers. A rise in the stock market may have two different short-term effects on loan interest rates. First, it stimulates demand for loans, which in turn results in higher interest rates. Second, it causes the economy to overheat, triggering the central bank to use tight monetary supply to cool down. The federal funds rate represents the short-term trend of monetary policy and is the reference for traditional commercial banks to adjust interest rates. It is also an indicator for judging the competitive and complementary relationship between traditional commercial banks and FinTech lending. The unemployment rate is an important indicator for evaluating economic prosperity, especially for developed countries. The higher the unemployment rate of the overall economy, the greater the impact on the income and employment of borrowers, and the greater the interest rate spread would be. The FinTech index constructed by Hieminga and Lande (2016) includes comprehensive indicators of the urgency of financial technology, financial technology infrastructure, financial technology ecosystem, and political and regulatory environment. In theory, the higher


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

the FinTech index is, the lower the risk of FinTech lending and the smaller the risk premium (the interest rate spread in this study) would be.

In terms of dummy variables, $H_i$, i=1,2,3 are dummy variables, representing the borrower's home ownership status, including own homes (H1=H2=H3=0), home mortgage (H1=1 and H2 =H3=0), rental housing (H2=1 and H1=H3=0), and others (H3=1 and H1=H2=0). *TERM* is a dummy variable, *TERM* =1 means the loan term is 5 years, and *TERM* =0 means the loan term is 3 years. The liquidity premium theory states that the longer the maturity is, the higher the interest rate would be, and the market segmentation theory argues that the interest rate is determined by the supply and demand of the individual loan terms (Cox *et al*., 1985). $P_i$, i=1,2 are dummy variables, representing different loan purposes: repaying credit cards (P1=P2=0), performing debt consolidation (P1=1 and P2=0), and other purposes (P2=1 and P1=0 ).

## 4. EMPIRICAL RESULTS

### 4.1. Data

Empirically, this study uses 1,201,658 observations of Lending Club during the period of 2007-2018 for estimation. The loan information includes specific information about the loan (i.e., loan interest rate), borrower's risk characteristics (i.e., credit rating, length of employment, DTI, and home ownership status), and other risk characteristics (i.e., loan term and loan purpose). This study focuses analysis on consumer loans for repayment of credit cards and debt consolidation because these loans account for more than 85% of Lending Club's overall consumer loans. Regarding the macroeconomic variables, stock return (S&P 500 index return rate, SR), federal funds rate (FFR), and unemployment rate (U) are used.

Hieminga and Lande (2016) construct a FinTech index covering three dimensions of demand, supply, and risk, which further includes four comprehensive indicators: the urgency of financial technology, financial technology infrastructure, financial technology ecosystem, and the political and regulatory environment. Wu *et al*. (2020) reconstruct the index by deleting the incomplete data of the reliability of the grid. In measuring the development environment of financial technology, this study adopts the FTI constructed by Wu *et al*. (2020).

The data sources and measurements of the variables used in this study are shown in Table 1.


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Table 1 Data source and measurement

| Type | Variable | Measurement | Source |
|---|---|---|---|
| Borrower's risk variables | | | |
| | Interest rate spread (IRS) | The difference between the loan interest rate and the risk-free interest rate (i.e. U.S. Treasury bond interest rate) (%). | Lending Club, Taiwan Economic Journal (TEJ) |
| | Debt-to-income ratio (DTI) | Borrower's total debt repayment / borrower's monthly income (%) | Lending Club |
| | Years of employment (YOE) | 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 |
| | Credit rating (GRADE) | 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 |
| | Home ownership status (H1, H2, H3) | H1=H2=H3=0 represents that borrowers have own homes; H1=1 and H2=H3=0 mean that borrowers have mortgage loans; H2=1 and H1=H3= 0 indicate that borrowers are renters, and H3=1 and H1=H2=0 represent that borrowers belong to other home ownership status. | Lending Club |
| | Loan purpose (P1, P2) | P1=P2=0 means loans for repaying 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 |
| | Loan term (TERM) | TERM=0 means a 36-month loan, and TERM=1 means a 60-month loan. | Lending Club |
| Macroeconomic variables | | | |
| | S&P500 return rate (SR) | A representative stock market return in the U.S. (%) | Datastream |
| | Federal Funds rate (FFR) | A representative short-run interest rate in the U.S. (%) | Datastream |
| | Unemployment rate (U) | | Datastream |
| | Financial technology index (FTI) | See Wu *et al*. (2020) | Wu *et al*. (2020) |


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Before conducting the empirical estimation and analysis, the descriptive statistics of the variables are presented in Table 2 to understand their basic characteristics. The Debt-to-income ratio has the largest standard deviation (15.092) among the borrower's risk characteristic variables, and the credit rating has the smallest one (1.2477). The Financial technology index (FTI) has the largest standard deviation (6.1690) among the macroeconomic variables, and the unemployment rate has the smallest one (0.6994), meaning that FTI is the most volatile among the macroeconomic variables. Except for the YOE, SP, and FTI, the remaining variables have positive a skewness coefficient, showing a right-skewed distribution. Except for YOE and FFR, the remainder has a kurtosis coefficient larger than 3, revealing a leptokurtic distribution. Among them, the debt-to-income ratio has the highest value (1627.8), implying that the data is highly concentrated on the mean. In addition, the test statistics for normal distribution (Jarque-Bera) all significantly reject the null hypothesis of a normal distribution, meaning that none of the variables belongs to a normal distribution.

Table 2 Descriptive statistics

| Panel (A) | | | | |
|---|---|---|---|---|
| Borrower's risk variables | IRS | DTI | YOE | GRADE |
| Mean | 9.5171 | 19.175 | 5.9427 | 2.6339 |
| Max. | 21.883 | 999.00 | 10.000 | 7.0000 |
| Min. | 4.7182 | -1.0000 | 0.5000 | 1.0000 |
| Std. Dev. | 4.9250 | 15.092 | 3.6747 | 1.2477 |
| Skewness | 0.7601 | 28.806 | -0.1473 | 0.6262 |
| Kurtosis | 3.5760 | 1627.82 | 1.4088 | 3.1576 |
| J-B statistic | 145993 | 2.36E+11 | 145173 | 142432 |
| P-value | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| Panel (B) | | | | |
| Macroeconomic variables | SP | FFR | U | FTI |
| Mean | 2.1615 | 0.9184 | 4.6548 | 73.756 |
| Max. | 13.066 | 2.4100 | 6.7000 | 89.118 |
| Min. | -13.972 | 0.0100 | 3.7000 | 52.555 |
| Std. Dev. | 5.6660 | 0.7841 | 0.6994 | 6.1690 |
| Skewness | -1.1232 | 0.5655 | 0.6805 | -0.6279 |
| Kurtosis | 5.1029 | 1.8979 | 3.0800 | 3.9611 |
| J-B statistic | 846542 | 222941 | 166152 | 47.517 |
| P-value | 0.0000 | 0.0000 | 0.0000 | 0.0000 |

*Note*: The dummy variables are not included in the table.


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

## 4.2. Empirical results

To avoid the use of highly linearly correlated macroeconomic variables for regression, this study performs correlation analysis, and the correlation coefficients between all macroeconomic variables are lower than 0.45. Besides, according to the results of the nonlinear unit root test in Table 3, the t-value and F-value of the four macroeconomic variables are significantly different from zero, meaning that these variables belong to stationary series.

Table 3 Nonlinear unit root test－Emirmahmutoglu and Omay (2014)

| Variable | $\bar{t}_{AE}^{as}$ | $\overline{F}_{AE}$ |
|---|---|---|
| SP | -4.2251*** | 9.0113*** |
| FFR | 3.1353*** | 6.4855*** |
| U | 1.8383* | 8.4662*** |
| FTI | 2.8774*** | 4.1962*** |

*Notes*: the lag length of the testing equations is determined by the minimum value of SIC (Schwarz information criterion). *** and * indicate the significance level of 1% and 10% according to the p value of sieve bootstrap.

The estimation results of Eq. (1) are shown in Table 4, and the important conclusions are summarized as follows.

### *Borrower's risk characteristics*

First, debt-to-income ratio (DTI) has a positive and significant effect on FinTech lending rate spread, revealing that when the borrower has a higher DTI, the loan default risk is also higher, resulting in a higher FinTech loan interest rate. Second, years of work (YOE) have an insignificantly negative impact on FinTech lending rate spread. The reason is that the borrower with higher seniority and average salary has more strong repayment ability and a lower default probability, which leads to a lower loan interest rate. Third, borrowers with existing mortgage loans (H1=1 and H2=H3=0) have a lower loan rate than borrowers with their own homes (H1=H2=H3=0). The possible reason is that they have collaterals for guarantee; therefore, the default risk is low. Borrowers belonging to renters (H1=H3=0 and H2=1) have a significantly higher loan rate than borrowers having own homes (H1=H2=H3=0) because they lack substantial collateral. Moreover, borrowers belonging to other home ownership status (H1=H2=0 and H3=1)


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have an insignificant impact on the loan rate because this kind of borrowers is quite complicated. Fourth, the longer the loan term (TERM) is, the higher the default risk of the FinTech platform and the platform’s loan rate would be. Fifth, borrowers to perform debts consolidation (P1=1 and P2=0) have a higher loan rate than borrowers to repay the debts of credit cards (P1=P2=0) because they have a complicated risk. Borrowers to perform other purposes (P1=0 and P2=1) are more difficult to grasp, so the loan rate is higher than that of borrowers to repay the debts of credit cards (P1=P2=0). Finally, the impact of the credit rating (GRADE) on FinTech loan rates is positive and significant, implying that when the borrower's credit rating is poor, the default probability and loan rate are high.

Table 4 Estimation result of FinTech lending rate spread

| Variable | Coefficient | Standard error | P value |
|---|---|---|---|
| *C* | 2.1943 | 0.0063 | 0.000 |
| *DTI* | 0.0034 | 0.0001 | 0.000 |
| *YOE* | -0.0004 | 0.0003 | **0.198** |
| *SR* | 0.0283 | 0.0005 | 0.000 |
| *FFR* | 0.5021 | 0.0021 | 0.000 |
| *U* | 0.2474 | 4.24E-05 | 0.000 |
| *FTI* | -0.0097 | 3.35E-05 | 0.000 |
| *H1* | -0.0400 | 0.0040 | 0.000 |
| *H2* | 0.0237 | 0.0041 | 0.000 |
| *H3* | 0.0434 | 0.0457 | **0.342** |
| *TERM* | 0.1121 | 0.0030 | 0.000 |
| *P1* | 0.0794 | 0.0030 | 0.000 |
| *P2* | 0.0474 | 0.0038 | 0.000 |
| *GRADE* | 3.7311 | 0.0011 | 0.000 |
| Adjusted R-squared | 0.8121 | | |
| F-statistic | 12177 | | |
| Prob(F-statistic) | 0.0000 | | |

Note: The estimation results pass the cross-sectional heterogeneity test.

***Macroeconomic variables***

First, S&P500 stock return (SR) has a positive and significant impact on FinTech lending rates. The possible reason is that the stock market will directly reflect the economic prosperity. The better the prosperity is, the higher the return would be. In this


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

situation, investors need more funds to invest in the stock market, which will increase the demand for money and increase the lending rate of physical banks, thereby driving the lending rates of FinTech to rise. Second, federal funds rate (FFR) also has a positive and significant impact on FinTech lending rates. The reason may be that after the rise of FFR, the lending rates of physical banks and FinTech lending will increase. Therefore, the services provided by traditional physical banks and FinTech lending platforms are mutually complementary. Third, unemployment rate (U) has a positive and significant impact on FinTech lending rates. According to Okun's rule, there is a negative relationship between economic growth and the unemployment rate. That is, the higher the unemployment rate is, the lower the economic growth and the greater the borrowing risk would be, thereby the higher the FinTech lending rate.

Finally, FinTech Index (FTI) has a negative and significant impact on FinTech lending rates. As mentioned above, the higher the FinTech index is, the lower the risk of FinTech lending, and the smaller the risk premium would be.

## 5. CONCLUSIONS

This study constructs a regression model to evaluate the impact of the FinTech index, borrower’s risk characteristics, and macroeconomic conditions on the pricing of FinTech lending. Empirically, we select 1,201,658 observations on the Lending Club platform from 2007 to 2018 for estimation.

The crucial results are summarized as follows. First, the financial technology index has a negative impact on the lending rate spreads. That is, the higher the degree of financial technology development is, the lower the lending rate spreads would be. Second, the debt-to-income ratio, loan term, credit rating, stock return, unemployment rate, and federal funds rate all have a positive impact on the lending rate spreads. Third, the services provided by traditional physical banks and financial technology lending platforms are complementary. Among different loan purposes, the loan rate for repaying credit card debt is the lowest. Finally, among different statuses of borrower’s home ownership, borrowers that have mortgage loans get the lowest lending rate.

Based on the above empirical results, this study provides the following policy suggestions. First, in evaluating the FinTech lending rate spreads, the participants of FinTech lending need to consider the variables of the financial technology development environment (measured by the FinTech index) and macroeconomic conditions; otherwise, the estimation results would be biased. Second, FinTech lending platforms and lenders can adjust loan interest rates and their algorithms based on the estimated coefficients of the FinTech index and the borrower's risk characteristic variables obtained from this study. Third, traditional banks can use the pricing model constructed


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

by this research as the reference to evaluate the impact of the FinTech index on their setting in loan rates. Fourth, the services provided by traditional financial institutions and FinTech Lending Platforms are complementary; therefore, traditional financial institutions must actively participate in financial technology lending platform services. Finally, the government should build a favorable FinTech development environment to help reduce the cost of FinTech lending. However, it must also assess the impact of the development environment on the FinTech lending rate to avoid excessive fluctuations in the rate and disturb the stability of financial markets.

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