The Risk-Taking Channel of Monetary Policy: Evidence from Individual Investors in the Peer-to-Peer Lending Market

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Abstract

This paper examines how monetary policy affects risk-taking and reaching-for-yield behavior of individual investors in the peer-to-peer lending market. Using data from Prosper.com from 2006 to 2013, we find that easy monetary policy, as measured by lower effective federal funds rates or the quantitative easing programs, induces individual investors to fund riskier loans and to fund loans with higher yields. We also find that loans originated during easy monetary policy regimes experience higher *ex post* default rates. The results suggest that the risk-taking channel of monetary policy transmission may be driven by individual behavior bias, instead of by frictions specific to financial institutions.

Keywords: Peer-to-Peer Lending, Monetary Policy, Reaching-for-Yield, Risk Taking, Quantitative Easing

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1 Introduction

The 2008-2009 financial crisis and the subsequent unconventional monetary policy responses have triggered the renewed debate on whether and how monetary policy may encourage excessive risk-taking, the so-called risk-taking channel of monetary policy transmission. Most recent papers find that easy monetary policy encourages risk-taking by financial institutions (e.g., Maddaloni and Peydró 2011; Jiménez et al. 2014; Ioannidou, Ongena, and Peydró 2014; Chodorow-Reich 2014; Choi and Kronlund 2017; Dell'Ariccia, Laeven, and Suarez 2017; Di Maggio and Kacperczyk 2017; Maggio, Kermani, and Palmer 2016). However, little attention has been paid to understanding whether monetary policy also affects individual investors' risk-taking behavior.[1] This paper tries to fill this gap by studying the effect of monetary policy on individual risk-taking.

Understanding the effect of monetary policy on individual risk-taking will not only provide a complete account of the risk implications of monetary policy but will also help us better understand the driving force of the risk-taking channel of monetary policy. The theory almost exclusively relies on mechanisms specific to financial institutions to explain the risk-taking channel of monetary policy transmission. Financial institutions often face different incentives, ownership structure, and constraints, all of which can affect how they respond to monetary policy shocks. For example, banks face regulatory capital requirements and agency conflict, which can driven banks' risk-taking behavior (Jiménez et al. 2014 and Dell'Ariccia, Laeven, and Suarez 2017). The long-term liability of life insurance companies is often significantly affected by interest rate changes, which in turn affects how insurance companies invest in the low-interest rate environment (Becker and Ivashina 2015). Agency problems faced by mutual fund managers can also trigger risk-taking and reaching-for-yield behavior (Choi and Kronlund 2017 and Di Maggio and Kacperczyk 2017). Individual investors have simpler incentives and ownership structures than financial institutions. Studying how monetary policy affects individual risk-taking will allow us to better distinguish between different

[1] The only exception is Lian, Ma, and Wang (2018), who examines individuals' risk-taking behavior in an experimental setting.

channels through which monetary policy affects risk-taking.

In this paper, we use the peer-to-peer (P2P) lending market as a laboratory to examine the effect of monetary policy on individual risk-taking behavior. We focus on the P2P lending market for the following reasons. First, the P2P lending market enables the examination of individual behavioral and hence to disentangle different mechanisms that can cause the risk-taking and reaching-for-yield behavior. Second, the setting and data of the peer-to-peer lending market enable a clean identification of the risk-taking channel of monetary policy. A critical identification challenge in studying the relationship between monetary policy and lending is the potential correlation between monetary policy and the demand for credit. Monetary policy can affect the quantity and quality of loan demand either through the interest rate channel or the balance sheet channel (Bernanke and Blinder 1992). Hence, a correlation between monetary policy and the riskiness of loans may not tell us about lenders' risk-taking or reaching-for-yield behavior at all. The P2P lending market allows us to better tackle this problem. First, we have access to both approved and rejected loan requests, allowing us to control for loan demand to a large extent. Second, and more importantly, we have access to all information lenders have, that is, we can control for all potential demand-side factors and hence effectively eliminate the possibility that unobservable demand-side factors drive the results.

Specifically, we use the data from Prosper.com (Prosper hereafter), the first and the second largest P2P lending platform in the US to conduct our analysis. We use the data from Prosper, instead of other platforms such as Lending Club, because it not only provides data on approved loans but also data on rejected loans, which enables us to better isolate demand-side factors. The data include a wide array of loan characteristics, such as loan size, loan term, loan interest rate, loan risk measures, whether the loan is approved, the percent funded, and an even larger set of borrower characteristics, such as income, home ownership, employment status, all existing debt, past credit history, location, and more. Potential lenders rely on the same set of information to make lending decisions, which is critically important for us to identify the risk-taking channel. In the context of bank lending, lenders often have access to information unobservable to researchers, and hence it is difficult for researchers to isolate the effect of demand-side factors. In our case, we have the same set of information as lenders do, and hence are able to control for all demand-side factors that may affect lending decisions.

Empirically, we follow the literature and use the effective federal funds rate to measure conventional monetary policy (e.g. Bernanke and Blinder 1992; Kashyap and Stein 2000; Dell'Ariccia, Laeven, and Suarez 2017; and Di Maggio and Kacperczyk 2017) and examine the effect of monetary policy on P2P lending on the Prosper.com. We first examine the effect of monetary policy on loan approval and find that lower federal funds rates lead to higher approval rates of riskier loans. A one-percentage-point reduction in the effective federal funds rate leads to an increase in the approval rate of risky loans, relative to safe loans, by more than six percentage points. We also find that it takes significantly less time to fund a riskier loan when the federal funds rate is low. Consistent with the argument that investors take excess risk to reach for yield, we also find that lower federal funds rates lead to higher approval rates of loans with higher yields. These results suggest that lower federal funds rates encourage individual investors' risk-taking and reaching-for-yield behavior.

A large part of our sample period is during and after the 2008-2009 financial crisis, during which the effective federal funds rate was close to zero and the Federal Reserve implemented the Large Scale Asset Purchase (LSAP) or the Quantitative Easing (QE) Programs to conduct monetary policy. A big concern for these unconventional monetary policy programs is that they may encourage excess risk-taking (Chodorow-Reich 2014; Woodford 2016; Di Maggio and Kacperczyk 2017; Kandrac and Schlusche 2017). We hence also examine the effect of these QE programs on individual risk-taking in the P2P market. To this end, we find that riskier loans originated during the QE programs, relative to safe loans, are more likely to be approved and take less time to be funded, suggesting that the QE programs also encourage individual risk-taking. We also find that loans with higher yields are also more likely to be approved during QE programs, suggesting that the QE programs lead to more individual reaching-for-yield behavior.

In addition to examining the effect of monetary policy on loan origination, we also examine *ex post* loan performance. We find that loans originated when the federal funds rate is low experience higher *ex post* default rates. The result holds even conditional on risk and other loan and borrower characteristics. Similarly, loans originated during the QE programs also experience higher *ex post* default rates. This effect compounds upon and magnifies the effect of monetary policy on loan origination, and leads to a much larger effect of monetary policy on risk.

To alleviate the concern that monetary policy may be correlated with other unobservable macroeconomic factors that may affect loan demand, we follow the literature to use the Taylor rule to extract the exogenous component of the federal funds rate (Altunbasa, Gambacortab, and Marques-Ibanezc 2014; Delis, Hasan, and Mylonidis 2017; Dell'Ariccia, Laeven, and Suarez 2017). We find that the Taylor rule residual has similar effects on individual risk-taking behavior in the P2P market, suggesting that the results are unlikely to be driven by unobservable macroeconomic factors that also affect individual risk-taking. We also find that including other macroeconomic variables, such as the inflation rate and the GDP growth data, does not eliminate the effect of monetary policy.

This paper contributes to the literature on the risk-taking channel of monetary policy transmission. The existing literature overwhelmingly focuses on risk-taking behavior of financial institutions. To the best of our knowledge, we are the first to empirically examine the effect of monetary policy on individual risk-taking. The existing literature often only relies on agency costs or other mechanisms specific to institutions to explain the behavior. Individual investors, on the other hand, are not subject to these agency costs and other frictions institutions face, and hence their risk-taking behavior cannot be driven by those factors. Our results therefore suggest that individual behavior bias or preference may also drive the risk-taking channel of monetary policy transmission. In this regard, the paper closest to ours is Lian, Ma, and Wang (2018), who examine the risk-taking effect of low interest rates under an experimental setting.

This paper also contributes to the growing literature on P2P lending (e.g. Duarte, Siegel, and Young 2012; Lin, Prabhala, and Viswanathan 2013; Butler, Cornaggia, and Gurun 2016; Hertzberg, Liberman, and Paravisini 2018). Most papers in the existing literature focus on micro-level or local level determinants of borrowing or lending in this market. Our paper is the first to examine the effect of macroeconomic factors on the P2P market.

The rest of the paper is organized as follows. Section 2 provides a simple description of the P2P lending market. Section 3 describes the data and sample construction. Section 4 presents some preliminary and graphical analysis of the effect of monetary policy on risk-taking. Section 5 presents the results of *ex ante* risk-taking. Section 6 presents the results of *ex post* loan performance. Section 7 performs additional and robustness analyses. Section 8 concludes.

2 Peer-to-Peer Lending and Prosper.Com

The peer-to-peer (P2P) lending market is an online platform that allows individual borrowers to borrow and individual lenders to lend directly. The first P2P platform, Prosper.com, started operation in 2006. The P2P loans are fixed term, fixed interest rate, fully amortizing, unsecured loans. The loans typically have maturities of three to five years, and range from $1,000 to $35,000.

In this paper, we use the data from Prosper.com to examine the effect of monetary policy on individual investors' risk-taking and reaching-for-yield behavior. When potential borrowers request loans from Prosper.com, they must report their income, employment status, other key information, and authorize Prosper to access their credit reports. The borrowers also specify the maximum interest rates they are willing to pay. The information is then posted on the platform. What happens next has evolved over time. Up until 2010, which is usually called the Prosper 1.0 era, potential investors bid with the minimum interest rates they are willing to accept and the amount of funding they are willing to provide in an auction process. The auction process will eventually determine the interest rate on the loan and the total amount investors are willing to provide. If the total amount pledged is more than 70%

of the requested loan amount, the loan is originated.

After 2010, usually referred to as the Prosper 2.0 era, Prosper uses a proprietary model to estimate the expected loss rate and determine the interest rate on the loan. Prosper uses both the borrower's credit report information and the data on Prosper loans in their estimates. In addition, the platform provides two risk measures. The first one is called the Prosper score, which is only based on Prosper loan data. The second one is called Prosper rating, which reflects the estimated loss rate on the loan. Potential investors, after seeing the loan interest rate and the risk measures, decide whether and how much to fund the loan. Again, if the total amount pledged is more than 70% of the requested loan amount, the loan is originated.

3 Data and Sample

To examine how monetary policy affects individual investors' risk-taking and reaching-for-yield in the P2P lending market, we use data of Prosper.com from 2006-2013.[2][3] We end the sample in 2013 for two reasons. First, institutions dominated the market after 2013 (Balyuk and Davydenko 2018). Second, we need to measure the performance of the loans, most of which have a maturity of three years. Ee excluded listings canceled by the platform or withdrawn by the borrowers. We also exclude loans funded by institutions to ensure that we are examining individual investor behavior.

The Prosper data contain all borrower and loan information available to investors, which mitigates the concern that investors may make lending decisions based on factors unobservable to the econometrician, a common and almost unavoidable problem in the bank lending literature.

We use the following variables to measure loan outcomes. The first one is *Approval*, which equals one if a loan request is funded, and zero otherwise. A loan request is funded if it is

[2]The data is downloaded from https://www.prosper.com/investor/marketplace/download

[3]We do not use lending club data because the lending club data do not have sufficient information on loan requests that are not funded, which is critical in identifying risk-taking and reaching-for-yield as shown in later discussion.

more than 70% funded by the deadline, otherwise it is rejected. We also use a continuous variable, *Percent Funded*, defined as the percent of loan request funded for both approved and rejected loans, to measure the listing outcome. Finally, we also use the number of hours it takes to fund a loan listing or until the listing expires, denoted as *Duration*.

We use three different measures of borrower risk. The first one is borrowers' ScoreX plus credit rating. Prosper reports the ScoreX rating in different-sized bins. We transform these bins to numerical values from 0 to 10, with 0 assigned to the bin with the ScoreX plus rating below 600, and with 10 assigned to the bin with the ScoreX plus rating above 778. We denote the transformed ScoreX plus credit rating as *ScoreX Rating*. A higher *ScoreX Rating* means lower risk. This measure is reported for the whole sample of our data, and will be our primary risk measure.

The second one is the *Prosper Score*, which is the risk measure calculated by Prosper based only on Prosper loan data. The *Prosper Score* ranges from 1-11, in which 1 represents loan requests with the highest risk, and 11 represents loan requests with the lowest risk. Prosper started to report this measure only after 2010, that is, during the Prosper 2.0 era. The third risk measure is *Prosper Rating*, which is also calculated by Prosper, but based on information both from the borrower's credit reports and from Prosper loans. The Prosper Rating corresponds to a range of estimated loss rate of the loan. We again convert the letter ratings into numerical ratings, ranging from 1 to 7, with 1 being the riskiest and 7 being the safest.

To capture reaching-for-yield, we use the lender yield, which is the difference between the loan interest rate and the servicing fee rate. During the Prosper 1.0 era, the lender yield is determined by the auction process. In the Prosper 2.0 era, the lender yield is determined by Prosper and then posted on the platform after reviewing the credit profiles of the potential borrowers but before investors' funding decisions.

In our analysis of *ex post* loan performance, we define an indicator variable, *Default*, which equals zero if the status of the loan is either completed, current or final payment in progress, and equals one otherwise (loan status being Charged off, Defaulted, or Past Due).

We also try categorizing those less than 30 days, 60 days, or 90 days overdue as current, and still find similar results.

In the baseline analysis, we follow Dell'Ariccia, Laeven, and Suarez (2017) and use the effective federal funds rate, *FF*, to measure monetary policy. In robustness checks, we also use the Taylor rule residual as a measure of monetary policy to address the potential endogeneity problems.

We include a broad set of control variables. To control for loan characteristics, we include *Listing Amount*, *Listing Term*, and *Listing Payment*. To control for borrower characteristics, we include *Monthly Income, Debt to Income, Months Employed, Homeowners, Prior Prosper Loan, Monthly Debt, Seven Year Credit Lines, Six Month Inquiries, Total Inquiries, Amount Delinquent, Current Credit Lines, Open Credit Lines, Bank Card Utilization, Total Open Revolving, Installment Balance, Real Estate Balance, Real Estate Payment, Revolving Balance, Revolving Available Percent, Current Delinquency*, and *Seven Year Delinquency*. The Appendix lists all the variables used in the empirical analyses.

The summary statistics of the main variables used in this paper are presented in Table 1. Among all loan requests received by Prosper, about 46% are eventually funded. The average requested loan amount is about $7,400 and the average loan term is 38 months, that is, a little over three years. The average ScoreX rating is 4.25, the average Prosper Score is 5.59 and the average Prosper Rating is 3.35. The average lender yield is 21%.

4 Graphical Evidence

Before we present the formal analysis of the effect of monetary policy on risk-taking in the P2P market, it is worthwhile to show some univariate results. We first split the sample period according to the effective federal funds rate into five bins (less than 0.25%, between 0.25% and 1%, between 1% and 2%, between 2% and 3%, and higher than 3%), and then calculate the loan approval rates in each federal funds rate bins for risky (*ScoreX Rating* less than the 25 percentile) and safe loans (*ScoreX Rating* greater than the 75 percentile) separately.

The results are presented in Panel A of Figure 1. The approval rates for risky loans are very low, except when the effective federal funds rate is extremely low (less than 25 basis points), during which the approval rate for risky loans is more than 80%. Note that we are not testing the monotonic relationship between the federal funds rate and the approval rates of risky loans. Instead, we are interested in the effect of the federal funds rate on the differences in the approval rates between safe and risky loans. In fact, the difference is small (or even negative) when the federal funds rate is low, and the difference increases with the federal funds rate. The results in Figure 1 is consistent with the risk-taking channel that riskier loans, relative to safer loans, are more likely to be approved when the federal funds rate is low.

We then split the sample period into non-QE and QE periods, and also calculate the approval rates for risky and safe loan requests during these different time periods. The results are presented in Panel B of Figure 1. The approval rates of risky loan requests are much higher and the difference in approval rates between safe and risky loan requests is much smaller during QE periods than during normal times.

The difference in the approval rates of risky loans in different monetary policy regimes can also be driven by demand-side factors. If loan requests during loose monetary policy regimes are riskier, and the lenders' funding decisions are random, more risk loans will get funded during loose monetary policy regimes. In this case, the effect of monetary policy on the appear-to-be risk-taking is driven by changes in demand, instead of by lenders' incentives for reaching-for-yield.[4] To assess to what extent this might be a problem, we examine the risk characteristics of all loan requests in different monetary policy regimes.

We again split the sample period according to the effective federal funds rate into five bins and then calculate the means of the *ScoreX Rating*, the *Debt-to-Income Ratio*, and the *Number of Delinquencies* of all loan requests (both approved and rejected). The results are presented in Panel A of Figure 2. The average *ScoreX Rating* is higher but the average

[4]In the regression analysis below, we use time fixed effects to control for this problem.

Debt-to-Income Ratio and the average *Number of Delinquencies* are lower of loan requests made when the federal funds rate is low, suggesting that the loan requests made during easy monetary policy regimes are in fact safer. We then also calculate the means of these measures for different QE periods, and the results are presented in Panel B of Figure 2. Again, it suggests that the loan requests made during the QE programs are likely to be safer than those made during normal times. Overall, these figures suggest that the higher approval rates of risky loans during easy monetary policy regimes are unlikely to be the result of shifts in demand.

5 Monetary Policy and *Ex Ante* Risk-Taking and Reaching-for-Yield

5.1 Federal funds rate and risk-taking

To identify how monetary policy affects risk-taking, we follow the literature (Dell'Ariccia, Laeven, and Suarez 2017 and Jiménez et al. 2014) and estimate the following model:

$$Y_{it} = \alpha_t + \beta FF_t \times Risk_{it} + \delta Risk_{it} + \gamma Z_{it} + \texttt{Fixed Effects} + \varepsilon_{it}, \tag{1}$$

where Y_{it} are measures of loan application outcomes, namely *Approval*, the natural logarithm of *Percent Funded*, and the natural logarithm of *Duration*, α_t is the time fixed effects (year-month), FF_t is the effective federal funds rate, $Risk_{it}$ is measured by the *ScoreX Rating*, Z_{it} is a set of other loan and borrower characteristics. We also include city, city $\times$ year-month, and borrower fixed effects in different specifications. Under Equation (1), β captures the effect of monetary policy on risk-taking. If easy monetary policy encourages risk-taking by individual investors in the P2P lending market, β should be positive. We cluster the standard errors by state and year-month.

A common challenge in identifying the supply-side determinants of credit supply is to separate the effect of demand-side factors because potentially unobservable demand-side factors can be correlated with the supply-side factors. In our context, monetary policy can obviously be correlated with many demand-side factors. However, the Prosper data enable us to mitigate this concern. First, we observe both approved and rejected loan requests instead of just approved loans, which allows us to make analysis conditional on observable loan demand. Second, with the Prosper data, we have access to the same set of borrower and loan characteristics as those available to potential lenders, that is, there are no demand-side factors that are observable to the lenders but not observable to the econometrician. We are therefore able to better control for demand-side factors using all these borrower and loan characteristics.

The results of estimating Equation (1) are presented in Table 2. The first three columns present the results with *Approval* as the dependent variable. We only include year-month fixed effects in Column (1), and then further include city fixed effect to control for location-specific time-invariant demand factors. To control for time-varying location-specific demand-side factors, we include city × year-month fixed effects in Column (3). In all columns, the coefficients on *FF* × *ScoreX Rating* are positive and statistically significant, suggesting that riskier loan requests, that is, requests with lower *ScoreX Rating*, are more likely to be approved when the federal funds rate is low. The result is consistent with the hypothesis that easy monetary policy encourages risk-taking by individual lenders in the P2P lending market.

The coefficient estimates in Columns (1) - (3) are about 0.9 percentage points. To gauge the economic magnitude, we consider the effect of reducing the effective federal funds rate by one percentage point on two loans with *ScoreX Rating* of zero (the 25th Percentile) and seven (the 75th Percentile). The probability of approving a risky loan (*ScoreX Rating* of zero) when the effective federal funds rate is lower is 6.3% percent (0.9%×7) higher than the probability of approving a safe loan (*ScoreX Rating* of seven) when the effective federal funds rate is higher. Given that only about 46% of the loan requests are approved, the economic magnitude is large. It is worthwhile to point out that the adjusted R-squares of these regressions are all very large (55%) and the unreported unadjusted R-squares are even larger (almost 90%). This is consistent with the fact that we are able to observe and hence control almost all factors lenders can observe, which leaves very little room for the omitted variables bias.

In Columns (4) - (6), we present the results with *Log Percent Funded* as the dependent variable. Consistent with the risk-taking channel, the coefficients on *FF* $\times$ *ScoreX Rating* are again positive and statistically significant. The results are consistent with those in Columns (1)-(3). Finally, in Columns (7) - (9), we present the results with *Log Duration* as the dependent variable. The coefficient estimates are all negative and statistically significant, suggesting that risky loans, relative to safe loans, are funded faster when the federal funds rate is low. When the federal funds rate decreases by one percentage point, the duration for risky loans, relative to safe loans, decrease by almost 21%. If evaluated at the mean, which is 147 hours, the magnitude amounts to about 30 hours.

Overall, the results in Table 2 suggest that easy monetary policy encourages individual investors in the P2P lending market to take more risk, consistent with findings on risk-taking by financial institutions. However, while the risk-taking channel of monetary policy found in financial institutions may be driven by agency problems or other financial frictions institutions face, the effect we document here is more likely to be driven by individual behavioral bias.

5.2 Federal funds rate and reaching-for-yield

Next, we proceed to examine whether individual investors' risk-taking behavior is driven by their incentives for reaching-for-yield. To this end, we estimate the following,

$$Y_{it} = \alpha_t + \beta FF_t \times Yield_{it} + \delta Yield_{it} + \gamma Z_{it} + \texttt{Fixed Effects} + \varepsilon_{it}, \tag{2}$$

where Yield is the lender yield provided by Prosper, which is the difference between the stated interest rates on the loan and the servicing fee. During the Prosper 1.0 era, the lender yield is determined by the auction process; and during the Prosper 2.0 era, the lender yield is determined by Prosper. When deciding whether to fund a loan, a potential investor does not know exactly what the lender yield will be during the Prosper 1.0 era. During the Prosper 2.0 era, however, a potential investor knows the yield before making the funding decision.

The results of estimating Equation (2) are presented in Table 3. The format of the table is exactly the same as those of Table 2. In Columns (1) - (3), the coefficient estimates on $FF \times Yield$ are all negative and statistically significant, suggesting that loans with higher yields are more likely to be approved when the effective federal funds rate is lower. The coefficient estimate in Column (3) is 33.4%. A one-percentage point decrease of the effective federal funds rate will cause the approval rate on a higher yield loan (yield of 30%, the 75th Percentile) to increase by 5.3 percentage points more than the increase in the approval rate of a lower yield loan (yield of 14%, the 25th Percentile). The results suggest that individual investors reach for yield in the P2P market when monetary policy is loose.

In Columns (4) - (6), we present the results for the logarithm of the percent funded. the coefficients on the interaction term are all negative and statistically significant, again consistent with the reaching-for-yield hypothesis. In Columns (7) - (9) for the results of duration, the coefficient estimates on $FF \times Yield$ are all positive and statistically significant, suggesting that high yield loans, relative to low yield loans, are funded faster when the Federal Fund rate is low. A one percentage point decrease of the federal funds rate can shorten the duration of a high yield loan (30%) by about 16% (or almost one day), relative to a low yield loan (14%).

Overall, the results in Table 2 are largely consistent with the hypothesis that lower interest rates encourage individual investors to reach for yield.

5.3 Quantitative easing and risk-taking

One potential problem with the above results is that much of the sample period is during or after the 2008-2009 financial crisis, during which the federal fund rate is low and has little variation. In fact, the federal funds rate is close to zero for most of the post-crisis period, and monetary policy is conducted via the Large Scale Asset Purchase (LSAP) programs, that is, the quantitative easing (QE) programs. To the extent that monetary policy affects individual risk-taking, the QE programs should also affect individual risk-taking.

As such, we examine how the Federal Reserve's quantitative easing programs affect P2P investors' risk-taking and reaching-for-yield behavior. QE1 lasted from late November 2008 until March 2010, and QE2 was first announced in mid-August 2010 and ran from November 2010 to June 2011. QE3 was announced in September 2012. In between QE2 and QE3, the Federal Reserve also implemented the maturity extension program (also called the operational twist program).

We follow Maggio, Kermani, and Palmer (2016) to first create dummy variables, QE1, QE2, MEP, and QE3, which equal one if the time period is during those programs, and zero otherwise. We then examine the effect of these QE programs on risk-taking using the following specification:

$$\begin{aligned} Y_{it} = \alpha_t + \beta_1 QE1 \times Risk_{it} + &+ \beta_2 QE2 \times Risk_{it} + \beta_1 MEP \times Risk_{it} \\ &+ \beta_1 QE3 \times Risk_{it} + \delta Risk_{it} + \gamma Z_{it} + \texttt{Fixed Effects} + \varepsilon_{it}. \end{aligned} \tag{3}$$

Under this specification, the β's capture the effects of the QE programs on risk-taking. If easy monetary policy does encourage risk-taking, we expect the β's to be negative. The results of estimating Equation (3) are presented in Table 4.

In Columns (1) - (3), the coefficient estimates of the interaction terms are all negative and statistically significant, consistent with the conjecture that easy monetary policy encourages risk-taking. The approval rates of a risky loan request (ScoreX Rating of zero), relative to a safe loan request (ScoreX Rating of seven) are about 9, 14, 25, and 19 percentage points higher during the QE1, QE2, MEP, and QE3 periods than normal times. Similarly, the coefficient estimates are also negative and statistically significant in Columns (4) - (6) for the logarithm of the percent funded. The coefficient estimates in Columns (7) - (9) are all positive and most are statistically significant, suggesting that risky loans are funded faster during the QE programs. Overall, the results in Table 4 suggest that individual investors are more willing to take risk during the QE programs.

5.4 Quantitative easing and reaching-for-yield

We then also examine how the quantitative easing programs affect individual investors' reaching-for-yield incentives by replacing the risk measures in Equation (3) with the lender yield, that is,

$$\begin{aligned} Y_{it} = \alpha_t + \beta_1 QE1 \times Yield_{it} + +\beta_2 QE2 \times Yield_{it} + \beta_1 MEP \times Yield_{it} \\ + \beta_1 QE3 \times Yield_{it} + \delta Yield_{it} + \gamma Z_{it} + \texttt{Fixed Effects} + \varepsilon_{it}, \end{aligned} \tag{4}$$

Under this specification, the β's should be positive if the QE programs encourage reaching-for-yield behavior, that is, loan requests with a higher yield are more likely to be approved during the QE programs.

The results of estimating Equation (4) are presented in Table 5. The coefficient estimates on the interaction terms in Columns (1) - (3) are mostly positive and statistically significant, with the exception of QE1. These results are largely consistent with the reaching-for-yield effect of the quantitative easing programs that investors are more likely to approve high yield loans during the QE programs. The inconsistent results of QE1 may again be driven by the fact that the lender yield during this period is determined by the auction process rather than posted by the platform before funding decisions are made. The results for the logarithm of the percent funded in Columns (4) - (6) are similar to those in Columns (1) - (3). Finally, the results in Columns (7) - (9) are consistent with the idea that investors fund high yield loans faster during the QE programs, again with the exception of QE1. Overall, the results in Table 5 suggest that investors prefer high yield loans during the QE programs.

6 Monetary Policy and *Ex Post* Loan Performance

Next, we proceed to examine the effect of monetary policy on *ex post* loan performance. This analysis serves two purposes. First, the *ex ante* risk measure we use, namely, the *ScoreX Rating*, is a summary measure, and may not capture all risk. Examining *ex post* loan performance therefore provides a complete account of the effect of monetary policy on risk-taking. Second, examining *ex post* loan performance allows us to assess the consequence of investors' *ex ante* risk-taking and reaching-for-yield behavior.

6.1 Federal funds rate and loan default

Empirically, we first examine the effect of the effective federal funds rate at the time of loan origination on *ex post* default. To this end, we follow Dell'Ariccia, Laeven, and Suarez (2017) and Di Maggio and Kacperczyk (2017) and estimate the following specification on all approved loans,

$$D_{it} = \beta FF_t + \delta Risk_{it} + \gamma Z_{it} + \theta X_t + \texttt{Fixed Effects} + \varepsilon_{it}, \tag{5}$$

where D_{it} is the indicator of loan default for loan i originated at time t, which equals one if the loan status is default, charged-off, or past due, and zero otherwise. Note that under this specification, we cannot include time fixed effects because they will subsume the federal funds rate. We acknowledge that the identification in Equation (6) is not as clean as those in the previous sections because we cannot control time-varying factors. It is therefore possible that the results may be driven by unobservable demand-side factors. We also control for risk and all other loan and borrower characteristics to examine the impact of monetary policy on *ex post* performance beyond those captured by the *ex ante* risk measures. We include city fixed effects or borrower fixed effects to control for additional demand-side factors.

The results of estimating Equation (6) are presented in Table 6. The coefficient estimates on the federal funds rate are all negative and statistically significant, suggesting that loans originated when the federal funds rate is low experience higher *ex post* default rates, even after controlling for risk and all other loan and borrower characteristics. A one percentage point reduction of the federal funds rate can lead to a more than one percentage point increase in the default probability. The effect is at least similar, if not larger than, the effect of increasing the ScoreX Rating by one notch.

6.2 QE programs and loan default

Next, we also examine the effect of the QE programs on *ex post* loan performance by estimating the following specification,

$$D_{it} = \beta_1 QE1 + \beta_2 QE2 + \beta_3 MEP + \beta_4 QE3 + \delta Risk_{it} + \gamma Z_{it} + \theta X_t + \texttt{Fixed Effects} + \varepsilon_{it}. \quad (6)$$

As in Equation (6), we again cannot control for time-fixed effects, and therefore cannot rule out the possibility that some unobservable demand-side factors correlated with macroeconomic conditions may drive the results.

The results are presented in Table 7. In all columns, the coefficient estimates on QE1, QE2, and MEP are mostly positive and statistically significant. These results suggest that loans originated during QE1, QE2, and MEP programs have higher *ex post* default rates than loans with similar *ex ante* risk measures and borrower and loan characteristics but originated during non-QE times. The economic magnitudes are also large. Loans originated during QE1 have about two percentage points higher default rates. The effects of QE2 and MEP are even larger, and these two programs increase loan default rates by almost four percentage points.

Different from the coefficients on QE1, QE2, and MEP, the coefficient estimates on QE3 are all negative and statistically significant. Several factors may be responsible for this result. First, after QE1, QE2, and MEP, the interest rates of the economy are already very low and QE3 probably had little impact on individuals' investment opportunity set. Second, it may be driven by demand side factors because economic conditions during QE3 have already significantly improved. As we discussed above, the specification in Equation (6) cannot rule out the possibility that the results may be driven by unobservable demand-side factors.

7 Robustness Checks

7.1 Using Prosper In-House Risk Measures

We use the *ScoreX Rating* as the risk measure in the analysis above because it is the only measure available for the whole sample period. However, after 2010 during the Prosper 2.0 era, Prosper started to provide two in-house risk measures, namely, the Prosper Rating and the Prosper Score. Prosper Score is a custom risk score built using historical Prosper data to assess the risk of Prosper listings. The Prosper Rating is developed with both Prosper data and credit agency reports, and corresponds to an estimated range of loss rates. Balyuk and Davydenko (2018) show that these in-house risk measures are more informative than borrower credit ratings. As such, we examine whether our results are robust to these in-house risk measures. Specifically, we replace ScoreX Rating with the Prosper Rating and the Prosper Score and re-estimate Equation (1).[5] The results are presented in Table 8, with Panel A using the Prosper Rating as the risk measure and Panel B using the Prosper Score as the risk measure.

Focusing on the results in Panel A first, the signs of the coefficient estimates on the interaction terms between the effective Federal Funds rate and the risk measures are the same as those in Table 2, again suggesting that lower interest rates encourage risk-taking. In fact, the results with the Prosper Rating are much stronger as the magnitudes of the coefficients are about 20 times larger than those in Table 2. The much larger effect can be driven by the fact that the federal funds rate is close to zero during this period, and hence the risk-taking incentive is much stronger. It can also be driven by the improved accuracy of the Prosper Rating over the ScoreX Rating. Different from the results in Table 2, most of the coefficients on the risk measures themselves change signs. For example, in Columns

[5] We do not re-estimate Equation 3 because most of the Prosper 2.0 era is during one of the QE programs, and there is almost no normal time to compare with.

(1) - (3) of Table 2, the coefficients on ScoreX Rating is positive and statistically significant, suggesting that loans with higher ScoreX Rating (safer loans) are much more likely to be approved. In contrast, the coefficients on Prosper Rating in Columns (1) - (3) of Table 8 are all negative and statistically significant, suggesting that the funding decisions become much less sensitive to risk after 2010.

The results in Panel B are mostly consistent with those in Panel A, but are much weaker, suggesting that the Prosper Score is less informative and individual investors rely less on the Prosper Score when making decisions.

7.2 Reaching for Yield in the Prosper 2.0 Era

One problem with the reaching-for-yield results, as shown in Table 4, is that during the Prosper 1.0 era, the lender yield is determined by the auction process after the funding decisions are already made. In this section, we re-estimate Equation 2 only for the Prosper 2.0 era to see if we can get stronger results. The results are presented in Table 9. Compared with the results in Table 3, the results are much stronger and are consistent with the reaching-for-yield hypothesis. The results are therefore consistent with the idea that the reaching-for-yield behavior is more pronounced in the Prosper 2.0 era when the yield is determined and posted before funding decisions are made.

7.3 Reaching for Yield Conditional on Risk Measures

Becker and Ivashina (2015) and Choi and Kronlund (2017) show that insurance companies and bond mutual funds prefer bonds with higher yields within each rating category, which, they argue, is driven by regulatory arbitrage. In this section, we follow their idea to examine whether individual investors also reach for yield conditional on risk measures. Empirically, we include year-month $\times$ Prosper Rating fixed effects in the regressions to compare loan requests during the same month and with the same prosper rating. The results are presented in Table 10. The results are indeed still consistent with the reaching-for-yield hypothesis, suggesting that the primary motive for investors to take risk is to reach for yield. Different from Becker and Ivashina (2015), however, the results are certainly not driven by regulatory arbitrage.

7.4 Using the Taylor Rule Residual to Measure Monetary Policy

One concern for the analysis is that monetary policy is endogenously determined and may be correlated with past and future economic conditions that may affect the quantity and quality of loan demand. To this end, we follow the literature to use the Taylor rule residual to capture the exogenous component of the federal funds rate and re-examine the effect of the Taylor rule residual on risk-taking in the P2P market. Specifically, we run rolling regressions of the federal funds rate on the deviation of CPI inflation from the 2% target rate and the difference between the actual and potential GDP growth rates, and then calculate the residuals from those regressions. We then replace the effective federal funds rate with the Taylor rule residual in the regressions above.

The results are reported in Table 11, with Columns (1) - (3) for *ex ante* risk-taking, with Columns (4) - (6) for reaching-for-yield, and Column (7) for *ex post* default. The results are consistent with those presented in Tables 2, 3, and 6. Overall, the results in Table 11 suggest that the baseline results are unlikely to be driven by the endogeneity of monetary policy because the Taylor rule residual is likely to capture the exogenous component of monetary policy.

7.5 Other Macroeconomic Factors and Risk Taking

We address a final concern that the results may be driven by other macroeconomic factors correlated with monetary policy. While the time fixed effects we have can control for the direct effect of other macroeconomic factors on loan outcomes, they cannot control for the interaction effect of risk-taking and monetary policy. To this end, we further include the interaction terms between the risk measure and inflation rate, and between the risk measure and the GDP growth rate to examine whether these other macroeconomic factors drive the results above. The results are presented in Columns (1) - (3) of Table 12. The results are still consistent with those presented in Table 2, confirming the effect of monetary policy on risk-taking.

We then add the interaction terms between lender yield and inflation, and between lender yield and the GDP growth rate in the reaching-for-yield to Equation (2). The results are presented in Columns (4) - (6) of Table 12. The results are again consistent with those presented in Table 3, confirming the effect of monetary policy on reaching-for-yield.

Finally, we add the inflation rate and the GDP growth rate to Equation (5). The coefficient on the federal funds rate remains negative and statistically significant, confirming that loans originated when the interest rate is low are more likely to default.

Overall, the results in Table 12 suggest that the risk-taking and reaching-for-yield behavior documented above are truly driven by monetary policy, instead of by other macroeconomic factors correlated with monetary policy.

8 Conclusions

We examine the effect of monetary policy on risk-taking by individual investors in the P2P lending market. We find that easy monetary policy encourages individual risk-taking and reaching-for-yield. The results suggest that the so-called risk-taking channel of monetary policy transmission can also be driven by individual behavioral bias, instead of by frictions specific to financial institutions.

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Appendix: Variable Definitions

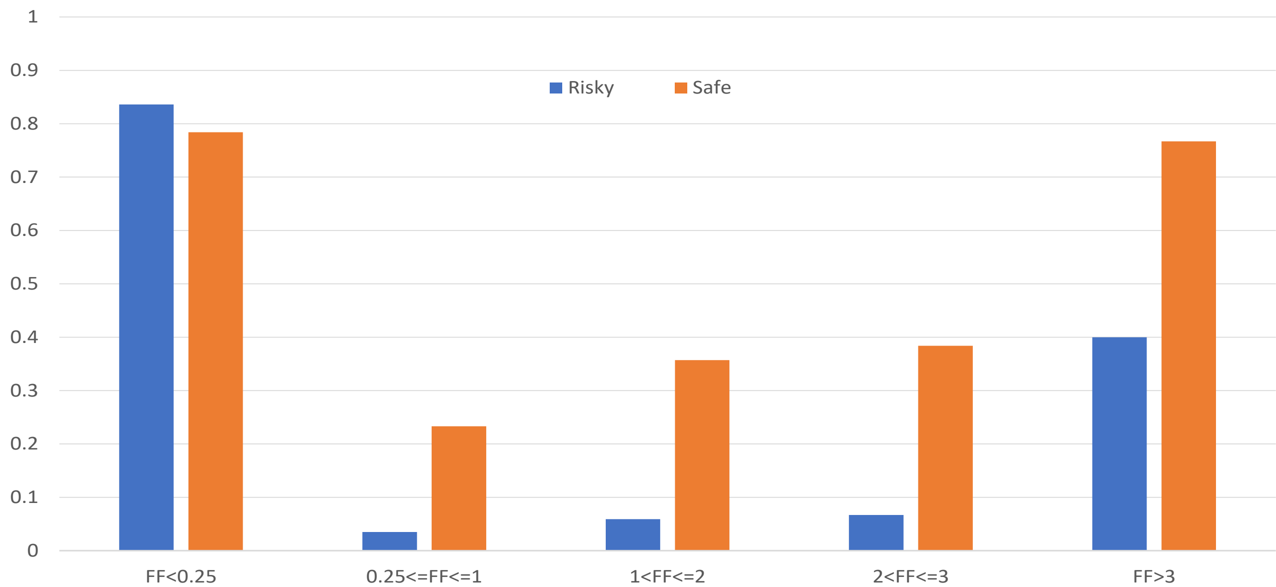
Variable	Definition
Approval	A dummy variable that equals one if the loan is approved, and zero otherwise
Percent Funded	The percent pledged by investors
Duration	The time it takes to fund the loan in hours
ScoreX Rating	The ScoreX Rating, ranges from 0-10
Prosper Rating	Prosper Rating, ranges from 1-7
Prosper Score	Prosper Score, ranges from 1-11
Lender Yield	The difference between loan interest rate and service fee rate
90-Day Delinquencies	Number of over 90-day delinquencies
60-Day Delinquencies	Number of over 60-day delinquencies
30-Day Delinquencies	Number of over 30-day delinquencies
Current Delinquencies	Number of current delinquencies
Loan Amount	The requested loan amount
Listing Term	The loan term in months
Monthly Payment	The monthly payment of the loan
Monthly Income	Reported borrower monthly income
Debt to Income	Debt to income ratio
Months Employed	Months employed
Prior Prosper Loan	Number of prior Prosper loans
Monthly Debt	Total monthly debt payment
7-Year Credit Lines	Credit lines in last seven years
6-Month Inquiries	Number of inquiries during the last size months
Total Inquiries	Total number of credit inquiries
Homeowner	A dummy variable that equals one if the borrower is a homeowner, and zero otherwise

Variable	Definition
Log Delinquent Amount	The logarithm of the amount delinquent
Current Credit Lines	Number of current credit lines
Open Credit Lines	Number of open credit lines
Bank Card Utilization	Bankcard utilization rate
Total Open Revolving	Total number of revolving credit accounts
Installment Balance	Installment loan balance
Real Estate Balance	Real estate loan balance
Real Estate Payment	Monthly real estate loan payment
Log Revolving Balance	Logarithm of revolving credit balance
Percent Revolving Available	The percent of revolving credit available
7-Year Delinquencies	Number of delinquencies during the last seven years

Figure 1: Monetary Policy, Loan Riskiness, and Loan Approval Rates

This figure presents the approval rates of safe (ScoreX Rating above the 75 percentile) and risky loan requests (ScoreX rating below the 25 percentile) under different monetary policy regimes.

Panel A: Effective federal funds rate



Panel B: Quantitative easing programs

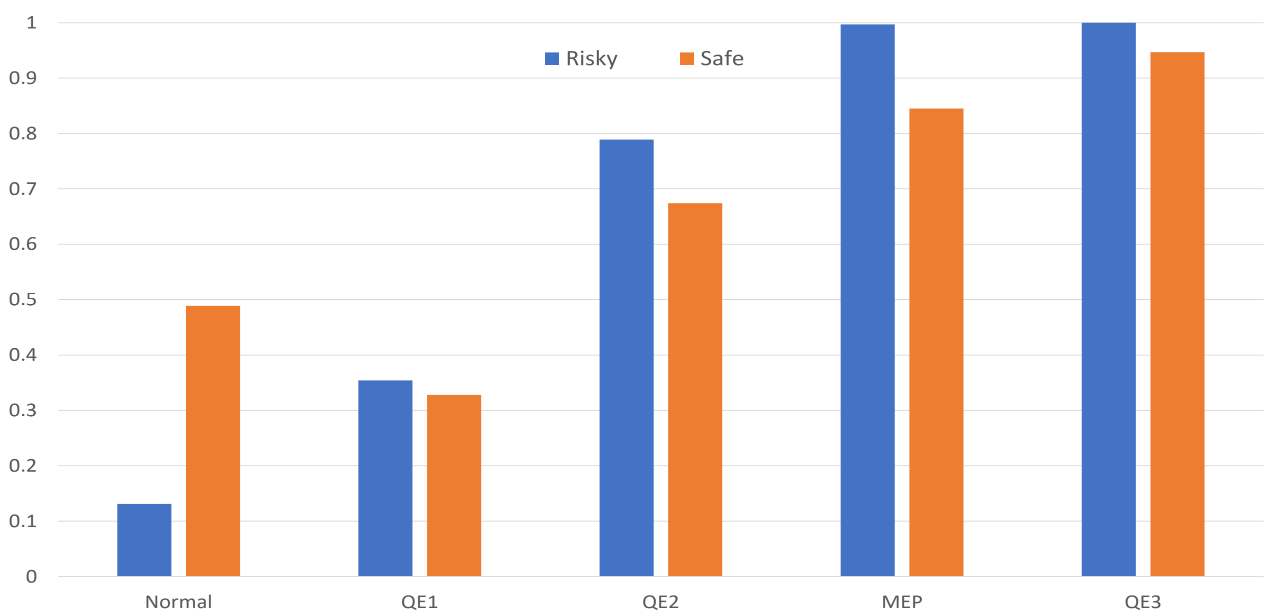
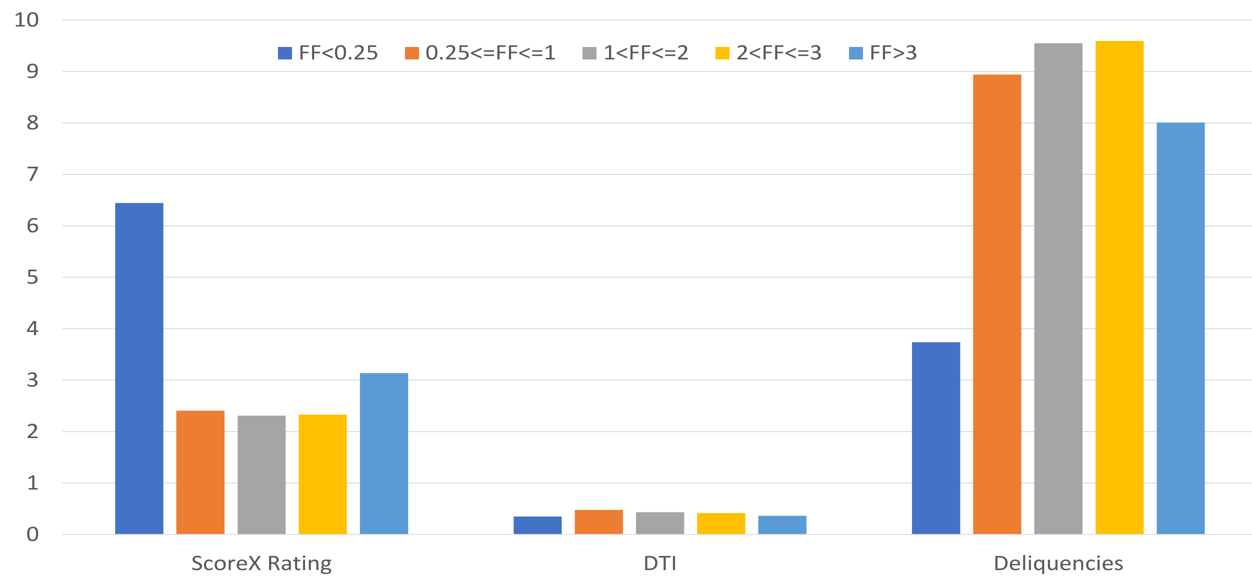


Figure 2: Monetary Policy, Loan Riskiness, and Loan Approval Rates

This figure presents the average ScoreX Rating, Debt to Income Ratio, and the Number of Delinquencies of all loan request under different monetary policy regimes

Panel A: Effective federal funds rate



Panel B: Quantitative easing programs

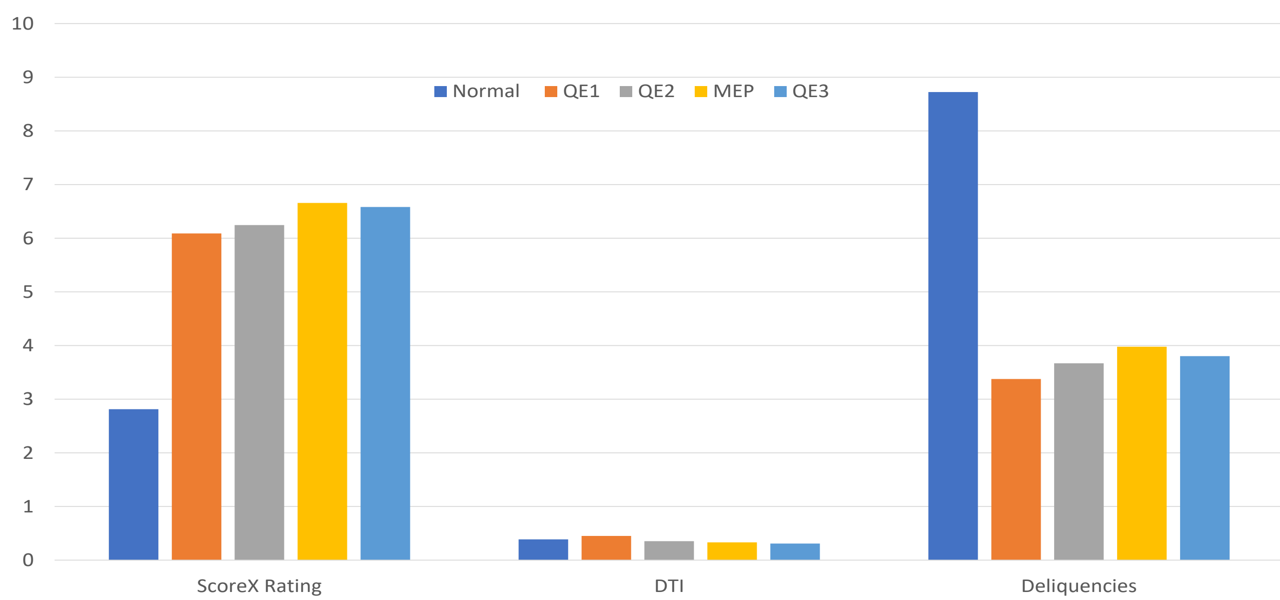


Table 1: Summary Statistics
This table presents the summary statistics of the variables used in the paper. The variable definitions are in the appendix.

	N	Mean	Std Dev	P25	Median	P75
Approval	164,326	0.46	0.50	0.00	0.00	1.00
Percent Funded	164,326	0.52	0.47	0.02	0.44	1.00
Duration	164,326	147.49	85.87	91.35	168.03	168.08
ScoreX Rating	164,326	4.25	3.42	0.00	4.00	7.00
Prosper Rating	53,174	3.35	1.95	1.00	3.00	5.00
Prosper Score	53,174	5.59	2.56	4.00	6.00	8.00
Lender Yield	164,326	0.21	0.09	0.14	0.21	0.30
90-Day Delinquencies	164,326	6.81	13.51	0.00	0.00	8.00
60-Day Delinquencies	164,326	3.37	5.86	0.00	1.00	5.00
30-Day Delinquencies	164,326	7.36	11.48	0.00	3.00	10.00
Current Delinquencies	164,326	1.70	3.71	0.00	0.00	2.00
Loan Amount	164,326	7438.96	6092.12	3000.00	5000.00	10000.00
Listing Term	164,326	37.89	7.24	36.00	36.00	36.00
Monthly Payment	164,326	270.77	214.20	123.00	198.77	351.57
Monthly Income	164,326	5081.87	34015.24	2583.33	4000.00	5996.58
Debt to Income	164,326	0.37	0.30	0.16	0.26	0.45
Months Employed	164,326	80.88	87.82	19.00	51.00	114.00
Prior Prosper Loan	164,326	0.19	0.52	0.00	0.00	0.00
Monthly Debt	164,326	910.31	1739.91	345.00	700.00	1207.00
7-Year Credit Lines	164,326	26.25	14.41	16.00	24.00	34.00
6-Month Inquiries	164,326	2.44	3.55	0.00	1.00	3.00
Total Inquiries	164,326	8.48	9.55	3.00	6.00	11.00
Homeowner	164,326	0.45	0.50	0.00	0.00	1.00
Log Delinquent Amount	164,326	2.38	3.60	0.00	0.00	5.93
Current Credit Lines	164,326	9.32	5.88	5.00	8.00	13.00
Open Credit Lines	164,326	8.29	5.30	4.00	7.00	11.00
Bank Card Utilization	164,326	0.58	0.38	0.26	0.65	0.91
Total Open Revolving	164,326	6.25	4.81	3.00	5.00	9.00
Installment Balance	164,326	28066.68	39144.04	5688.00	17658.50	35932.00
Real Estate Balance	164,326	106533.95	200347.00	0.00	0.00	162045.50
Real Estate Payment	164,326	818.04	1974.83	0.00	0.00	1314.00
Log Revolving Balance	164,326	8.90	1.59	7.98	9.05	9.97
Percent Revolving Available	164,326	40.38	31.76	11.00	36.00	66.00
7-Year Delinquencies	164,326	6.54	13.24	0.00	0.00	7.00

Table 2: Federal Funds Rate and Risk Taking

This table presents the results of estimating $Y_{it} = \alpha_t + \beta FF_t \times Risk_{it} + \delta Risk_{it} + \gamma Z_{it} + \texttt{Fixed Effects} + \varepsilon_{it}$. The dependent variable in Columns (1) - (3) is loan Approval, that in Columns (4)-(6) is the logarithm of the percent funded, and that in Columns (7)-(9) is the logarithm of the duration of the listing. All regressions include all the loan and borrower characteristics as defined in the Appendix. Standard errors clustered by stat and year-month are presented in the parentheses below the coefficient estimates. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	Approval			Log Percent Funded			Log Duration		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
FF × *ScoreX Rating*	0.009***	0.010***	0.011***	0.005***	0.006***	0.007***	-0.032***	-0.033***	-0.037***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)
ScoreX Rating	0.016***	0.016***	0.015***	0.016***	0.016***	0.016***	0.076***	0.077***	0.080***
	(0.001)	(0.001)	(0.002)	(0.000)	(0.000)	(0.001)	(0.002)	(0.002)	(0.005)
Loan Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes		Yes	Yes		Yes	Yes	
City Fixed Effects		Yes			Yes			Yes	
City × Month Fixed Effects			Yes			Yes			Yes
Observations	164,326	164,326	164,326	164,326	164,326	164,326	164,324	164,324	164,324
Adjusted R-squared	0.551	0.554	0.558	0.608	0.614	0.625	0.572	0.579	0.696

Table 3: Federal Funds Rate and Reaching-for-Yield

This table presents the results of estimating $Y_{it} = \alpha_t + \beta FF_t \times Yield_{it} + \delta Yield_{it} + \gamma Z_{it} + \texttt{Fixed Effects} + \varepsilon_{it}$. The dependent variable in Columns (1) - (3) is loan Approval, that in Columns (4)-(6) is the logarithm of the percent funded, and that in Columns (7)-(9) is the logarithm of the duration of the listing. All regressions include all the loan and borrower characteristics as defined in the Appendix. Standard errors clustered by state and year-month are presented in the parentheses below the coefficient estimates. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	Approval			Log Percent Funded			Log Duration		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
FF × *Yield*	-0.082***	-0.138***	-0.334***	0.018***	-0.014**	-0.131***	0.882***	0.903***	1.056***
	(0.009)	(0.010)	(0.025)	(0.006)	(0.006)	(0.016)	(0.024)	(0.028)	(0.077)
Yield	-0.069***	-0.080***	-0.028	0.066***	0.058***	0.104***	-2.297***	-2.294***	-2.348***
	(0.018)	(0.019)	(0.047)	(0.011)	(0.011)	(0.029)	(0.055)	(0.061)	(0.169)
Loan Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month Fixed Effects	Yes	Yes		Yes	Yes		Yes	Yes	
City Fixed Effects		Yes			Yes			Yes	
City × Year-Month Fixed Effects			Yes			Yes			Yes
Observations	164,326	164,326	164,326	164,326	164,326	164,326	164,324	164,324	164,324
Adjusted R-squared	0.546	0.549	0.560	0.603	0.608	0.621	0.571	0.578	0.694

Table 4: Quantitative Easing Programs and Risk Taking

This table presents the results of estimating $Y_{it} = \alpha_t + \beta_1 QE1 \times Risk_{it} + +\beta_2 QE2 \times Risk_{it} + \beta_1 MEP \times Risk_{it} + \beta_1 QE3 \times Risk_{it} + \delta Risk_{it} + \gamma Z_{it} + \texttt{Fixed Effects} + \varepsilon_{it},$. The dependent variable in Columns (1) - (3) is loan Approval, that in Columns (4)-(6) is the logarithm of the percent funded, and that in Columns (7)-(9) is the logarithm of the duration of the listing. All regressions include all the loan and borrower characteristics as defined in the Appendix. Standard errors clustered by state and year-month are presented in the parentheses below the coefficient estimates. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	Approval			Log Percent Funded			Log Duration		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
QE1 × *ScoreX Rating*	-0.013***	-0.014***	-0.016***	-0.010***	-0.011***	-0.013***	-0.023***	-0.025***	-0.017***
	(0.001)	(0.001)	(0.004)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.005)
QE2 × *ScoreX Rating*	-0.020***	-0.021***	-0.023***	-0.015***	-0.015***	-0.016***	0.015***	0.016***	0.025*
	(0.002)	(0.002)	(0.005)	(0.001)	(0.001)	(0.003)	(0.004)	(0.005)	(0.013)
MEP × *ScoreX Rating*	-0.036***	-0.036***	-0.039***	-0.025***	-0.025***	-0.027***	0.119***	0.119***	0.129***
	(0.001)	(0.001)	(0.002)	(0.000)	(0.001)	(0.001)	(0.005)	(0.005)	(0.013)
QE3 × *ScoreX Rating*	-0.027***	-0.027***	-0.027***	-0.021***	-0.021***	-0.021***	0.230***	0.230***	0.227***
	(0.001)	(0.001)	(0.002)	(0.000)	(0.000)	(0.001)	(0.004)	(0.005)	(0.013)
ScoreX Rating	0.042***	0.043***	0.044***	0.032***	0.033***	0.035***	-0.021***	-0.021***	-0.021***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)
Loan Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month Fixed Effects	Yes	Yes		Yes	Yes		Yes	Yes	
City Fixed Effects		Yes			Yes			Yes	
City × Year-Month Fixed Effects			Yes			Yes			Yes
Observations	164,326	164,326	164,326	164,326	164,326	164,326	164,324	164,324	164,324
Adjusted R-squared	0.552	0.554	0.558	0.611	0.617	0.627	0.588	0.594	0.705

Table 5: Quantitative Easing Programs and Reaching-for-Yield

This table presents the results of estimating $Y_{it} = \alpha_t + \beta_1 QE1 \times Risk_{it} + +\beta_2 QE2 \times Risk_{it} + \beta_1 MEP \times Risk_{it} + \beta_1 QE3 \times Risk_{it} + \delta Risk_{it} + \gamma Z_{it} + \texttt{Fixed Effects} + \varepsilon_{it},$. The dependent variable in Columns (1) - (3) is loan Approval, that in Columns (4)-(6) is the logarithm of the percent funded, and that in Columns (7)-(9) is the logarithm of the duration of the listing. All regressions include all the loan and borrower characteristics as defined in the Appendix. Standard errors clustered by state and year-month are presented in the parentheses below the coefficient estimates. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	Approval			Log Percent Funded			Log Duration		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
QE1 × *Yield*	-0.302***	-0.184***	0.091*	-0.315***	-0.245***	-0.035	0.698***	0.783***	0.543***
	(0.037)	(0.039)	(0.049)	(0.024)	(0.026)	(0.064)	(0.051)	(0.062)	(0.128)
QE2 × *Yield*	0.257***	0.385***	0.696***	0.180***	0.265***	0.485***	0.026	0.107	-0.176
	(0.046)	(0.048)	(0.128)	(0.027)	(0.029)	(0.078)	(0.115)	(0.127)	(0.351)
MEP × *Yield*	0.560***	0.638***	0.854***	0.323***	0.372***	0.521***	-0.428***	-0.451***	-0.587
	(0.029)	(0.031)	(0.075)	(0.015)	(0.016)	(0.038)	(0.160)	(0.171)	(0.481)
QE3 × *Yield*	0.241***	0.319***	0.435***	0.110***	0.165***	0.248***	-7.643***	-7.647***	-7.597***
	(0.028)	(0.031)	(0.079)	(0.015)	(0.016)	(0.041)	(0.176)	(0.191)	(0.559)
yield	-0.540***	-0.666***	-0.994***	-0.187***	-0.269***	-0.476***	-0.469***	-0.498***	-0.228***
	(0.017)	(0.017)	(0.034)	(0.011)	(0.011)	(0.022)	(0.026)	(0.034)	(0.059)
Loan Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month Fixed Effects	Yes	Yes		Yes	Yes		Yes	Yes	
City Fixed Effects		Yes			Yes			Yes	
City × Year-Month Fixed Effects			Yes			Yes			Yes
Observations	164,326	164,326	164,326	164,326	164,326	164,326	164,324	164,324	164,324
Adjusted R-squared	0.535	0.540	0.549	0.581	0.589	0.600	0.584	0.591	0.701

Table 6: Federal Funds Rate and Loan Default

This table presents the results of estimating $D_{it} = \beta FF_t + \delta Risk_{it} + Z_{it} + \theta X_t + \texttt{Fixed Effects} + \varepsilon_{it}$. The dependent variable default, which equals one if the loan was not fully paid, and zero otherwise. All regressions include all the loan and borrower characteristics as defined in the Appendix. Standard errors clustered by state and year-month are presented in the parentheses below the coefficient estimates. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	(1)	(2)	(3)
FF	-0.013***	-0.010***	-0.026***
	(0.003)	(0.003)	(0.004)
ScoreX Rating	-0.022***	-0.021***	-0.008***
	(0.002)	(0.002)	(0.002)
Loan Characteristics	Yes	Yes	Yes
Borrower Characteristics	Yes	Yes	Yes
City Fixed Effects		Yes	
Borrower Fixed Effects			Yes
Observations	74,979	74,979	74,979
Adjusted R-squared	0.133	0.169	0.720

Table 7: Quantitative Easing and Loan Default

This table presents the results of estimating $D_{it} = \beta_1 QE1 + \beta_2 QE2 + \beta_3 MEP + \beta_4 QE3 + \delta Risk_{it} + \gamma Z_{it} + \theta X_t + \texttt{Fixed Effects} + \varepsilon_{it}$. The dependent variable default, which equals one if the loan was not fully paid, and zero otherwise. All regressions include all the loan and borrower characteristics as defined in the Appendix. Standard errors clustered by state and year-month are presented in the parentheses below the coefficient estimates. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	(1)	(2)	(3)
QE1	0.022**	0.021**	-0.040***
	(0.009)	(0.009)	(0.014)
QE2	0.034***	0.036***	0.041***
	(0.011)	(0.011)	(0.015)
MEP	0.041***	0.039***	0.021
	(0.012)	(0.012)	(0.017)
QE3	-0.071***	-0.065***	-0.039*
	(0.015)	(0.014)	(0.020)
ScoreX Rating	-0.023***	-0.022***	-0.008***
	(0.002)	(0.002)	(0.002)
Loan Characteristics	Yes	Yes	Yes
Borrower Characteristics	Yes	Yes	Yes
City Fixed Effects		Yes	
Borrower Fixed Effects			Yes
Observations	74,979	74,979	74,979
Adjusted R-squared	0.133	0.169	0.720

Table 8: Federal Funds Rate and Risk Taking: Alternative Risk Measure

This table presents the results of estimating $Y_{it} = \alpha_t + \beta FF_t \times Risk_{it} + \delta Risk_{it} + \gamma Z_{it} + \texttt{Fixed Effects} + \varepsilon_{it}$ using Prosper Rating (Panel A) and Prosper Score as risk measures. The dependent variable in Columns (1) - (3) is loan Approval, that in Columns (4)-(6) is the logarithm of the percent funded, and that in Columns (7)-(9) is the logarithm of the duration of the listing. All regressions include all the loan and borrower characteristics as defined in the Appendix. Standard errors clustered by stat and year-month are presented in the parentheses below the coefficient estimates. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

Panel A: Using Prosper Rating as the risk measure

	Approval			Log Percent Funded			Log Duration		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
FF × *Prosper Rating*	0.187***	0.176***	0.226***	0.035***	0.033***	0.059	-4.288***	-4.246***	-4.704***
	(0.023)	(0.027)	(0.078)	(0.011)	(0.012)	(0.036)	(0.117)	(0.137)	(0.412)
Prosper Rating	-0.012***	-0.011***	-0.017*	0.002	0.002	-0.002	0.641***	0.639***	0.677***
	(0.003)	(0.003)	(0.010)	(0.001)	(0.002)	(0.005)	(0.015)	(0.018)	(0.055)
Loan Characteristics	Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
Borrower Characteristics	Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
Year-Month Fixed Effects	Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
City Fixed Effects		Yes					Yes		
City × Year-Month Fixed Effects			Yes					Yes	
Observations	53,174	53,174	53,174	53,174	53,174	53,174	53,174	53,174	53,174
Adjusted R-squared	0.220	0.232	0.176	0.229	0.247	0.200	0.527	0.532	0.536

Panel B: Using Prosper Score as the risk measure

	Approval			Log Percent Funded			Log Duration		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
FF × *Prosper Score*	0.057***	0.063***	0.060	-0.013*	-0.008	-0.008	-2.521***	-2.534***	-2.929***
	(0.016)	(0.019)	(0.056)	(0.008)	(0.009)	(0.026)	(0.088)	(0.102)	(0.311)
Prosper Score	-0.008***	-0.009***	-0.009	0.002*	0.001	0.001	0.444***	0.452***	0.485***
	(0.002)	(0.002)	(0.006)	(0.001)	(0.001)	(0.003)	(0.011)	(0.012)	(0.037)
Loan Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month Fixed Effects	Yes	Yes		Yes	Yes		Yes	Yes	
City Fixed Effects		Yes			Yes			Yes	
City × Year-Month Fixed Effects			Yes			Yes			Yes
Observations	53,174	53,174	53,174	53,174	53,174	53,174	53,174	53,174	53,174
Adjusted R-squared	0.217	0.230	0.174	0.226	0.244	0.197	0.532	0.538	0.541

Table 9: Reaching-for-Yield: Propser 2.0

This table presents the results of estimating $Y_{it} = \alpha_t + \beta FF_t \times Yield_{it} + \delta Yield_{it} + \gamma Z_{it} + \texttt{Fixed Effects} + \varepsilon_{it}$ after 2010. The dependent variable in Columns (1) - (3) is loan Approval, that in Columns (4)-(6) is the logarithm of the percent funded, and that in Columns (7)-(9) is the logarithm of the duration of the listing. All regressions include all the loan and borrower characteristics as defined in the Appendix. Standard errors clustered by state and year-month are presented in the parentheses below the coefficient estimates. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	Approval			Log Percent Funded			Log Duration		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$FF \times Yield$	-3.467***	-3.140***	-4.224**	-0.806***	-0.707***	-1.367*	93.787***	92.549***	102.335***
	(0.523)	(0.593)	(1.766)	(0.236)	(0.269)	(0.810)	(2.703)	(3.169)	(9.619)
$Yield$	0.220***	0.194***	0.337	0.005	-0.004	0.090	-14.347***	-14.229***	-14.988***
	(0.065)	(0.075)	(0.220)	(0.029)	(0.033)	(0.100)	(0.348)	(0.408)	(1.256)
Loan Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month Fixed Effects	Yes	Yes		Yes	Yes		Yes	Yes	
City Fixed Effects		Yes			Yes			Yes	
City × Year-Month Fixed Effects			Yes			Yes			Yes
Observations	53,174	53,174	53,174	53,174	53,174	53,174	53,174	53,174	53,174
Adjusted R-squared	0.218	0.231	0.175	0.228	0.245	0.199	0.526	0.530	0.534

Table 10: Reaching-for-Yield Conditional on Risk Measures

This table presents the results of estimating $Y_{it} = \alpha_t + \beta FF_t \times Yield_{it} + \delta Yield_{it} + \gamma Z_{it} + \texttt{Fixed Effects} + \varepsilon_{it}$ with year-month $\times$ Prosper Rating fixed effects fter 2010. The dependent variable in Columns (1) - (3) is loan Approval, that in Columns (4)-(6) is the logarithm of the percent funded, and that in Columns (7)-(9) is the logarithm of the duration of the listing. All regressions include all the loan and borrower characteristics as defined in the Appendix. Standard errors clustered by state and year-month are presented in the parentheses below the coefficient estimates. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	Approval			Log Percent Funded			Log Duration		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
FF × *Yield*	-1.734**	-0.465	-4.024***	-1.018***	-0.525	-2.213***	77.388***	73.414***	74.374***
	(0.805)	(0.898)	(1.539)	(0.352)	(0.394)	(0.692)	(4.595)	(5.110)	(8.415)
Yield	-0.337***	-0.451***	0.024	-0.103**	-0.149***	0.083	-10.604***	-10.178***	-9.781***
	(0.101)	(0.112)	(0.194)	(0.042)	(0.048)	(0.085)	(0.584)	(0.651)	(1.090)
Loan Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month Fixed Effects	Yes	Yes		Yes	Yes		Yes	Yes	
City Fixed Effects		Yes			Yes			Yes	
City × Year-Month Fixed Effects			Yes			Yes			Yes
Observations	53,173	49,382	23,642	53,173	49,382	23,642	53,173	49,382	23,642
Adjusted R-squared	0.246	0.251	0.279	0.276	0.280	0.309	0.587	0.590	0.589

Table 11: Using Taylor Rule Residual as the Measure of Monetary Policy

This table presents the results using Taylor rule residual as the measure of monetary policy. The dependent variable in Columns (1) and (4) is loan Approval, that in Columns (2) and (5) is the logarithm of the percent funded, that in Columns (3) and (6) is the logarithm of the duration of the listing, and that in Column (7) is default. All regressions include all the loan and borrower characteristics as defined in the Appendix. Standard errors clustered by state and year-month are presented in the parentheses below the coefficient estimates. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	(1) Approval	(2) Log Percent Funded	(3) Log Duration	(4) Approval	(5) Log Percent Funded	(6) Log Duration	(7) Default
Taylor × *ScoreX Rating*	0.007***	0.004***	-0.036***				
	(0.002)	(0.001)	(0.010)				
ScoreX Rating	0.039***	0.029***	0.022				-0.017***
	(0.006)	(0.004)	(0.021)				(0.002)
Taylor × *Yield*				0.296***	0.141***	-3.932***	
				(0.089)	(0.050)	(0.834)	
Yield				0.332	0.163	-7.869***	
				(0.229)	(0.118)	(2.387)	
Taylor							-0.015***
							(0.003)
Loan Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	
City Fixed Effects	Yes	Yes		Yes	Yes	Yes	Yes
Observations	164,326	164,326	164,326	164,326	164,326	164,326	74,979
Adjusted R-squared	0.444	0.500	0.385	0.546	0.549	0.560	0.177

Table 12: Other Macroeconomic Factors

This table presents the results of other macroeconomic factors on risk taking and reaching for yield by individual investors. The dependent variable in Columns (1) and (4) is loan Approval, that in Columns (2) and (5) is the logarithm of the percent funded, that in Columns (3) and (6) is the logarithm of the duration of the listing, and that in Column (7) is default. All regressions include all the loan and borrower characteristics as defined in the Appendix. Standard errors clustered by state and year-month are presented in the parentheses below the coefficient estimates. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	(1) Approval	(2) Log Percent Funded	(3) Log Duration	(4) Approval	(5) Log Percent Funded	(6) Log Duration	(7) Default
FF × *ScoreX Rating*	0.009***	0.005***	-0.029***				
	(0.000)	(0.000)	(0.001)				
ScoreX Rating	0.020***	0.019***	0.052***				-0.021***
	(0.001)	(0.000)	(0.002)				(0.002)
FF × *Yield*				-0.160***	-0.032***	0.662***	
				(0.012)	(0.007)	(0.028)	
Yield				-0.341***	-0.165***	-1.344***	
				(0.025)	(0.016)	(0.066)	
FF							-0.010***
							(0.003)
Loan Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	
City Fixed Effects	Yes	Yes		Yes	Yes	Yes	Yes
Observations	164,326	164,326	164,326	164,326	164,326	164,326	74,979
Adjusted R-squared	0.554	0.615	0.582	0.539	0.587	0.580	0.177