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In December Days Are Shorter but Loans Are Cheaper

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Abstract

This study analyzes the month-of-the-year effect on lending decisions. Using data from a large US peer-to-peer lender, we perform regressions of loan acceptance and loan spread on month dummy variables, including a large set of borrower and loan control variables. We find evidence of a month-of-the-year effect on loan acceptance and loan pricing. December is the best month to ask for a loan, with the highest chance of acceptance and the lowest spread. Loan applications have the lowest chance of acceptance in January while loan pricing is highest in August and September. We test the potential explanations of the calendar anomalies and find some support for trade loading, such that granted loans might be inflated at the end of the quarter to hit quarterly targets.

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1. Introduction

The factors that influence lending decisions, such as the decision to grant a loan and to set the loan rate, have been widely studied at the loan, borrower, and country levels (e.g., Qian and Strahan, 2007; Gambacorta, 2008). However, calendar influences on lending decisions have never been investigated, despite evidence of calendar anomalies in the stock markets. These anomalies occur at different times of the day (Ariel, 1987), different days of the week (Jaffe and Westerfield, 1985), and different months of the year (Gultekin and Gultekin, 1983). Therefore, we can investigate whether calendar anomalies influence bank lending decisions.

The objective of this paper is to investigate the presence of a month-of-the-year effect on lending decisions. We analyze lending decisions from one of the largest peer-to-peer lenders in the United States. It provides an ideal case for the investigation since it provides all data on loan applications, including the month in which they occur, and the loan conditions after acceptance. We perform regressions of loan acceptance and loan rate using monthly dummy variables, including a large set of borrower and loan control variables. The data set provides a nationwide sample of about 12.6 million loan applications and 1.8 million granted loans from 2007–2017. Thus, we can investigate the criteria for loan acceptance by comparing granted and rejected loans, and we can control for loan and borrower characteristics when explaining loan acceptance and loan spread.

The peer-to-peer lender states that loan acceptance is determined by individual characteristics of the loan application including borrower information and by big data use of the historical performance of granted loans, whereas loan pricing is determined by a credit grade assigned to each approved loan on the basis of the borrower criteria and the data for all loans. Thus, the month of the loan application should not influence loan acceptance and loan pricing. If we concede that lending decisions are not based solely on borrower and loan characteristics, several reasons might explain a month-of-the-year effect.

First, the calendar effects can result from seasonality in loan applications. The distribution of loan applications is not equal across all months. It can then occur that the peer-to-peer lender adjusts loan acceptance and loan pricing to the intensity of the demand. When loan demand is higher for a given month, the lender can increase loan pricing but also reduce loan acceptance since the funding of the lender does not evolve with demand.

Second, the presence of behavioral biases can influence lending decisions and thus generate calendar anomalies. Investors are subject to behavioral biases when making investment decisions (Daniel, Hirshleifer, and Teoh, 2002; Barberis and Thaler, 2003). People in a positive mood tend to assess bad outcomes as being less likely than do people in a negative mood (Johnson and Tversky, 1983; Wright and Bower, 1992). These biases might generate calendar anomalies. Thus, the positive mood of stock market investors prior to holidays or during religious holidays might contribute to higher returns (Lakonishok and Smidt, 1988; Ariel, 1990). In a related vein, the employees of the peer-to-peer lender might be subject to similar behavioral biases when making lending decisions.

Third, calendar anomalies can be driven by trade loading, that is, the practice of offering discounts to customers at the end of a quarter to hit quarterly targets. In the context of the lender, this practice would result in higher loan acceptance in the last month of each quarter. This practice might also result in lower loan pricing to incentivize borrowers to accept loan offers. Trade loading contributes to improved financial statements and, as such, is a form of window dressing observed in banking (Allen and Saunders, 1992; Kotomin and Winters, 2006), whereby banks manipulate accounting values near quarter-end reporting dates.

This research in turn contributes to two debates. First, we improve our understanding of what shapes lending decisions and loan pricing. We provide the first work to the best of our knowledge looking at the influence of the month of the year. This information helps borrowers, bank regulators, and lenders better appraise the lending process. Second, we augment behavioral finance literature by investigating the existence of calendar anomalies in lending activity. Bank credit plays a key role in the financing of the economy and as such it is important to understand how behavioral biases influence lending activity.

The rest of the paper is organized as follows. Section 2 describes data and variables. Section 3 reports the baseline results. Section 4 displays the additional estimations testing the explanations. Section 5 concludes.

2. Data and variables

2.1 Data and methodology

We use publicly available data on loan applications and loans funded by a large peer-to-peer lender. The dataset has approximately 12.6 million loan applications and 1.8 million granted loans from 2007–2017. It features information at the loan level and the individual level for all loan applications.

We use two loan-level dependent variables. First, we consider loan acceptance with a dummy variable equal to 1 if the loan is obtained, and 0 otherwise (*Obtain*). Second, we use the loan spread, defined as the difference between the loan rate and the Federal Funds Rate (*Spread*). The key independent variables are dummy variables for each month of the year. We define January as the benchmark month by omitting the dummy variable for January, meaning that each month variable is interpreted relative to January.

We control for several loan characteristics that might affect loan acceptance and loan pricing. We use the grade the peer-to-peer lender assigns to each loan application. The lender uses the borrower's FICO credit score and additional information to assign a credit grade (e.g., requested loan amount, length of credit history, number of recent inquiries). The grades range alphabetically from A to G, with A being the highest grade. We include dummy variables for each grade ranging from *Grade A* (the best) to *Grade G* (the worst).

Because the lender grants loans for two possible terms (36 months or 60 months), we create a dummy variable equal to 1 when the loan is for 36 months, and 0 otherwise (*Short Term*). We use the natural logarithm of the loan amount (*Log(Amount)*) and a series of dummies denoting the loan purpose, as follows: *Business*, *Car Rinancing*, *Credit Card Refinancing*, *Debt Consolidation*, *Home* (for home buying and home improvement purposes), and *Other*, with *Car Financing* being the omitted variable.

We also control for several borrower characteristics that can influence loan acceptance and loan conditions. We use the ratio of monthly debt payments divided by monthly income (*Debt-to-Income Ratio*), the number of past-due incidences of delinquency in the borrower's credit file for the past two years (*Past Delinquency*), the employment length in years (*Employment Length*), the natural logarithm of the annual income (*Log(Annual Income)*), and two dummy variables to describe whether the borrower owns (*House Owner*) or rents her or his home (*House Rent*).

Because there is less information in the dataset about loan applications than in the dataset pertaining to obtained loans, the set of control variables is smaller for estimations explaining *Obtain* relative to those explaining Spread. It does not include four borrower characteristics: *Past Delinquency, Log(Annual Income), House Owner,* and *House Rent*.

We test the existence of the month-of-the-year effect in lending decisions. Our baseline estimation is as follows:

$$Loan\ Outcome_i = \alpha + \beta * Month\ dummies_i + \chi * X_i + \delta * Z_i + \varepsilon_i \qquad (1)$$

Where i is the application; *Loan Outcome* stands for one of the two dependent variables (*Obtain, Spread*); X is the set of loan-level control variables; Z is the set of borrower-level control variables; and ε is a random error term. We include year dummies to control for annual effects. We use a logit model to explain *Obtain* and an ordinary least squares (OLS) model to explain *Spread*. Appendix summarizes the definitions of all the variables used and their sources.

2.2 Descriptive statistics

We start the analysis by looking at the descriptive statistics of the sample. Table 1 contains the summary statistics for the full sample of loans and the subsample of obtained loans. Obtained loans represent only 13.9% of all loans, showing the high rejection rate of loan applications. The mean spread for obtained loans is 11.971%.

The monthly distribution for both samples shows important features. First, the distribution of loan applications is not equal across all months. In an equal distribution, 8.33% of annual loan applications would be submitted each month, but the monthly percentage ranges from 3.3% in December to 11.6% in October. The four months with the lowest frequency of loan applications are, in increasing order, December (3.3%), September (3.5%), June (5.2%), and March (8.3%), that is, the last month of each quarter. Second, the distribution of granted loans shows smaller differences across months than the distribution of loan applications. It ranges from 6.7% in February to 10.4% in October. Combining these observations suggests that loan acceptance varies considerably from month-to-month. For example, December represents only 3.3% of loan applications but 8.8% of obtained loans, suggesting a much higher-than-average monthly acceptance rate.

This conclusion is surprising if loans are granted using an algorithm that factors in the characteristics of the loan and the borrower. If that were the case, it would be hard to understand why loan acceptance would vary from month-to-month, unless the borrower and loan characteristics differ significantly throughout the year (e.g., poor-quality borrowers apply for more loans during certain months). We address this possibility in the multivariate estimations, in which we control for borrower and loan characteristics.

Figures 1 and 2 provide the distribution of loan acceptance and of loan spread by month. Two striking results emerge from the distribution of loan acceptance. First, the last month of each quarter is clearly associated with the highest loan acceptance. Second, loan acceptance increases consistently in the last month of each quarter. In other words, March, June, September, and December have the highest loan acceptance rates, in increasing order. In contrast, the distribution of loan spread over the months tends to be homogenous throughout the year.

These figures provide a first look but do not take into account the borrower and loan characteristics, which might vary over months. Thus, we perform multivariate estimations to investigate these results and their potential explanations.

3. Main results

3.1 Baseline estimations

We report in Table 2 the baseline estimations we conducted to explain loan acceptance and loan spread. For each dependent variable, we perform regressions first without control variables, then with control variables to test the sensitivity of our results.

First, we consider the estimations for loan acceptance. The key result is that all month dummies are significantly positive in both estimations. This finding suggests that January is the worst month to ask for a loan, because all other months are associated with greater chances of acceptance. Thus, there are significant differences in loan acceptance across months. In addition, the comparison of both estimations shows that the inclusion of control variables does not affect the results on the month variables; that is, we obtain exactly the same sign and the significance of month variables in the two columns.

We follow the methodology of Campbell and Yogo (2006) and Lopez-Gracia and Aybar-Arias (2000) and use Bonferroni tests to obtain a better view of the monthly loan acceptance rankings. The Bonferroni test is a multiple comparison test that can compare the mean response for a selected factor, adjusted for any other variables in the model. The test allows us to compare the mean value of the probability of loan acceptance across months, factoring in the model control variables. Each month is classified into a group (defined by a letter), and margins with the same letter in the group code are not significantly different at a 5% level. Campbell and Yogo (2006) explain that this test is really interesting in our case since it allows a quick, easy and accurate reading of the results.

Table 3 displays the results of the Bonferroni tests for the specification with control variables and gives a holistic view of the differences across months. Results confirm the existence of significant differences in monthly loan acceptance rates. If we look first at the results for loan acceptance, we can notice that no month has a letter, this means that the average acceptance rate per month is significantly different each month. The results are sorted by average acceptance rate, hence the borrower has the highest chance of acceptance by applying for a loan in December, followed by September and June. Finally, the worst month to ask for a loan is January, followed by February and May.

Second, we analyze the estimations for loan spread to determine if loan pricing is affected by the month-of-the-year effect. Including control variables does not have a major influence on the results (i.e., only the significance of February is influenced). Month dummies are mostly significant in all estimations. This finding confirms that monthly differences exist in the loan spread; that is, for a given set of borrower and loan characteristics, the loan spread varies, depending on the month. This finding is of critical importance, because the peer-to-peer lender explicitly states that its interest rates are determined primarily by borrowers' loan grade. It appears as a surprise, then, that calendar anomalies occur in such a process.

We use the Bonferroni tests in Table 3 for the specification with control variables to gain a better view of the monthly loan acceptance rankings. December has the cheapest loan pricing, followed by March and November. September and August are the most expensive months, followed by October.

The results for loan acceptance and loan spread thereby provide key advice for borrowers: December is the best month to ask for a loan, because it combines the highest chance of acceptance and the lowest spread. There is no clear ranking of months when considering both criteria for the remainder of the year. For example, there is a high chance of acceptance in September, but it is also the most expensive month.

Thus the key conclusion is the existence of calendar anomalies for loan acceptance and loan pricing. Borrowers should be aware of these significant differences in loan acceptance rates and loan pricing, depending on the month of their application.

We state above that trade loading and behavioral biases might explain calendar anomalies. In line with this prediction, we confirm that both hypotheses explain the loan acceptance results. First, trade loading can explain why loan acceptance is higher in end-of-the-quarter months. The peer-to-peer lender can take great care with the financial statements it issues every quarter, especially with its end-of-year financial information. Quarterly financial reporting announcements thus appear to drive the high chances of loan acceptance seen in December, as well as the increased acceptance in June and September.

Second, behavioral biases might play a role to explain some of the results. For example, the higher stock market returns prior to holidays or during religious holidays, due to stock investors' good moods, aligns with greater loan acceptance in December and June. In addition, employees' bad mood in January could explain the low loan acceptance rate in that month (Hirshleifer and Shumway, 2003).

The results on loan spread are more difficult to explain. Both hypotheses explain some results (e.g., that December is the cheapest month). The peer-to-peer lender might reduce loan pricing in December as a result of trade loading, or employees' better moods might motivate them to lower loan prices. Yet September, an end-of-quarter month, is one of the most expensive months and has one of the lowest volumes of loan applications, at odds with the trade loading hypothesis. In addition, a behavioral bias hypothesis does not clearly explain why loan pricing would be higher in August and September.

Neither hypothesis explains all the results, indicating that there may be unreported, internal factors in the loan pricing process that explain these calendar anomalies.

We find evidence of calendar anomalies for loan acceptance and loan pricing, with a powerful quarter-end effect. These anomalies can be explained by trade loading or behavioral biases.

We perform additional estimations to test the relevance of each of these explanations.

3.2 Estimations by grade

Our main estimations show differences across months for loan acceptance and loan spread. We can question whether the main results stand for all grades. It is of importance to appraise the relevance of any explanation for the results. For instance, we find the highest loan acceptance and the lowest loan spread in December, which could be interpreted as the result of trade loading or behavioral biases. If these hypotheses are correct, the outcomes should affect all borrowers equally, regardless of their grade. We therefore redo the estimations by grade. In Table 4, we display the results of the Bonferroni tests for loan acceptance and loan pricing by month for each grade of borrowers.

First, borrowers with the same grade exhibit similar patterns of loan acceptance rates from month-to-month. For example, December is the best month for loan acceptance for A borrowers, and it is one of the three best months for all other grades, with the exception of F borrowers. Thus, December is a good month to ask for a loan overall, regardless of the borrowers' grade. Similarly, September is one of the two best months for loan acceptance for all grades of borrowers. By contrast, January is a bad month to ask for a loan, regardless of the borrowers' grade: it is the worst month for loan acceptance for borrowers with grades B to F, and it is one of the three worst months for A and G borrowers. Except for A borrowers, February is also a bad month to ask for a loan, because it always ranks among the two worst months for loan acceptance.

Second, borrowers with the same grade do not follow the same patterns for loan spread from month-to-month. While December has the lowest loan pricing in the main estimations, this broad conclusion is conditional on the grade of the borrower (e.g., loan spread in December is the lowest for borrowers with grades A to C but highest for borrowers with grades F and G). Thus, December is the cheapest month for high-grade borrowers and the most expensive month for low-grade borrowers. In contrast, March is the cheapest month for low-grade borrowers (E to G). August and September are the most expensive months in the main estimations. This observation holds for several grades (C to E) but is not totally accurate for the highest grades, in that September is the fourth best month for B borrowers.

Therefore, the comparison of the results by grade shows some similarities but also some differences across grades. We however still find support for the quarter-end effect with the result of December and September being the months associated with high loan acceptance for all grades.

4. Testing the explanations

The baseline estimations have provided evidence of calendar anomalies for loan acceptance and loan pricing. We aim now at investigating the potential explanations of these calendar anomalies. As stated above, three explanations can be suggested: seasonality in loan applications, behavioral biases, and trade loading. We provide additional estimations testing successively the relevance of each of these explanations in this section.

4.1 The influence of the seasonality in loan applications

We investigate the influence of the demand side as a potential source of seasonality in loans. The calendar effects might be driven by the seasonality of loan applications. It might occur that some months are associated with greater loan demand which may lead to higher loan spreads, in line with the view that greater demand increases prices, and to lower loan acceptance since the peer-to-peer lender is unlikely to have funding evolving with demand. Hence our conclusion of calendar anomalies can be driven by seasonality in demand.

To this end, we redo our estimations by taking into account monthly demand. We include the variable *Demand side* defined as the ratio of loan applications for the month divided by all loan applications over the year. We first perform the regression without the month dummies, then with the month dummies to test the influence of the demand side. The results are reported in Table 5. Two key results emerge.

First, the seasonality of loan applications exerts an influence on lending decisions in accordance with the expected signs. *Demand side* is significantly negative when explaining loan acceptance and significantly positive when explaining loan spread. These findings mean that greater demand is associated with lower loan acceptance and higher loan spread.

Second, the fact that we control for the demand side does not change our main conclusion of calendar anomalies for loan acceptance and loan pricing. We find again that all month dummies are significant. Hence the calendar anomalies are not fully explained by the seasonality in loan applications. It is however of interest to observe that there are some changes in the calendar anomalies as can be seen in Table 6 displaying the Bonferroni tests.

Regarding loan acceptance, we now observe that the borrower has the highest chance of acceptance by applying for a loan in October, followed by December and July (to be compared before with December, followed by September and June). The worst month to ask for a loan is February, followed by January and March (to be compared before with January, followed by February and May). Regarding loan spread, we now point out that the cheapest month is March, followed by January and December (to be compared before with December, followed by March and November) and the most expensive month is September, followed by August and June (to be compared before with September and August, followed by October).

Therefore, the ranking of the months for loan acceptance and loan spread is modified when controlling for the seasonality of loan applications. But we still observe some evidence of end-of-the-quarter effect with notably December combining high chances of acceptance and low spread. To sum it up, the seasonality in demand side influences the calendar anomalies but does not constitute a global explanation for these anomalies.

4.2 The influence of behavioral biases

One potential explanation for the calendar anomalies is the impact of behavioral biases. They can influence the mood of the employees of the peer-to-peer lender and thus affect the decisions to grant loans or to charge loan interest rates. One way to investigate the influence of behavioral biases is to check whether sentiment affects lending decisions. A large set of papers (e.g., Stambaugh, Yu and Yuan, 2012) have documented the influence of investor sentiment on anomalies on stock markets. In a related vein, we want to check the presence of sentiment effects which would corroborate the role of behavioral biases. To this end, we consider two sentiment indicators from the literature.

First, we consider investor sentiment with the investor sentiment index from Baker and Wurgler (2006).[1] It is a composite market-based index measuring market-wide sentiment computed on a monthly basis, which is commonly used in the literature on the investor sentiment on stock markets (e.g., Stambaugh, Yu and Yuan, 2012). Our *Investor sentiment* variable is the orthogonalized index for investor sentiment provided by Baker and Wurgler (2006). They provide a raw sentiment index and an orthogonalized sentiment index, and we adopt the second one for two reasons. First, the raw index measure does not allow distinguishing between a common sentiment component and a business cycle component, while we want to distinguish both for our analysis. Second, the orthogonalized index is explained to explicitly remove business cycle variation. Thus, the orthogonalized index is a better measure for the investor sentiment in our framework where we care only for the common sentiment.

Second, we consider consumer sentiment with the Michigan Consumer Confidence Index from the University of Michigan.[2] It is based on a survey of randomly chosen households performed on a monthly basis. This indicator is widely adopted in the literature to measure consumer sentiment (Dominitz and Manski, 2004; Stambaugh, Yu and Yuan, 2012; Akhtar et al., 2012).

Our empirical strategy is to consider an investor sentiment index and a consumer sentiment index since we focus on the behavioral biases which can impact the employees of the peer-to-peer lender. As such their mood can be influenced by the same information than stock market investors or than consumers.

We redo our estimations by including both sentiment indices. For each dependent variable, we test four specifications all including control variables. We first include only both sentiment indices to test their influence on the dependent variable. We then add *Demand Side* variable to see if this influence is affected by the fact that we control for seasonality in loan applications. We then redo both estimations by adding the month dummies. We are then able

[1] The database is available at http://people.stern.nyu.edu/jwurgler/
[2] The database is available at http://www.sca.isr.umich.edu/tables.html

to see whether calendar anomalies are still observed once behavioral biases and seasonality in demand are controlled. The estimations are reported in Table 7.

We find two main conclusions. First, the sentiment indices are significant in all estimations, supporting the view that behavioral biases influence lending decisions. We observe that *Consumer Sentiment* and *Investor Sentiment* are significantly negative in all estimations explaining loan acceptance, meaning that better sentiment is associated with lower loan acceptance. We furthermore find that *Consumer Sentiment* is significantly negative in all estimations explaining loan spread while evidence is mixed for Investor Sentiment only significantly negative when Demand Side is taken into account in the estimations. Hence our estimations also suggest that better sentiment is associated with lower spread. Second, we observe that all month dummies are still significant once we control for the sentiment indices and demand side. This finding reveals that calendar anomalies do not disappear once we control for behavioral biases and seasonality in loan applications.

Table 8 reports the Bonferroni tests for the specifications with all variables. We observe the same ranking of months for loan acceptance and for loan spread than the ones we find in Table 6 when taking into account the seasonality in demand. The borrower has again the highest chance of acceptance by applying for a loan in October, followed by December and July, while the worst month to ask for a loan is February, followed by January and March. The cheapest month is again March, followed by January and December, while the most expensive month is September, followed by August and June.

It thus means that the ranking of the months for loan acceptance and loan spread is not affected by the inclusion of sentiment indices controlling for behavioral biases. Thus, we have provided evidence that behavioral biases affect lending decisions but no support that they affect calendar anomalies.

4.3 Investigating trade loading

We find evidence of calendar anomalies for loan acceptance and loan pricing, with a powerful quarter-end effect. One potential explanation for these anomalies is trade loading. This explanation is hard to be proven empirically since it is based on the incentives for employees to facilitate higher loan acceptance in in the last month of each quarter.

We cannot consider that the calendar anomalies remaining once we control for the seasonality in loan applications and for behavioral biases are necessarily driven by trade loading for two reasons. First, our measures of behavioral biases are proxies which do not necessarily take into account all these biases. They are by nature hard to measure and the use of sentiment indices to proxy them has only been of use to test their potential influence on calendar anomalies. Second, our three explanations are not necessarily exclusive.

However, since the peer-to-peer lender went public in December 2014, we can investigate the relevance of trade loading. The trade loading hypothesis relies on the importance of the company's quarterly financial statements. If this hypothesis is accurate, the quarter-end effect should have become more pronounced after the initial public offering (IPO) of the peer-to-peer lender, because financial announcements are more important for publicly listed companies.

We therefore test whether calendar anomalies were greater after the IPO than before it. Since the observed calendar anomalies are mainly related to a quarter-end effect, we perform the study estimations again, by creating a variable *End Quarter*, equal to 1 if the month is the end of a quarter (March, June, September, December) and 0 otherwise. We also build the variable *Post IPO*, equal to 1 for all months following December 2014 and 0 otherwise. We explain *Obtain* in the first two specifications and *Spread* in the last two specifications. We test several sets of control variables to check the robustness of the results and report the results in Table 9.

When considering loan acceptance, we observe that the interaction term *End Quarter* × *Post IPO* is significantly positive when explaining *Obtain*. The probability that a borrower obtains a loan during an end-of-the-quarter month increases following the IPO. It is worthwhile to compare the overall coefficient of *End Quarter* before and after the IPO. The coefficient for *End Quarter* is -0.272, whereas it is 1.514 for *End Quarter* × *Post IPO*, and both coefficients are significant at the 1% level. Thus, the overall coefficient before the IPO is -0.272, but it is 1.242 (-0.272 + 1.514) after the IPO. In other words, there was no quarter-end effect of higher loan acceptance before the IPO. But the quarter-end effect emerges after the IPO. This finding provides strong support for the trade loading hypothesis.

When looking at the loan spread, the interaction term *End Quarter* × *Post IPO* is significantly negative when explaining *Spread*. Loan spread for quarter-end months diminishes following the IPO. The analysis of the overall coefficient for *End Quarter* shows that the coefficient was 0.064 before the IPO and -0.068 after the IPO. Thus, there is a reduction of the loan spread for quarter-end months following the IPO, in accordance with the trade loading hypothesis.

Thus we show that the quarter-end effect is more pronounced for loan acceptance and for loan spread after the IPO. This finding provides support for the existence of trade loading.

5. Conclusion

We investigate the influence of months on lending decisions, to test if calendar anomalies documented in stock markets also take place in lending processes of a large US peer-to-peer lender. There is strong evidence for a month-of-the-year effect in lending decisions. Loan acceptance decisions and loan pricing differ depending on the month. December is the best month to ask for a loan; it combines the highest chances of acceptance and the lowest spread. Loan applications in January have the lowest chances of acceptance. Loan pricing is highest for loans granted in August and September. Loan acceptance is higher in end-of-the-quarter months.

We test the relevance of three potential explanations for the calendar anomalies: seasonality in loan applications, behavioral biases, and trade loading. First, we find that seasonality in loan applications influences the calendar anomalies without explaining all anomalies such as the end-of-the-quarter effect. Second, behavioral biases proxied by sentiment indices influence lending decisions but they do not affect the ranking of months for loan acceptance and loan pricing. Third, we find empirical support for trade loading, meaning that the peer-to-peer lender would inflate granted loans at the end of each quarter to hit quarterly targets. The quarter-end effect became more pronounced for loan acceptance and loan spread following the IPO of the lender in December 2014, which supports the trade loading explanation.

These findings provide useful insights for borrowers, by determining the best month to ask for a loan. They are also of value for the peer-to-peer lender, because they reveal the existence of a phenomenon that might be detrimental for the company in the long term. Higher loan acceptance, associated not with the better quality of the borrower but rather with an arbitrary factor, such as the month, likely will be associated with lower loan performance.

Further research might investigate whether similar calendar anomalies can be observed with other lenders, such as banks involved in retail and corporate banking. Moreover, alternative effects might occur at other stages of the lending process (e.g., day-of-the-week, or turn-of-the-month effects). Research into these effects would further benefit households and companies in their efforts to make informed lending decisions.

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Table 1
Descriptive Statistics

	All Loans		**Granted Loans**	
	Mean	Std. Dev.	Mean	Std. Dev.
	Dependent Variables			
Obtain	0.139	0.346		
Spread			11.971	4.683
	Independent Variables			
	Month Variables			
January	0.105	0.306	0.072	0.258
February	0.091	0.287	0.067	0.251
March	0.083	0.275	0.088	0.283
April	0.102	0.302	0.077	0.267
May	0.100	0.300	0.076	0.265
June	0.052	0.221	0.076	0.266
July	0.11	0.313	0.096	0.295
August	0.087	0.281	0.089	0.284
September	0.035	0.184	0.074	0.261
October	0.116	0.321	0.104	0.305
November	0.087	0.282	0.093	0.291
December	0.033	0.179	0.088	0.283
	Loan Characteristics			
Log(Amount)			9.391	0.698
Short Term			0.716	0.451
Business	0.023	0.150	0.011	0.106
Credit Card	0.132	0.338	0.221	0.415
Debt Consolidation	0.490	0.500	0.577	0.494
Home	0.072	0.259	0.072	0.258
Other	0.143	0.350	0.060	0.238
	Borrower Characterstics			
Grade A	0.503	0.500	0.169	0.374
Grade B	0.054	0.226	0.296	0.456
Grade C	0.082	0.274	0.297	0.457
Grade D	0.130	0.336	0.145	0.352
Grade E	0.187	0.390	0.066	0.248
Grade F	0.043	0.203	0.022	0.146
Grade G	0.001	0.031	0.007	0.080
Debt to Income Ratio	139.828	15083.070	18.598	11.844
Employment length	1.680	3.001	5.970	3.711
Past Delinquency			0.329	0.898
Log(Annual Income)			11.092	0.581
House Rent			0.396	0.489
House Owner			0.109	0.312
Observations	12,628,221		1,760,097	

Table 2
Month Effect

This table reports coefficients and p-values (in parentheses). The dependent variable is *Obtain* in columns (1) and (2), *Spread* in columns (3) and (4). All variables are defined in the Appendix. Estimation method is logistic regression in columns (1) and (2) and OLS regression in columns (3) and (4). *, **, *** denote statistical significance at the 10%, 5%, 1% level respectively.

	(1) Obtain	(2) Obtain	(3) Spread	(4) Spread
February	0.091***	0.154***	0.024	0.021***
	(21.303)	(20.017)	(1.319)	(3.611)
March	0.500***	0.959***	-0.164***	-0.169***
	(123.741)	(132.949)	(-9.380)	(-31.859)
April	0.116***	0.921***	0.090***	0.037***
	(28.093)	(127.382)	(5.023)	(6.785)
May	0.113***	0.945***	0.078***	-0.013**
	(27.313)	(130.819)	(4.311)	(-2.460)
June	0.899***	1.987***	0.026	-0.000
	(211.372)	(262.145)	(1.429)	(-0.016)
July	0.272***	1.217***	0.301***	0.035***
	(69.240)	(173.139)	(17.682)	(6.739)
August	0.451***	1.441***	0.259***	0.077***
	(112.040)	(200.736)	(14.823)	(14.429)
September	1.359***	2.351***	0.420***	0.095***
	(306.753)	(293.130)	(22.589)	(16.829)
October	0.294***	1.093***	0.052***	0.047***
	(75.859)	(157.482)	(3.142)	(9.146)
November	0.511***	1.269***	-0.264***	-0.147***
	(128.258)	(176.533)	(-15.515)	(-27.576)
December	1.704***	2.380***	-0.398***	-0.266***
	(391.220)	(291.738)	(-22.874)	(-49.321)
Grade A		-5.909***		-20.542***
		(-157.946)		(-797.475)
Grade B		-1.401***		-17.118***
		(-37.397)		(-667.065)
Grade C		-2.531***		-13.761***
		(-67.677)		(-537.967)
Grade D		-4.258***		-10.015***
		(-113.721)		(-390.066)
Grade E		-5.185***		-6.498***
		(-138.318)		(-246.415)
Grade F		-4.572***		-2.751***
		(-120.739)		(-94.537)
Debt to Income Ratio		-0.026***		0.004***
		(-278.280)		(22.528)
Employment length		0.446***		-0.001*
		(987.444)		(-1.886)
Business		-0.234***		0.003
		(-17.449)		(0.261)
Credit Card		1.432***		-0.073***
		(247.876)		(-14.683)
Debt Consolidation		1.199***		0.025***
		(229.579)		(5.286)
Home		0.706***		-0.020***
		(100.404)		(-3.421)
Other		0.062***		0.083***
		(9.291)		(13.258)
Short Term				0.316***
				(112.802)
Log(Amount)				0.066***

				(34.404)
Past Delinquency				0.018***
				(15.691)
Log(Annual Income)				-0.140***
				(-56.905)
House Rent				0.077***
				(32.261)
House Owner				0.039***
				(11.030)
Year dummies		Yes		Yes
Constant	-2.248***	-0.057	11.940***	20.098***
	(-760.508)	(-0.399)	(939.751)	(132.101)
Observations	12,628,221	12,014,678	1,760,097	1,655,273
R^2			0.002	0.919
Adjusted R^2			0.002	0.919
Pseudo R^2	0.029	0.585		

Table 3
Bonferroni tests for the month effect

This table reports the Bonferroni tests for the estimations with control variables in Table 2. The Bonferroni test is a multiple comparison test that can compare the mean response for a selected factor, adjusted for any other variables in the model. Each month is classified into a group (defined by a letter), and margins with the same letter in the group code are not significantly different at the 5% level. No letter indicates that all months are significantly different at the 5% level.

Obtain			Spread		
Month	Margin	Bonferroni	Month	Margin	Bonferroni
January	0.039		December	1.906	A
February	0.052		March	2.006	B
May	0.078		November	2.025	C
April	0.081		May	2.159	D
March	0.092		June	2.172	D
July	0.104		January	2.173	E
October	0.119		February	2.191	F
August	0.125		July	2.204	G
November	0.136		April	2.210	G
June	0.174		October	2.219	H
September	0.231		August	2.247	I
December	0.258		September	2.263	I

Table 4 - Bonferroni tests by grade of borrowers

This table reports the Bonferroni tests for the estimations by grade of borrowers. The Bonferroni test is a multiple comparison test that can compare the mean response for a selected factor, adjusted for any other variables in the model. Each month is classified into a group (defined by a letter), and margins with the same letter in the group code are not significantly different at the 5% level. No letter indicates that all months are significantly different at the 5% level.

	Obtain			Spread		
Grade A	Month Issue	Margin	Group	Month Issue	Margin	Group
	May	0.337	A	December	8.375	A
	April	0.344	B	March	8.525	B
	January	0.351	C	November	8.535	B
	July	0.357	D	April	8.718	C
	February	0.359	E	October	8.729	C
	March	0.360	E	May	8.740	C
	August	0.369	F	July	8.782	D
	October	0.382	G	September	8.786	D
	June	0.389	H	June	8.792	D
	November	0.394	I	August	8.802	D
	September	0.427	J	January	8.841	E
	December	0.513	K	February	8.852	E
Grade B	Month issue	Margin	Group	Month Issue	Margin	Group
	January	0.519	A	December	10.617	A
	February	0.520	A	November	10.759	B
	October	0.572	B	March	10.861	C
	November	0.598	B	October	10.879	D
	April	0.636	C	September	10.889	D
	March	0.642	C	July	10.899	D
	May	0.652	D	June	10.901	D
	July	0.660	E	May	10.913	E
	August	0.690	F	August	10.931	F
	December	0.721	G	February	11.027	G
	September	0.758	H	April	11.029	G
	June	0.767	I	January	11.062	H
Grade C	Month issue	Margin	Group	Month Issue	Margin	Group
	January	0.122	A	December	12.074	A
	February	0.131	B	November	12.202	B
	October	0.224	C	March	12.315	C
	November	0.242	D	May	12.435	D
	March	0.265	E	October	12.444	E
	April	0.283	F	February	12.461	E
	May	0.306	G	January	12.465	E
	July	0.323	H	July	12.469	F
	August	0.352	I	June	12.470	F
	December	0.420	J	September	12.471	F
	September	0.445	K	April	12.499	G
	June	0.453	K	August	12.508	G
Grade D	Month issue	Margin	Group	Month Issue	Margin	Group
	January	-0.055	A	January	14.599	A
	February	-0.052	B	March	14.664	B
	March	0.026	C	December	14.703	B
	November	0.065	D	February	14.777	C
	October	0.065	D	November	14.815	C
	April	0.073	E	May	14.857	D
	May	0.088	F	April	14.877	D
	July	0.104	G	June	14.895	D
	August	0.115	H	July	14.970	E
	September	0.187	I	October	14.992	E
	December	0.191	I	August	15.085	F

	June	0.197	J	September	15.104	F
Grade E	Month Issue	Margin	Group	Month Issue	Margin	Group
	January	-0.001	A	March	17.278	A
	February	0.005	B	January	17.333	A
	March	0.040	C	February	17.526	B
	November	0.060	D	April	17.729	C
	October	0.062	D	May	17.887	D
	April	0.064	E	June	18.004	E
	May	0.068	F	November	18.007	E
	July	0.072	G	December	18.016	E
	August	0.078	H	July	18.084	F
	December	0.090	I	October	18.141	F
	September	0.114	J	August	18.219	G
	June	0.135	K	September	18.246	G
Grade F	Month Issue	Margin	Group	Month Issue	Margin	Group
	January	0.071	A	March	19.715	A
	February	0.081	B	January	19.831	B
	March	0.123	C	February	19.879	B
	December	0.133	D	April	20.240	C
	November	0.133	D	May	20.333	C
	October	0.137	D	June	20.410	C
	April	0.157	E	July	20.634	D
	July	0.160	E	September	20.715	D
	May	0.160	E	August	20.755	D
	August	0.167	F	October	20.788	D
	September	0.195	G	November	20.916	E
	June	0.226	H	December	21.106	F
Grade G	Month Issue	Margin	Group	Month Issue	Margin	Group
	February	1.086	A	January	20.554	A
	November	1.086	A	February	20.655	A
	January	1.093	A	March	20.673	A
	October	1.137	B	April	20.738	A
	March	1.165	C	May	21.140	B
	April	1.175	C	June	21.398	C
	May	1.181	C	July	21.484	C
	December	1.190	C	September	21.497	C
	July	1.193	C	August	21.554	E
	August	1.198	C	October	21.642	E
	June	1.234	D	November	21.728	F
	September	1.239	D	December	21.885	G

Table 5
Demand Effect

This table reports coefficients and p-values (in parentheses). The dependent variable is *Obtain* in columns (1) and (2), *Spread* in columns (3) and (4). All variables are defined in the Appendix. Estimation method is logistic regression in columns (1) and (2) and OLS regression in columns (3) and (4). *, **, *** denote statistical significance at the 10%, 5%, 1% level respectively.

	(1) Obtain	(2) Obtain	(3) Spread	(4) Spread
Demand Side	-25.007***	-25.499***	2.502***	3.181***
	(-671.573)	(-614.603)	(120.840)	(126.784)
February		-0.480***		0.102***
		(-66.646)		(18.394)
March		0.249***		-0.073***
		(36.359)		(-13.969)
April		0.471***		0.116***
		(69.346)		(21.747)
May		0.638***		0.060***
		(93.473)		(11.027)
June		0.577***		0.256***
		(75.653)		(44.256)
July		1.041***		0.174***
		(153.806)		(32.841)
August		0.611***		0.261***
		(88.991)		(47.576)
September		0.749***		0.396***
		(93.876)		(65.135)
October		0.992***		0.165***
		(148.027)		(31.915)
November		0.434***		0.040***
		(61.656)		(7.311)
December		0.815***		0.023***
		(99.758)		(3.911)
Grade A	-6.002***	-6.044***	-20.564***	-20.532***
	(-150.210)	(-158.510)	(-792.396)	(-795.634)
Grade B	-1.463***	-1.432***	-17.137***	-17.111***
	(-36.559)	(-37.516)	(-662.821)	(-665.585)
Grade C	-2.633***	-2.587***	-13.780***	-13.756***
	(-65.911)	(-67.896)	(-534.642)	(-536.770)
Grade D	-4.385***	-4.338***	-10.037***	-10.012***
	(-109.644)	(-113.681)	(-388.004)	(-389.255)
Grade E	-5.277***	-5.229***	-6.514***	-6.490***
	(-131.838)	(-136.911)	(-245.368)	(-245.808)
Grade F	-4.667***	-4.610***	-2.765***	-2.745***
	(-115.631)	(-119.553)	(-94.520)	(-94.285)
Debt to Income Ratio	-0.026***	-0.026***	0.004***	0.004***
	(-263.007)	(-258.578)	(22.496)	(22.794)
Employment length	0.440***	0.443***	-0.001**	-0.001*
	(948.529)	(936.977)	(-2.567)	(-1.747)
Business	-0.258***	-0.218***	-0.005	0.005
	(-19.066)	(-15.934)	(-0.448)	(0.409)
Credit Card	1.376***	1.404***	-0.079***	-0.074***
	(229.767)	(231.806)	(-15.973)	(-15.028)
Debt Consolidation	1.175***	1.185***	0.020***	0.021***
	(217.433)	(216.952)	(4.330)	(4.508)
Home	0.691***	0.698***	-0.020***	-0.022***
	(94.683)	(94.409)	(-3.348)	(-3.697)
Other	0.100***	0.087***	0.079***	0.080***
	(14.542)	(12.469)	(12.550)	(12.838)
Short Term			0.315***	0.316***

			(112.302)	(113.344)
Log(Amount)			0.064***	0.067***
			(33.392)	(35.373)
Past Delinquency			0.018***	0.018***
			(15.662)	(15.400)
Log(Annual Income)			-0.139***	-0.139***
			(-56.561)	(-56.761)
House Rent			0.077***	0.077***
			(32.681)	(32.804)
House Owner			0.040***	0.040***
			(11.255)	(11.159)
Year dummies	Yes	Yes	Yes	Yes
Constant	10.693***	10.188***	19.460***	19.110***
	(37.836)	(37.664)	(130.321)	(127.769)
Observations	12,014,678	12,014,678	1,655,273	1,655,273
R^2			0.919	0.920
Adjusted R^2			0.919	0.920
Pseudo R^2	0.620	0.628		

Table 6
Bonferroni tests for the demand effect

This table reports the Bonferroni tests for the estimations with control variables in Table 5. The Bonferroni test is a multiple comparison test that can compare the mean response for a selected factor, adjusted for any other variables in the model. Each month is classified into a group (defined by a letter), and margins with the same letter in the group code are not significantly different at the 5% level. No letter indicates that all months are significantly different at the 5% level.

Obtain			Spread		
Month	Margin	Bonferroni	Month	Margin	Bonferroni
February	0.416		March	1.588	A
January	0.455		January	1.659	B
March	0.469		December	1.679	C
April	0.477		November	1.696	D
May	0.494		May	1.718	E
August	0.501		February	1.759	F
June	0.505		April	1.775	F
November	0.513		October	1.822	G
September	0.523		July	1.828	G
July	0.552		June	1.913	H
December	0.560		August	1.915	H
October	0.577		September	2.049	I

Table 7
Sentiment Effect

This table reports coefficients and p-values (in parentheses). The dependent variable is *Obtain* in columns (1) to (4), *Spread* in columns (5) to (8). All variables are defined in the Appendix. Estimation method is logistic regression in columns (1) to (4) and OLS regression in columns (5) to (8). *, **, *** denote statistical significance at the 10%, 5%, 1% level respectively.

	(1) Obtain	(2) Obtain	(3) Obtain	(4) Obtain	(5) Spread	(6) Spread	(7) Spread	(8) Spread
Consumer Sentiment	-0.016***	-0.048***	-0.019***	-0.044***	-0.029***	-0.030***	-0.023***	-0.023***
	(-31.870)	(-88.713)	(-32.231)	(-70.211)	(-73.473)	(-76.165)	(-51.772)	(-52.235)
Investor Sentiment (Orth.)	-0.014***	-0.004***	-0.018***	-0.003***	0.001***	-0.002***	0.000**	-0.004***
	(-69.227)	(-19.508)	(-83.038)	(-14.216)	(5.138)	(-12.409)	(2.089)	(-23.877)
Demand Side		-25.271***		-25.481***		2.674***		3.472***
		(-665.798)		(-610.518)		(127.083)		(134.475)
February			0.182***	-0.514***			-0.011**	0.086***
			(23.414)	(-70.077)			(-1.972)	(15.259)
March			0.973***	0.178***			-0.219***	-0.103***
			(130.807)	(25.235)			(-40.180)	(-19.088)
April			0.803***	0.378***			0.005	0.075***
			(109.846)	(55.269)			(0.863)	(14.002)
May			0.934***	0.630***			-0.035***	0.047***
			(127.805)	(92.773)			(-6.430)	(8.699)
June			2.034***	0.619***			-0.014**	0.270***
			(268.563)	(79.865)			(-2.526)	(46.177)
July			1.106***	0.916***			-0.026***	0.129***
			(149.488)	(132.141)			(-4.843)	(23.673)
August			1.418***	0.527***			0.025***	0.227***
			(193.799)	(75.891)			(4.552)	(40.606)
September			2.362***	0.665***			0.015**	0.352***
			(289.636)	(81.672)			(2.482)	(55.456)
October			1.118***	0.899***			0.003	0.123***
			(155.989)	(126.511)			(0.615)	(23.620)
November			1.309***	0.448***			-0.154***	0.043***
			(181.811)	(62.566)			(-29.011)	(7.849)
December			2.399***	0.933***			-0.249***	0.064***
			(289.834)	(111.845)			(-46.040)	(11.006)
Grade A	-5.823***	-6.010***	-5.912***	-6.055***	-20.564***	-20.557***	-20.544***	-20.531***
	(-161.025)	(-151.101)	(-158.661)	(-158.588)	(-799.351)	(-795.805)	(-799.234)	(-798.597)
Grade B	-1.403***	-1.447***	-1.397***	-1.428***	-17.137***	-17.133***	-17.121***	-17.113***
	(-38.736)	(-36.331)	(-37.426)	(-37.345)	(-668.704)	(-665.752)	(-668.589)	(-668.162)
Grade C	-2.515***	-2.622***	-2.529***	-2.585***	-13.779***	-13.777***	-13.764***	-13.758***

	(-69.565)	(-65.937)	(-67.906)	(-67.759)	(-539.370)	(-537.037)	(-539.216)	(-538.898)
Grade D	-4.259***	-4.372***	-4.254***	-4.334***	-10.033***	-10.031***	-10.017***	-10.011***
	(-117.631)	(-109.839)	(-114.086)	(-113.453)	(-391.269)	(-389.577)	(-390.944)	(-390.686)
Grade E	-5.197***	-5.263***	-5.186***	-5.226***	-6.510***	-6.509***	-6.498***	-6.489***
	(-143.347)	(-132.104)	(-138.899)	(-136.647)	(-247.222)	(-246.262)	(-246.928)	(-246.658)
Grade F	-4.575***	-4.648***	-4.576***	-4.604***	-2.758***	-2.760***	-2.750***	-2.743***
	(-124.916)	(-115.672)	(-121.296)	(-119.262)	(-94.906)	(-94.675)	(-94.665)	(-94.496)
Debt to Income Ratio	-0.026***	-0.026***	-0.026***	-0.026***	0.004***	0.004***	0.004***	0.004***
	(-287.506)	(-262.745)	(-277.721)	(-258.280)	(22.327)	(22.725)	(22.647)	(22.925)
Employment length	0.442***	0.439***	0.445***	0.442***	-0.001**	-0.001***	-0.001**	-0.001**
	(1010.116)	(944.002)	(982.595)	(933.770)	(-2.223)	(-2.890)	(-2.108)	(-2.015)
Business	-0.289***	-0.262***	-0.238***	-0.222***	-0.003	-0.004	0.002	0.004
	(-21.751)	(-19.289)	(-17.733)	(-16.226)	(-0.263)	(-0.364)	(0.189)	(0.336)
Credit Card	1.392***	1.375***	1.427***	1.402***	-0.075***	-0.081***	-0.074***	-0.076***
	(245.802)	(229.196)	(246.793)	(231.272)	(-15.072)	(-16.322)	(-14.919)	(-15.506)
Debt Consolidation	1.184***	1.175***	1.197***	1.185***	0.027***	0.021***	0.025***	0.021***
	(230.539)	(217.054)	(229.071)	(216.624)	(5.765)	(4.435)	(5.424)	(4.588)
Home	0.695***	0.689***	0.705***	0.697***	-0.018***	-0.020***	-0.020***	-0.022***
	(100.982)	(94.269)	(100.184)	(94.298)	(-3.020)	(-3.443)	(-3.345)	(-3.666)
Other	0.087***	0.110***	0.068***	0.095***	0.082***	0.082***	0.084***	0.082***
	(13.291)	(15.897)	(10.172)	(13.616)	(12.933)	(12.972)	(13.403)	(13.122)
Short Term					0.318***	0.313***	0.316***	0.314***
					(113.514)	(112.219)	(112.960)	(113.057)
Log(Amount)					0.064***	0.064***	0.065***	0.067***
					(33.687)	(33.442)	(34.248)	(35.440)
Past Delinquency					0.018***	0.018***	0.018***	0.017***
					(15.804)	(15.320)	(15.620)	(14.969)
Log(Annual Income)					-0.142***	-0.140***	-0.141***	-0.141***
					(-57.518)	(-57.245)	(-57.358)	(-57.771)
House Rent					0.076***	0.078***	0.077***	0.078***
					(32.170)	(33.132)	(32.443)	(33.183)
House Owner					0.038***	0.041***	0.039***	0.040***
					(10.716)	(11.472)	(11.049)	(11.298)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	3.698***	14.608***	2.201***	13.582***	22.372***	21.920***	21.972***	21.081***
	(27.004)	(51.013)	(14.574)	(51.111)	(146.090)	(144.198)	(142.210)	(137.811)
Observations	12,014,678	12,014,678	12,014,678	12,014,678	1,655,273	1,655,273	1,655,273	1,655,273
R^2					0.919	0.919	0.919	0.920
Adjusted R^2					0.919	0.919	0.919	0.920
Pseudo R^2	0.564	0.621	0.586	0.629				

Table 8
Bonferroni tests for the sentiment effect

This table reports the Bonferroni tests for the estimations with control variables in Table 7. The Bonferroni test is a multiple comparison test that can compare the mean response for a selected factor, adjusted for any other variables in the model. Each month is classified into a group (defined by a letter), and margins with the same letter in the group code are not significantly different at the 5% level. No letter indicates that all months are significantly different at the 5% level.

Obtain			Spread		
Month	Margin	Bonferroni	Month	Margin	Bonferroni
February	0.608		March	3.372	A
January	0.648		January	3.474	B
March	0.659		November	3.514	C
April	0.664		May	3.521	D
May	0.686		December	3.535	E
August	0.691		April	3.550	F
June	0.702		February	3.556	G
November	0.709		October	3.595	H
September	0.712		July	3.597	H
July	0.736		August	3.696	I
December	0.759		June	3.741	J
October	0.770		September	3.818	K

Table 9 – Trade Loading

This table reports coefficients and p-values (in parentheses). The dependent variable is *Obtain* in columns (1) and (2), *Spread* in columns (3) and (4). All variables are defined in the Appendix. Estimation method is logistic regression in columns (1) and (2) and OLS regression in columns (3) and (4). *, **, *** denote statistical significance at the 10%, 5%, 1% level respectively.

	(1) Obtain	(2) Obtain	(3) Spread	(4) Spread
End Quarter	0.815***	-0.272***	-0.069***	0.064***
	(283.064)	(-44.598)	(-27.578)	(11.761)
Post IPO		-0.480***		-0.801***
		(-117.417)		(-245.548)
End Quarter × Post IPO		1.514***		-0.132***
		(218.545)		(-21.864)
Grade A	-5.918***	-5.940***	-17.950***	-17.841***
	(-170.318)	(-171.432)	(-1.2e+03)	(-1.2e+03)
Grade B	-1.445***	-1.431***	-14.448***	-14.353***
	(-41.505)	(-41.227)	(-1.0e+03)	(-939.328)
Grade C	-2.538***	-2.525***	-11.109***	-11.004***
	(-73.037)	(-72.910)	(-779.136)	(-725.480)
Grade D	-4.241***	-4.221***	-7.346***	-7.299***
	(-121.885)	(-121.724)	(-508.442)	(-474.822)
Grade E	-5.159***	-5.133***	-3.858***	-3.822***
	(-148.077)	(-147.827)	(-244.241)	(-228.318)
Grade F	-4.581***	-4.557***		
	(-130.101)	(-129.843)		
Grade G			2.695***	2.736***
			(90.659)	(84.228)
Debt to Income Ratio	-0.026***	-0.026***	0.001***	0.005***
	(-300.165)	(-298.553)	(5.573)	(24.415)
Employment length	0.451***	0.450***	0.003***	0.002***
	(1031.093)	(1026.437)	(10.313)	(5.672)
Business	-0.220***	-0.224***	0.025*	-0.043***
	(-17.083)	(-17.342)	(1.827)	(-3.081)
Credit Card	1.486***	1.490***	-0.062***	-0.093***
	(267.394)	(266.589)	(-11.381)	(-17.456)
Debt Consolidation	1.265***	1.261***	0.046***	0.019***
	(249.993)	(248.155)	(8.937)	(3.823)
Home	0.731***	0.730***	-0.018***	-0.007
	(108.412)	(107.664)	(-2.836)	(-1.153)
Other	0.058***	0.063***	0.086***	0.093***
	(8.992)	(9.622)	(12.477)	(13.549)
Short Term			0.410***	0.385***
			(130.363)	(123.529)
Log(Amount)			0.094***	0.087***
			(44.382)	(42.005)
Past Delinquency			-0.001	0.011***
			(-0.907)	(8.650)
Log(Annual Income)			-0.185***	-0.128***
			(-68.937)	(-47.965)
House Rent			0.047***	0.070***
			(17.612)	(27.348)
House Owner			-0.015***	0.040***
			(-3.942)	(10.405)
Constant	0.654***	1.032***	24.700***	24.577***
	(18.715)	(29.486)	(780.413)	(767.794)
Observations	12,014,678	12,014,678	1,655,273	1,655,273
R^2			0.899	0.905
Adjusted R^2			0.899	0.905
Pseudo R^2	0.549	0.555		

Figure 1 - Acceptance by month

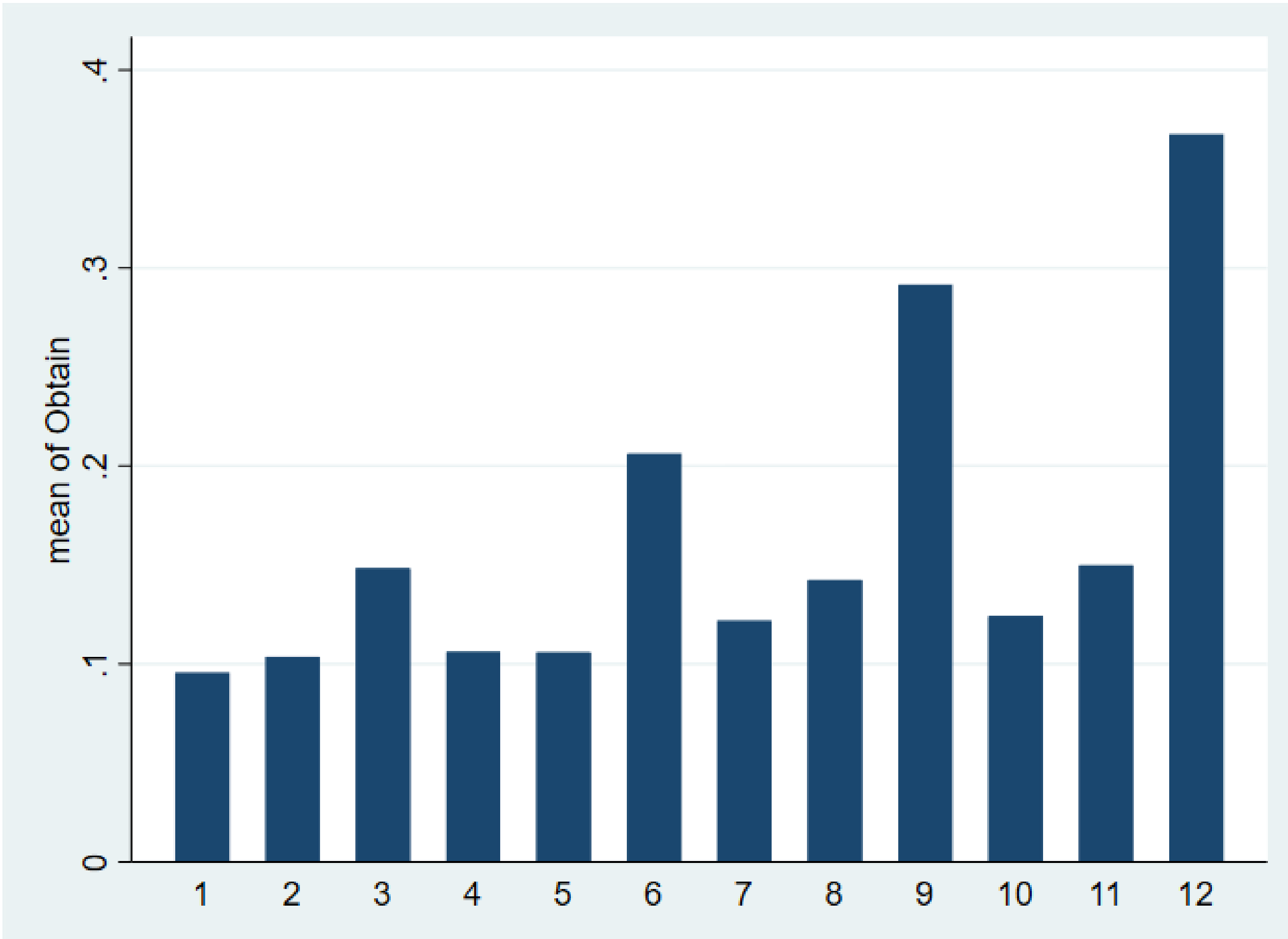
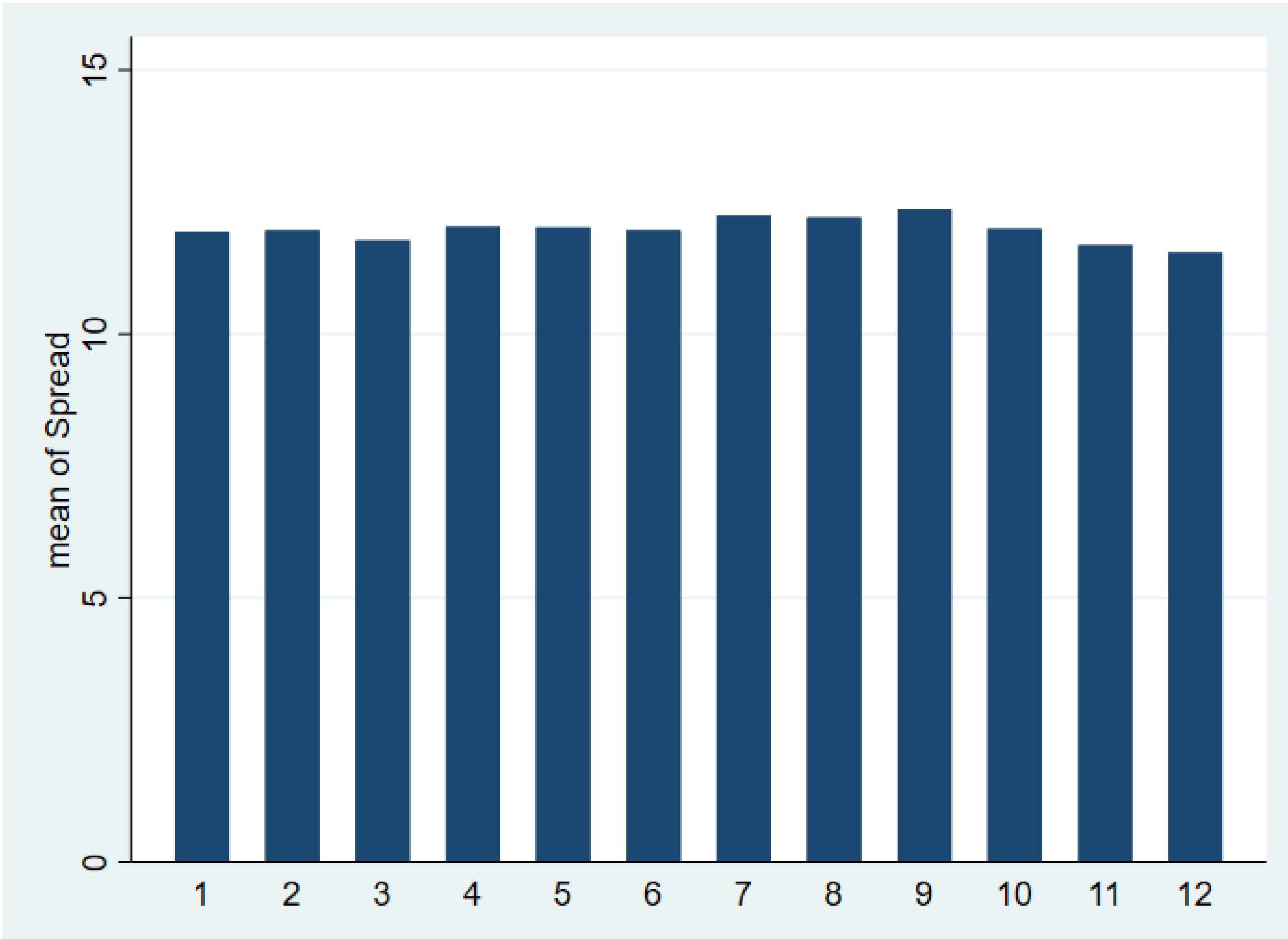


Figure 2 - Loan spread by month



Appendix: Definition of variables

Variable Name	Description
Dependent variables	
Obtain	Dummy variable equal to one if the borrower obtains the credit, zero otherwise
Spread	Spread on the loan measured by the difference between the loan rate and the Federal Funds Rate
Independent variables	
Month variables	
January	Dummy variable equal to one if the month issue for the loan is January, zero otherwise
February	Dummy variable equal to one if the month issue for the loan is February, zero otherwise
March	Dummy variable equal to one if the month issue for the loan is March, zero otherwise
April	Dummy variable equal to one if the month issue for the loan is April, zero otherwise
May	Dummy variable equal to one if the month issue for the loan is May, zero otherwise
June	Dummy variable equal to one if the month issue for the loan is June, zero otherwise
July	Dummy variable equal to one if the month issue for the loan is July, zero otherwise
August	Dummy variable equal to one if the month issue for the loan is August, zero otherwise
September	Dummy variable equal to one if the month issue for the loan is September, zero otherwise
October	Dummy variable equal to one if the month issue for the loan is October, zero otherwise
November	Dummy variable equal to one if the month issue for the loan is November, zero otherwise
December	Dummy variable equal to one if the month issue for the loan is December, zero otherwise
Borrower characteristics	
Debt to Income Ratio	A ratio calculated using the borrower's total monthly debt payments on the total debt obligations, excluding mortgage and the requested loan, divided by the borrower's self-reported monthly income
Past Delinquency	The number of 30+ days past-due incidences of delinquency in the borrower's credit file for the past 2 years
Employment length	Employment length in years
Log(Annual Income)	Log of the self-reported annual income provided by the borrower during registration
House Owner	Dummy variable equal to one of the borrower owns his house, zero otherwise
House Rent	Dummy variable equal to one if the borrower rents his house, zero otherwise
Grade	Loan grade from A - the best - to G - the worst
Grade A	Dummy variable equal to one if the grade is A, zero otherwise
Grade B	Dummy variable equal to one if the grade is B, zero otherwise
Grade C	Dummy variable equal to one if the grade is C, zero otherwise
Grade D	Dummy variable equal to one if the grade is D, zero otherwise
Grade E	Dummy variable equal to one if the grade is E, zero otherwise
Grade F	Dummy variable equal to one if the grade is F, zero otherwise
Grade G	Dummy variable equal to one if the grade is G, zero otherwise
Loan characteristics	
Log(Amount)	The total amount committed to that loan at that point in time
Short Term	Dummy variable equal to one if the maturity of the loan if equal to 36 months, zero otherwise (60 months)
Purpose	A category provided by the borrower for the loan request
Business	Dummy variable equal to one if the category is Business, zero otherwise
Car financing	Dummy variable equal to one if the category is Car financing, zero otherwise
Credit card refinancing	Dummy variable equal to one if the category is Credit card refinancing, zero otherwise
Debt consolidation	Dummy variable equal to one if the category is Debt consolidation, zero otherwise
Home	Dummy variable equal to one if the category is Home buying or Home improvement, zero otherwise
Other	Dummy variable equal to one if the category is Other, zero otherwise

Additional variables	
Consumer Sentiment	Michigan Consumer Confidence Index from the University of Michigan
Demand Side	Ratio of loan applications for the month divided by all loan applications over the year
End Quarter	Dummy variable equal to one if the month is the end of a quarter, zero otherwise
Investor Sentiment	Orthogonalized index for investor sentiment provided by Baker and Wurgler (2006)
Post IPO	Dummy variable equal to one for all months following December 2014, zero otherwise

Working Papers

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