Monetary Normalizations and Consumer Credit: Evidence from Fed Liftoff and Online Lending*

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Abstract

On December 16th of 2015, the Fed initiated "liftoff," a critical step in the monetary normalization process. We use a unique panel dataset of 640,000 loan-hour observations to measure the impact of liftoff on interest rates, demand, and supply in the online primary market for uncollateralized consumer credit. We find that credit supply increased, reducing the spread by 16% and lowering the average interest rate by 16.9-22.6 basis points. Our findings are consistent with an investor-perceived reduction in default probabilities; and suggest that liftoff provided a strong, positive signal about the future solvency of borrowers. (*JEL* D14, E43, E52, G21)

Keywords: monetary normalization, monetary policy signaling, consumer loans, credit risk.

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1 Introduction

Between July of 2007 and December of 2008, the Federal Open Market Committee (FOMC) lowered its target rate from a pre-crisis high of 5.25% to 0%. The federal funds rate then remained near 0% for 7 years until the FOMC announced "liftoff"–a 25 basis points (bps) hike on December 16th of 2015 that signaled an end to emergency measures (FOMC 2015a,b). According to the FOMC's "Policy Normalization Principles and Plans" statement, which marked the return to conventional monetary policy, liftoff constituted the first step in a monetary normalization plan that will ultimately include additional rate hikes and balance sheet adjustments (FOMC 2014; Williamson 2015). Since the FOMC explicitly conditioned normalization on the state of the economy (FOMC 2014), this choice also provided a strong, positive signal about the Fed's private assessment of the economy.[1]

We use a unique panel dataset of 640,000 loan-hour observations to estimate Fed liftoff's impact on the peer-to-peer (P2P) market for uncollateralized online consumer credit. Our work complements the empirical literature that identifies the effects of monetary policy on credit availability, consumption, bond interest rates, stock prices, and risk premia[2]; however, we focus exclusively on the first step of the monetary normalization process, use primary market data, and explore cross-sectional implications. The existing literature finds that monetary contractions tend to decrease loan supply, increase interest rates, and increase spreads. Our findings differ in sign; and our empirical evidence suggests that the contractionary component of liftoff–an interest rate hike that exceeded expectations–was dominated by the positive signal provided by the choice to proceed with normalization. The signaling effect is particularly strong in the market we study because many P2P borrowers exhibit subprime characteristics[3]; and, thus, may benefit from improvements in the future outlook

[1]James Bullard, President of the St. Louis Fed, emphasized the signaling channel in a December 7th, pre-liftoff interview: "If we do move in December ... [it] does signal confidence. It does signal that we can move away from emergency measures, finally" (Bullard 2015).

[2]See Bernanke and Blinder (1992), Bernanke and Gertler (1995), Kashyap and Stein (2000), and Jimenez, Ongena, Peydro and Saurina (2012) on credit availability and Di Maggio, Kermani and Ramcharan (2014) on consumption. For the effect of surprise monetary contractions on bond interest rates see Cook and Hahn (1989), Kuttner (2001), Cochrane and Piazzesi (2002), Wright (2012), and Hanson and Stein (2015). On stock prices see Rigobon and Sack (2004) and Bernanke and Kuttner (2005). On risk premia see Gertler and Karadi (2015) and for the effects of quantitative easing see Krishnamurthy and Vissing-Jorgensen (2011).

[3]Borrowers in the P2P market are typically above the subprime FICO cutoff; however, many exhibit

of the economy–including the labor market–that lower perceived default probabilities.

The main results consist of estimates for two outcomes: 1) the change in the average interest rate on uncollateralized consumer loans; and 2) the change in the spread between high and low credit risk borrowers. We show that the average interest rate on loans in our dataset fell by 16.9-22.9 bps; and the spread between high and low credit-risk borrowers decreased by 16%. Moreover, we find that the spread reduction was primarily driven by a decrease in rates for the riskiest borrower segments, which experienced the largest increase in supply of funds. These results are robust to the inclusion of all observable loan and borrower characteristics, as well as intra-day fixed effects and intra-week fixed effects. We also show that our results are not driven by a change in borrower composition, a collapse in demand, a shift in investor risk appetite, a seasonal adjustment, or Fed undershooting[4]; and are robust to the choice of time window. Both narrow and wide windows (including 3-day, 7-day and 14-day windows around liftoff) yield statistically significant results. Additionally, both visual inspection and placebo tests suggest that the change happened precisely at liftoff.

Additional evidence using separate hourly measures for demand and supply allows us to discriminate between different candidate explanations for our main results, and points clearly to a supply-side explanation. We show that demand does not decline after liftoff, which rules out most plausible alternative stories that rely on a demand decrease. To the contrary, supply increases sharply–especially for the riskiest borrower groups. The probability of individual loans getting funded also increases.In sum, we can rule out explanations that are driven by the demand side, including those that rely on borrower composition shifts.

We cannot, however, achieve statistical significance for our main results in a 30-minute window around the event, as is typically done in the empirical event studies literature. There are two reasons for this. First, we use primary market data, which means that new loans must be originated in sufficient quantity before it is possible to measure a statistically significant effect. And second, we are attempting to capture the impact of a rare monetary normalization event, which means that we cannot achieve identification using repeated observations of the same event category. In this sense, we are closer methodologically to the literature on the

other characteristics associated with subprime borrowing (e.g. missing documentation).

[4]We show that it is unlikely that the Fed undershot with respect to either the federal funds rate adjustment or the announced forward guidance plan; however, our results do not depend on this assumption and would hold if the opposite were true.

bank lending channel of monetary policy (Kashyap and Stein 2000; Jimenez, Ongena, Peydro and Saurina 2012; Di Maggio, Kermani and Ramcharan 2014).

The primary dataset we use was scraped at an hourly frequency from Prosper.com, the oldest and second largest U.S.-based P2P lender. One useful feature of this panel dataset is that it contains separate measures of demand and supply, unlike time series market data or bank-based loan origination data. It also contains rejected loans, unlike most bank-based loan datasets. Moreover, it is uncommon that borrowers are discouraged from applying for loans in this platform, since the application cost is low. Demand is constructed by aggregating the amount requested on all loans posted on Prosper at a point in time. Supply measures are constructed using three different definitions: 1) the aggregate amount that has been funded across all loans at a point in time; 2) the aggregate change in funding over a given time interval; and 3) the realized probability that a loan will be funded. Exploiting this unique feature of our dataset, we show that all measures of supply increased after liftoff. Demand also increased, but only slightly. Additionally, we also show that the funding gap–the aggregate amount that has been demanded, but not yet supplied–decreased after liftoff, suggesting that the increase in supply was larger than the increase in demand. Overall, these results point to a supply-side explanation for the reduction in interest rates.

We also collected a secondary dataset from LendingClub.com by compiling Securities and Exchange Commission (SEC) records. This dataset contains a higher number of individual loans, but is available only at a daily frequency, since we were unable to track Lending Club originations in real time. This means that we cannot repeat the supply, demand, and funding gap exercises for this data; and cannot observe interest rates at an intra-day frequency. We can, however, replicate the average interest rate and spread results: both decline in the Lending Club data, and the magnitudes of the declines are nearly identical to our original findings. Taken together, both datasets cover more than 70% of the U.S. P2P market.

To further establish robustness, we demonstrate that the direction and magnitude of the liftoff results are not common to FOMC decisions by performing the same analysis on the January 27th, 2016 decision not to raise rates. In contrast to liftoff, we find that this decision had no statistically significant impact on interest rates. This holds for both wide and narrow time windows, suggesting that there is no common announcement effect. We also perform a sequence of rolling regressions of the interest rate on loan-borrower characteristic controls using a narrow time window. We show that the results are only significant when liftoff is selected as the center of the window.[5]

Two additional findings strengthen the plausibility of the hypothesis that liftoff reduced the perceived default probabilities of P2P borrowers. First, borrowers in states with higher unemployment rates receive higher interest rates, even after controlling for borrower and loan characteristics, including their own employment status. And second, expected future improvements in the economy, as measured by changes in the real yield curve, induce decreases in interest rates in the P2P market. These findings suggest that a channel exists in the P2P market for macroeconomic factors to affect perceived default probabilities; and, therefore, individual loan interest rates. More specifically, we argue that liftoff cannot be reduced to an increase in the risk-free rate, since it was paired with a signal about the economic outlook, which had implications for perceived default probabilities. This resonates with the view that monetary policy is reacting to changes in macroeconomic conditions (e.g., Rigobon and Sack (2003)) and with the extensive literature on the signaling role of central bank communication (e.g., Blinder, Ehrmann, Fratzscher, De Haan and Jansen (2008)).

Our paper relates to several different strands of literature. First, as discussed earlier, our work complements the existing empirical literatures on the bank lending channel and on event studies. We employ panel data to study how a monetary normalization affects uncollateralized consumer credit with a focus on the cross-sectional dimension.[6] Conversely, the aforementioned event studies typically use a large number of events to measure the impact of monetary policy announcements. This is done by regressing changes in asset prices or interest rates on a monetary surprise measure that is constructed using information about market expectations (see footnote 2 for references).

This paper also relates to the extensive literature on monetary policy signaling with an interest in both the disclosure of monetary policy actions and revelation of information about macroeconomic variables (Blinder et al. 2008; Andersson, Dillén and Sellin 2006). While the desired degree of transparency about the central bank's information on economic

[5]In addition to performing robustness tests, we have also discussed the paper with practitioners in the P2P market to ensure that the findings and proposed mechanism are credible.

[6]There exist only a few works on monetary policy interest rate pass-through to consumer credit. See Ludvigson (1998) for monetary policy transmission and automobile credit and Agarwal, Chomsisengphet, Mahoney and Stroebel (2016) for a recent study on credit cards.

fundamentals has been intensely debated,[7] the literature suggests that the disclosure of information by central banks plays an important role in coordinating market expectations and provides relevant macroeconomic information to market participants (Swanson 2006; Ehrmann and Fratzscher 2007; Ehrmann, Eijffinger and Fratzscher 2016; Campbell, Evans, Fisher and Justiniano 2012; Boyarchenko, Haddad and Plosser 2016; Schmitt-Grohé and Uribe 2016).[8] Symptomatically, Faust and Wright (2009) document the Fed's good nowcasting performance. Moreover, in line with our findings on the P2P lending market, perceived probabilities of default play an important role (e.g. in the context of bank lending policies (Rodano, Serrano-Velarde and Tarantino 2016)) and employment risk appears to be a key contributing factor (e.g. as an predictor of mortgage defaults (Gerardi, Herkenhoff, Ohanian and Willen 2015)).

We also contribute to the growing literature on P2P lending and on consumer credit, more broadly.[9] P2P lending targets a slice of the consumer credit market–namely, high-risk and small-sized loans–that is neglected by traditional banks (De Roure, Pelizzon and Tasca 2016). A number of papers employ the P2P market as a laboratory to study different aspects of lending, such as the role of informational frictions, using U.S. data from the Prosper.com[10] and LendingClub.com[11] crowdlending platforms; however, to our knowledge, the only other paper attempting to link online lending markets to macroeconomic developments is Crowe and Ramcharan (2013), who study the effect of home prices on borrowing conditions. Finally, there is a large literature on household credit that spans a broad range of topics from mortgage debt to the different types of consumer credit (e.g., Bertola, Disney and Grant

[7] E.g., Morris and Shin (2002), Svensson (2006), Angeletos and Pavan (2004), Hellwig (2005), and Cornand and Heinemann (2008).

[8] Furthermore, monetary policy action might also provide a signal about inflationary shocks to unaware market participants (Melosi 2015).

[9] For a recent review of the literature on crowdfunding see Belleflamme, Omrani and Peitz (2015).

[10] There are papers using data from Prosper.com to study the role of soft information, such as the appearance of borrowers (Duarte, Siegel and Young 2012; Pope and Sydnor 2011; Ravina 2012), the importance of screening in lending decisions (Iyer, Khwaja, Luttmer and Shue 2015; Hildebrand, Puri and Rocholl 2015), the herding of lenders (Zhang and Liu 2012), the importance of geography-based informational frictions (Lin and Viswanathan 2016; Senney 2016), the auction pricing mechanism that existed prior to December 2010 (Chen, Ghosh and Lambert 2014; Wei and Lin 2015), and the ability of marginal borrowers to substitute between financing sources (Butler, Cornaggia and Gurun 2015).

[11] There are papers using data from LendingClub.com to study adverse selection (Hertzberg, Liberman and Paravisini 2015) and retail investor risk-aversion (Paravisini, Rappoport and Ravina 2016).

(Eds.) (2006) and Agarwal and Ambrose (Eds.) (2007)). Nourished by increasing household indebtedness in many advanced economies over the last decade, the field has enjoyed increased attention (Guiso and Sodini 2013). A close substitute to a personal loan from a P2P platform is credit card debt, since it is also uncollateralized. We expect access to new alternative sources of finance to be relevant for the spending behavior of consumers.

The rest of the article proceeds as follows. Section 2 provides an overview of Fed liftoff and the P2P lending market, as well as the expected effects. Section 3 describes the data and how it was collected. Section 4 presents our findings on the P2P market during Fed liftoff, and performs several robustness and external validity exercises. Finally, we conclude in section 5. All additional material can be found in the Online Appendix.

2 Market setting and theoretical framework

We proceed by describing Fed liftoff and market expectations in section 2.1. Thereafter, we describe the P2P lending market in the United States and the Prosper P2P lending platform in section 2.2. Finally, we discuss the theoretical framework that guides our empirical investigation and the expected effects in section 2.3.

2.1 Fed liftoff

During the second half of 2015, the prospect of Fed liftoff was considered by many to be an important event with historic connotations. It marked the end of an unprecedented era of monetary easing and was regarded as an important step towards monetary normalization. On the day prior to liftoff, market participants largely anticipated that the FOMC would vote to raise rates. This is perhaps best reflected in futures contracts, which implied a .84 probability of the federal funds rate range increasing from 0-25 bps to 25-50 bps and a near-zero probability for a rate hike above the 25-50 bps range.[12] This suggests that the FOMC's

[12]Source: The probability of a federal funds rate increase is based on futures, computed by Bloomberg one day prior to liftoff. The underlying contracts are written for the effective federal funds rate, rather than the Fed's target rate range, which means that the range probabilities are not assumption-free. Importantly, however, Bloomberg's calculations were not anomalous and aligned closely with other estimates, including those produced by the Chicago Mercantile Exchange. Interest rates on short maturity debt, such as commercial paper, also increased after liftoff, which reinforces the claim that the Fed did not undershoot relative

rate decision overshot, rather than undershot, market expectations. Furthermore, interest rate changes on longer maturity debt, shown in Table I, suggest that the announced path of forward guidance may have also overshot, pulling up longer term rates after liftoff.

Table I: Selected interest rates around Fed liftoff

Date	Commercial Paper	Corporate Bonds
Dec. 9	0.23	2.76
Dec. 16	0.35	2.93
Dec. 23	0.39	2.92

Notes. The rates given are for 1-month, AA financial commercial paper and 3-5 year effective yields on US corporate bonds. The series are available in the St. Louis Federal Reserve's FRED database.

Overall, we interpret the interest rate adjustment and forward guidance path announcement as contractionary relative to expectations; however, our main results do not depend on this assumption. Even if the decisions were expansionary, the interpretation of all results in the paper would remain unchanged.[13]

Finally, while Fed liftoff was widely expected, there was uncertainty about the timing of the move, which drew substantial attention in discussions among P2P market practitioners. Our identifying assumption is that Fed liftoff was the key event within the narrowest window around liftoff we use (±3 days). Furthermore, we argue that there were no other relevant events that could credibly explain the shift in the P2P lending market, such as substantial and unexpected news from economic data releases.

2.2 The Prosper P2P lending platform

The P2P lending market is growing rapidly. According to a Federal Reserve Bank of Cleveland study, US P2P lending grew by an average of 84% per quarter between 2007 and 2014 (Demyanyk 2014). The accounting firm PricewaterhouseCoopers expects P2P lending to reach 10% of revolving US consumer debt by 2025.[14] Our primary dataset comprises a panel

to expectations.

[13]If the FOMC statement undershot the expected forward guidance path, this would be captured entirely by changes in rates for near prime borrowers in our sample. In fact, we find that the reduction in rates is substantially larger for the riskiest borrowers.

[14]See market study by PricewaterhouseCoopers (2015).

of loan-hour observations from the P2P lending platform *Prosper.com*, which operates the oldest and second-largest lending-based crowdfunding platform for uncollateralized consumer credit in the US, and has been operating since February of 2006. As of January of 2016, Prosper has more than 2 million members (investors and borrowers) and has originated loans in excess of $6 billion. Borrowers ask for personal uncollateralized loans ranging from $2,000 to $35,000 with a maturity of 3 or 5 years. The highest rated borrowers may have access to traditional sources of credit from banks and credit cards, but the lowest rated borrowers are unlikely to have such outside options.

After the loan application is submitted, the platform collects self-reported and publicly available information, including the borrower's credit history. Prosper uses a credit model to decide on the borrower's qualification for the loan, to assign a credit score, and to set a fixed interest rate and repayment schedule. The process is fast and qualified borrowers can expect to receive an offer within 24 hours. The funding phase takes place during a 14-day listing period. Investors review loan listings that meet their criteria and invest (e.g. in $25 increments). A loan can be originated as soon as 100% of the funding goal is reached or if a minimum of 70% is reached by the end of the listing period. Provided borrowers accept the loan, the total funding volume (net of an origination fee) is disbursed. Prosper services the loan throughout the duration and transfers the borrower's monthly installments to lenders.

According to its website, Prosper assigns rates to loans based on a proprietary measure of expected loss (Prosper rating), the loan term, the economic environment, and the competitive environment. Similarly, LendingClub's website explains that rates are adjusted in response to "macroeconomic conditions, supply and demand on the LendingClub platform, and evolving default and chargeoff rates." Prosper and LendingClub provide lists of average rates and rate ranges associated with their respective proprietary rating groups. These current minimum value of the best-rated group, the base rate, is lower than 5% on both platforms. The maximum value in the worst-rated group is 30.25%. Importantly, shifts in these averages and ranges reflect all of the aforementioned pricing factors, as well as changes in how individuals are assigned to different rating groups. For this reason, interest rate change announcements cannot be meaningfully interpreted without first controlling for loan and borrower characteristics.[15]

[15]Prosper is privately-owned and is not obligated to announce rate changes. LendingClub announced an

P2P lending platforms generate fee income that relates to the transaction volume. Specifically, Prosper's fee structure consists of: 1) an origination fee of 0.5-5% paid by borrowers at loan disbursement; 2) an annual loan servicing fee of 1% paid by lenders; 3) a failed payment fee of $15; 4) a late payment fee of 5% of the unpaid installment or a minimum of $15; and 5) a collection agency recovery fee in the case of a defaulting borrower. The first three fees generate income for Prosper, while the late payment fee and the collection agency recovery fee are passed on to the lenders. The net profit from late payment fees is likely to be negligible after accounting for administrative costs. Hence, origination and servicing fees are the key contributors to platform profits. Given the fee structure, we argue that maximizing of the origination volume is a close approximation to Prosper's interest rate setting problem; conditional on Prosper maintaining appropriate underwriting standards that shield it from potential reputational losses.

2.3 Expected effects

The interest rate set for individual Prosper loans can be understood as a function of the risk-free reference rate, economic risk premia, and market conditions. The risk-free reference rate is influenced by monetary policy. The Federal Reserve targets the overnight federal funds rate and, thereby, affects the nominal risk-free reference rate. Moreover, monetary policy also influences the term structure of the risk-free reference rate via expectations of future federal funds rates. The risk premium on Prosper P2P loans comprises credit risk and term risk.[16] Given the uncollateralized nature of the P2P consumer credit segment, the credit risk of individual borrowers is arguably the dominant determinant of the risk premium and of key interest in our study. Moreover, our evidence from section 2.1 suggests that term risk does not appear to be a substantial driver for our study.[17] The dominant role of credit risk also resonates with our analysis of the cross-sectional dimension. Important factors of influence are unemployment risk, health risk, divorce, or expenditure needs.

interest rate shift after Fed liftoff. After controlling for loan and borrower characteristics, this shift had a negative impact on the average rate of a constant-quality borrower.

[16] Recall that the interest rate on Prosper loans is fixed at origination and the average maturity is between 3 to 5 years. As a result, investors are exposed to term risk since the short-term risk-free reference rate may not evolve as expected.

[17] This also excludes forward guidance channels (e.g., Del Negro, Giannoni and Patterson (2012)).

Risk-free reference rate channel. Based on the existing literature on event studies, which identifies the effect of monetary policy on bond prices, we expect to observe at least partial interest pass-through (e.g., Cook and Hahn (1989) or Kuttner (2001)). Namely, an unexpected increase in the reference rate is, in isolation, associated with an increase in the funding costs of P2P borrowers.

Credit risk channel. Monetary contractions can also affect credit risk, the key determinant of the risk premium in the P2P segment for consumer credit. There can be two opposing effects. First, the empirical literature finds that surprise monetary contractions are associated with an increase in credit spreads (e.g., Gertler and Karadi (2015)). Second, credit spreads are known to be countercyclical and are regarded as leading indicator for economic activity (e.g., Gilchrist and Zakrajsek (2012)).[18] As a result, a monetary contraction that ushers in monetary normalization may be associated with a reduction in credit spreads if the decision sends a strong positive signal about the state of the economy. This is even more so true if the normalization is conditioned on an improvement in the economic outlook, which tends to be associated with a reduction in spreads.

More specifically, taking a significant step towards monetary normalization, such as the Fed liftoff decision to move away from near-zero rates, constitutes a strong positive signal about the Fed's private assessment of future employment and growth prospects.[19] This interpretation is supported by empirical studies that demonstrate the Fed's good nowcasting performance (Faust and Wright 2009) and suggest that the disclosure of information by central banks plays an important role in coordinating market expectations and provides relevant macroeconomic information to markets (Swanson 2006; Ehrmann and Fratzscher 2007; Ehrmann, Eijffinger and Fratzscher 2016; Campbell, Evans, Fisher and Justiniano 2012; Boyarchenko, Haddad and Plosser 2016).

For uncollateralized consumer credit, the assessment of future employment prospects is an important determinant of perceived credit risk. Moreover, the default risk of low credit rating borrowers is arguably most sensitive to changes in the employment outlook. Hence, we would expect a strong credit risk channel associated with the positive signal of a monetary

[18] This countercyclical nature of credit spreads has been rationalized most prominently in the financial accelerator proposed by Bernanke and Gertler (1989).

[19] Following the end of quantitative easing in October 2014, liftoff can be regarded as the first step towards monetary normalization, with the reduction of the Fed's balance sheet being the second step (FOMC 2014).

normalization, which outweighs the risk-free rate channel, to crystallize in a reduction of the spread between high and low credit rating borrowers.[20] Prediction 1 follows.

Prediction 1: *If we observe that liftoff is associated with a reduction in the average funding costs of P2P borrowers, then the credit risk channel should become visible as a reduction of the spread between high and low credit rating borrowers.*

When setting the interest rates on individual loans, the Prosper P2P lending platform faces changing market conditions in the form of stochastic supply and demand. One way to understand the interest rate setting problem is to compare it to a joint pricing and inventory control problem with perishable inventory. Such problems have been discussed in the Operations Research literature.[21] In the context of the P2P lending platform, the inventory corresponds to the funding gap, which is the difference between the cumulative inflows of funds and the target for the outstanding total loan amount for all listings at a given point in time. It is in the interest of the lending platform to safeguard against a scenario where the supply of funds cannot be met by means of an inventory of unfunded loans at a given point in time. The inventory, however, is perishable, since loans are not originated and are permanently delisted if not funded by at least 70% within a 14-day period. Hence, it is undesirable to maintain a large funding gap.

In contrast to other markets, the inventory is not produced, but the interest rate set by the lending platform affects both supply and demand. Moreover, the interest rate is set before an individual loan is listed on the platform and cannot subsequently be adjusted. This differs, for instance, from the case of event admission tickets, which can be discounted when demand is revealed to be weak.[22] In addition, Prosper's interest rate setting is complicated by the fact that newly listed loans compete with previously listed loans, resulting in potential crowding-out effects when rates differ. This latter feature is likely to prevent Prosper from significantly changing the pricing as long as it does not face lasting changes in market conditions.

An observed reduction in interest rates on Prosper loans may be driven by supply or demand factors. First, we would expect a reduction in perceived default probabilities on P2P loans to be associated with higher loan attractiveness, leading to an increase in the

[20] See Appendix B for a formalization.
[21] See, e.g., Petruzzi and Dada (1999); McGill and van Ryzin (1999); Elmaghraby and Keskinocak (2003).
[22] See Sweeting (2012).

supply of funds, as measured by an increase in the funding speed and the funding success. As Prosper learns about such a lasting change in market conditions, it reduces the interest rates on individual loans to attract more borrowers and, therefore, match the supply increase. Second, an observed reduction in interest rates on Prosper loans is also consistent with a lasting reduction in demand, which leads Prosper to counteract a demand reduction by reducing rates. Prediction 2 follows.

Prediction 2: *If we observe that liftoff is associated with a reduction in the funding costs of P2P borrowers, but not with a reduction in demand, then the credit risk channel should become visible as an increase of the funding speed and probability of success.*

Finally, to establish the relevance of signaling about the Fed's assessment of future employment prospects, it must be the case that the employment outlook is, in fact, an important macro factor in the P2P market. Thus, we need to validate Prediction 3.

Prediction 3: *The employment outlook is an important determinant of interest rates in the P2P segment of consumer credit.*

3 Data and descriptive statistics

Our primary dataset comprises loan-hour observations from the Prosper P2P lending platform.[23] We collected hourly observations of loan funding progress and loan-borrower characteristics from Prosper's website between November 20, 2015 and January 20, 2016 using web scraping.[24] In total, our sample covers 326,044 loan-hour observations.[25] Among the 4,257

[23] To provide external validity, we use data from *LendingClub.com*, another P2P lending platform. This secondary dataset comprises loan-level origination data from the US P2P lending platform LendingClub.com starting from December 2014, which we obtained from the public SEC records. The LendingClub.com and Prosper.com platforms both specialize in uncollateralized consumer credit and target a very similar slice of the market. As a result, the descriptive statistics for our secondary dataset are similar with an average loan size of $15,775.86, an average interest rate of 12.92%, and an average DTI of 19.85%.

[24] We use scraping to obtain hourly microdata about loans posted on *Prosper.com*. Specifically, we collected all information posted publicly about Prosper loans–including their funding and verification statuses–using custom Bash and Python scripts.

[25] Our sample starts from November 20, 2015 and is updated hourly until the current date. Initially, we used a sample of 640,000 loan-hour observations, which overlaps with two FOMC meetings: December 15-16, 2015 and January 27-28, 2016. We decided to drop the data after January 20, 2016–about one week before the January meeting–to avoid picking up interest rate changes related to the January FOMC meeting. The complete sample of 640,000 loan-hour observations is, however, used for a placebo test.

loan listings in the dataset, 3,015 loans can be identified as having successfully originated using the 70% funding rule.[26] Loan listings occur continuously around the clock. The loan terms are fixed by Prosper and posted online once the funding phase starts. The verification status of a loan does occasionally improve as more documents are verified by Prosper.

The dataset contains loan information, such as size, purpose, interest rate, maturity, and monthly payment; and borrower information, including employment status, income bracket, debt-to-income ratio, and a credit score issued by Prosper. Panel A gives summary statistics for the full sample of borrowers with loans posted. The loan size varies from $2,000 to $35,000, but has an (unweighted) sample average of $13,100. The majority of loans have a 3-year maturity. Loan purpose categories include Business, Consumption (e.g. Auto, Boat, Vacation, etc.), Debt Consolidation, Special Loans (e.g. Baby & Adoption, Medical, etc.), and Others. More than 75% of the listings are in the Debt Consolidation category. The average interest rate, without taking into account the loan-borrower characteristics, is 14.22%. Figure I shows two histogram plots of the interest rates, divided into pre and post-liftoff subsamples. After liftoff, the interest rate distribution appears more skewed to the left. This is consistent with the direct observation from descriptive statistics that the average interest rate drops from 14.29% to 14.15% after liftoff.

Prosper provides rich information about borrowers on its website, including a credit rating that is mostly based on the borrower's Fair Isaac Corporation (FICO) score and credit history. Prosper assigns one of eight credit ratings to each borrower: AA, A, B, C, D, E, and HR, which are monotonically increasing in the perceived credit risk.[27] For our analysis, we later group credit ratings into three bins: high ratings (AA and A), middle ratings (B and C), and low ratings (lower than C). This classification helps us to divide the borrowers into three groups of similar sizes. The employment status is another important variable in assessing the borrower's default risk, which contains three categories: employed, self-employed, and unemployed.[28]

[26]Recall that, according to the Prosper documentation, a loan is originated when reaching a funding status of at least 70%. However, the funding phase continues if the funding status reaches the 70% level before the end of the listing period.

[27]While it was possible to translate Prosper's credit ratings from the FICO scores (Butler, Cornaggia and Gurun 2015), we expect that Prosper now uses additional information to assign credit ratings, such as behavioral user data, the user's history on the platform, and social media data.

[28]A few employed borrowers indicate their employment status as "full-time." The last category is reported

Table II: Descriptive statistics

Panel A: Full Sample

	mean	sd	min	max	obs		obs	pct		obs	pct
size	13.10	7.13	2.00	35.00	4,257	Business	93	2.18	$1-24,999	175	4.11
int-rate	14.22	6.46	4.32	30.25	4,257	Cons.	415	9.75	$25,000-49,999	1,682	39.51
DTI	27.32	12.33	1	68	4,257	Debt	3,222	75.69	$50,000-74,999	1,213	28.49
maturity	3.77	0.97	3	5	4,257	Other	344	8.08	$75,000-99,999	601	14.12
verif.	2.30	0.76	1	3	4,257	Special	183	4.30	$100,000+	586	13.77
Δfunding	0.95	3.91	0	99	322,600	Total	4,257	100	Total	4,257	100

Panel B1: Sample before the Liftoff	mean	sd	min	max	obs	Panel B2: Sample after the Liftoff	mean	sd	min	max	obs
size	13.05	7.25	2.00	35.00	2,029	size	13.14	7.01	2.00	35.00	2,228
int-rate	14.29	6.46	4.32	30.25	2,029	int-rate	14.15	6.46	4.32	30.25	2,228
DTI	27.10	12.24	1	63	2,029	DTI	27.52	12.41	1	68	2,228
maturity	3.85	0.99	3	5	2,029	maturity	3.69	0.95	3	5	2,228
verif.	2.30	0.76	1	3	2,029	verif.	2.30	0.76	1	3	2,228

	mean	sd	min	max	obs		mean	sd	min	max	obs
	Panel C1: ES=Employed						Panel D1: CR=High				
size	13.80	7.43	2.00	35.00	3,166	size	13.28	6.44	2.00	35.00	1,198
int-rate	13.66	6.35	4.32	30.25	3,166	int-rate	7.28	1.37	4.32	9.43	1,198
DTI	27.35	12.05	1	68	3,166	DTI	24.84	10.21	1	62	1,198
maturity	3.77	0.97	3	5	3,166	maturity	3.80	0.98	3	5	1,198
CreditBin	0.95	0.76	0	2	3,166						
	Panel C2: ES=Self-employed						Panel D2: CR=Middle				
size	10.59	3.66	2.00	15.00	520	size	14.38	7.84	2.00	35.00	1,825
int-rate	17.42	6.40	5.76	30.25	520	int-rate	13.06	2.21	9.49	16.97	1,825
DTI	23.60	12.12	1	63	520	DTI	27.87	12.52	1	66	1,825
maturity	3.74	0.97	3	5	520	maturity	3.79	0.98	3	5	1,825
CreditBin	1.34	0.66	0	2	520						
	Panel C3: ES=Unemployed						Panel D3: CR=Low				
size	11.49	7.07	2.00	35.00	571	size	11.02	6.11	2.00	30.00	1,234
int-rate	14.37	6.27	4.32	30.25	571	int-rate	22.65	3.90	17.61	30.25	1,234
DTI	30.54	13.12	1	63	571	DTI	28.90	13.53	2	68	1,234
maturity	3.75	0.97	3	5	571	maturity	3.69	0.95	3	5	1,234
CreditBin	1.04	0.73	0	2	571						

Notes. The sample includes all loan listings on *Prosper.com* over the period between November 20, 2015 and January 20, 2016. The loan size is measured in thousands of dollars. The interest rates are quoted in percentage points. DTI is the monthly debt-service-to-income cost. ES is the employment status. CR is short for the borrower credit rating. Verif. denotes the verification stage. It takes on a discrete value from 1 to 3, where 3 indicates that most of the documents have been verified by Prosper. Δfunding is the hourly percentage change in the funding status. Cons. denotes the purpose consumption.

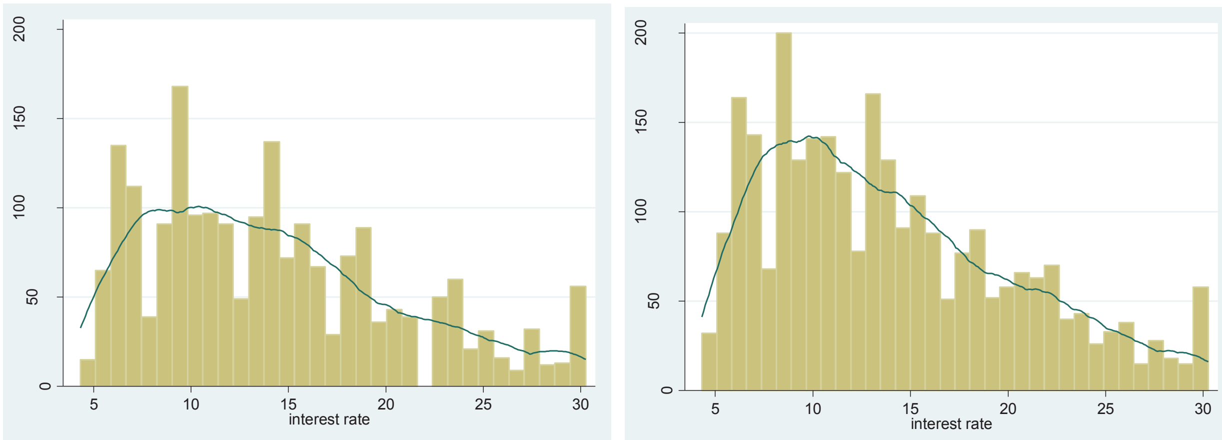

Figure I: Histogram of interest rates for loans in our observed period, before (left panel) and after (right panel) Fed liftoff on December 16th, 2015.

We track all observed loans with an hourly frequency by scraping Prosper's website to update the sample. The major advantage of an hourly dataset is that we see funding status changes over time. This provides an up-to-date snapshot of the P2P lending market, which is potentially reacting to the monetary policy announcement. Furthermore, this dataset enables us to construct an hourly measure of fund inflows to different loans and determine the size of aggregate demand at any hour in our sample. The loan-hour observations are used to calculate the funding gap, defined as the gap between cumulative inflow of funds and the loan amount target, for each listing, borrower group, and the whole market. The funding gap is an essential variable for understanding Prosper's interest rate setting problem and interest rate dynamics.

4 Results

Section 4.1 presents our main findings on interest rates and spreads for the P2P lending market after Fed liftoff. These results speak to Prediction 1. Section 4.2 suggests a mechanism for the interest rate and spread results by exploring measures of supply, demand, and the funding gap in the P2P market. The analysis of supply and demand speaks to Prediction

as "other" in Prosper, but we interpret it as unemployed.

2. Thereafter, section 4.3 considers state-level evidence that supports Prediction 3. Finally, section 4.4 provides external validity.

4.1 Interest rates and the credit spread

We analyze interest rates of loans listed within ±3-day, ±7-day, and ±14-day windows around December 16th of 2015, the date of Fed liftoff. Our longest window–hereafter, "LONG"– spans the entirety of our main sample for Prosper, which runs from November 20th, 2015 to January 20th, 2016. Note that this window starts with the first day of data collection and ends one week prior to the first 2016 FOMC meeting.

The baseline model regresses the interest rate of loans posted around the Fed's liftoff decision and a large number of observed loan-borrower characteristics. Table III summarizes the results for our sample with various window sizes. We use the following specification:

$$\begin{aligned} \text{InterestRate}_{i,t} &= \alpha + \alpha_h + \alpha_d + \beta_1 \text{Liftoff}_t + \gamma_1 \text{LoanCharacteristics}_i \\ &\quad + \gamma_2 \text{BorrowerCharacteristics}_i + \epsilon_{i,t}, \end{aligned} \tag{1}$$

where α captures the constant term, while α_h and α_d control for hour-of-day and day-of week effects, respectively. The inclusion of loan-borrower controls and fixed effects ensures we compare interest rates of loans with similar characteristics before and after liftoff. Liftoff_t is an indicator that takes on a value of 1 if the loan i is posted at a time t, which is after the Fed liftoff announcement. The estimated value of β_1 is between -0.169 and -0.229 and is highly significant at multiple time windows. Hence, the average interest rate for loans drops by $16.9 - 22.9$ bps post-liftoff, after controlling for all loan and borrower characteristics. When narrowing the event window to ±3 days around liftoff, we still observe a drop in average interest rates by a similar magnitude, as shown in column (1).[29]

To rule out the possibility that the regression results are mainly driven by the econometric model's (mis-)specification, we run two additional estimations to check the validity of the interest rate reduction result. The first robustness check expands the baseline regression

[29]We have to drop weekday fixed effects in the ±3 days regression, due to the multicollinearity between the weekday dummies and the liftoff variable.

Table III: Baseline regressions

	Dependent variable: Interest rate			
	(1)	(2)	(3)	(4)
Explanatory variables				
Liftoff	-0.195*	-0.229***	-0.173***	-0.169***
	(-1.74)	(-3.10)	(-3.17)	(-4.36)
Controls				
Loan Characteristics	✓	✓	✓	✓
Borrower Characteristics	✓	✓	✓	✓
Main Effects				
Weekday FE		✓	✓	✓
Hour FE	✓	✓	✓	✓
Window size	±3d	±7d	±14d	LONG
Adj. R^2	0.971	0.972	0.972	0.970
Observations	445	987	1,818	4,257

Notes. The dependent variable is the interest rate, in percentage points, posted on Prosper. The variable Liftoff_t is a dummy that equals 1 after the liftoff announcement on December 16, 2015. The borrower characteristics controls include her debt-to-income ratio, income group, prosper credit rating, and employment status. The loan characteristics include the loan size, maturity, purpose, and verification stage. We also include weekday fixed effects, hour-of-the-day fixed effects, and additional covariates, such as cross products of loan-borrower characteristics and the liftoff dummy, to validate the robustness of our findings. We run the regression for different window sizes (±3-day, ±7-day, ±14-day, LONG), including in the main sample over the period November 20, 2015 to January 20, 2016. We drop the weekday dummies in the ±3-day regression because of multicollinearity. t statistics are shown in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

by including the cross products of various loan-borrower characteristics (DTI, maturity, verification, etc.) and the liftoff dummy as regressors. The interest rate reduction survives this test. In the second robustness check, we regress the interest rate on all combinations of loan-borrower characteristics and the liftoff dummy. After obtaining the coefficients on liftoff, we run a sample mean test of the coefficient differences for the groups sharing similar loan-borrower characteristics before and after liftoff. The t-test statistics suggest that the interest rate is lower after liftoff and the difference is significantly negative. The estimation results are available in Table A.I of the Online Appendix. Changes in borrower composition or substitution into shorter maturity loans are not driver of our main results.

Both visual inspection and placebo tests suggest that the change in P2P lending rates happened precisely at liftoff. In Figure II we take the residuals from a regression of the interest rate on all loan-borrower information, regress them on daily time dummies and plot the coefficients on the daily dummies over time. We observe a clear drop in the average level of interest rates after the liftoff, controlling for all observable loan-borrower characteristics.[30]

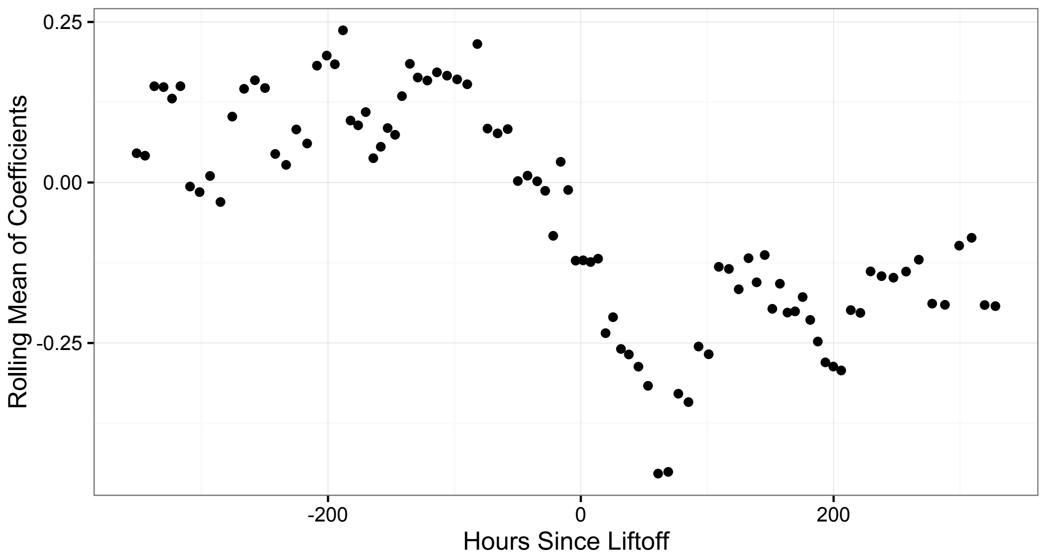

Figure II: The figure above plots the rolling mean of the coefficients from a regression of the interest rate residuals on time dummies over a ±14-day window around liftoff.

In a separate exercise, we run a placebo test that conducts a rolling regression of the interest rate with loan-borrower characteristic controls and the narrowest window of ±3 days. Within the window, we define a pseudo-liftoff variable $D(\tau)_t$ to replace Liftoff_t from Equation (1). The variable $D(\tau)_t$ is a dummy whenever t is in the second half of the time window, where $\tau = -3, \cdots, 3$ refers to the number of days since the liftoff date. Figure III illustrates that only the time dummy coinciding with the liftoff dummy is significantly different from zero. This suggests that our results are unlikely to be driven by pre-existing

[30]While Prosper and Lending Club occasionally announce rate changes, this communication is primarily directed at investors and is voluntary for Prosper. Additionally, these announcements may be accompanied by reallocations of borrowers across internal credit rating bins. For this reason, the meaning of interest rate change announcements is unclear. Lending Club, for instance, announced a rate increase in late December, while Prosper made no such announcement. In the data, however, the net effect of all changes appears to be a decline in average rates and spreads for borrowers with similar characteristics on both platforms. We also observe unannounced shifts in rates associated with credit bins in the data, which reinforces this point.

trends or other news events unrelated to liftoff.

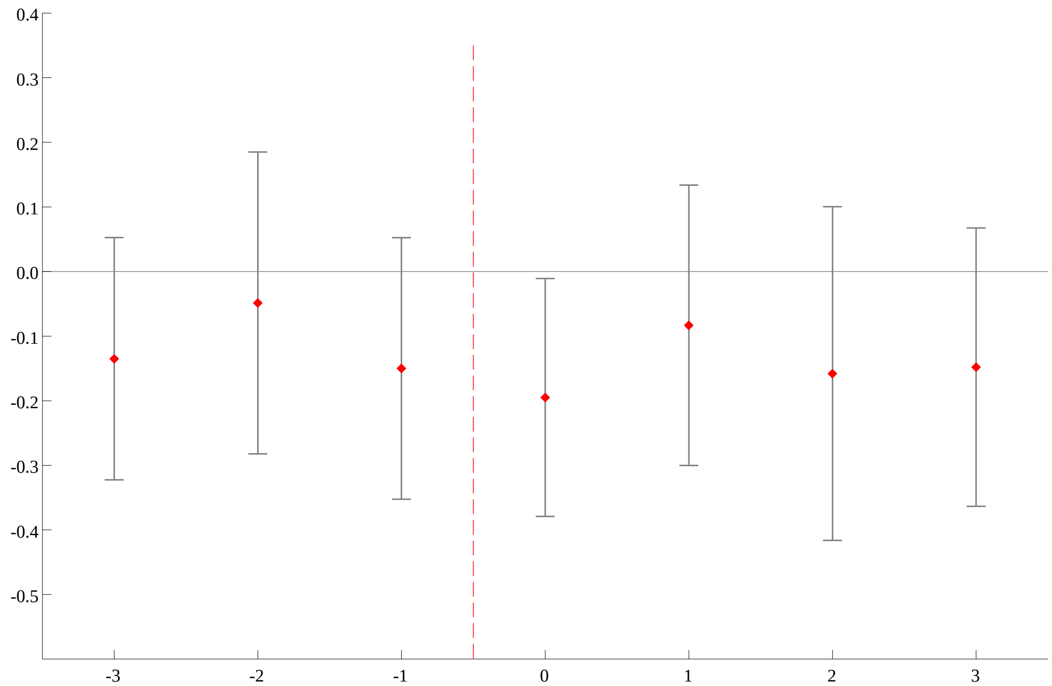

Figure III: The figure above plots the 90% confidence interval of the pseudo-liftoff coefficient estimates from a rolling regression of the interest rate with loan characteristics controls over a ±3-day window.

The estimated coefficients in regression (1) also confirm the presence of the usual channels for default risk in Prosper data. The coefficients on credit risk and employment, reflected in Prosper credit scores, are positive, indicating that the interest rate is higher for borrowers with higher perceived credit risk. Detailed estimation results are provided in Table A.II of the Online Appendix. Since our panel data contains loan listings with various characteristics, we estimate the model on data in different categories that are defined using the borrower's employment status and credit score. The equation we estimate is still the baseline regression, but we divide the data into subsample categories. We find a statistically significant interest rate reduction of approximately 40 bps for borrowers with lower Prosper credit ratings (lower than A). The interest rate reduction is significant for both employed and unemployed borrowers, but the drop is 6 bps larger for unemployed borrowers.

To further establish robustness, we also expand the sample to include observations until

February 26, 2016, a few days before the March FOMC meeting. We run a regression to measure the impact of the January 27, 2016 FOMC decision to keep the federal funds rate range at 0-25 bps on Prosper loan interest rates. The results are reported in Table A.V of the Online Appendix. We find that the January announcement did not have a statistically significant impact on the P2P lending rate. This suggests that the reduction in interest rates at liftoff cannot plausibly be attributed to a placebo effect, since no such effect is present at the January 27 meeting, where there was neither strong Fed signaling nor an unexpected adjustment in interest rates.

Although Fed liftoff was partially anticipated by the market (see section 2.1), the difference in the pre-announcement trend for different segments of the P2P lending market was negligible, especially close to the FOMC's policy meeting. We next narrow in on a window of ± 7 days around the announcement date to pin down the effect on the credit spread between less risky and risky borrowers. We divide the loan listing observations into three groups: employed borrowers with high credit ratings (AA and A), unemployed borrowers with middle or low credit ratings (not AA or A), and others. We focus on the first two groups in the regression, using the unemployed and lower credit rating borrower groups as the benchmark to control for any shared trend before the liftoff decision. The sample size is reduced to 355 loan listings, of which one third are from unemployed borrowers with a low credit rating.

$$\begin{aligned}
\text{InterestRate}_{i,t} \;=\;& \alpha + \alpha_h + \alpha_d + \beta_0 1\{EMP, High\}_i \\
&+ \beta_1 \text{Liftoff}_t + \beta_2 1\{EMP, High\}_i \times \text{Liftoff}_t \\
&+ \gamma_1 \text{LoanCharacteristics}_i + \gamma_2 \text{BorrowerCharacteristics}_i + \epsilon_{i,t}. \qquad (2)
\end{aligned}$$

Table IV reports the estimation results with different controls. Columns (1)-(4) show results with all possible controls at the loan level, three dummies corresponding to before-after group differences, and the cross product of group and liftoff time periods. It appears that the interest rate spread before liftoff between the two borrower groups is around 960 bps, and the gap is reduced by 166 bps after liftoff. This indicates that the credit spread between the good borrowers and the lower credit rated borrowers drops by around 16% on average, after controlling for all observable loan-borrower characteristics and possible time trends. Our findings are robust to the choice of econometric specification and standard error clustering.

Table IV: Before/after regressions on the interest rates for different groups

	Dependent variable: Interest rate			
	(1)	(2)	(3)	(4)
Explanatory variables				
Liftoff	-1.810***	-1.884***	-1.891***	-1.934***
	(-2.81)	(-2.92)	(-2.87)	(-2.94)
$1\{EMP, High\}$	-10.360***	-10.376***	-9.605***	-9.629***
	(-21.52)	(-21.37)	(-17.61)	(-17.55)
$1\{EMP, High\}\times$Liftoff	1.536**	1.654**	1.601**	1.658**
	(2.01)	(2.16)	(2.08)	(2.15)
Controls				
Loan Characteristics			✓	✓
Borrower Characteristics			✓	✓
Main Effects				
Weekday FE		✓		✓
Hour FE		✓		✓
Window size	±7d	±7d	±7d	±7d
Pre-Liftoff, int.rate mean $1\{EMP, High\} = 0$	17.805	16.085	19.974	19.315
Adj. R^2	0.663	0.668	0.671	0.675
Observations	355	355	355	355

Notes. We focus on ±7-day windows centered around the liftoff date. The interest rate is regressed on the liftoff dummy, borrower riskiness (Employment and Credit Rating), and their interaction terms. Additional controls include loan characteristics, borrower characteristics, and time dummies. The empirical specification treats the borrower with high credit ratings and employment as the focus, and benchmarks their interest rate variation with unemployed borrowers who receive a low credit rating from Prosper. t statistics are shown in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Moreover, as we demonstrate in Table A.III of the Online Appendix, they also survive the inclusion of the Variance Risk Premium (Bollerslev, Tauchen and Zhou 2009) as a control for shifts in risk appetite over time.[31]

Overall, the Fed liftoff announcement was associated with a sharp drop in the average interest rate of around 16.9-22.9 bps. Moreover, the spread between high and low credit risk groups experienced a relatively large drop of around 16% after liftoff. These results confirm Prediction 1, which suggests that the spread between high and low risk borrowers should decrease if the risk-free rate channel is outweighed by the credit risk channel, as suggested by the reduction in P2P lending rates after liftoff. Nevertheless, it is, perhaps, counterintuitive

[31] See the Online Appendix for more details about the VRP's construction.

that the increase of the risk-free reference rate is associated with a reduction in interest rates, especially for borrowers with low credit ratings and no stable labor income. We will argue in the remainder of the paper that a reduction in perceived default probabilities, induced by positive Fed signaling, is the most plausible explanation for these findings.

Before identifying the employment outlook as a key driver of default risk in section 4.3, which suggests that a channel exists in the P2P market for macroeconomic factors to affect perceived default probabilities and individual loan rates, we proceed by linking our main results to supply-side factors in section 4.2.

4.2 Supply and demand analysis

In addition to the interest rate dataset, we also obtain hourly updates of loan funding progress for each listing. The latter variable is of key interest in this section. Specifically, we examine how the funding gap is affected by liftoff and find that it drops significantly. We also show that this funding gap reduction appears to be driven by an increase in supply, rather than a reduction in demand. Our supply measures–funding speed and funding success–both increase, validating Prediction 2. Taken together, the results support the mechanism for the post-liftoff reduction in average interest rates, discussed in section 4.1.

The funding gap, defined as the size of the unfunded portion of the loan at each time t for loan listing i, provides a natural metric for the P2P platform when choosing individual interest rates to maximize the origination volume. We can aggregate the funding gap for the whole sample and also for different categories (e.g. according to credit ratings and/or employment status). This allows us to distinguish between different market segments.

Demand and supply in the lending market are endogenous to the interest rate decision in equilibrium, making it difficult to identify the driving forces behind observed interest rate changes after liftoff. However, the funding gap, defined as:

$$\text{FundingGap} = \text{RequestedLoanAmount} - \text{FundedLoanAmount} \tag{3}$$

is a key variable in the P2P platform's profit maximization problem. Specifically, the platform maximizes the origination volume by assuring that the funding gap remains narrow, especially after lasting changes in supply and demand conditions.

The first two columns in Table V show the corresponding regressions for the effect of liftoff on the funding gap measure. We first study the impact of liftoff on the aggregate funding gap over time with the following regression:

$$\text{FundingGap}_t = \alpha + \alpha_h + \alpha_d + \beta_1 \text{Liftoff}_t + \gamma \text{LoanBorrowerCharacteristics}_t + \epsilon_t. \quad (4)$$

Columns (1) and (2) in Table V present results for the aggregate funding gap over time. We find that it is reduced after liftoff, dropping significantly by around $400,000. This result is robust to inclusion of intra-day and intra-week fixed effects, as well as average loan and borrower characteristics. To explore the funding gap in different market segments classified by credit riskiness, we run the regression of funding gap the market segment j shown in Table VI:

$$\begin{aligned} \text{FundingGap}_{j,t} &= \alpha + \alpha_h + \alpha_d + \beta_0 1\{EMP, High\}_j + \beta_1 \text{Liftoff}_t \\ &\quad + \beta_2 1\{EMP, High\}_j \times \text{Liftoff}_t + \epsilon_{j,t}. \end{aligned} \quad (5)$$

In columns (1) and (2) of Table VI, we use a ±7-day window, centered around the liftoff announcement, to study the dynamics of the funding gap in two distinct groups: employed borrowers with high credit ratings and unemployed borrowers with low credit ratings. We find that the funding gap is higher for employed borrowers with high credit ratings. Furthermore, it increases after the liftoff decision by $57,000 (summing up β_1 and β_2 in column (2) of Panel B). We also run the regression on the funding gap in percentage points, rather than the dollar amount, to control for the impact of loan size. We find similar effects in the same direction. Taken together, this differential impact of the liftoff on the funding gap for different borrower groups also reinforces our second main finding in section 4.1 on the spread reduction between high and low credit rating borrowers. This is because a lasting reduction in the funding gap for low credit rating borrowers is associated with downward pressure on the interest rates of these borrowers.

We next test whether the funding gap reduction was driven by an increase in supply or a decrease in demand. We investigate aggregate new demand in different market segments of

Table V: Before/after regressions for the aggregate funding gaps and demand

	(1) FundingGap	(2) FundingGap	(3) Demand	(4) Demand
Explanatory variables				
Liftoff	-0.474***	-0.383***	0.031***	0.017**
	(-23.12)	(-10.84)	(5.81)	(2.23)
Controls				
Loan Characteristics		✓		✓
Borrower Characteristics		✓		✓
Main Effects				
Weekday FE		✓		✓
Hour FE		✓		✓
Window size	LONG	LONG	LONG	LONG
Adj. R^2	0.113	0.555	0.023	0.397
Observations	1,403	1,403	1,403	1,403

Notes. We focus on the LONG window size, using the main sample over the period November 20, 2015 to January 20, 2016. We regress funding gaps and demand (in millions of USD) on liftoff, and intra-day and intra-week dummies. We include all borrower types in the aggregation. Additional controls include sample average loan characteristics and average borrower characteristics. t statistics are shown in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

the P2P lending platform. A decrease in demand would suggest that the mechanism behind the reduction in the funding gap and reduction in interest rates is not identified. To the contrary, we find that demand increases slightly after liftoff, reinforcing our supply-driven hypothesis. The following regression uses aggregate new demand as the dependent variable,

$$\text{Demand}_t = \alpha + \alpha_h + \alpha_d + \beta_1 \text{Liftoff}_t + \gamma \text{LoanBorrowerCharacteristics}_t + \epsilon_t. \tag{6}$$

Column (3) and (4) in Table V show that new demand increases after liftoff for all groups by \$17,000. This provides strong evidence that the interest rate reduction results are not driven by a collapse of demand in the market.

In order to capture the demand shifts in market segment j, we also employ the following

Table VI: Before/after regressions for the funding gaps and demand of different groups

Panel B: market segments	(1) FundingGap	(2) FundingGap	(3) Demand	(4) Demand
Explanatory variables				
Liftoff	-0.047***	-0.044***	0.005*	0.006**
	(-7.99)	(-9.81)	(1.70)	(2.01)
$1\{EMP, High\}$	0.181***	0.181***	0.031***	0.031***
	(31.09)	(41.40)	(10.36)	(11.77)
$1\{EMP, High\}\times$Liftoff	0.101***	0.101***	0.030***	0.030***
	(12.03)	(16.03)	(6.87)	(7.77)
Controls				
Main Effects				
Weekday FE		✓		✓
Hour FE		✓		✓
Window size	±7d	±7d	±7d	±7d
Pre-Liftoff, $\{UnEMP, LowCR\}$ mean	0.232	0.184	0.028	0.007
Adj. R^2	0.828	0.903	0.463	0.583
Observations	650	650	650	650

Notes. We focus on ±7-day windows centered around the liftoff date to study the aggregate funding gap and demand in different market segments. This table shows regressions of funding gaps and demand (in millions of USD) on liftoff, borrower-loan characteristics (Employment and Credit Rating), intra-day, and intra-week dummies. The two borrower categories are defined as borrowers with high credit ratings and employment, versus unemployed borrowers with low credit ratings from Prosper. t statistics are shown in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

regression

$$\begin{aligned}\text{Demand}_{j,t} &= \alpha + \alpha_h + \alpha_d + \beta_0 1\{EMP, High\}_j + \beta_1 \text{Liftoff}_t \\ &\quad + \beta_2 1\{EMP, High\}_j \times \text{Liftoff}_t + \epsilon_{j,t}. \end{aligned} \tag{7}$$

Hour-of-day and day-of-week fixed effects are included as α_h and α_d. In columns (3) and (4) in Table VI, we separate the market into high and low credit risk segments using a ±7-day window around liftoff. We find that the increase is stronger for high creditworthiness borrowers, which is consistent with the interest rate changes and funding gap dynamics in these segments.

Finally, we construct three separate measures of loan funding supply. A post-liftoff increase in these variables supports the hypothesis that the average interest rate reduction was driven by an increase in supply. Furthermore, taken together with the reduction in the interest rate spread, it also supports the hypothesis that perceived default probabilities fell, leading to a stronger inflow of funds.

We first test the supply increase hypothesis using the realized probability that a loan listing is funded $Pr(1\{LoanFunded\} = 1)$ as a measure of supply. The logit regression for a loan posted at time t is:

$$\begin{aligned} 1\{LoanFunded\}_i &= \alpha + \alpha_h + \alpha_d + \beta_1 \text{Liftoff}_t + \gamma_1 \text{LoanCharacteristics}_i \\ &\quad + \gamma_2 \text{BorrowerCharacteristics}_i + \epsilon_{i,t}. \end{aligned} \tag{8}$$

We also use other measures of supply to study whether the funding game changed after liftoff, such as:

$$\text{Funding Increase}_{i,t} = \Delta(\text{Funding Percentage})_{i,t} \tag{9}$$

for each loan posting at time t. A loan is more likely to be funded (reaching at least 70% of the total funding target) if the increase is large. With this approach, we can exploit variation in the loan-time observations. Similarly, we replace the dependent variable in Equation (5) with the funding speed increase:

$$\text{Funding Speed}_{i,t} = \Delta(\text{Funding Increase})_{i,t} \tag{10}$$

to calculate the speed of reaching the funding target. We select loans posted on the Prosper website from November 20, 2015 to January 5, 2016, such that we observe the whole funding process of the loan listings.

The estimation results are reported in Table VII. In column (1), the logistic regression for funding probability yields a coefficient estimate of 0.24, which translates into an odds ratio of 1.27 or a 5.37% increase in the funding probability after liftoff. Moreover, this result is statistically significant. The second column shows that the funding increase is larger after liftoff by 0.14 percentage points.

The last regression, which uses funding speed indicates as the dependent variable, indicates that liftoff increased the rate of funding progress by 0.03 percentage points over time. These supply results, coupled with the average interest rate and spread reductions, suggests

Table VII: Before/after regressions for the funding success measures

Dependent variable	(1) $1\{LoanFunded\}$	(2) Funding Increase	(3) Funding Speed
Explanatory variables			
Liftoff	0.238**	0.137***	0.028**
	(2.39)	(11.23)	(1.98)
Controls			
Loan Characteristics	✓	✓	✓
Borrower Characteristics	✓	✓	✓
Main Effects			
Weekday FE	✓	✓	✓
Hour FE	✓	✓	✓
Window size	LONG	LONG	LONG
R^2	0.094	0.098	0.015
Observations	2,858	237,296	237,296

Notes. We focus on the LONG window size, using the main sample over the period November 20, 2015 to January 20, 2016 and the loan listings where we observe the whole funding process. Funding success is regressed on a liftoff dummy, loan-borrower characteristics (as in previous regressions), intra-day and intra-week dummies. The funding success variable is measured as the probability of getting funded, the funding increase, and the funding speed. t statistics are shown in parentheses. Results are from OLS regressions, except for a Logit regression with the funding probability $1\{LoanFunded\}$. The variables Funding Increase and Funding Speed are in percentage (%). Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

that liftoff may have been associated with a reduction in the perceived probability of default. This is reinforced by our findings in section 4.3, where we show that unemployment at the state level affects the rates that borrowers receive, even when we control for employment status at the individual level. Section 4.4 demonstrates this further by showing that improvements in the expected future state of the economy, as measured by changes in the real yield curve, are associated with a reduction in interest rates in the P2P market.

4.3 State level evidence

In previous sections, we focused primarily on the funding process of loans with individual characteristics. In this section, we exploit state-level heterogeneity in unemployment rates, alternative consumer credit (credit card) stocks, and access to bank finance channels to deepen our understanding of the interest rate dynamics. Most importantly, we provide support for Prediction 3 by demonstrating that the employment outlook is an important determinant of interest rates in the P2P segment of consumer credit after controlling for all available borrower-loan characteristics. This result points to a strong credit risk channel, given the importance of future employment risk as determinant of perceived credit risk, especially for high credit risk borrowers. Furthermore, we take a closer look at potential factors influencing borrower outside options, since demand effects showed up as an additional driver behind the decrease in the credit spread in the section 4.2 regressions. Taken together, our econometric results provide evidence that the default risk reduction and borrower outside option variation explain the interest rate and credit spread decrease after Fed liftoff. We proceed by describing four regression specifications.

We first examine the effect of unemployment risk, which is a key determinant of perceived default risk and, therefore, interest rates. Unemployment is particularly important in our market because many borrowers have uncertain employment statuses and may be regarded as risky. Additionally, all loans are uncollateralized, so default risk is almost entirely driven by borrowers' inability to make payments. We define a new variable $1\{\text{Unemp}\}_i$, which takes a value of 1 if the borrower for loan i resides in a state with an unemployment rate higher than the national average (i.e. $> 5.2\%$, as of 2015), and use the following regression specification:

$$\begin{aligned} \text{InterestRate}_{i,t} &= \alpha + \alpha_h + \alpha_d + \gamma_1 \text{LoanCharacteristics}_i + \gamma_2 \text{BorrowerCharacteristics}_i \\ &+ \beta_0 1\{\text{Unemp}\}_i + \beta_1 \text{Liftoff}_t + \beta_2 1\{\text{Unemp}\}_i \times \text{Liftoff}_t + \epsilon_{i,t}. \end{aligned} \tag{11}$$

If liftoff sent a positive signal about future employment probabilities, we would expect interest rates to react more in states with relatively high unemployment rates, where the associated reduction in the perceived default risk should be strongest.

We next examine the role of borrowers' outside options. We construct a proxy to disentangle the substitution effect between the P2P lending market and alternative consumer credit sources. The proxy is the outstanding credit card debt balance per capita in each state, which measures the use of an important alternative consumer credit market. We use the FRBNY Consumer Credit Panel / Equifax data for the last quarter (Q4) of 2015. Similar to P2P lending, credit card debt is unsecured, but with a different contract structure. We define a new dummy variable, where $1\{\text{CreditCard}\}_i = 1$ for loans in states with credit card balances above the national median level, and run the following regression:

$$\begin{aligned}&\text{InterestRate}_{i,t} = \alpha + \alpha_h + \alpha_d + \gamma_1 \text{LoanCharacteristics}_i + \gamma_2 \text{BorrowerCharacteristics}_i \\ &+\beta_0 1\{\text{CreditCard}\}_i + \beta_1 \text{Liftoff}_t + \beta_2 1\{\text{CreditCard}\}_i \times \text{Liftoff}_t + \epsilon_{i,t}. \qquad (12)\end{aligned}$$

From the consumer perspective, good borrowers should have access to both markets and may choose between them strategically. The rates credit card companies charge may vary over time, but should be stickier than in the online lending market, since most credit card borrowing occurs within an existing contract at a pre-determined rate. In expectation of liftoff, credit card companies may start to increase interest rates earlier than P2P lenders because of their relatively more rigid pricing regime. If that's the case, we should see an increase in the demand from good borrowers in the P2P lending market. From the study in section 4.2, we know that the demand increase is indeed greater for employed borrowers with high credit ratings.

The third test also relates to borrowers' outside options, but looks beyond the consumer credit market. We follow Becker (2007) and Butler, Cornaggia and Gurun (2015) to investigate the potential competition between traditional bank finance and the new P2P lending market. We use total deposits per capita in each state to measure geographic differences in access to traditional bank finance. The data are sourced from the FDIC Summary of Deposits database as reported in June 2014. The state population number is taken from the Census Bureau as of year 2014. We aggregate total deposits to the state level and rescale it by the state population. We introduce a new variable, $1\{\text{BankDeposit}\}_i$, which takes a value of 1 for loans in states with low deposits per capita and with outstanding credit card balances per capita below the national median value. The regression specification is as follows:

$$\begin{aligned}&\text{InterestRate}_{i,t} = \alpha + \alpha_h + \alpha_d + \gamma_1 \text{LoanCharacteristics}_i + \gamma_2 \text{BorrowerCharacteristics}_i \\ &+\beta_0 1\{\text{BankDeposit}\}_i + \beta_1 \text{Liftoff}_t + \beta_2 1\{\text{BankDeposit}\}_i \times \text{Liftoff}_t + \epsilon_{i,t}. \qquad (13)\end{aligned}$$

The OLS regression results are reported in Table VIII, with each column corresponding to one of the four different regressions. After controlling for loan-borrower characteristics, we find in column (1) that borrowers from states with a higher unemployment rate pay a 0.21% higher interest rate. This finding highlights the link between macroeconomic employment conditions and the interest rates on individual loans, validating Prediction 3. As argued in section 2.3 and formalized in Online Appendix B, the positive association of higher state-level unemployment rates with higher interest rates is consistent with an employment risk induced credit risk channel. Moreover, we find that the liftoff event brings down the interest rate by 30 bps for all borrowers. We also find that liftoff had a negative, but insignificant impact on rates in states with higher post-liftoff unemployment rates. However, the insignificance of the finding is unsurprising for two reasons: 1) there is very little variation in state unemployment rates at the frequency of our data; and 2) investors are primarily interested in unemployment rate forecasts over the maturity of the loan.

Columns (2) and (3) indicate the existence of a substitution effect and competition between the P2P lending market and consumer credit / bank finance channels. In states with a higher outstanding credit card balance per capita, borrowers have to pay a 0.24% higher interest rate than those in other states after the liftoff. On the other hand, borrowers from states with bad local access to finance and low credit card debt will experience a 0.40% greater reduction in average interest rate after the liftoff.

A few concerns regarding the state-level results may arise. First, we are not able to carefully control for local economic development in our regression, so it is possible that some findings can be attributed to omitted state level heterogeneity. However, we do not have county-level information on our borrowers in this setting; and it is difficult to control for state-wide factors cleanly. Another possible problem is that our findings could be driven by unobserved borrower composition changes at the state level due to liftoff. To deal with this, we ran additional regressions using the cross product of state dummies and the liftoff dummy. Our main findings survive the robustness check. The interpretation, however, is difficult, since the number of observations per cluster is small.

Overall, we find evidence that the unemployment rate is an important determinant of interest rate setting on Prosper. There is a systematic difference in the interest rate for borrowers from different states. Moreover, the interest rate reduction after Fed liftoff is stronger for states with lower outstanding credit card balances and weaker access to bank financial services. Finally, local banking competition affects the P2P lending market interest

Table VIII: Before/after regressions on the interest rates using states heterogeneity

	Dependent variable: Interest rate		
	(1)	(2)	(3)
Explanatory variables			
Liftoff	-0.294***	-0.438***	-0.237***
	(-3.26)	(-3.70)	(-3.90)
1{Unemp}	0.207**		
	(2.35)		
1{Unemp}×Liftoff	-0.049		
	(-0.39)		
1{CreditCard}		-0.058	
		(-0.62)	
1{CreditCard}×Liftoff		0.244*	
		(1.69)	
1{BankDeposit}			0.191**
			(2.10)
1{BankDeposit}×Liftoff			-0.398**
			(-2.65)
Controls			
Loan Characteristics	✓	✓	✓
Borrower Characteristics	✓	✓	✓
Main Effects			
Weekday FE	✓	✓	✓
Hour FE	✓	✓	✓
Window size	LONG	LONG	LONG
Benchmark int.rate mean	15.291	15.500	15.463
Adj. R^2	0.839	0.838	0.839
Observations	4,257	4,257	4,257

Notes. We focus on the LONG window size, using the main sample over the period November 20, 2015 to January 20, 2016. The interest rate is regressed on liftoff, loan characteristics, borrower characteristics, intra-day and intra-week dummies. The exact set of controls is similar as in previous loan-level regressions. We include dummy variables to capture state level heterogeneity in unemployment rate changes, outstanding credit card debt, local access to capital markets and local deposit market competition. Standard errors are clustered at the state level. t statistics are shown in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

rate, leading to a bigger drop after the Fed liftoff decision. Our findings provide new evidence for geographical differences in financial services, reflected in the P2P lending rates.

4.4 External validity

This paper emphasizes the role that Fed liftoff played as a strong, positive signal about future macroeconomic conditions. In the P2P segment of the online credit market, it translated into a lower perceived default probability and, thus, a lower interest rate. In this section, we provide evidence for the external validity of these findings over time and across markets.

First, we generalize the link between improvements in the expected economic outlook and our key findings on the interest rate and credit spread. If the improvement of future economic conditions affects the P2P lending rate, then changes in the slope of the real yield curve, a proxy for measuring future economic development used in the literature (Harvey 1988, Estrella and Hardouvelis 1991), should induce interest rate adjustments in the market we study. In Table A.IV, we regress the interest rates observed in the Prosper market on the slope, defined as the difference between the 5-year TIPS yield and the 1-month real interest rate.[32] An increase in the real slope is usually associated with an improvement in fundamental economic conditions. We find that interest rates for high credit risk borrowers decrease by 2.03% for every percentage point increase in the real slope variable $\text{Slope}_t^{(5)}$. We also see that the credit spread between low credit rating and high credit rating borrowers is reduced by 21.5% for every percentage point increase in the real slope.

The effect of the real yield curve slope on P2P lending rates is large and statistically significant. Replacing the 5-year real slope with the 10-year real slope yields does not change the direction and does not substantially change the magnitude. Furthermore, if we include the real slope as an explanatory variable, the impact of liftoff becomes less significant. This suggests that the information revealed by liftoff is similar to the information embodied by real yield curve slope adjustments, which provides further support for the claim that liftoff was interpreted as a positive signal about future economic conditions.

Second, we validate our key findings by studying LendingClub, another major P2P lending platform in the US. We obtain daily loan-origination reports of LendingClub to the US Securities and Exchange Commission for the same sample period from November 20, 2015 to January 20, 2016. The reports provide interest rates and loan-borrower information variables

[32] The construction of the real interest rate and the corresponding data sources are explained in the Online Appendix.

for all loan postings that have been successfully originated on the LendingClub platform. Unfortunately, the reports do not contain information about loans that have not been funded and cannot be used to construct intraday measures of demand and supply in the market. We explore the interest rate data for originated loans and report the regression results for the liftoff dummy and different interest dynamics for high versus low risk borrowers in Table A.VI. We find that the average interest rate drops and the credit spread narrows after liftoff. This result confirms our findings from the Prosper dataset; and suggests that the monetary policy signaling associated with the Fed liftoff decision also affected other lending markets where many borrowers exhibit risky characteristics.

5 Conclusion

This paper contributes to the emerging literature on monetary normalizations by measuring the effect of Fed liftoff on the P2P segment of the uncollateralized online consumer credit market. We compile a unique panel dataset of loan-hour observations from the online primary market for uncollateralized consumer credit. This allows us to monitor the funding process in real time, and to separately measure supply and demand. We find that liftoff lowered the average interest rate by 16.9-22.9 bps and reduced the spread by 16% between high and low credit rating borrowers. This change was not caused by Fed undershooting, a reduction in demand, a change in borrower composition, or a shift in risk appetite, but appears to be driven by a drop in investor-perceived default probabilities. We also use a separate dataset to demonstrate that this effect generalizes to over 70% of the P2P market; and also show that these findings are not common to all FOMC announcements by performing the same tests on the January 27th, 2016 decision to leave rates unchanged.

In addition to our interest rate results, we exploit a unique feature of our dataset to demonstrate that 1) supply increased after liftoff; and 2) demand did not fall. This is consistent with the narrative that liftoff revealed the Fed's strong, positive assessment of the future state of the economy. Borrowers in the P2P market are particularly sensitive to such assessments, since many of them have risky characteristics, including partial documentation and uncertain unemployment statuses. Indeed, we find that the net effect of the interest rate hike and FOMC signaling (i.e. proceeding with normalization) was small for highly rated borrowers, but was large and negative for borrowers with poor credit histories. This suggests that the effect we identify may be difficult to measure in other markets, such as the market for corporate or government debt, where default probabilities are less sensitive to signaling about future employment probabilities. Our findings are most easily generalizable to the uncollateralized consumer credit market.

Finally, we show that macroeconomic news translates into interest rate adjustments in the P2P market. In particular, we find support for two claims: 1) borrowers in states with higher rates of unemployment also receive higher interest rates, even after controlling for all observables; and 2) improvements in the expected future state of the economy, as measured by changes in the real yield curve, reduce interest rates for borrowers in the P2P market. These two findings suggest plausible channels for Fed liftoff to affect investor perceptions and, therefore, interest rates in the P2P market.

Overall, our work complements the empirical event studies literature on monetary contractions, but is closer methodologically to work on the bank lending channel of monetary policy. We contribute to the literature by providing one of the first assessments of a critical stage in the monetary normalization process; and use a unique panel dataset that allows us to monitor funding in real time and to disentangle supply and demand. Our results suggest that monetary normalizations may actually decrease interest rates for borrowers with poor credit histories by lowering their perceived default probabilities. This may, of course, depend on the content of the signals a central bank sends about its monetary normalization plan. In this case, the FOMC explicitly announced that liftoff would be contingent on the state of the economy, which framed the event as a positive revelation about the Fed's private assessment.

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For Online Publication: Online Appendix

A Appendix to the empirical models

A.1 Robustness

Table A.I: One-sample t test: before/after liftoff interest rate differences

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
Δ Int-Rate	273	-0.266	0.120	1.987	-0.503	-0.029

mean = mean(Δ Int-Rate)	t = -2.213
H0: mean = 0	degrees of freedom = 272

Ha: mean $<$ 0	Ha: mean $\neq$ 0	Ha: mean $>$ 0
Pr(T $<$ t) = 0.014	Pr(|T| $>$ |t|) = 0.028	Pr(T $>$ t) = 0.986

Notes. We focus on the LONG window size, using the main sample from the Prosper dataset over the period November 20, 2015 to January 20, 2016. To conduct the sample t test, we measure the difference in regression coefficients by regressing the interest rate on a large set of dummies with all possible combinations of borrower characteristics: loan size, loan type, borrower income, debt-to-income ratio, credit rating, employment status, maturity, and a liftoff dummy. After the regression, we take the difference of the coefficients for the dummies that share all characteristics before and after liftoff. We then test whether the sample mean of the differences is smaller than 0. It is significant at the 5% level.

Table A.II: Robustness: regressions with sub-samples

	Dependent variable: interest rate					
	(1)	(2)	(3)	(4)	(5)	(6)
	High CR	Middle CR	Low CR	Employed	Self-emp	Unemp
Explanatory variables						
Liftoff	-0.0854	-0.415***	-0.393*	-0.368***	0.143	-0.427*
	(-0.95)	(-3.56)	(-1.71)	(-3.60)	(0.46)	(-1.69)
ES=Self-employed	-0.206	0.136	-0.686**			
	(-1.61)	(0.89)	(-2.10)			
ES=Unemployed	0.932***	0.848***	0.275			
	(4.82)	(5.26)	(0.96)			
CR=Middle				5.621***	5.737***	5.979***
				(52.30)	(11.88)	(21.61)
CR=Low				14.980***	14.698***	15.070***
				(123.24)	(29.63)	(47.70)
Controls						
Loan Characteristics	✓	✓	✓	✓	✓	✓
Borrower Characteristics	✓	✓	✓	✓	✓	✓
Main Effects						
Weekday FE	✓	✓	✓	✓	✓	✓
Hour FE	✓	✓	✓	✓	✓	✓
Window size	LONG	LONG	LONG	LONG	LONG	LONG
Average Int.Rate.	4.240	11.91	60.98	15.55	32.41	13.56
Observations	1,198	1,825	1,234	3,166	520	571
Adj. R^2	0.047	0.027	0.148	0.843	0.775	0.832

Notes. We focus on the LONG window size, using the main sample from the Prosper dataset over the period November 20, 2015 to January 20, 2016. The interest rate is regressed on Fed liftoff, borrower characteristics, and time dummies. Regressions are performed separately on subsamples that are divided according to credit rating ("CR", or "Credit Bin" as regressors) or employment status (ES). "High CR" includes Prosper ratings AA and A, "Middle CR" includes B and C, and "Low CR" includes the rest. We have four employment statuses in the study: Employed (reported as "Full-time" or "Employed"), Self-employed, and Unemployed (reported as "Other"). t statistics are in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.III: Robustness: control changes in risk appetite

	Dependent variable: Interest rate	
	(1)	(2)
Explanatory variables		
Liftoff	-0.174***	-1.933***
	(-4.38)	(-2.92)
$1\{EMP, High\}$		-9.630***
		(-17.52)
$1\{EMP, High\}\times$Liftoff		1.658**
		(2.14)
VRP	-0.0264	-0.0203
	(-1.21)	(-0.03)
Controls		
Loan Characteristics	✓	✓
Borrower Characteristics	✓	✓
Main Effects		
Weekday FE	✓	✓
Hour FE	✓	✓
Window size	LONG	±7d
Adj. R^2	0.971	0.674
Observations	4,257	355

Notes. In column (1) we focus on the LONG window size, using the main sample from the Prosper dataset over the period November 20, 2015 to January 20, 2016. Column (2) uses a ±7-day window centered around the liftoff date. The interest rate is regressed on the liftoff dummy and variance risk premium (VRP), a model-free measure of investors' risk appetite proposed in Bollerslev et al. (2009). It is simply the difference between risk-neutral expected future volatility and the ex-post realized return volatility, measured by the VIX index from the Chicago Board of Options Exchange (CBOE) and the 5-min. realized variance measure from the Oxford-Man Institute of Quantitative Finance Realized Library. We also include borrower riskiness (Employment and Credit Rating), and the interaction between riskiness and the liftoff dummy. Additional controls include loan characteristics, borrower characteristics, and time dummies. The empirical specification treats the borrower with high credit rating and employment as the focus, and benchmarks their interest rate variation with unemployed borrowers who receive a low credit rating from Prosper. t statistics are shown in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.IV: Robustness: regressions with slope of the real yield curve

	Dependent variable: interest rate	
	(1)	(2)
Explanatory variables		
Liftoff	-0.490***	-0.451**
	(-2.59)	(-2.45)
$1\{EMP, High\}$	-8.298***	-8.801***
	(-28.46)	(-47.25)
Slope$^{(5)}$	-2.026***	
	(-3.00)	
$1\{EMP, High\} \times$ Slope$^{(5)}$	1.781**	
	(2.15)	
Slope$^{(10)}$		-1.816***
		(-3.02)
$1\{EMP, High\} \times$ Slope$^{(10)}$		1.749***
		(2.19)
Controls		
Loan Characteristics	✓	✓
Borrower Characteristics	✓	✓
Main Effects		
Weekday FE	✓	✓
Hour FE	✓	✓
Window size	LONG	LONG
Observations	4,257	4,257
Adj. R^2	0.390	0.390

Notes. We focus on the LONG window size, using the main sample from the Prosper dataset over the period November 20, 2015 to January 20, 2016. The interest rate is regressed on the slope of real yield curve, borrower riskiness (Employment and Credit Rating), and their interaction terms. Additional controls include loan characteristics, borrower characteristics, time dummies and the liftoff dummy. The empirical specification treats the borrowers with high credit ratings and employment as the focus, and benchmarks their interest rate variation with unemployed borrowers who receive low credit ratings from Prosper. The slope of real yield curve Slope$^{(5)}$ is the difference of 5-year TIPS bond yield and 1-month real interest rate at each day. We also include another variable Slope$^{(10)}$ that takes the difference between 10-year and 1-month real interest rate. The TIPS yield is taken from the Federal Reserve Board website. The real interest rate is computed with 1-month nominal yield, and inflation expectation is calculated using the Billion Price Project inflation index series from FRED. t statistics are in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A.2 January 27, 2016 FOMC meeting results

Table A.V: Robustness: baseline regressions for the Jan. 27, 2016 FOMC meeting

	Dependent variable: Interest rate		
	(1)	(2)	(3)
Explanatory variables			
Post-Announcement	-0.105	0.002	0.025
	(-0.54)	(0.08)	(0.72)
Controls			
Loan Characteristics		✓	✓
Borrower Characteristics		✓	✓
Main Effects			
Weekday FE	✓		✓
Hour FE	✓		✓
Sample	PLACEBO	PLACEBO	PLACEBO
Adj. R^2	0.001	0.969	0.969
Observations	6,589	6,589	6,589

Notes. We focus on the placebo sample from the Prosper dataset over the period November 20, 2015 to February 26, 2016. The dependent variable is the interest rate, in percentage points, posted on the P2P lending platform. The variable Post-Announcement$_t$ is a dummy that is equal to 1 after the FOMC's decision on January 27, 2016 to leave the target federal funds rate range unchanged. The characteristic controls include the borrower's debt-to-income ratio, income group, Prosper credit score, and employment status. The loan characteristics include the loan size, maturity, purpose, and verification stage. We also include weekday fixed effects, hour-of-the-day fixed effects, and additional covariates, such as cross products of loan-borrower characteristics and the liftoff dummy. We notice that the January 27, 2016 announcement has a positive, but statistically insignificant impact on the P2P lending rate. t statistics are shown in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A.3 Evidence from another P2P lender: LendingClub

Table A.VI: Robustness: before/after regressions using LendingClub data

	Dependent variable: Interest rate					
	(1)	(2)	(3)	(4)	(5)	(6)
Explanatory variables						
Liftoff	-0.158***	-0.210***	-0.169***	-0.363**	-0.335**	-0.279*
	(-3.55)	(-5.55)	(-4.33)	(-2.33)	(-2.34)	(-1.93)
$1\{EMP, High\}$				-2.670***	-1.263***	-1.200**
				(-21.14)	(-2.70)	(-2.57)
$1\{EMP, High\}\times$Liftoff				0.389**	0.289*	0.262*
				(2.26)	(1.82)	(1.65)
Controls						
Loan Characteristics		✓	✓		✓	✓
Borrower Characteristics		✓	✓		✓	✓
Main Effects						
Weekday FE	✓		✓	✓		✓
Window size	LONG	LONG	LONG	±7d	±7d	±7d
Adj. R^2	0.002	0.231	0.232	0.058	0.196	0.198
Observations	37,717	37,717	37,717	13,880	13,880	13,880

Notes. These regressions use the daily loan-origination reports of LendingClub, another major P2P lender in the US, to the US Securities and Exchange Commission. The first three columns focus on a LONG window size, using a sample over the period November 20, 2015 to January 20, 2016. Columns (4)–(6) focus on ±7-day windows centered around the liftoff date. The estimation setting is the same as in the Prosper results. The dependent variable is the interest rate, in percentage points. The variable Liftoff$_t$ is a dummy that equals 1 after the liftoff announcement on December 16, 2015. The borrower characteristics controls include variables such as the debt-to-income ratio, income group, prosper credit rating, and employment status. The loan characteristics include the loan size, maturity, purpose, and verification stage. We also include weekday fixed effects here, but not the intraday hourly dummy because of the daily data frequency. t statistics are shown in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B Appendix to the theoretical framework

In this section, we formalize the link between employment risk and default probabilities. More specifically, we treat employment risk as the key determinant of default risk and present a stylized model that links changes in the employment outlook to changes in default risk.

Let δ_H (δ_L) be the default probability of a high (low) credit risk borrower and consider a two period model with time indexed by $t = 1, 2$ and no discounting. The two periods capture in a stylized way the duration of a loan until maturity at the end of $t = 2$. Let $1 > p_L^E \geq p_H^E > 0$ represent the probabilities of a low and high credit risk borrower, respectively, to stay employed in a given period. Furthermore, let $1 > p_L^U \geq p_H^U > 0$ represent the probabilities of an unemployed low and high credit risk borrower, respectively, finding a new job in a given period. We assume job finding probabilities to be weakly lower than the probabilities of staying employed, i.e. $p_L^U \leq p_L^E$, $p_H^U \leq p_H^E$. Finally, let $0 < s^E < s^U < 1$ capture the probabilities of an unemployed and employed borrower, respectively, failing servicing their debt in a given period, which is considered as a permanent default.

Based on these assumptions, the default probabilities of type $k = H, L$ borrowers who are both employed at the beginning of $t = 1$ are:

$$\begin{aligned}\delta_k \quad = \quad & \overbrace{(p_k^E s^E + (1 - p_k^E) s^U)}^{\substack{probability\ of\ defaulting\ in\ t=1 \\ when\ staying\ employed\ or\ getting\ unemployed}} \quad + \\ & \underbrace{p_k^E (1 - s^E)(p_k^E s^E + (1 - p_k^E) s^U)}_{\substack{prob.\ of\ defaulting\ in\ t=2 \\ cond.\ on\ staying\ emp.\ in\ t=1}} + \underbrace{(1 - p_k^E)(1 - s^U)(p_k^U s^E + (1 - p_k^U) s^U)}_{\substack{prob.\ of\ defaulting\ in\ t=2 \\ cond.\ on\ getting\ unemp.\ in\ t=1}}.\end{aligned} \tag{14}$$

We have that $\delta_H > \delta_L$ if either the probability of staying employed and/or the probability of finding a job are higher for type L borrowers.

Next, let $p_L^E > p_H^E$ and assume that the improved economic outlook signaled by liftoff is associated with an increase in the job finding probabilities of high and low credit risk borrowers by some $\eta > 0$, i.e. $1 > p_L^U + \eta \geq p_H^U + \eta > 0$. Observe that:

$$\frac{d\delta_H}{d\eta} = (1 - p_H^E)(1 - s^U)(s^E - s^U) < \frac{d\delta_L}{d\eta} = (1 - p_L^E)(1 - s^U)(s^E - s^U). \tag{15}$$

Hence, the difference in default probabilities $(\delta_H - \delta_L)$ is decreasing in η. To the extent that the impact of the improved economic outlook on the difference in default probabilities is sufficiently high, the observed reduction in the spread between high and low credit risk borrowers after liftoff can be explained.