Fed Liftoff and Subprime Loan Interest Rates: Evidence from the Peer-to-Peer Lending Market*

Christoph Bertsch
Sveriges Riksbank

Isaiah Hull
Sveriges Riksbank

Xin Zhang
Sveriges Riksbank

June 13, 2016

Abstract

On December 16th of 2015, the Fed initiated "liftoff," raising the federal funds rate range by 25 basis points and ending a 7-year regime of near-zero rates. We use a unique dataset of 640,000 loan-hour observations to measure the impact of liftoff on interest rates in the peer-to-peer lending segment of the subprime market. We find that the average interest rate dropped by 16.9-22.6 basis points. This holds for 14 and 28 day windows centered around liftoff, and is robust to the inclusion of a broad set of loan-level controls and fixed effects. We also find that the spread between high and low credit rating borrowers decreased by 16%; and reject a number of candidate explanations for these results, including a change in borrower composition, a collapse in demand, and a shift in risk appetite. 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 subprime borrowers, reducing their borrowing cost, even as short term rates increased in other markets. (*JEL* D14, E43, E52, G21)

Keywords: peer-to-peer lending, subprime consumer loans, Fed liftoff, monetary policy signaling, default channel, household debt.

---

*Research Division, Sveriges Riksbank, SE-103 37 Stockholm, Sweden. We would like to thank Lieven Baele, Christoph Basten, Bruno De Backer, Geert Bekaert, John Cochrane, Christopher Foote, Stefano Giglio, Florian Heider, Tor Jacobson, Rodney Ramcharan, Ricardo Reis, Emanuele Tarantino, Robert Vigfusson, and seminar participants at the Belgium Financial Research Forum 2016, the GSMG Workshop, Stockholm University, and Sveriges Riksbank. All remaining errors are our own. The views expressed in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the official views of Sveriges Riksbank.

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"–an interest rate regime change that started with a 25 basis points (bps) hike on December 16th of 2015 and signaled an upward trajectory for future rates, including four additional 25 bps hikes in 2016 (FOMC 2015a,b).

Discussion of the timing and impact of liftoff has grown in recent years, as the Fed openly pondered its increasing likelihood.[1] Approaching the December 16th decision, market participants also concluded that liftoff was likely. This was reflected in short-maturity, low-risk rates–such as the rate on AA, 30-day commercial paper–which increased throughout early December, ultimately peaking after the Fed's announcement. This shift in market expectations was also apparent in the futures market for federal funds, where most traders anticipated an increase of the target federal funds rate's range from 0-25 bps to 25-50 bps.

These pre-liftoff adjustments suggest that the increase in the short-term, risk-free rate was at least partially anticipated and priced into the market. What was less clear, however, is how risky debt–such as debt in the subprime market–would be affected by the regime change. In normal times, an increase in the short-term rate might be expected to partially pass-through to other rates, moving them in the same direction and having a weakly positive effect on default probabilities.[2] However, the circumstances surrounding liftoff were not normal. The Fed's decision to move away from near-zero rates for the first time in seven years was a rare event; and could be interpreted as a strong, positive signal about the Fed's private assessment of future employment and

[1]See Bauer and Rudebusch (2013); Evans et al. (2015); Cooke and Gavin (2014); Orphanides (2015); Ozdagli (2015) for an overview of the discussion that preceded Fed liftoff.

[2]Standard New Keynesian models assume a complete (Woodford 2003) or at least partial (Kobayashi 2008) interest rate pass-trough. Empirical studies document that surprise monetary contractions increase interest rates (Nakamura and Steinsson 2015), lower stock prices by raising the expected equity premium (Bernanke and Kuttner 2005), and are associated with an increase in credit spreads (Gertler and Karadi 2015).

growth prospects. If this was how the Fed argued for it and how market participants evaluated it, then perceived default probabilities might fall; and–if the signal was strong enough–dominate the short term rate increase, lowering interest rates for subprime borrowers.

Indeed, 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). The Fed reinforced this sentiment in the rationale they provided for the December 16th decision: "The Committee judges that there has been considerable improvement in labor market conditions this year, and it is reasonably confident that inflation will rise, over the medium term, to its 2 percent objective" (FOMC 2015a). Although the outlook for four gradual hikes in 2016 has since been revised after a deterioration of the global economic environment, liftoff was unambiguously framed as a strong, positive signal about the Fed's assessment of the state of the economy when it was announced.[3]

This article attempts to advance the dialogue on liftoff by measuring its impact on 3-5 year rates and credit spreads in the peer-to-peer (P2P) segment of the uncollateralized subprime lending market. Focusing on a segment of the subprime market allows us to capture the impact of liftoff on the group of market participants who is arguably most sensitive to changes in perceived default probabilities. Concentrating on the P2P lending segment enables us to monitor the funding process in real time, which could not have been done with traditional bank borrowing data, where lending decisions are not incremental and are not made publicly available during the funding process. This approach also permits us to observe a wide variety of loan-level characteristics, which is not possible for time series market data, such as bonds. Finally, using P2P lending data allows us to separately identify how much borrowers request and how much they receive from investors, which enables us to test competing explanations about the

[3]Economic projections of the committee members from March 16th, 2016 suggest two 25 bps hikes (FOMC 2016).

underlying reasons for rate changes. This feature is unique to our dataset, since we observe high-frequency, incremental funding outcomes for all posted loan applications, rather than simply the set of originated loans.

We conduct our empirical investigation using a novel dataset of 640,000 loan-hour observations, collected between November 20, 2015 and March 8, 2016. The data was obtained by scraping loan listings on *Prosper.com*–one of the largest P2P lending platforms in the United States–and matching those listings over time using unique loan IDs. Once posted, the loan characteristics remain the same, with the exception of the loan's level of funding, which is updated in real time. Our sample period includes the FOMC's liftoff decision on December 16th, as well as the January 27th, 2016 decision not to change the target rate. The second FOMC decision allows us to perform a placebo test to determine if there is a common interest rate reaction surrounding all Fed announcements.

We estimate two outcomes of interest related to liftoff: 1) the change in the average interest rate; and 2) the change in the spread between high and low credit risk borrowers. For the first set of estimates, we use a variety of regression specifications and incorporate intra-day and intra-week time fixed effects, group fixed effects, and a broad set of loan-level controls, such as the debt-service-to-income ratio, the income bracket, the credit score, the loan maturity, and the loan purpose. We show that the average interest rate on Prosper loans fell by $16.9 - 22.6$ bps; and the spread between high and low credit-risk borrowers decreased by 16%. Furthermore, the spread reduction is primarily driven by a decrease in rates for low credit rating borrowers. High credit rating borrowers also see a small, negative change in interest rates, but it is not statistically significant.

To evaluate the robustness of the average interest rate reduction, we run the same regression specification for different time windows. We find that tightening the estimation window increases the size of the effects. For a 14-day window, centered around liftoff, we find that the average interest rate on Prosper loans fell by 22.6 bps. For a

28-day window and the complete sample, the reductions fall to 19 bps and 16.9 bps, respectively. These results are consistent with the claim that Fed liftoff caused the shift in rates.

We also 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 14-day and 28-day windows around the announcement. To further establish robustness, we run the baseline regression on narrowly-defined groups of borrowers using interactions of all observable characteristics. We find negative and significant interest rate changes for identical groups after liftoff, suggesting that a shift in composition over observables does not solely explain the reduction in interest rates. We also test and rule out a number of other minor competing explanations for our findings, including a shift in risk appetite over time.

To guide our analysis, we construct a stylized model motivated by the literature on platform pricing[4] that captures Prosper's interest rate setting problem: to choose rates that will maximize origination volume and, hence, fee-based income. The theoretical model suggests that the decrease in both the average interest rate and the credit spread are consistent with a story that centers around the signaling channel of monetary policy decisions. Additionally, the model offers testable predictions that we use to guide further empirical analysis of supply and demand factors.

Prosper's key trade-off is to offer each borrower an interest rate that is likely to be accepted (e.g. a rate that is not too high compared to the borrower's outside options: credit card, bank finance) and that is sufficiently attractive to investors. The model, which is constructed around this stylized fact, predicts that the average interest rate set by the platform is increasing in both the reference rate for safe investments and in the perceived default probability of borrowers. Our empirical findings imply that the

[4]See, e.g., Rochet and Tirole (2006), Armstrong (2006).

latter channel–a reduction in perceived default probabilities–must have dominated at liftoff, since the average rate fell.

The model also makes predictions about the interest rate spread and the funding gap. It suggests that an increase in the supply of funds relative to demand–captured as a decrease in the observed funding gap in a given market segment–is associated with a decrease of the average interest rate in this segment. It also indicates that the observed decrease in the interest rate spread can be explained by a differential reduction in perceived default probabilities.

We first evaluate the funding gap prediction, following the theoretical model's implications. Our dataset allows us to compute high frequency funding gap changes, and to differentiate between the amount the borrower requests and the amount that investors have funded. We compute funding gaps at each point in time by aggregating the loan size variable across borrowers. We find that the funding gap decreases on average for all borrowers, but decreases more for high credit risk borrowers. These findings provide support for the model's prediction of a positive relationship between funding gaps and interest rates. Not only is the relationship borne out in aggregate, but it also holds within credit risk segments, since the spread decreases. In addition to this, we show that newly posted demand rises for both the high credit rating and low credit rating groups after liftoff. This indicates that the reduction in the average interest rate and spread must be attributed to a supply side factor, such as a reduction in perceived default probabilities, which we examine next.

If the positive signal from Fed liftoff lowered perceived default probabilities, then posted loans should be funded faster and should be more likely to reach full funding status. In fact, we find a significant increase in the probability of getting funded, the size of funding increases, and the speed of funding inflows after liftoff. These results are consistent with the signaling channel of monetary policy. We find further support for the default probability reduction hypothesis by performing state-level regressions. In particular, we show that borrowers in states with high unemployment rates also face higher interest rates, even after controlling for all observables, including the borrower's own employment status. This suggests that information about the aggregate state of the economy may also impact a borrower's perceived probability of default–and, thus, interest rate–in the P2P segment of the subprime market. In addition, we demonstrate that state-level access to bank credit and state-level per capita credit card balances also affect P2P market interest rate outcomes.

Although we focus primarily on the effects of Fed liftoff in the P2P market, our findings are likely to generalize beyond this event and market segment. Borrowers in the P2P market often face high interest rates and lack complete documentation, which suggests that our findings may be reflective of the broader subprime segment for consumer credit. Furthermore, as we demonstrate in robustness exercises, the channels activated by liftoff are also present in other periods; however, liftoff provides us with an unusually large–and possibly unique–signaling event, where interest rate pass-through is dominated in the market we observe.

Our article contributes to the literature analyzing monetary policy's impact on market interest rates (Cook and Hahn 1989; Kuttner 2001) with an event-study approach. To the best of our knowledge, we are the first to study monetary policy interest rate pass-through to uncollateralized subprime lending. More generally, there exist only a few works on interest rate pass-through to consumer credit.[5] If P2P lending markets continue to grow in importance, our results bear relevance for the consumption behavior of households in the economy and monetary policy transmission.[6] Therefore, our paper contributes to the literature analyzing the interest rate channel of monetary policy (Taylor 1995) and complements the extensive literature on the credit channel going back to Bernanke and Blinder (1992).[7]

The literature on monetary policy has extensively discussed the signaling role of cen-

[5]See Ludvigson (1998) for monetary policy transmission and automobile credit, and Di Maggio et al. (2014) for mortgage debt.

[6]For a recent review on the monetary policy transmission mechanism and its channels see Boivin et al. (2011).

[7]See also Bernanke and Gertler (1995), Kashyap and Stein (2000), and Jiménez et al. (2014).

tral bank communication (Blinder et al. 2008) with an interest in both the disclosure of monetary policy actions and revelation of information about macroeconomic variables (Andersson et al. 2006). While the desired degree of transparency about the central bank's information on economic fundamentals has been intensely debated,[8] 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 et al. 2016; Campbell et al. 2012; Boyarchenko et al. 2016).[9] Symptomatically, Faust and Wright (2009) document the Fed's good nowcasting performance. Moreover, in line with our findings on the P2P lending market, perceived default probabilities play an important role (e.g. in the context of bank lending policies (Rodano et al. 2016)) and employment risk appears to be a key contributing factor (e.g. as an predictor of mortgage defaults (Gerardi et al. 2015)).

We also contribute to the growing literature on P2P lending and on subprime consumer credit, more broadly.[10] A number of papers also use data from the *Prosper.com* lending platform to study the role of soft information, such as the appearance of borrowers (Duarte et al. 2012; Pope and Sydnor 2011; Ravina 2012), the importance of screening in lending decisions (Iyer et al. 2015), the effect of home prices on borrowing conditions (Crowe and Ramcharan 2013), geography-based informational frictions (Senney 2016), the auction pricing mechanism that existed prior to December 2010 (Chen et al. 2014; Wei and Lin 2015), and the ability of marginal borrowers to substitute between financing sources (Butler et al. 2015).

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 et al. (2006), Agarwal and Ambrose (Eds.) (2007), and Guiso and Sodini (2013)). Nourished

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

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

[10]For a recent review of the literature on crowdfunding see Belleflamme et al. (2015).

by an increasing household indebtedness in many advanced economies during the last decade (Guiso and Sodini 2013), the field has enjoyed increased attention. 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 (Agarwal et al. 2007).

The rest of the article proceeds as follows. Section 2 provides an overview of Fed liftoff and the P2P lending market. Section 3 describes the data and how it was collected. Section 4 presents our main findings on the P2P lending market during the Fed liftoff and offers a theoretical model for the interest rate setting mechanism, which is used to interpret the results and evaluate our hypothesis. Section 5 analyzes demand and supply, and tests the model implications. It also discusses the robustness of the results and provides evidence for the relevance of the proposed channels. Section 6 establishes the external validity of our main findings by demonstrating that the channels activated by liftoff are also present in other periods and in another P2P lending market. Finally, we conclude in section 7. All additional material can be found in the Online Appendix.

2 Description of Fed liftoff and of *Prosper.com*

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.

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, marking the end to an unprecedented era of monetary easing. Market participants largely anticipated that liftoff would occur on December 16, 2015. 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 on December 16, 2015.[11] Importantly, the implied probability was nearly 0 for a rate hike above 25-50 bps, which suggests that the FOMC's decision to raise rates to the 25-50 bps range slightly overshot, rather than undershot, market expectations.

This slight overshooting is also reflected in short and medium term interest rates. Table I shows selected interest rates at liftoff, as well as 7-days before and 7-days after. The "commercial paper" column shows rates for 1-month, AA financial commercial paper; and the "corporate bonds" column shows 3-5 year effective yields on US corporate bonds. In both cases, rates rise at liftoff relative to their values 7 days prior. Furthermore, 7 days after liftoff, rates remain roughly unchanged, increasing slightly for the commercial paper series.

Importantly, our findings suggest that average rates and credit spreads both declined in the P2P segment of the subprime market after liftoff. The claim that the FOMC's federal funds rate adjustment at liftoff "undershot" market expectations is not supported by the data; and, thus, is not a compelling explanation for the interest rate level and spread reductions we find. Furthermore, the increase in rates on 3-5 bonds suggests that unexpected forward guidance adjustments are not a plausible explanation for the reduction in interest rates we find in the P2P market.

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.

Finally, within the liftoff window, the FOMC's announcement is the only significant news event. The longest window we consider includes two favorable nonfarm payroll employment reports, but these fall on December 4th of 2015 and January 8th of 2015, both of which are outside of the narrowest window (14 days) we use–and, thus, un-

[11]Source: The probability of a Fed rate increase is based on futures, computed by Bloomberg.

likely to affect our results. Additionally, economic turmoil in China moved markets in January, but is also outside of the narrowest window.

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.[12] Prosper 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. The P2P lending platform is specialized in consumer credit. Borrowers ask for personal uncollateralized loans ranging from $2,000 to $35,000 with a maturity of 3 or 5 years. Borrowers in the market are best characterized as subprime. 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 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

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

and transfers the borrower's monthly installments to lenders.

Prosper's income is generated by fees related to the transaction volume on the platform. Specifically, the 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 taking administrative costs into account. Hence, we focus on the origination and servicing fee as 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.

3 Data

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.[13] Liftoff happens on December 16, 2015, which leaves us 26 days before and 34 days after its announcement. In total, our sample covers 326,044 loan-hour observations.[14] Among the 4,257 loan listings in the dataset, 3,015 loans can be identified as having successfully originated using the 70% funding rule.[15] Loan listings occur

[13]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.

[14]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 main findings, however, are robust to the time window selection procedure.

[15]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.

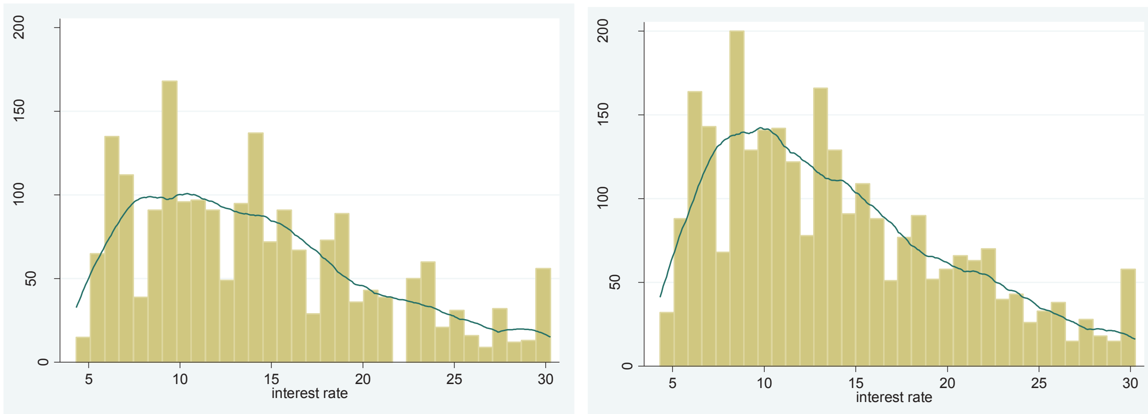

Figure I: Histogram of interest rates for loans in our observed period, before (left panel) and after (right panel) Fed liftoff on December 16th, 2015.

continuously around the clock. The Prosper loan terms are fixed once the funding phase starts and are posted on the online platform. 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 purposes 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 score that is mostly based on the borrower's Fair Isaac Corporation (FICO) score and

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						Panel B2: Sample after the Liftoff				
	mean	sd	min	max	obs		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

	Panel C1: ES=Employed						Panel D1: CR=High				
	mean	sd	min	max	obs		mean	sd	min	max	obs
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.

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.[16] 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.[17]

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 Main empirical findings and theoretical model

Section 4.1 presents our main findings on the P2P lending market during Fed liftoff. Thereafter, section 4.2 offers a stylized theoretical model for the interest rate setting mechanism. The model predictions are summarized in section 4.3.

[16] While it was possible to translate Prosper's credit ratings from the FICO scores (Butler et al. 2015), we might 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.

[17] A few employed borrowers indicate their employment status as "full-time." The last category is reported as "other" in Prosper, but we interpret it as unemployed.

4.1 Reduction in the average interest rate and in the spread

In this section, we analyze data on the interest rate of loans listed during the sample period of Nov. 20, 2015–Jan. 20, 2016. The baseline model regresses the interest rate of loans posted on the Fed's liftoff decision and a large number of observed loan-borrower characteristics. Table III summarizes the results. Column (3) reports the following regression:

$$\begin{aligned}\text{InterestRate}_{i,t} \quad = \quad & \alpha_t + \beta_1 \text{Liftoff}_t + \gamma_1 \text{LoanCharacteristics}_i \\ & + \gamma_2 \text{BorrowerCharacteristics}_i + \epsilon_{i,t} \qquad (1)\end{aligned}$$

where α_t captures the constant term, and the time dummies used to control for intra-week and intra-day seasonality. 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 -0.169. Hence, the average interest rate for loans drops by 16.9 bps post-liftoff, after controlling for all loan and borrower characteristics; and is robust to the exclusion of borrower-loan characteristics and/or intraday and intraweek fixed effects, as demonstrated in the remaining columns of Table III. This suggests that the pass-through component of liftoff was dominated by another channel. 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.

Table III also confirms the presence of the usual channels for default risk in Prosper data. The coefficients on the debt-to-income ratio and credit risk, reflected in Prosper credit scores, are positive, indicating that the interest rate is higher for borrowers with higher perceived credit risk. Additionally, the significantly positive coefficient on self-employed and unemployed borrowers suggests that the default risk for these types is higher.

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

Table III: Baseline regressions

	Dependent variable: Interest rate		
	(1)	(2)	(3)
Explanatory variables			
Liftoff	-0.476**	-0.136***	-0.169***
	(-2.13)	(-3.93)	(-4.36)
Controls			
Loan Characteristics		x	x
Borrower Characteristics		x	x
Main Effects			
Weekday FE	x		x
Hour FE	x		x
Adj. R^2	0.004	0.970	0.970
Observations	4,257	4,257	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. t statistics are shown in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

the validity of the interest rate reduction result. The first robustness check expands the baseline regression by including the cross products of various loan-borrower characteristics 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 B.I of the Online Appendix.

To further establish robustness, we narrow the estimation window to 14 and 28 days around the Fed announcement date, and find that the interest rate reduction is robust to time horizon choice. 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. 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.

In a separate exercise, we take the residuals from a regression of the interest rate on all loan-borrower information, and regress them on daily time dummies. Figure II plots the coefficients on the daily dummies over time. We observe a clear drop in the average level of interest rates after the liftoff decision, controlling for all observable loan-borrower characteristics.

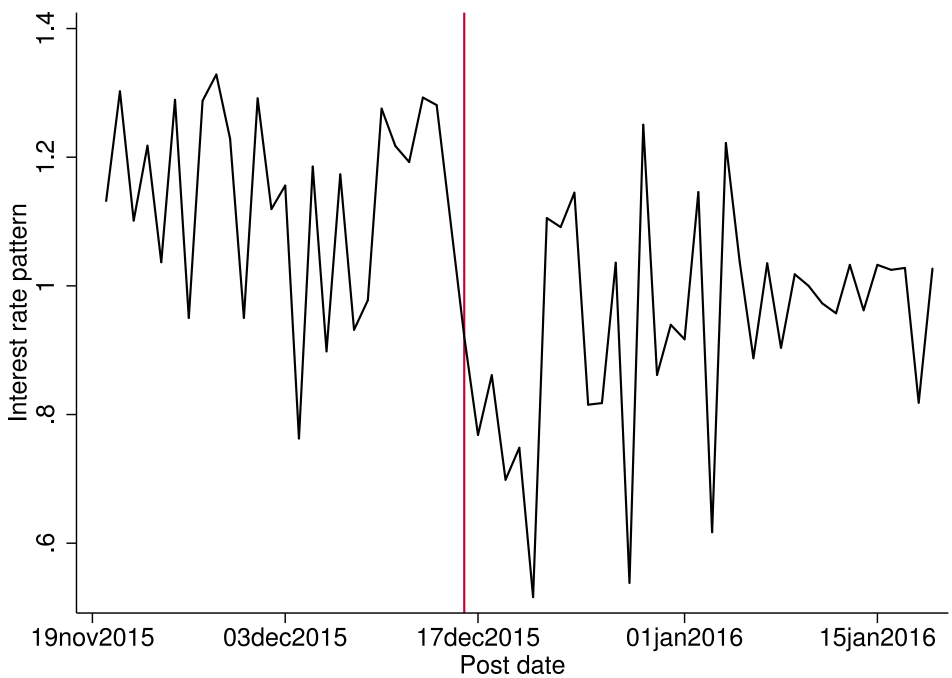

Figure II: The figure above plots the coefficients from a regression of the interest rate residuals on time dummies over the sample period of Nov. 20, 2015 to Jan. 20, 2016.

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. Detailed estimation results are provided in Table B.III of the Online Appendix.

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 zoom into a window of 14 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 group 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.

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

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

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			x	x
Borrower Characteristics			x	x
Main Effects				
Weekday FE		x		x
Hour FE		x		x
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. 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: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

specification and standard error clustering. Furthermore, as we demonstrate in Table B.II of the Online Appendix, they also survive the inclusion of the Variance Risk Premium (Bollerslev et al., 2009) as a control for shifts in risk appetite over time.[18]

Overall, this analysis shows that the Fed liftoff announcement was associated with a sharp drop in the average interest rate of 16.9 bps. The spread between high and low credit risk groups experiences a relatively large drop of around 16% after liftoff. It is intriguing that the increase of the risk-free reference rate is associated with a reduction in interest rates in the P2P lending market, especially for borrowers with low credit ratings and no stable labor income. In the next section, we propose a theoretical explanation for these phenomena based on monetary policy signaling and derive a few testable hypotheses for a more detailed empirical analysis thereafter.

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

4.2 Prosper's interest rate setting problem

In this section, we develop a stylized theoretical model for the crowdlending market. As argued in Section 2.2, Prosper's objective is to maximize fee-based income by facilitating a high transaction volume on its platform. We henceforth consider the individual pricing problem for a loan to applicant i. Assuming that the proportional origination fee (paid by the borrower), say $f^O > 0$, and the servicing fee (paid by the lender), say $f^S > 0$, are not choice variables in the short term (since they are pre-set and advertised on the website) and assuming that the loan volume for an individual loan applicant i is taken as given, the only remaining choice variable for Prosper is the gross interest rate $r_i \geq 1$.

We divide the Prosper market into $N > 1$ segments indexed by $n \in \{1, ..., N\}$. Each segment consists of a group of borrowers that are characterized by certain credit risk characteristics, which are captured by key control variables, such as the Prosper credit score, the applicant's debt-to-income and the employment status. Due to the observed heterogeneity, we allow the supply of funds to be specific to each market segment. Prosper optimally sets the interest rate r_i for an individual loan i in segment n as to maximize the probability of originating the loan times the net return. After normalizing the loan volume to one, the pricing problem writes:

$$\max_{r_i \geq 0} \{(f^O - c) \cdot Prob\{accept | r_i, f^O, \Theta_i\} \cdot Prob\{funding | r_i, \delta_i, r^r, f^S, M_n\}, \tag{3}$$

where $0 < c < f^O$ is Proser's marginal cost. The term $Prob\{accept|r_i, f^O, \Theta_i\} \equiv p_b \in [0, 1]$ is the probability that loan applicant i accepts a loan with an interest rate r_i and origination fee f^O. The variable Θ_i captures Prosper's belief about applicant i's outside options. Since f^O is a variable cost, the applicant's total funding cost can be written as $r_{B,i} = r_i + f^O$. Moreover, $Prob\{funding|r_i, \delta_i, f^S, M_n\} \equiv p_l \in [0, 1]$ is the probability that applicant i's loan is successfully funded. The lender's expected return on loan i can be written as $\overline{r}_{L,i} = (1-\delta_i)\cdot(r_i - f^S)$.[19] It depends on r_i and the perceived default probability δ_i, which itself is strongly affected by factors governing income risk such as employment risk. The variable r^r is the risk-free reference rate[20] at the posting time and M_n captures the market conditions in segment n, which can be proxied by the observed segment-specific funding gap at the posting time.

Borrower decisions We would expect the acceptance probability, p_b, to be decreasing in $r_{B,i}$, as well as decreasing if the outside options of applicant i improve.

Investment decisions When making their investment choice, lenders compare the expected return on Prosper loans with the risk-free reference rate. We assume that lenders have a common prior on the perceived default probability of applicant i, δ_i. Hence, we can compute the risk premium on a posted loan to applicant i as $\vartheta_i(r_i, \delta_i, r^r, f^S) = \overline{r}_{L,i} - r^r$. Consistent with risk-averse lenders, a necessary condition for lender participation is given by $\vartheta_i(r_i, \delta_i, r^r, f^S) > 0$. Notice that $\frac{d\vartheta_i}{d\overline{r}_{L,i}} > 0$ and $\frac{d\vartheta_i}{dr^r} < 0$. As a result, a higher perceived default probability or a higher reference rate requires, ceteris paribus, that lenders are still willing to invest despite a reduced risk premium. Similarly, a higher r_i might facilitate investments by increasing the risk premium. We would expect the probability that applicant i's loan is successfully funded, p_l, to be increasing in the offered risk premium ϑ_i.

[19] In practice, δ_i may vary with the interest rate (Stiglitz and Weiss 1981). We abstract from such a relationship, since Iyer et al. (2015) study Prosper data and do not find evidence for a causal effect of interest rates on default probabilities after controlling for borrower characteristics. Moreover, similar to Wei and Lin (2015) we focus on the individual loan pricing problem in isolation without taking into account the possibility that Prosper might be worried that a newly posted loan could have crowding-out effects vis-à-vis other recently posted loans. In other words, when formulating the problem, we abstract from potential negative same-sided network effects that may arise due to competition among borrowers. Different from Wei and Lin (2015), we introduce a borrower margin and allow the lender margin to depend on market conditions (supply and demand factors).

[20] The rate r^r can be thought of as the interest rate on treasuries with a similar maturity.

Trade-off The first-order necessary condition to the problem in (3) is written:

$$I \equiv (f^O - c) \cdot \left[\tfrac{\partial p_b(r_i, f^O, \Theta_i)}{\partial r_i} \cdot p_l(\vartheta_i, M_n) + p_b(r_i, f^O, \Theta_i) \cdot \tfrac{\partial p_l(\vartheta_i, M_n)}{\partial r_i} \right] = 0. \tag{4}$$

Intuitively, it is plausible to expect that, first, borrowers are less likely to participate the higher the interest rate and, second, lenders are more likely to offer funding. Hence, provided there are gains from trade (i.e. an interior solution exists), the key trade-off for the P2P platform is to optimally select r_i to balance the two opposing effects. We continue by discussing the individual loan level demand and supply side.

Demand side Applicant i will only accept the loan if $r_{B,i}$ falls short of her outside option u_i, i.e. if $r_i + f^O \leq u_i$. The precise outside option of applicant i is not known to Prosper. We assume for simplicity that Prosper's belief, Θ, about the outside options of applicant i in market segment n follows a uniform distribution $u_i \sim U[\underline{u}_n, \overline{u}_n]$, where $\overline{u}_n > \underline{u}_n > 0$. Hence, the probability of acceptance is given by:

$$p_b(r_i, f^O) = \frac{\overline{u}_n - (r_i + f^O)}{\overline{u}_n - \underline{u}_n}. \tag{5}$$

Taking derivatives describes the borrower margin (or sensitivity):

$$\frac{\partial p_b(r_i, f^O)}{\partial r_i} < 0, \quad \frac{\partial^2 p_b(r_i, f^O)}{\partial r_i^2} = 0. \tag{6}$$

Supply side When Prosper sets the rate for an individual loan, it has to take the funding conditions in market segment n into account. Suppose for simplicity that there is a continuum of equally-sized ongoing funding games and a continuum of lenders. Furthermore, denote the mass of ongoing funding games, or better the total outstanding funding gap in market segment n at the posting time, as $M_n \geq 0$. Let the mass of lenders who potentially supply funds to segment n be denoted as S_n.

We assume that the mass of lenders who happen to consider the posting of loan applicant i and examine her credit worthiness is inversely related to the total funding gap relative to the total mass of lenders. This can be interpreted as capturing market conditions in a stylized way.[21] Specifically, we assume that the mass of investors who consider applicant i follows a linear relationship:

$$g\left(\frac{S_n}{M_n}\right) \in [0, S_n], \quad with \;\; g' > 0 \;,\; g'' = 0. \tag{7}$$

Furthermore, we assume that individual lenders have minimum accepted risk premia that are distributed following $\vartheta \sim U[\underline{\vartheta}_n, \overline{\vartheta}_n]$, where $\overline{\vartheta}_n > \underline{\vartheta}_n \geq 0$, and that the random total mass of lenders who potentially supply funds to segment n is distributed following $S_n \sim U[\underline{S}_n, \overline{S}_n]$, where $\overline{S}_n > \underline{S}_n > 0$. Furthermore, each individual lender who is willing to fund a given applicant i (which occurs if loan i exceeds the lender's minimum accepted risk premium) is assumed to invest one unit in her loan. Recall that a given project goes ahead only if it reaches a funding of at least 70%. Based on these assumptions, the probability of loan i to be successfully funded is:

$$p_l(\vartheta_i, M_n) = \frac{\overline{S}_n - g^{-1}\left(0.7\frac{\overline{\vartheta}_n - \underline{\vartheta}_n}{\vartheta_i - \underline{\vartheta}_n}\right) M_n}{\overline{S}_n - \underline{S}_n}. \tag{8}$$

Taking derivatives describes the lender margin (or funding success sensitivity):

$$\frac{\partial p_l(\vartheta_i, M_n)}{\partial \vartheta_i} > 0, \quad \frac{\partial^2 p_l(\vartheta_i, M_n)}{\partial \vartheta_i^2} < 0, \quad \frac{\partial p_l(\vartheta_i, M_n)}{\partial M_n} < 0, \quad \frac{\partial^2 p_l(\vartheta_i, M_n)}{\partial \vartheta_i \partial M_n} > 0. \tag{9}$$

The positive cross-derivative with respect to M_n stems from the effect of market conditions on the mass of lenders who consider an individual posting of loan applicant i. This effect increases in magnitude with the funding gap and is associated with upward pressure on the interest rate r_i set by Prosper.

Given the described loan level demand and supply side, it can be shown that there exists at most one interest rate solving equation (4). We proceed by summarizing the

[21] This effect can be motivated by limits to the capacity of lenders to screen potential applicants.

testable implications stemming from a comparative statics analysis of the model.

4.3 Model predictions

We next reconcile the findings of section 4.1 using the stylized theoretical model developed in section 4.2. Specifically, we first analyze the comparative statics by studying a change in the risk-free reference rate r^r and the perceived default probability δ_i in isolation. We can derive the following two predictions:

Prediction 1: The optimal interest rate is increasing in the

(a) risk-free reference rate r^r, i.e. $\frac{dr_i}{dr^r} > 0$

(b) perceived default probability of borrower i, i.e. $\frac{dr_i}{d\delta_i} > 0$.

Notably, both results hold not only for the stylized demand and supply schedules presented above, but more generally provided that, first, the applicant's acceptance probability is decreasing in the loan's interest rate r_i at a weakly increasing rate; and, second, the probability of getting funded is increasing in the risk premium offered by the loan, ϑ_i, at a weakly decreasing rate.[22] The derivations are in section A.2 of the Online Appendix.

According to Prediction 1(a), the increase in the risk-free reference rate after Fed liftoff should, in isolation, be associated with an increase in interest rates on the P2P platform, which disagrees with our empirical finding. Contrastingly, a decrease in the perceived default probability is associated with a reduction in interest rates on the P2P platform, as prescribed by Prediction 1(b). Thus, the Fed's announcement of a monetary tightening can–if perceived as a sufficiently strong positive signal about the future solvency of subprime borrowers–reduce the cost of borrowing, even though it is associated with an increase in the risk-free reference rate.[23]

[22]Figure A.I illustrates the interest rate setting problem graphically for such a scenario.

[23]While the comparative static result in Prediction 1(a) considers the effect of a change in the risk-free reference rate in isolation, one may argue that also the outside options of borrowers could be affected by changes in r^r. In the Online Appendix A.3, we demonstrate that the result is unaffected when considering this possibility and taking into account the supporting evidence from section 5.1.

We claim that this signaling channel best explains our main findings. Specifically, we argue that employment risk is a key determinant of default risk (see Gerardi et al. 2015 for empirical evidence from mortgage defaults). Furthermore, we link the reduction in the perceived default risk to an improved employment outlook and provide supporting evidence in section 5.2 for the importance of state-level differences in unemployment rates for Prosper's rate setting. To the extent that the default risk of low rated borrowers is more sensitive to changes in the employment outlook, Prediction 1(b) can also explain the observed reduction in the spread between high and low credit rating borrowers, i.e.:[24]

$$\frac{dr_i}{d\delta_i}(high\ risk\ borrower) > \frac{dr_i}{d\delta_i}(low\ risk\ borrower). \tag{10}$$

Next, we derive a set of predictions related to the funding gap, the funding success probability, and borrower's outside options, which we will test in section 5. As before, the derivations can be found in section A.2 of the Online Appendix.

Prediction 2:

(a) The optimal interest rate is increasing in the funding gap, i.e. $\frac{dr_i}{dM_n} > 0$

(b) The probability of getting funded is decreasing in the funding gap, $\frac{dp_l}{dM_n} < 0$

(c) The probability of getting funded is decreasing in the perceived default probability of borrower i, i.e. $\frac{dp_l}{d\delta_i} < 0$

(d) The optimal interest rate is decreasing when the outside options of borrowers improve, captured as a downward shift in the support of the distribution, i.e. if $u_i \sim U[\underline{u}_n - \epsilon, \overline{u}_n - \epsilon]$ with $\epsilon > 0$.

While taken as given for the individual loan pricing problem, the funding gap at the market-level is likely to be affected by changes in default risk. Specifically, when

[24] In Online Appendix A.4, we present a stylized model that links changes in the employment outlook to changes in default risk, which appear to be more pronounced for high credit risk borrowers.

aggregating up, a perceived reduction in default probabilities will increase individual funding probabilities and, thus, will be associated with a reduction in the market-level funding gap. This can be interpreted as a funding speed acceleration. Hence, a reduction in the perceived default probability has a direct, positive effect on the probability of getting funded (Prediction 2(c)); and a direct, negative effect on the optimal interest rate (Prediction 1(b)). Furthermore, the model suggests that there will be an indirect effect operating in the same direction if the reduction in perceived default probabilities is associated with a reduction in the funding gap, which translates into a negative effect on the optimal interest rate (Prediction 2(a)). Finally, to the extent that the outside options of high and low credit rating borrowers are differentially affected by a relative deterioration of the outside options of high credit rating borrowers, Prediction 2(d) can also help to explain the observed reduction in the spread of high and low credit rating borrowers.[25]

5 Testing the model predictions

This section uses empirical tests to evaluate the model's theoretical predictions. We first consider the predictions about P2P lending market funding gaps. Specifically, in section 5.1, we measure how the gap between demand and supply is related to the interest rate drop. Thereafter, in section 5.2, we analyze loan applications at the state level, testing the predictions related to the default risk reduction channel. The state level evidence also suggests that the borrower's outside option is an important interest rate determinant. The direction of this effect is consistent with the model's prediction.

[25]Figure A.II illustrates the interest rate setting problem graphically for such a scenario. A deterioration of outside options of high credit rating borrowers dampens the total effect relative to the effect on low credit rating borrowers, resulting in a reduction in the spread.

5.1 Funding gap and funding success

In addition to the interest rate dataset, we also obtain hourly updates of loan funding progress for each listing. The theoretical model suggests a relationship between interest rates and funding gaps. 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. Prediction 2(a) provides us with a relationship that allows us to connect this finding with our first main result on the reduction of the average interest rate after liftoff, as 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 fairly difficult to separate the driving force of observed interest rate changes after liftoff. However, the funding gap, defined as:

$$\text{Funding Gap} = \text{Outstanding Loan Amount} - \text{Funded Loan Amount}, \qquad (11)$$

is a key variable in the profit maximization problem of the P2P platform. Specifically, it makes sense to set interest rates on individual loans to minimize the funding gap, which is closely related to the objective of maximizing the origination volume.

Table V shows the corresponding regressions for the effect of liftoff on the funding gap measure. Columns (1) and (2) present results for the aggregate gap over time. We find that it is reduced after liftoff, dropping significantly by \$477,000. This result is robust to inclusion of intra-day and intra-week fixed effects. In columns (3) and (4), we use a 14-day window, centered around the liftoff decision, to study the dynamics of

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

	Dependent variable: Funding gap			
	(1)	(2)	(3)	(4)
Explanatory variables				
Liftoff	-0.474***	-0.477***	-0.047***	-0.044***
	(-23.12)	(-23.47)	(-7.99)	(-9.81)
$1\{EMP, High\}$			0.181***	0.181***
			(31.09)	(41.40)
$1\{EMP, High\}\times$Liftoff			0.101***	0.101***
			(12.03)	(16.03)
Controls				
Main Effects				
Weekday FE		x		x
Hour FE		x		x
Pre-Liftoff, $\{UnEMP, LowCR\}$ funding gap mean	2.475	2.347	0.232	0.184
Adj. R^2	0.113	0.128	0.828	0.903
Observations	1,403	1,403	650	650

Notes. The regression of funding gaps (in millions of USD) on liftoff, borrower characteristics (Employment and Credit Rating), and intra-day and intra-week dummies. The two borrower categories are the same as before: employed borrowers with high credit ratings versus unemployed borrowers with low credit ratings from Prosper. t statistics are shown in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

the funding gap in two distinct groups: employed borrowers with high credit ratings and unemployed borrowers with low credit ratings. The specification is:

$$\begin{aligned} \text{FundingGap}_{i,t} &= \alpha_t + \beta_0 1\{EMP, High\}_i + \beta_1 \text{Liftoff}_t \\ &\quad + \beta_2 1\{EMP, High\}_i \times \text{Liftoff}_t + \epsilon_{i,t}. \end{aligned} \tag{12}$$

The funding gap is higher for the good borrower group. Furthermore, it increases after the liftoff decision by \$57,000 (summing up β_1 and β_2 in column (4)). 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 allows us to link to our second main finding in section 4.1 on the reduction of the spread between high and low credit rating borrowers.

Prediction 2(c) suggests that the individual loan funding probability increases if the perceived default probability is lower after liftoff. Furthermore, we find evidence for a decrease in the funding gap after liftoff, which is also associated with an increase in the funding probability following Prediction 2(b). To test the hypothesis, we construct a few measures of funding success to fit the theory setup. The obvious candidate is the realized probability of the loan listings getting funded $Pr(1\{LoanFunded\} = 1)$. The logit regression for a loan posted at time t is:

$$
\begin{aligned}
1\{LoanFunded\}_i \quad = \quad & \alpha_t + \beta_1 \text{Liftoff}_t + \gamma_1 \text{LoanCharacteristics}_i \\
& + \gamma_2 \text{BorrowerCharacteristics}_i + \epsilon_{i,t}.
\end{aligned} \tag{13}
$$

We also use other measures for the dependent variable to study whether the funding game is changed after the liftoff decision, such as:

$$
\text{Funding Increase}_{i,t} = \Delta(\text{Funding Percentage})_{i,t} \tag{14}
$$

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 funding increase is large. With this approach, we can exploit variation in the loan-time observations. Using percentage changes, rather than dollar amount of fund inflows, is consistent with the assumption in the theoretical model that all loan postings are homogenous in size. Similarly, we replace the dependent variable in Equation (12) with the funding speed increase:

$$
\text{Funding Speed}_{i,t} = \Delta(\text{Funding Increase})_{i,t} \tag{15}
$$

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 VI. In column (1), the logistic regression for funding probability estimates the coefficient to be 0.24, which translates to an

Table VI: 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	x	x	x
Borrower Characteristics	x	x	x
Main Effects			
Weekday FE	x	x	x
Hour FE	x	x	x
R^2	0.094	0.098	0.015
Observations	2,858	237,296	237,296

Notes. 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: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

odds ratio of 1.27. This means the odds of a loan getting funded increased by 27% after liftoff. Moreover, this increase is statistically significant. The second column shows that the funding increase is larger after liftoff by 0.14 percentage points.

The last regression using funding speed indicates that liftoff increases the rate of funding progress by 0.03 percentage points over time. Note that these results and the interest rate findings are consistent with the model predictions. As discussed earlier, the theoretical model takes the funding gap as exogenous, but the observed decrease in the gap itself could stem from a reduction in perceived default probabilities. This leaves the reduction in perceived default probabilities after the liftoff policy signal as the key driver for our interest rate findings in section 4.1. In fact, in section 5.2, we demonstrate the importance of the default channel via unemployment risk and thereby present further evidence in favor of the hypothesis that liftoff lowered the perceived default probabilities.

Finally, we investigate aggregate new demand in different market segments of the

Table VII: Before/after regressions for the aggregate demand

	Dependent variable: Demand			
	(1)	(2)	(3)	(4)
Explanatory variables				
Liftoff	0.031***	0.030***	0.005*	0.006**
	(5.81)	(5.79)	(1.70)	(2.01)
$1\{EMP, High\}$			0.031***	0.031***
			(10.36)	(11.77)
$1\{EMP, High\}\times$Liftoff			0.030***	0.030***
			(6.87)	(7.77)
Controls				
Main Effects				
Weekday FE		x		x
Hour FE		x		x
Pre-Liftoff, $\{UnEMP, LowCR\}$ demand	0.103	0.087	0.028	0.007
Adj. R^2	0.023	0.039	0.463	0.583
Observations	1,403	1,403	650	650

Notes. This table shows regressions of demand (in millions of USD) on liftoff, borrower characteristics (Employment and Credit Rating), intra-day, and intra-week dummies. The two borrower categories are the same as before: borrowers with high credit ratings and employment, versus unemployed borrowers with low credit ratings from Prosper. t statistics are shown in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

P2P lending platform to understand whether the interest rate drop is merely responding to a sharp decline of demand. The following regression uses aggregate new demand as the dependent variable,

$$\text{Demand}_t = \alpha_t + \beta_0 1\{EMP, High\} + \beta_1 \text{Liftoff}_t + \beta_2 1\{EMP, High\} \times \text{Liftoff}_t + \epsilon_{i,t}. \quad (16)$$

Intra-day and intra-week fixed effects are included in the time varying variable α_t. The estimation results are reported in Table VII.

Column (1) and (2) in Table VII show that new demand increases after liftoff for all groups by $30,000. It provides strong evidence that the interest rate reduction results are not driven by a collapse of demand in the market. We also look at different market segments to confirm this finding. In columns (3) and (4), we separate the market into high and low credit risk segments using a 14-day window around liftoff. The increase is stronger for high creditworthiness borrowers, which is consistent with the interest rate changes and funding gap dynamics in these segments.

5.2 State level evidence

For many tests in previous sections, we focused on the funding process of loans with individual characteristics. In this section, we exploit state-level heterogeneity in unemployment rate, alternative consumer credit (credit card) stocks, and access to bank finance channels to deepen our understanding of the interest rate dynamics. 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 test Prediction 1(b) by examining the effect of unemployment risk, which is a key determinant of the perceived default risk, on interest rates. We define a new variable $1\{\text{Unemp}\}_i$, which takes a value of 1 for loan i from states with an unemployment rate higher than the national average, i.e. $> 5.2\%$ as of 2015, and use the following regression specification:

$$\begin{aligned}\text{InterestRate}_{i,t} &= \alpha_t + \gamma_1 \text{LoanCharacteristics}_i + \gamma_2 \text{BorrowerCharacteristics}_i \\ &+ \beta_0 1\{\text{Unemp}\}_i + \beta_1 \text{Liftoff}_t + \beta_2 1\{\text{Unemp}\}_i \times \text{Liftoff}_t + \epsilon_{i,t}. \qquad (17)\end{aligned}$$

The premise underlying the model is that unemployment is an important risk factor in the P2P lending market, because borrowers in this subprime market are vulnerable to negative labor market shocks. If liftoff sends a positive signal about employment status looking ahead, we 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 test Prediction 2(d) by examining the role of borrower 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 shorter maturity of 1 month. We define a new dummy variable, where $1\{\text{CreditCard}\}_i = 1$ for loans in states with credit card balance above the national median level, and run the following regression:

$$\begin{aligned}\text{InterestRate}_{i,t} &= \alpha_t + \gamma_1 \text{LoanCharacteristics}_i + \gamma_2 \text{BorrowerCharacteristics}_i \\ &+ \beta_0 1\{\text{CreditCard}\}_i + \beta_1 \text{Liftoff}_t + \beta_2 1\{\text{CreditCard}\}_i \times \text{Liftoff}_t + \epsilon_{i,t}. \qquad (18)\end{aligned}$$

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 the online loan market in principle. In expectation of liftoff, the credit card company may start to increase the interest rate earlier than a P2P lender because of their relatively 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 5.1, we find that the demand increase is indeed greater for employed borrowers with high credit ratings.

The third test also relates to Prediction 2(d), but we step aside from the consumer credit market. We follow Becker (2007) and Butler et al. (2015) to investigate the potential competition between traditional bank finance and the new online P2P lending market. We use total deposits per capita in each state to measure the geographical difference in access to traditional bank finance. The data are sourced from the FDIC Summary of Deposit database as reported in June 2014. The state population number is 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 lower outstanding credit card balances per capita than the national median value. The regression specification is as follows:

$$\text{InterestRate}_{i,t} = \alpha_t + \gamma_1 \text{LoanCharacteristics}_i + \gamma_2 \text{BorrowerCharacteristics}_i$$
$$+ \beta_0 1\{\text{BankDeposit}\}_i + \beta_1 \text{Liftoff}_t + \beta_2 1\{\text{BankDeposit}\}_i \times \text{Liftoff}_t + \epsilon_{i,t}. \quad (19)$$

In addition, we run a regression to see if the state-level bank competition affects local borrowing cost, leading to a spillover to the P2P lending market. We use the Summary of Deposit data in 2014 to compute the Herfindahl-Hirschman Index (HHI) of the bank branch deposits in each state. There is a large literature using bank deposit concentration as a proxy for bank competition (e.g., Cetorelli and Strahan (2006)). We define a new dummy variable $1\{\text{BankComp}\}_i$ as an indication of stronger local bank competition (HHI lower than the sample median). The specification is similar to previous regressions:

$$\text{InterestRate}_{i,t} = \alpha_t + \gamma_1 \text{LoanCharacteristics}_i + \gamma_2 \text{BorrowerCharacteristics}_i$$
$$+ \beta_0 1\{\text{BankComp}\}_i + \beta_1 \text{Liftoff}_t + \beta_2 1\{\text{BankComp}\}_i \times \text{Liftoff}_t + \epsilon_{i,t}. \quad (20)$$

The OLS regression results are reported in Table VIII, with each column corresponding to one of the four different regressions. After controlling for loan and borrower characteristics, we find that borrowers from states with a higher unemployment rate pay a 0.21% higher interest rate. The liftoff event brings down the interest rate by 30 bps for all borrowers. We also find liftoff had a negative, but insignificant impact on rates in states with higher post-liftoff unemployment rates. Importantly, though, the insignificance of this result is plausible 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 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. The last regression tests the impact of bank competition on the interest rate in the lending market. We do not find direct evidence of the bank competition spillover effect, with insignificant regression coefficients for variables related to the bank competition dummy. The cross-product of competition and liftoff is marginally insignificant at 10%, suggesting that the interest rate experienced a further reduction of −0.21%–on top of the first-order impact–after liftoff in states with strong bank competition.

A few concerns regarding the state-level results may arise. It is clear that local economic development is not carefully controlled for 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 extremely 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 the liftoff decision. To deal with this, we ran additional regressions using the cross product of state dummies and the liftoff dummies. 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 weak access to bank financial services. Furthermore, local banking competition affects the P2P lending market interest rate, leading to a bigger drop after the Fed liftoff decision. Our findings provide new evidence for geographical differences in financial services,

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

	Dependent variable: Interest rate			
	(1)	(2)	(3)	(4)
Explanatory variables				
Liftoff	-0.294***	-0.438***	-0.237***	-0.212**
	(-3.26)	(-3.70)	(-3.90)	(-2.87)
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)	
1{BankComp}				0.121
				(1.48)
1{BankComp}×Liftoff				-0.210
				(-1.64)
Controls				
Loan Characteristics	x	x	x	x
Borrower Characteristics	x	x	x	x
Main Effects				
Weekday FE	x	x	x	x
Hour FE	x	x	x	x
Benchmark int.rate mean	15.291	15.500	15.463	15.507
Adj. R^2	0.839	0.838	0.839	0.838
Observations	4,257	4,257	4,257	4,257

Notes. The interest rate is regressed on liftoff, loan characteristics, borrower characteristics, intra-day and intra-week dummies. The exact set of controls is similar to 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: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

reflected in the P2P lending rates.

6 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 subprime 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 B.IV, we regress the interest rates observed in the Prosper market on the real slope, defined as the difference between the 5-year TIPS yield and the 1-month real interest rate.[26] An increase in the real slope is usually associated with an improvement in the fundamental economic condition. We find that interest rates for high credit risk borrowers decrease by 2.62% 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 25.1% for one percentage point increase in the real slope.

The effect of the real slope on P2P lending rates is large and statistically significant. Replacing the 5-year real slope with the 10-year real slope yields results in the same direction and of a similar 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. The reports provide interest rates and loan-borrower information variables for all loan postings that have been successfully

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

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. However, we explore the interest rate data for originated loans in a 14-day window around Fed liftoff. Table B.VI reports the regression results for the liftoff dummy and different interest dynamics for high versus low risk borrowers. We find that the average interest rate drops and the credit spread narrows after liftoff. This result conforms with our findings from the Prosper data; and suggests that the monetary policy signaling associated with the Fed liftoff decision also affected other subprime lending markets.

7 Conclusion

This paper contributes to the emerging literature on Fed liftoff by measuring its effects on the peer-to-peer (P2P) lending segment of the subprime market using a unique dataset of 640,000 loan-hour observations. Relative to traditional bank lending data, using P2P market data allows us to monitor credit market conditions at a high frequency and in granular detail around the event. We find that liftoff may have reduced the cost of subprime borrowing by sending a strong, positive signal about the future employment prospects and solvency of low credit rating borrowers. In particular, average interest rates in the segment of the subprime market we evaluated fell by 16.9-22.6 bps, driven by a spread reduction of 16% between high and low credit rating borrowers. We show that this change was not caused by 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 demonstrate that these findings are not common to all FOMC decisions by performing the same tests on the January 27th, 2016 decision to leave rates unchanged.

Furthermore, we find that the channels activated by liftoff bear relevance over and above the episode itself; however, liftoff provides us with an unusually large signaling event, where interest rate pass-through is dominated in the market we observe. Specifically, we document that improvements in the expected economic outlook–when proxied by changes in the real yield curve–are negatively associated with average interest rates and credit spreads in the P2P lending segment of the subprime market. We validate our key findings by demonstrating that they hold for a second P2P lending platform. In sum, we provide two pieces of evidence that support the external validity of our key findings over time and across markets.

Against the backdrop of the exiting literature, this paper expands our understanding of the monetary transmission mechanism by providing an empirical and theoretical treatment of a new channel: the P2P lending market. We show that this channel may be important for understanding Fed liftoff, since it is highly sensitive to news that affects default probabilities. Furthermore, this channel is likely to gain greater relevance over time, since P2P lending is a rapidly growing market, and may play an increasingly important role in the monetary transmission mechanism.

Finally, our results underpin the importance of the market's interpretation of monetary policy decisions. This is especially true during periods of high uncertainty or when policy regimes shift. Under such circumstances, clarifying the rationale for an interest rate decision may provide more information than the rate change itself. We show that this appears to be particularly important for the P2P segment of the subprime market, which is sensitive to information about borrower default probabilities. In particular, we find that aggregate (state-level) information on unemployment rates, credit card debt, and local access to credit has an impact on interest rates in the P2P market, even after we control for borrower and loan characteristics. Furthermore, we demonstrate that liftoff–which was justified by the FOMC as a response to improving labor market conditions–may have operated through this same channel to lower interest rates in a segment of the subprime lending market.

References

Agarwal, Sumit and Brent W. Ambrose (Eds.), *Household Credit Usage: Personal Debt and Mortgages*, Palgrave Macmillan, 2007.

_ **, Chunlin Liu, and Nicholas S. Souleles**, "The Reaction of Consumer Spending and Debt to Tax RebatesEvidence from Consumer Credit Data," *Journal of Political Economy*, 2007, *115* (6), 986–1019.

Andersson, Malin, Hans Dillén, and Peter Sellin, "Monetary policy signaling and movements in the term structure of interest rates," *Journal of Monetary Economics*, 2006, *53* (8), 1815–1855.

Angeletos, George-Marios and Alessandro Pavan, "Transparency of Information and Coordination in Economies with Investment Complementarities," *American Economic Review*, 2004, *94* (2), 91–98.

Armstrong, Mark, "Competition in two-sided markets," *The RAND Journal of Economics*, 2006, *37* (3), 668–691.

Bauer, Michael D. and Glenn D. Rudebusch, "Expectations for Monetary Policy Liftoff," *FRBSF Economic Letter 2013-34*, 2013.

Becker, Bo, "Geographical segmentation of US capital markets," *Journal of Financial Economics*, 2007, *85* (1), 151–178.

Belleflamme, Paul, Nessrine Omrani, and Martin Peitz, "The Economics of Crowdfunding Platforms," *mimeo*, 2015.

Bernanke, Ben S. and Alan S. Blinder, "The Federal Funds Rate and the Channels of Monetary Transmission," *The American Economic Review*, 1992, *82* (4), 901–921.

_ **and Kenneth N. Kuttner**, "What explains the stock market's reaction to federal reserve policy?," *Journal of Finance*, 2005, *60* (3), 1221–1257.

— **and Mark Gertler**, “Inside the Black Box: The Credit Channel of Monetary Policy Transmission,” *Journal of Economic Perspectives*, 1995, *9* (4), 27–48.

Bertola, Giuseppe, Richard Disney, and Charles Grant (Eds.), *The Economics of Consumer Credit*, Cambridge, MA: The MIT Press, 2006.

Blinder, Alan S., Michael Ehrmann, Marcel Fratzscher, Jakob De Haan, and David-Jan Jansen, “Central bank communication and monetary policy: A survey of theory and evidence,” *Journal of Economic Literature*, 2008, *46* (4), 910–945.

Boivin, Jean, Michael T Kiley, and Frederic S Mishkin, “How Has the Monetary Transmission Mechanism Evolved Over Time?,” in Benjamin M. Friedman and Michael Woodford, eds., *Handbook of Monetary Economics*, volume 3a ed., North-Holland, 2011, pp. 369–422.

Bollerslev, Tim, George Tauchen, and Hao Zhou, “Expected stock returns and variance risk premia,” *Review of Financial Studies*, 2009, *22* (11), 4463–4492.

Boyarchenko, Nina, Valentin Haddad, and Matthew C Plosser, “The Federal Reserve and Market Confidence,” *Federal Reserve Bank of Minneapolis Staff Report No. 773*, 2016.

Bullard, James, “Fed official: Not raising rates in September was a ’mistake’,” *Interview in Washington Post, 7 December, 2015, available at: https://www.washingtonpost.com/news/wonk/wp/2015/12/07/fed-official-not-raising-rates-in-september-was-a-mistake/*, 2015.

Butler, Alexander W, Jess Cornaggia, and Umit G. Gurun, “Substitution between Sources of Finance in Consumer Capital Markets,” *forthcoming in Management Science*, 2015.

Campbell, Jeffrey R., Charles L. Evans, Jonas D. M. Fisher, and Alejandro Justiniano, “Macroeconomic Effects of Federal Reserve Forward Guidance,” *Brookings Papers on Economic Activity*, 2012, *Spring 201*, 1–80.

Cetorelli, Nicola and Philip E. Strahan, "Finance as a Barrier to Entry: Bank Competition and Industry Structure in Local U.S. Markets," *The Journal of Finance*, 2006, *61* (1), 437–461.

Chen, Ning, Arpita Ghosh, and Nicolas S. Lambert, "Auctions for social lending: A theoretical analysis," *Games and Economic Behavior*, 2014, *86*, 367–391.

Cook, Timothy and Thomas Hahn, "The effect of changes in the federal funds rate target on market interest rates in the 1970s," *Journal of Monetary Economics*, 1989, *24* (3), 331–351.

Cooke, Diana A. and William T. Gavin, "Three scenarios for interest rates in the transition to normalcy," *Federal Reserve Bank of St. Louis Review Working Paper 2014-027A*, 2014.

Cornand, Camille and Frank Heinemann, "Optimal Degree of Public Information Dissemination," *The Economic Journal*, 2008, *118* (528), 718–742.

Crowe, Christopher and Rodney Ramcharan, "House Prices and Household Credit Access: Evidence from an Internet Bank," *Journal of Money, Credit & Banking*, 2013, *45* (6), 1085–1115.

Demyanyk, Yuliya, "Peer-to-Peer Lending Is Poised to Grow," *Federal Reserve Bank of Cleveland*, 2014, (August 14).

Di Maggio, Marco, Amir Kermani, and Rodney Ramcharan, "Monetary Policy Pass-Through: Household Consumption and Voluntary Deleveraging," *mimeo*, 2014.

Duarte, Jefferson, Stephan Siegel, and Lance Young, "Trust and Credit: The Role of Appearance in Peer-to-peer Lending," *Review of Financial Studies*, 2012, *25* (8), 2455–2484.

Ehrmann, Michael and Marcel Fratzscher, "Transparency, Disclosure, and the Federal Reserve," *International Journal of Central Banking*, 2007, *3* (1), 179–225.

—, **Sylvester C.W. Eijffinger, and Marcel Fratzscher**, "The Role of Central Bank Transparency for Guiding Private Sector Forecasts," *The Scandinavian Journal of Economics*, 2016, *114* (3), 1018–1052.

Estrella, Arturo and Gikas A. Hardouvelis, "The term structure as a predictor of real economic activity," 1991.

Evans, C, J Fisher, F Gourio, and S Krane, "Risk Management for Monetary Policy Near the Zero Lower Bound," *Brookings Papers on Economic Activity*, 2015, (Spring).

Faust, Jon and Jonathan H. Wright, "Comparing Greenbook and Reduced Form Forecasts Using a Large Realtime Dataset," *Journal of Business & Economic Statistics*, 2009, *27* (4), 468–479.

FOMC, "Announcement," *Press release, Washington, D.C., 16 December 2015, available at: http://www.federalreserve.gov/newsevents/press/monetary/20151216a.htm*, 2015.

—, "Decisions Regarding Monetary Policy Implementation," *Press release, Washington, D.C., 16 December 2015, available at: http://www.federalreserve.gov/newsevents/press/monetary/20151216a1.htm*, 2015.

—, "Projections," *Press release, Washington, D.C., 16 March 2016, available at: https://www.federalreserve.gov/monetarypolicy/files/fomcprojtabl20160316.pdf*, 2016.

Gerardi, Kristopher, Kyle F. Herkenhoff, Lee E. Ohanian, and Paul S. Willen, "Can't Pay or Won't Pay? Unemployment, Negative Equity and Strategic Default," *Federal Reserve Bank of Boston, Working Paper No. 15-13*, 2015.

Gertler, Mark and Peter Karadi, "Monetary Policy Surprises, Credit Costs and Economic Activity," *American Economic Journal: Macroeconomics*, 2015, *7* (1), 44–76.

Guiso, Luigi and Paolo Sodini, "Household Finance: An Emerging Field," in George M. Constantinides, Harris Milton, and Rene M. Stulz, eds., *Handbook of the Economics of Finance*, Vol. 2, Elsevier B.V., 2013, pp. 1397–1532.

Harvey, Campbell R., "The real term structure and consumption growth," *Journal of Financial Economics*, 1988, *22* (2), 305–333.

Hellwig, Christian, "Heterogeneous information and the benefits of transparency," *mimeo*, 2005.

Iyer, Rajkamal, Asim Ijaz Khwaja, Erzo F.P. Luttmer, and Kelly Shue, "Screening peers softly: inferring the quality of small borrowers," *forthcoming in Management Science*, 2015.

Jiménez, Gabriel, Steven Ongena, José-Luis Peydró, and Jesús Saurina, "Hazardous Times for Monetary Policy: What Do Twenty-Three Million Bank Loans Say About The Effects of Monetary Policy on Credit Risk-Taking?," *Econometrica*, 2014, *82* (2), 463–505.

Kashyap, Anil K and Jeremy C Stein, "What Do a Million Banks Have to Say About the Transmission of Monetary Policy?," *The American Economic Review*, 2000, *90* (3), 407–428.

Kobayashi, Teruyoshi, "Incomplete Interest Rate Pass-Through and Optimal Monetary Policy," *The Journal of Central Banking*, 2008, *4* (3), 77–118.

Kuttner, Kenneth N., "Monetary policy surprises and interest rates: Evidence from the Fed funds futures market," *Journal of Monetary Economics*, 2001, *47* (3), 523–544.

Ludvigson, Sydney, "The Channel of Monetary Transmission to Demand: Evidence from the Market for Automobile Credit," *Journal of Money, Credit & Banking*, 1998, *30* (3), 365–383.

Melosi, Leonardo, "Signaling Effects of Monetary Policy," *mimeo*, 2015.

Morris, S. and H. Shin, "Social Value of Public Information," *American Economic Review*, 2002, *92* (5), 1521–1534.

Nakamura, Emi and Jón Steinsson, "High Frequency Identification of Monetary Non-Neutrality," *mimeo*, 2015.

Orphanides, Athanasios, "Fear of Liftoff: Uncertainty, Rules and Discretion in Monetary Policy Normalization," *Federal Reserve Bank of St. Louis Review Working*, 2015, (Third Quarter).

Ozdagli, Ali, "The Final Countdown: The Effect of Monetary Policy during Wait-for-It and Reversal Periods Introduction," *Federal Reserve Bank of Boston, Working Paper No. 15-15*, 2015.

Pope, Devin G and Justin R Sydnor, "What's in a Picture? Evidence of Discrimination from Prosper.com," *The Journal of Human Resources*, 2011, *46* (1), 53–92.

PricewaterhouseCoopers, "Peer pressure: How peer-to-peer lending platforms are transforming the consumer lending industry," 2015, (February).

Ravina, Enrichetta, "Love & loans: the effect of beauty and personal characteristics in credit markets," *mimeo*, 2012, pp. 1–79.

Rochet, Jean-Charles and Jean Tirole, "Two-Sided Markets: A Progress Report," *The RAND Journal of Economics*, 2006, *35* (3), 645–677.

Rodano, Giacomo, Nicolas Serrano-Velarde, and Emanuele Tarantino, "Lending Standards Over the Credit Cycle," *mimeo*, 2016.

Senney, Garrett T, "The Geography of Bidder Behavior in Peer-to-Peer Lending Markets," *mimeo*, 2016.

Stiglitz, J.E. and A. Weiss, "Credit rationing in markets with imperfect information," *The American Economic Review*, 1981, *71* (3), 393–410.

Svensson, Lars E O, "Social Value of Public Information: Morris and Shin (2002) Is Actually Pro-Transparency, Not Con," *American Economic Review*, 2006, *96* (1), 448–452.

Swanson, Eric T, "Have Increases in Federal Reserve Transparency Improved Private Sector Interest Rate Forecasts?," *Journal of Money, Credit and Banking*, 2006, *38* (3), 791–819.

Taylor, J. B., "The monetary transmission mechanism: an empirical framework," *The Journal of Economic Perspectives*, 1995, *9* (4), 11–26.

Wei, Zaiyan and Mingfeng Lin, "Market Mechanisms in Online Crowdfunding," *mimeo*, 2015.

Woodford, Michael, *Foundations of a Theory of Monetary Policy*, Princeton N.J.: Princeton University Press, 2003.

Online Appendix

A Appendix to the theoretical model

A.1 Figures

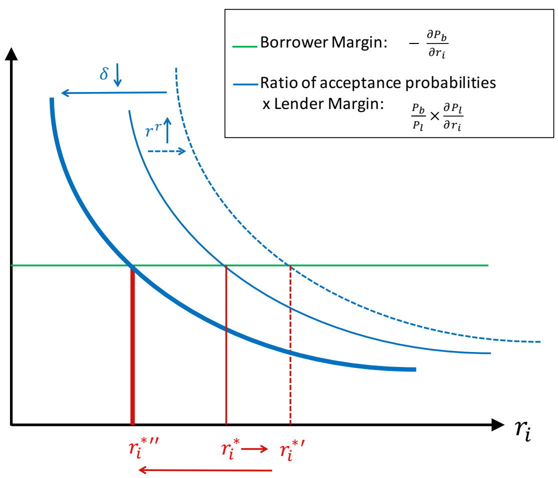

Figure A.I: Scenario when the effect of a reduction in the perceived default probability ($\delta \downarrow$) outweighs the effect of an increase in the risk free reference rate ($r^r \uparrow$).

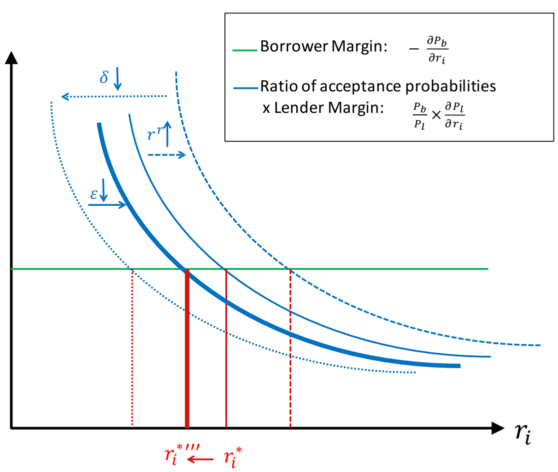

Figure A.II: The total effect is dampened relative to Figure A.I in the scenario when the outside options of the borrower type in market segment n deteriorate ($\epsilon \downarrow$).

A.2 Derivations for Predictions 1 and 2

We first derive the two results in Prediction 1. By application of the implicit function theorem:

$$\frac{dI}{dr_i} = (f^O - c) \cdot \left[\frac{\partial^2 p_b}{\partial r_i^2} \cdot p_l + \frac{\partial p_b}{\partial r_i} \cdot \frac{\partial p_l}{\partial r_i} + \frac{\partial p_b}{\partial r_i} \cdot \frac{\partial p_l}{\partial r_i} + p_b \cdot \frac{\partial^2 p_l}{\partial r_i^2} \right] < 0$$

provided that $\frac{\partial p_b}{\partial r_i} < 0$, $\frac{\partial p_l}{\partial r_i} = (1-\delta_i)\frac{\partial p_l}{\partial \vartheta_i} > 0$, $\frac{\partial^2 p_b}{\partial r_i^2} \leq 0$ and $\frac{\partial^2 p_l}{\partial r_i^2} = (1-\delta_i)^2 \frac{\partial^2 p_l}{\partial \vartheta_i^2} \leq 0$.

$$\frac{dI}{dr^r} = (f^O - c) \cdot \left[\frac{\partial p_b}{\partial r_i} \cdot \frac{\partial p_l}{\partial r^r} + p_b \cdot \frac{\partial^2 p_l}{\partial r_i \partial r^r} \right] > 0$$

provided that $\frac{\partial p_b}{\partial r_i} < 0$, $\frac{\partial p_l}{\partial r^r} = -\frac{\partial p_l}{\partial \vartheta_i} < 0$, $\frac{\partial p_b}{\partial r^r} = 0$ and $\frac{\partial^2 p_l}{\partial r_i \partial r^r} = -(1-\delta_i)\frac{\partial^2 p_l}{\partial \vartheta_i^2} \geq 0$.

$$\frac{dI}{d\delta_i} = (f^O - c) \cdot \left[\frac{\partial p_b}{\partial r_i} \cdot \frac{\partial p_l}{\partial \delta_i} + p_b \cdot \frac{\partial^2 p_l}{\partial r_i \partial \delta_i} \right] > 0$$

provided that $\frac{\partial p_b}{\partial r_i} < 0$, $\frac{\partial p_l}{\partial \delta_i} = -(r_i - f^s)\frac{\partial p_l}{\partial \vartheta_i} < 0$, $\frac{\partial p_b}{\partial \delta_i} = 0$ and $\frac{\partial^2 p_l}{\partial r_i \partial \delta_i} = -(r_i - f^s)(1 - \delta_i)\frac{\partial^2 p_l}{\partial \vartheta_i^2} \geq 0$.

Given that $\frac{\partial p_b}{\partial r^r} = \frac{\partial p_b}{\partial \delta_i} = 0$ by assumption, we can derive:

$$\left.\begin{aligned} \frac{dr_i}{dr^r} &= -\frac{dI}{dr^r} / \frac{dI}{dr_i} > 0 \\ \frac{dr_i}{d\delta_i} &= -\frac{dI}{d\delta_i} / \frac{dI}{dr_i} > 0 \end{aligned}\right\} \; if \; \frac{\partial p_b}{\partial r_i} < 0, \frac{\partial p_l}{\partial \vartheta_i} > 0, \frac{\partial^2 p_b}{\partial r_i^2} \leq 0 \; and \; \frac{\partial^2 p_l}{\partial \vartheta_i^2} \leq 0. \tag{21}$$

In sum, both results of Prediction 1 hold for the stylized demand and supply schedules presented in section 4.2, but also more generally provided the sufficient conditions in (21) hold. Furthermore, it can be shown that the solution to equation (4) is unique.

We next turn to the results in Prediction 2. By application of the implicit function theorem:

$$\frac{dI}{dM_n} = (f^O - c) \cdot \left[\frac{\partial p_b}{\partial r_i} \cdot \frac{\partial p_l}{\partial M_n} + p_b \cdot \frac{\partial^2 p_l}{\partial r_i \partial M_n} \right] > 0$$

since $\frac{\partial p_b}{\partial r_i} < 0$, $\frac{\partial p_l}{\partial M_n} < 0$ and $\frac{\partial^2 p_l}{\partial r_i \partial M_n} > 0$. Hence, the result in Prediction 2 (a) follows. Furthermore, the results in Prediction 2 (b) and (c) follow from equation (9). Finally, the result in Prediction 2 (d) follows from:

$$\frac{dI}{d\epsilon} = (f^O - c) \cdot \left[\frac{\partial^2 p_b}{\partial r_i \partial \epsilon} \cdot p_l + \frac{\partial p_b}{\partial \epsilon} \cdot \frac{\partial p_l}{\partial r_i} \right] > 0$$

since $\frac{\partial p_b}{\partial \epsilon} < 0$, $\frac{\partial p_l}{\partial r_i} > 0$ and $\frac{\partial^2 p_b}{\partial r_i \partial \epsilon} = 0$.

To conclude, we highlight relevant assumptions and discuss them in the context of the predictions. The aim of the theoretical model is to capture the key trade-off from Prosper's viewpoint in a stylized way. First, we assume that the arrival of applicants to the platform is not a function of market conditions. Hence, when setting the interest rate for an individual loan, Prosper does not have to take into account how this may affect market conditions and, hence, the arrival rate of future loan applicants. We believe this assumption is reasonable, since applicants do not know their exact credit score before applying and are predominantly attracted by Prosper when lacking good outside options. Second, we invoke distributional assumptions about borrower's outside options and the arrival of investors for different risk premia. Specifically, using uniform distributions throughout simplifies the analysis. In principle, we can consider more general distributions and the predictions are fairly robust.

Finally, the problem in (3) may be expanded to account for a more dynamic environment where newly posted loans compete with recently posted loans that are not yet fully funded. This would give rise to negative same-sided network effects. In such a complex setting, Prosper may have lower incentives to select a higher interest rate if this entails the crowding-out of other loans. If these negative same-sided network effects are strong, the predictions related to the funding gap may be affected.

A.3 Robustness of Prediction 1(a)

In principle, the borrower's outside options could be affected by changes in the risk-free reference rate. If this is the case, then $\frac{dI}{dr^r}$ needs to be modified:

$$\frac{dI}{dr^r} = (f^O - c) \cdot \left[\frac{\partial^2 p_b}{\partial r_i \partial \epsilon} \frac{\partial \epsilon}{\partial r^r} \cdot p_l + \frac{\partial p_b}{\partial r_i} \cdot \frac{\partial p_l}{\partial r^r} + \frac{\partial p_b}{\partial \epsilon} \frac{\partial \epsilon}{\partial r^r} \cdot \frac{\partial p_l}{\partial r_i} + p_b \cdot \frac{\partial^2 p_l}{\partial r_i \partial r^r} \right] > 0.$$

Since $\frac{\partial^2 p_b}{\partial r_i \partial \epsilon} = 0$ and $\frac{\partial p_b}{\partial \epsilon} < 0$, a sufficient condition for $\frac{dI}{dr^r}$ to be unambiguously positive is given by $\frac{\partial \epsilon}{\partial r^r} \leq 0$.

The empirical evidence in section 5.1 suggests that the demand for loans increases after liftoff and that this effect was strongest for high credit worthiness borrowers. Given that credit cards are the major determinant for outside options of high credit worthiness borrowers, the persistent increase in average interest rates on credit cards before and after liftoff suggests that borrowers' outside options (weakly) deteriorated after liftoff, i.e. $\frac{\partial \epsilon}{\partial r^r} \leq 0$.[27] Thus, the qualitative result of Prediction 1(a) is unaffected when incorporating the impact of an outside option.

A.4 Employment risk and default probabilities

In this section, 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 till 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,

[27] Average interest rates on US commercial bank credit card plans increased from 12.22% in November 2015 to 12.31% in February 2016. The series are available in the St. Louis Federal Reserve's FRED database.

respectively, to find a new job in a given period. We assume job finding probabilities to be weakly lower than the probabilities to stay 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, to fail 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:

$$\begin{aligned}\delta_k \quad = \quad & \overbrace{(p_k^E s^E + (1 - p_k^E) s^U)}^{\substack{probability\ of\ defaulting\ in\ t=1 \\ when\ staying\ employed\ or\ getting\ unemployed}} \quad + \\ & \underbrace{p_k^E (1 - s^E)(p_k^E s^E + (1 - p_k^E) s^U)}_{\substack{prob.\ of\ defaulting\ in\ t=2 \\ cond.\ on\ staying\ emp.\ in\ t=1}} + \underbrace{(1 - p_k^E)(1 - s^U)(p_k^U s^E + (1 - p_k^U) s^U)}_{\substack{prob.\ of\ defaulting\ in\ t=2 \\ cond.\ on\ getting\ unemp.\ in\ t=1}}.\end{aligned} \tag{22}$$

We have that $\delta_H > \delta_L$ if either the probability to stay employed and/or the probability to find 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:

$$\frac{d\delta_H}{d\eta} = (1 - p_H^E)(1 - s^U)(s^E - s^U) < \frac{d\delta_L}{d\eta} = (1 - p_L^E)(1 - s^U)(s^E - s^U). \tag{23}$$

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 (see equation (10)).

B Appendix to the empirical models

B.1 Robustness

Table B.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. 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 B.II: Robustness: control changes in risk appetite

	Dependent variable: Interest rate					
	(1)	(2)	(3)	(4)	(5)	(6)
Explanatory variables						
Liftoff	-0.484**	-0.162***	-0.174***	-1.903***	-1.815***	-1.933***
	(-2.09)	(-4.40)	(-4.38)	(-2.94)	(-2.75)	(-2.92)
$1\{EMP, High\}$				-10.37***	-9.605***	-9.630***
				(-21.31)	(-17.65)	(-17.52)
$1\{EMP, High\}\times$Liftoff				1.652**	1.625**	1.658**
				(2.15)	(2.11)	(2.14)
VRP	0.0550	-0.0257	-0.0264	0.288	-0.787	-0.0203
	(0.43)	(-1.23)	(-1.21)	(0.40)	(-1.60)	(-0.03)
Controls						
Loan Characteristics		x	x		x	x
Borrower Characteristics		x	x		x	x
Main Effects						
Weekday FE	x		x	x		x
Hour FE	x		x	x		x
Adj. R^2	0.001	0.971	0.971	0.667	0.673	0.674
Observations	4,257	4,257	4,257	355	355	355

Notes. 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 B.III: 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	x	x	x	x	x	x
Borrower Characteristics	x	x	x	x	x	x
Main Effects						
Weekday FE	x	x	x	x	x	x
Hour FE	x	x	x	x	x	x
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. 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 B.IV: Robustness: regressions with slope in the real yield curve

	Dependent variable: interest rate					
	(1)	(2)	(3)	(4)	(5)	(6)
Explanatory variables						
Liftoff	-0.311	-0.439**	-0.337*	-0.286	-0.425**	-0.314
	(-1.54)	(-2.26)	(-1.68)	(-1.44)	(-2.26)	(-1.60)
$1\{EMP, High\}$	-8.852***	-8.382***	-8.379***	-9.519***	-8.972***	-8.982***
	(-30.42)	(-28.32)	(-28.01)	(-51.69)	(-44.28)	(-43.75)
$\text{Slope}^{(5)}$	-2.757***	-2.386***	-2.620***			
	(-3.05)	(-3.27)	(-2.93)			
$1\{EMP, High\} \times \text{Slope}^{(5)}$	2.327***	2.054**	2.104**			
	(2.78)	(2.49)	(2.53)			
$\text{Slope}^{(10)}$				-2.783***	-2.542***	-2.710***
				(-3.37)	(-3.68)	(-3.33)
$1\{EMP, High\} \times \text{Slope}^{(10)}$				2.488***	2.252***	2.302***
				(3.09)	(2.85)	(2.88)
Controls						
Loan Characteristics		x	x		x	x
Borrower Characteristics		x	x		x	x
Main Effects						
Weekday FE	x		x	x		x
Hour FE	x		x	x		x
Observations	1434	1434	1434	1434	1434	1434
Adj. R^2	0.652	0.666	0.663	0.653	0.666	0.664

Notes. 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 $\text{Slope}^{(5)}$ is the difference of 5-year TIPS bond yield and 1-month real interest rate at each day. We also include another variable $\text{Slope}^{(10)}$ 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: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B.2 January 27, 2016 FOMC meeting results

Table B.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		x	x
Borrower Characteristics		x	x
Main Effects			
Weekday FE	x		x
Hour FE	x		x
Adj. R^2	0.001	0.969	0.969
Observations	6,589	6,589	6,589

Notes. 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: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B.3 Evidence from another P2P lender: LendingClub

Table B.VI: Robustness: use LendingClub data during the liftoff

	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		x	x		x	x
Borrower Characteristics		x	x		x	x
Main Effects						
Weekday FE	x		x	x		x
Adj. R^2	0.002	0.231	0.232	0.058	0.196	0.198
Observations	37717	37717	37717	13880	13880	13880

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 estimation setting is the same as in the Prosper results. The dependent variable is the interest rate, in percentage points. We focus on a 14-day window around the liftoff date. 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: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.