FinTech Lending When Things Look Gloomy, Friend or Foe?

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Abstract

Applying a random forest classification model to construct Prosper's rating distribution as if in a normal economic condition, I demonstrate that the FinTech peer to peer lending platforms such as Prosper modified the risk signals it sent to investors facing an unexpected, sudden, exogenous economic shock caused by the Covid-19. I show that investors are more risk averse during a recession; adjusting investors' perceptions on borrowers risk levels by making some borrowers look safer would increase loans' probabilities to be funded. FinTech lending firms facilitate liquidities in the credit market, a precious diamond during an economic downturn, while investors are likely being under-compensated with the amount of risks undertaken.

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Introduction

This paper applies a machine learning (random forest) approach to study how Peer to Peer (P2P) lending platforms such as Prosper responded facing an exogenous economic shock caused by the Covid-19 pandemic. It further investigates investors' reactions on the platform and discusses the motivations behind these phenomena. P2P lending platform is a type of FinTech companies which match investors and borrowers online with automated algorithms and little human involvements for the loan evaluation, generation and completion process. This type of companies evolves from being a hands off auction-like platform into a role which is like traditional loan officers, who are responsible for evaluating borrowers' risks and recommending loans and interest rates to investors. With up to 90% of the investors as institutional investors who implement robots and accept almost all loans the platforms recommend, P2P lending platforms such as Prosper gradually gain power in the decision making process in recent years.

One important metric in the loan recommending process is the estimated loss rate (ELR). ELR is the estimated loss of loan principal per year if the borrower were to default. It fully determines the interest rates on the loans. One can take it as the 'risk signal' Prosper is sending to investors about its assessment of the loan's default risk. Prosper maps the ELR into one of seven ratings, which range from AA (the safest) to HR (high risk). This mapping, loan interest rates, and the credit-scoring model are adjusted periodically. Through using a year's loan transaction observations with 372 predictive features from March 2019 to February 2020, I trained a random forest (RF) classification model to predict the seven Prosper ratings (AA, A, B, C, D, E, HR) from March 2020 to October 2020. I use March 2020 as the divide line. March 2020 was the time when the pandemic cases started to be aggressively reported in the US, and the CDC issued official guidelines to the public. The model predicted Prosper ratings (from March

2020 to October 2020) are the ratings as if the economic condition did not have significant changes or in a normal economic condition compare to a year before. The methodology is comparable to diff and diff. The observable difference between real time and predicted distribution reveals Prosper's responses during the economic downturn caused by the pandemic.

The model manifests that Prosper made significant credit model adjustments after the pandemic broke out. On its official website, Prosper published an announcement to investors stating that facing an economic downturn, it would tighten its business model to protect investors and ensure sustainable returns. However, this is far from reality. Through comparing the real time Prosper rating distribution and the machine learning model predicted distribution from March 2020 to October 2020, I conclude that Prosper loosened its model to calibrate investors' perceptions on borrowers' risk levels through changing the 'risk signals' it sent to investors when it recommended loans. During the post-pandemic period, overall the platform shifted around 18% of the loans which should have belonged to B and C baskets before the pandemic into the A and AA baskets, which represent safer groups. The statement is not completely false. Based on the predicted and real time distribution, the platform stopped accepting extremely high risk loans for two consecutive months (May and June 2020). One conjecture is that Prosper tried to prevent high volumes of defaults in the future, which could drive away valuable investors and devastate profitability.

Furthermore, the paper establishes that investors paid more attention to Prosper's 'risk signals' after the pandemic. Investors became more risk averse and were less willing to fully fund loans. Finally, I examine the motivations behind the credit model adjustments. The platform charges a fixed percentage of funded loans from borrowers and 1% of the received principal payments from investors. Thus, ensuring more loans are funded by investors and avoiding high volumes of default rates are in Prosper's best interest. It is the art of balancing to maximize profits. The platform has been in business since 2006 and it may have learned from the past experience that investors would behave more risk averse during a recession. Investors were much more likely to lend to those who were in safer groups when the economy looked gloomy, so the company calibrated investors' perceptions on loan risk levels to encourage more transactions. For some investors, this means that they were funding loans which were risker than the 'risk signals' they received from the platform. Meanwhile, the FinTech company increased liquidities in the credit market during the recession, which should have some relieving effects on average Americans. The following sections are comprised of market overview, Prosper's background, dataset description, methodology, summary of findings, motivations, and conclusions.

1.1 P2P Market Overview

Peer-to-Peer (P2P) lending platforms facilitate online matching between borrowers and investors. It first started in the U.S. in 2006. Since then it has become one of the fastest growing FinTech innovations. The P2P lending market is predicted to reach $370 billion by 2025. The top 10 players in the market are Prosper, Upstart, Funding Circle, Lending Tree, Lending Club, Perform and others (IndustryARC). Borrowers request loans ranging from $1000 to $40,000 on their platforms, with fixed interest rate between 5% and 35%. These loans are fully amortized and unsecured. Most of these P2P loans are used for credit card repayment or debt consolidation with traditional banks. In this paper, my analysis will be focused on Prosper.

1.2 Prosper Background

Like many FinTech innovations, Prosper automates all steps of lending process with little or no human involvement through its algorithm-based system. Borrowers who have FICO score of 640 or greater are eligible to fill out an online application, where they self-report annual income, occupation, employment status, loan purpose, and give Prosper authorization to request credit report from TransUnion. Prosper then uses its proprietary algorithm-based credit model to evaluate estimated loss rate (ELR) on the loan. ELR is the estimated loss of loan principal per year if the borrower were to default, and it fully determines the interest rate on the loan. One can take it as the 'risk signal' Prosper is sending to investors about its assessment of the loan's default risk. Prosper maps the ELR into one of seven ratings, which range from AA (the safest) to HR (high risk). This mapping, loan interest rates, and the credit-scoring model are adjusted periodically.

P2P lending platforms such as Prosper, play an crucial and active role in evaluating and screening loans. There are both institutional and retail investors on Prosper's platform. Institutional investors dominates the platform, providing nearly 90% of the capital. In 2013, Prosper added a passive investment feature to their platform. If opt in this feature, Prosper is responsible for almost all loan screening and recommendations. Since then, many investors (especially institutional investors) became extremely passive. They usually specify very broad criteria and instruct Prosper to purchase in full on their behalf all loans that satisfy this criteria. P2P investors treat the lending platform as an intermediary rather than as a passive match-maker through outsourcing loan evaluation and screening (Balyuk & Davydenko 2019).

What information would these investors obtain from Prosper when they get 'profiles' of borrowers? When Prosper first started, there were the soft information parts which included borrowers pictures and a description of each borrower. To prevent borrower discrimination based on race, gender, and appearance, and to increase loan application completion, in 2013, Prosper canceled this feature. Since then, only hard information such as age, FICO score range, occupation, prosper rating based on ELR were passed down to investors. After borrowers submit applications, Prosper then conducts a pre-funding review which may result the loan being fully funded, partially funded, or canceled. The platform uses its proprietary algorithms to screen out loans which are too risky and cannot be sufficiently compensated with interest rates or simply appear to be fraudulent. If a loan passes this review, borrower will be funded at least 70% of the amount requested.

Prosper makes money through charging borrowers a fixed percentage from 1% to 5% of the total amount of the funded loans. In addition, they charge investors 1% per year on all principal payments. In another word, they generate profits through the successfully funded loans. If borrowers submit applications but not funded by investors, they do not make any money. If they blindly match extremely high risk borrowers (high default rate) with investors, and large number of borrowers end up not paying back the principal, it would also damage its profits. To maximize profits, Prosper needs to master the art of balancing. This business model plays a critical explanatory role in how they behaved during the pandemic.

1.3 Data Description

The Prosper dataset contains transaction level data, which spans from March 2019 to October 2020. Some feature examples include age, income level, education, number of months employment, FICO score range, prior loan history with Prosper, estimated loss rate (ELR), Prosper rating (7 levels from AA, A, B, C, D, E, HR), etc. If a variable has over 60% of missing value, I drop it in the dataset since it has insufficient observations and replacing the missing value would potentially cause misleading conclusions. Otherwise, I replace the missing value with the median if it's a numerical variable, and replace it with the most frequent value if it's a categorical variable (for example, occupation). This gives me a 246,882 transaction observations with 372 feature variables.

The next step is to convert all the categorical variables into numerical ones in order to train the dataset using the machine learning model. Prosper rating is solely based on the estimated loss rate. The platform gives the loan an AA rating if its ELR falls between 0% to 1.99%, indicating the loan is the safest and should have a very low probability of default. It gives the loan a HR (high risk) rating if its ELR is greater than 15%, indicating it has a high chance of default. Please see Table 1 for loan rating, its corresponding ELR, and how I labeled the rating into numbers in the model. I then utilize Python to convert categorical variables such as FICO score range, income range, education, occupation, etc. into numerical variables. Although the dataset contains very detailed information about loan characteristics (372 features), it does not include the subsequent performance of the loan, which is an limitation.

Table 1 – Prosper rating numerical notations

Prosper rating	estimated loss rate (ELR)	Numerical label
AA	0.00-1.99%	7
A	2.00-3.99%	6
B	4.00-5.99%	5
C	6.00-8.99%	4
D	9.00-11.99%	3
E	12.00-14.99%	2
HR	≥ 15.00%	1

1.4 Methodology

I utilize a random forest approach to study how P2P lending platforms like Prosper reacted facing an unexpected, sudden economic downturn caused by the Covid-19 pandemic, which broke out in March 2020. Python is the major language for this task. I briefly explain conceptually how random forest classification method works. One first bootstraps the datasets, and grow decision trees for each bootstrapped dataset. Then one bootstraps features at each node, iterate over all possible splitting pairs within the bootstrapped features, and select the best splitting pair. After splitting the data into two partitions based on the selected splitting pair, one repeats the process until the pre-specified criteria are met. Finally one combines the trained decision trees and get a model which would be able to classify each observation into different classification labels, in this case, one of the seven Prosper's ratings.

The target variable of this classification prediction task is Prosper's rating based on the estimated loss rate, as shown in Table 1. It has been converted into numbers in the previous step (7 stands for AA, 1 stands for HR). The predictive features include 372 variables ranging from FICO score range, prior transaction history with Prosper, income range, age, education, occupation, etc. Firstly, I use a year's of data from the beginning of March 2019 to the end of Feb 2020 (right before the pandemic broke out) and randomly select 80% of the observations to train the random forest (RF) model. Secondly, I use the rest of the 20% to test the model accuracy. The prediction accuracy for the pre-Covid period is greater than 99.3%. Thirdly, I combine the whole year's data (from March 2019 to Feb 2020) to train the final RF model. Finally, I applied this RF model to predict Prosper's rating each month from March 2020 to October 2020, and test the model accuracy for each month.

In this study, I treat March 2020 as the divide line in the time table. The economic turndown caused by Covid-19 was a surprising event. One can regard it as an exogeneous shock. In the previous step, I have achieved a very high out of sample model accuracy for pre-Covid period (greater than 99.3%). The RF model trained based on pre-Covid period would predict the Prosper rating as if the unexpected and sudden economic turndown caused by the pandemic had not happened (in a normal economic condition). If Prosper did not adjust its model, the RF model accuracy should still be fairly high for the post-Covid months. However, the reality is far from this. I would explore the motivations of Prosper's credit model adjustments in the following section.

1.5 Feature Selections

To understand what features contribute to the model accuracy the most, I conduct a random forest feature selection, give each feature a score, and rank the 372 features. The top 50 features are all significant at 1% level. Figure 1 provides a graphic representation of the top 20 important features for the model trained based on the data from March 2019 to February 2020. Table 2 shows explanations of some of the feature notations. As shown below, lender yield rate, estimated returns, effective yield, borrower annual percentage rate, listing amount, and information about open credit card trades are important for the accuracy of the random forest model. Prior transaction histories with Prosper are crucial top 50 features.

Figure 1

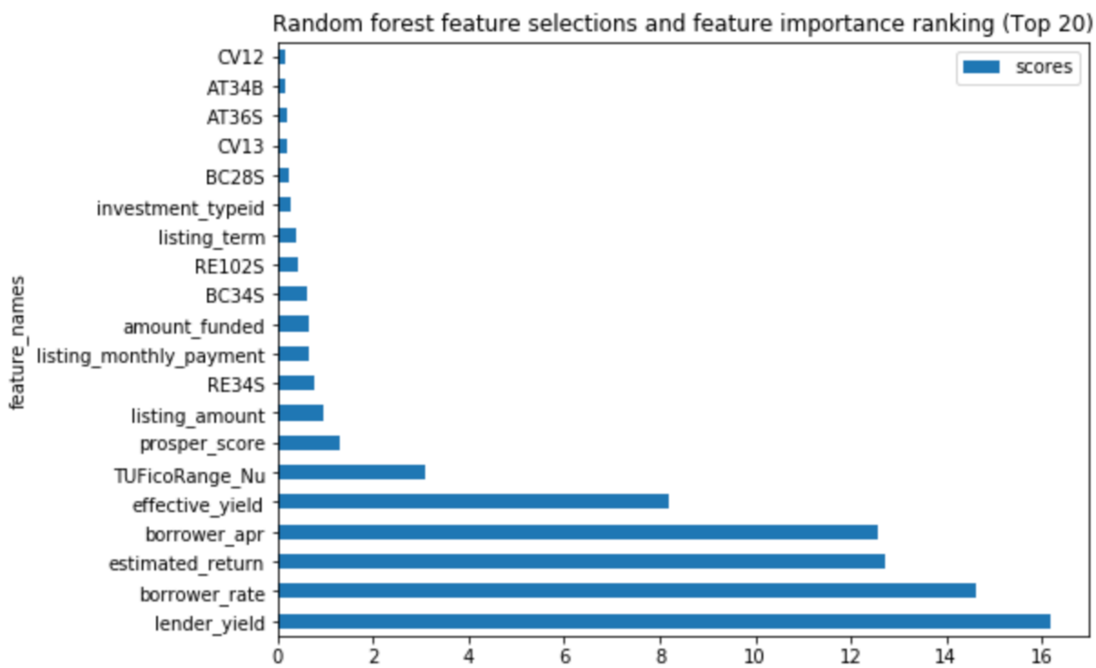


Table 2

Feature Notations

RE34S	Utilization for open revolving trades verified in past 12 months
BC34S	Utilization for open credit card trades verified in past 12 months
RE102S	Average credit line of open revolving trades verified in past 12 months
BC28S	Total credit line of open credit card trades verified in past 12 months
CV13	Percentage of trades ever delinquent
AT36S	Months since most recent delinquency
AT34B	Utilization for open trades verified in past 12 months (excluding mortgage and home equity)
CV12	Number of trades 90 or more days past due ever

Summary of Findings

2.1 Prediction Accuracy

Table 3 reports out of sample RF model accuracy for pre-Covid period (03/2019 – 02/2020) and each month after the pandemic broke out. The RF model achieves a very high out-of-sample prediction accuracy before the pandemic (greater than 99.3%). This means the RF model can tell very accurately the risk level of each loan before March 2020. Applying the same model after the pandemic, the RF model accuracy drops dramatically. The lowest point is in May 2020 with a prediction accuracy lower than 40%. The accuracy in March 2020 is reasonable, which is around 90%. However, the accuracy drops for three consecutive months after Covid-19 became well-aware across the U.S. and CDC issued official pandemic guidelines. As mentioned in the methodology section, the prediction provides a rating distribution as if the pandemic had not happened (in a normal economic condition similar to 2019). The sudden drop in model prediction accuracy indicates that Prosper adjusted their credit model facing an unexpected economic downturn. Based on the drastic decline in April 2020, the adjustment was most likely conducted in late March or early April. From June 2020 to October 2020, the accuracy gradually recovers but still fell below the pre-Covid level, most likely because Prosper kept the changes due to the economic uncertainty during that time period.

Table 3 – Random forest model accuracy (before and after Covid)

Out-of-sample RF Model Accuracy	
Testing period	Accuracy
pre-Covid (03/2019 - 02/2020)	>99.3%
March, 2020	89.9%
April, 2020	53.4%
May, 2020	39.5%
June, 2020	42.8%
July, 2020	47.3%
August, 2020	50.0%
September, 2020	50.6%
October, 2020	55.8%

2.2 Prosper Rating Distribution

What had changed in their credit model since after the pandemic? Can we learn about how P2P lending platforms responded during an unexpected economic turndown? Comparing the overall pre-Covid Prosper rating distribution with the month right before the burst of pandemic, I conclude that up until March 2020, Prosper did not make noticeable adjustment in their credit model. Figure 2 shows Prosper rating distribution a year before the pandemic, from March 2019 to Feb 2020. C (25.35%), B (23.72%), and A (23%) have the highest rating percentages and occupies over 70% of the total sample population combined. 11.96% of the loans were categorized in the AA (safest) rating, and only 1.3% of the loans were regarded as high risk type. I then look into Prosper rating the month (February 2020) right before the pandemic. As shown in Figure 3, the distribution is very similar with the overall distribution in Figure 2. C (27.67%), B (22.26%), A (21.8%), and AA (12.37%) occupy very similar proportions compared with the overall pre-Covid distribution. HR (0.97%) group declined slightly compared to the overall pre-Covid distribution but the change in almost ignorable.

Figure 2

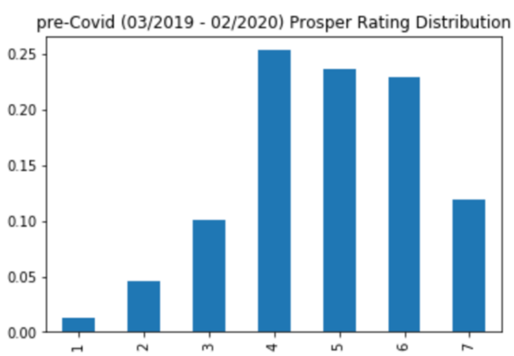
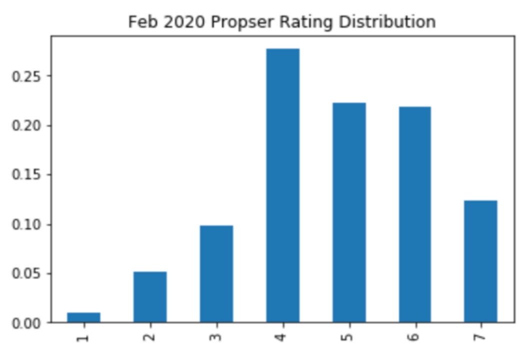


Figure 3



Examining the post-pandemic distribution, I reach the conclusion that the P2P platform loosened its credit model facing the sudden economic ordeal through shifting some lower rated loans into the safer baskets such as A and AA. Figure 4 shows an overall post-pandemic distribution, based on the rating given by Prosper in real time. Figure 5 exhibits predicted

Prosper rating distribution, based on the random forest (RF) model trained in the previous steps using 12 months pre-pandemic observations. Just from looking at the graphics, it is clear that the two distributions are very different. This means Prosper made credit model adjustments. Figure 6 demonstrates the difference between these two distributions. Prosper added 9.11% more loans into the AA (safest) category, and added 10.35% more loans into the A category by reducing loans in E (-0.38%), D (-0.94%), C (-12.78%) and B (-5.38%) categories. This indicates that Prosper loosened its credit model after the pandemic broke out. The predicted distribution on HR, E, and D rating loans is similar to the distribution in real time with almost ignorable discrepancies. Loans belonged to B and C pre-pandemic with estimated loss rate between 4% and 8.99% were most likely to be shifted into safer baskets after March 2020.

Figure 4

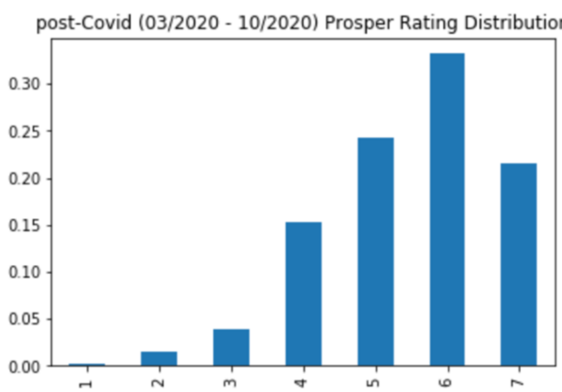


Figure 5

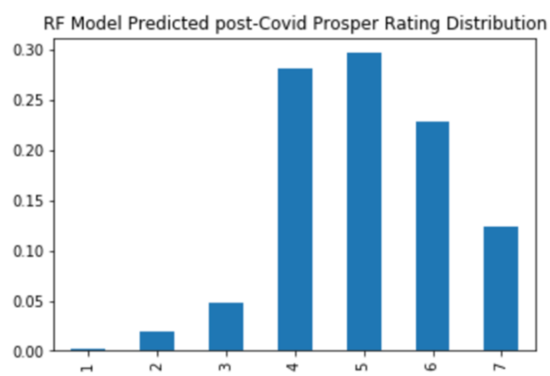
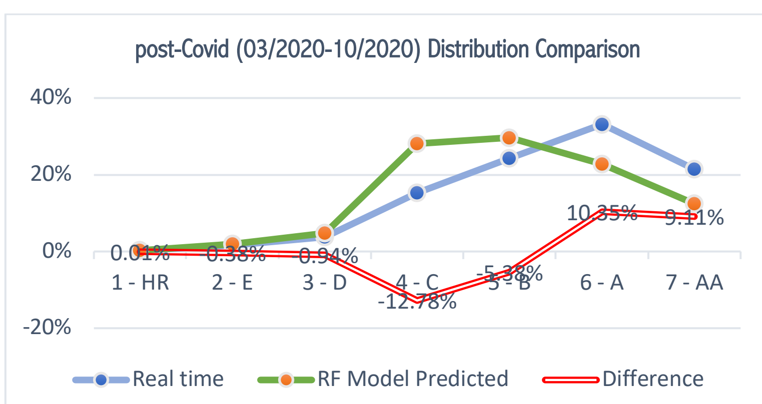


Figure 6



I then investigate the post-pandemic distribution month by month. Table 4 reports Prosper rating distribution difference between real time and model predicted ones from April to September 2020. Figure 7 provides some visual representations of the two types of rating distributions from March to June 2020. In April 2020, Prosper shifted around 19% of the loans from B and C into A and AA baskets. In May 2020, it shifted around 26% of the loans from B and C into A and AA. In June 2020, the platform shifted around 23% of the loans from B and C categories into A and AA. This rating shifting pattern continued until the end of my sample period (October 2020). In May and June 2020, Prosper stopped accepting loans which were rated as HR. This may be a strategy to protect investors from extremely risky borrowers and prevent uncontrollable high volumes of default rates in the future.

Table 4

Month by Month Real vs. Predicted Prosper Rating Distribution (April, May, June, July, Aug, Sep 2020)

Propser Rating	April Real	April Predicted	Difference
HR	0.003943	0.003627	0.000316
E	0.025548	0.031225	-0.005677
D	0.05425	0.067182	-0.012932
C	0.181202	0.343164	-0.161962
B	0.277401	0.288913	-0.011512
A	0.293014	0.175367	0.117647
AA	0.164643	0.090522	0.074121
Sum	1.0	1.0	0.0

Propser Rating	May Real	May Predicted	Difference
HR	0.0	0.0	0.0
E	0.00018	0.0009	-0.00072
D	0.00558	0.010439	-0.004859
C	0.044276	0.259899	-0.215623
B	0.331174	0.37833	-0.047156
A	0.384629	0.232721	0.151908
AA	0.234161	0.117711	0.11645
Sum	1.0	1.0	0.0

Propser Rating	June Real	June Predicted	Difference
HR	0.0	0.0	0.0
D	0.015055	0.02388	-0.008825
C	0.107112	0.311819	-0.204707
B	0.301782	0.321336	-0.019554
A	0.35058	0.231874	0.118706
AA	0.225472	0.108496	0.116976
Sum	1.0	1.0	0.0

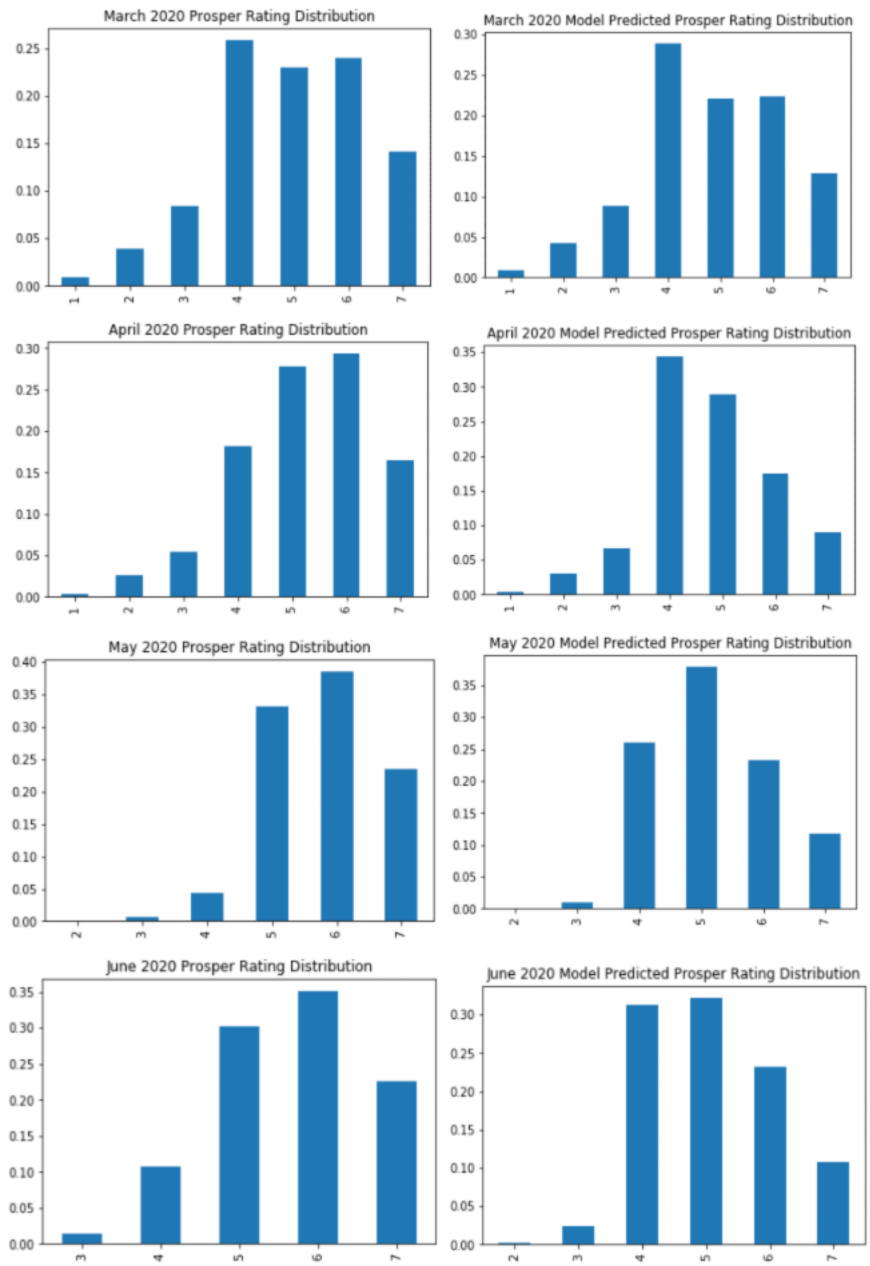
Propser Rating	July Real	July Predicted	Difference
HR	0.000221	0.000221	0.0
D	0.024288	0.036873	-0.012585
C	0.133473	0.27346	-0.139987
B	0.241554	0.335615	-0.094061
A	0.375248	0.234047	0.141201
AA	0.220799	0.111835	0.108964
Sum	1.0	1.0	0.0

Propser Rating	Aug Real	Aug Predicted	Difference
HR	0.002208	0.002208	0.0
E	0.017108	0.0234	-0.006292
D	0.035099	0.046909	-0.01181
C	0.156843	0.287638	-0.130795
B	0.223179	0.304194	-0.081015
A	0.346137	0.220751	0.125386
AA	0.219426	0.114901	0.104525
Sum	1.0	1.0	0.0

Propser Rating	Sep Real	Sep Predicted	Difference
HR	0.001411	0.001411	0.0
E	0.014545	0.019103	-0.004558
D	0.036036	0.047976	-0.01194
C	0.154347	0.280582	-0.126235
B	0.21741	0.302399	-0.084989
A	0.342994	0.225117	0.117877
AA	0.233257	0.123413	0.109844
Sum	1.0	1.0	0.0

Figure 7

Month by Month Prosper Rating Distribution - Real vs. Predicted



2.3 Investor Attentions on Risk Signal

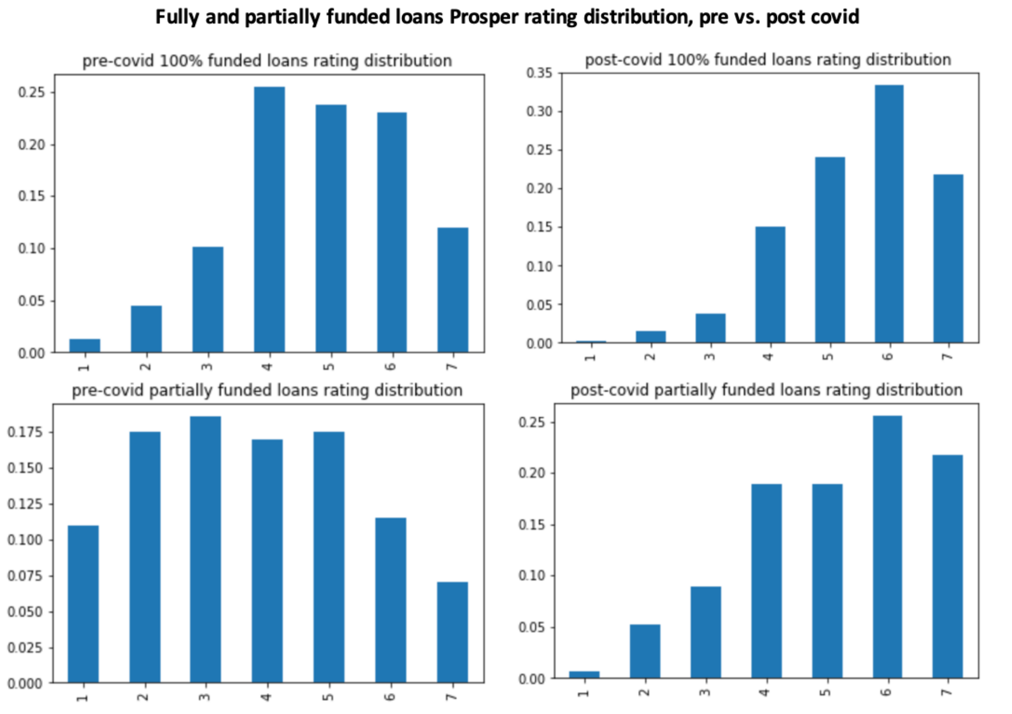
How did investors responded on the P2P platform? I define fully funded loans as the ones investors funded 100% of the requested amount, and partially funded loans as the ones investors funded between 0% and 100% of the requested amount. Figure 8 and Table 5 exhibit the fully funded loans Prosper rating distribution before and after the pandemic, and partially funded loans rating distribution before and after the pandemic (7 indicates AA basket and 1 indicates high risk) . One can see that after the unexpected economic shock, the safer loans were more likely to be fully funded, with almost monotonic increasing trend and the exception that group A had higher proportion than group AA. This was not the case before the pandemic, with C being the most likely fully funded loans and a monotonic decreasing trend from C to AA. This means that investors did not take Prosper's rating (risk signal) as one of the most important considerations when they made the decisions of fully funding loans. Figure 8 also demonstrates the comparison of partially funded loans. Before the pandemic, it was hard to detect any relationship between Prosper's ratings and investors' funding decisions, meaning investors did not pay as much attention to Prosper's risk signal when it came down to partially funding loans. Other factors such as the corresponding interest rates may be more important to investors. After the economic downturn, the likelihood of partially funding loans increased almost monotonically with Prosper's risk signals, meaning investors paid more attention to Prosper's risk signals. The safer the loans were perceived to be after the pandemic, the more likely the loans were being partially funded by investors.

Table 5

Fully & partially funded loans pre vs. post pandemic rating distribution

Propser Rating	pre-covid fully funded	post-covid fully funded	pre-covid partially funded	post-covid partially funded
HR	0.012738	0.00282	0.10991	0.006897
E	0.04525	0.015633	0.174775	0.051724
D	0.101129	0.03781	0.185586	0.089655
C	0.254215	0.151015	0.169369	0.189655
B	0.237159	0.24056	0.174775	0.189655
A	0.229699	0.333473	0.115315	0.255172
AA	0.11981	0.218689	0.07027	0.217241
Sum	1.0	1.0	1.0	1.0

Figure 8



2.4 Investors Risk Aversion

Table 6 exhibits the distribution of investors' funding decisions before and after the shock. I define the pre-pandemic period as from March 2019 to February 2020, and the post-pandemic period as from March 2020 to October 2020 (the end of my sample dataset). As shown, the percentage of fully funded loans decreased by 3.12%, which means loans which were partially funded or not funded at all increased by 3.12%. This means that investors became more risk averse after the economic downturn and were less likely to fully fund loans due the uncertainty of the economic conditions and vaccinations.

Table 6
Investors' funding decisions

Percentage funded	Pre-pandemic	Post-pandemic	Difference
Fully funded	98.64%	95.52%	3.12%
Partially funded	0.31%	0.45%	-0.14%
Zero funded	1.06%	4.04%	-2.98%
Number of Observations	181702	64960	116742

3. Motivations

Prosper's business model is combined with charging borrowers a fixed amount of funded loans (from 1% to 5%) and charging investors 1% per year on all principal payments. Therefore, the more loans get funded by investors, the more profitable Prosper would be. However, blindly facilitating transactions with extremely high risks and default rates would hurt its profits from the investors' side since Prosper also collects 1% on all principal payments. Therefore, Prosper does have incentives to facilitate more loans to be funded.

One conjecture is that Prosper learned from the past experience that investors tend to become more risk averse through paying more attention to its risk signals (Prosper ratings) and less likely to participate or fully fund loans during an economic downturn. Thus in order to ensure its profitability, the platform manipulated investors' perceptions on borrowers' risk levels through shifting some of the loans belonged to B and C baskets into the safer baskets A and AA. On Prosper's official website, it writes to investors that the platform would tighten the credit model facing an recession to protect investor and make sure their returns are sustainable. Table 5 shows that in May and June, the platform stopped accepting high risk loans completely. This may be a strategy to prevent high volumes of defaults in the future. It is not in Prosper's interest to have an insane amount of default loans to an extend that it loses valuable investors. For those loans they do allow on their platform, some borrowers are more likely to appear to be less risky after the pandemic. If this conjecture is true, investors were lending to borrowers who were risker than they appeared to be on Propser's website. Since the returns of investments (interest rates) are solely depends on the estimated loss rate (the risk level or the likelihood of default), it is very likely that investors were underpaid with the amount of risks involved in the loans.

Conclusions

Utilizing a machine learning approach, I construct Prosper's rating distribution as if it is in a normal economic condition. Comparing the predicted distribution with the real time distribution after the pandemic, this paper reveals some insights about the reactions of peer to peer lending platform such as Prosper with an exogenous economic shock. The approach is comparable to a diff and diff method with the assumption of parallel trend. Contrary to Prosper's statement to investors on their website, it loosened the credit model since March 2020 by shifting some loans from the B and C baskets (neither super risky nor very safe) into the A and AA baskets (the safest groups). One conjecture is that Prosper learned from the past experience that investors tend to be more risk averse and pay more attention to its risk signals during an economic recession. Therefore, through adjusting their perceptions on borrowers' risk levels, loans would be more likely to be funded to ensure Prosper's profitability. To avoid high volumes of defaults and to prevent losing valuable investors, Prosper stopped accepting the high risk loans for two consecutive months after March 2020. Overall, Prosper increases liquidity in the credit market during an economic downturn through helping borrowers gain access to loans and credits. Since liquidity is the key and a precious diamond when the economy looks gloomy, peer to peer FinTech firms in general have positive impacts in terms of relieving financial difficulties for average Americans.

In addition, this paper uses an innovative approach and provides insights for investors who look to make investments during a recession. It is highly recommended that investors to be extremely cautious with their investments on peer to peer lending platforms during a bad economic condition since the loans may be risker than what the platform presented and investors may be under-compensated for the amount of risks undertaken. It is crucial that retail investors do their own research, and institutional investors rely less on Prosper's automatic recommendation system during special times such as Covid-19. When things look bad, turning off the auto pilot mode of accepting whatever loans the platform suggests, and switching to the doing your own homework mode may just be the smart thing to do. It is worth mentioning that due to the nature of the dataset, subsequential default information is not available. Future research should search for this piece of information and find further insights and proof. Finally, the paper raises awareness to policy makers who want to learn more about this sector of the FinTech industry and make regulations to protect investors while ensure sustainable liquidity in the credit market. Is FinTech P2P lending a friend or foe? It depends on your perspective.

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