The Pricing Strategies and the Default Patterns of Unsecured Consumer Loan*

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Abstract

This paper explores the dynamic pricing strategies of an unsecured consumer loan issuer and the default patterns of the loans. We examine a unique proprietary data set of about 3 million unsecured consumer loans from a representative sample of households provided by a Business-to-Consumer (B2C) online retailer in China. First, the likelihood of a customer being solicited by the loan issuer increases monotonically in credit worthiness and age. Second, the pricing strategies of the loan issuer demonstrate a trade-off across the borrowers. The unsecured consumer loan lender reduces the credit supply for the *non-solicited* more risky borrowers, and charges less for these borrowers. After the passage of the China Banking Regulatory Commission (CBRC) Act (the CBRC Act), this trade-off is exacerbated. Third, the consumer loan default probability, arrears amount, and the time in arrears are lower for *solicited* customers, higher for more risky borrowers, higher for younger borrowers, and higher after the passage of the Act.

JEL Classification: D12, D14, D18, D31, D91, E21, G11, G21, G23, G28.
Keywords: Consumer finance, Business-to-consumer (B2C), FinTech

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Abstract

This paper explores the dynamic pricing strategies of an unsecured consumer loan issuer and the default patterns of the loans. We examine a unique proprietary data set of about 3 million unsecured consumer loans from a representative sample of households provided by a Business-to-Consumer (B2C) online retailer in China. First, the likelihood of a customer being solicited by the loan issuer increases monotonically in credit worthiness and age. Second, the pricing strategies of the loan issuer demonstrate a trade-off across the borrowers. The unsecured consumer loan lender reduces the credit supply for the *non-solicited* more risky borrowers, and charges less for these borrowers. After the passage of the China Banking Regulatory Commission (CBRC) Act (the CBRC Act), this trade-off is exacerbated. Third, the consumer loan default probability, arrears amount, and the time in arrears are lower for *solicited* customers, higher for more risky borrowers, higher for younger borrowers, and higher after the passage of the Act.

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1 Introduction

Consumer finance is a burgeoning field which investigates how consumer financial engineering facilitates consumers to realize their objectives (e.g., Campbell (2006) and Agarwal, Chomsisengphet, and Lim (2017)). All consumers are subject to the consumer debt. In U.S., the consumer debt includes housing debt–mortgage loans, and non-housing debt–auto loans, student loans and credit card loans. In the first quarter of 2019, the housing debt reached $9.65 trillion and the non-housing debt reached $4.02 trillion, which is about 50% and 20% of the expected GDP of 2019, respectively. The mortgage loans and auto loans are secured debts. The student loans and the credit card loans are unsecured debts. Traditionally, consumer debt is mainly issued by banks which only issue the loans to the customers with the lowest credit risk, and hence charge low interest rates. However, due to the recent development of FinTech, the consumer loan market has been flourishing with other major competitors which offer consumer credit to a much more diversified population of all credit risk levels by relaxing the loan requirement and charging a relatively high interest rate. For example, the Business-to-Consumer (B2C) online retailers. B2C short-term unsecured cash loan has become one of the most recent popular consumer financial engineering instruments. As of 2018, in term of numbers, approximately 70% of the US households and 50% of Chinese households are digital buyers. In terms of the market size, the market size of the US online B2C consumer retail market is $450 billion as of 2017, which is smaller than the Chinese online B2C consumer retail market of $600 billion as of 2018. Although there has been plethora of studies on the traditional US consumer finance,[1] there has been virtually no empirical study of B2C short-term unsecured cash loans driven by the recent development of FinTech. In this paper, we intend to bridge this gap. We utilize a unique proprietary data set of about 3 million B2C unsecured loan information of about 1.4 million loan borrow-

[1]See for example, Domowitz and Sartin (1999), Fay, Hurst, and White (2002), Gross and Souleles (2002a), Gross and Souleles (2002b), Gabaix and Laibson (2006), Elul, Souleles, Chomsisengphet, Glennon, and Hunt (2010), Avery and Turner (2012), Guiso, Sapienza, and Zingales (2013), Dobbie and Song (2015), and Yannelis (2017).

ers from a representative sample of households provided by a Chinese e-commerce company (lender), which is one of the two largest B2C online retailers in China by transaction volume and revenue.

In this paper, we investigate both the supply side and the demand side of the B2C short-term unsecured cash loan market to explore the dynamic pricing strategies of unsecured consumer loan lenders and the default patterns of the loan borrowers. We document five main findings. First, we show that the likelihood of a customer being solicited by lender increases monotonically in credit worthiness and age. The customers with more credit worthiness are more likely to be solicited by lender. The customers with the lowest default risk are most likely to be solicited by lender, and the customers with highest default risk are least possible to be selected by lender. If a customer is older than 32 years old, she is most likely to be solicited by lender. The second most likely age group is from 26 to 32 years old. If a customer is from 23 to 26 years old, she is less likely to be solicited by lender. If a customer is younger than 23 years old, she is least likely to be solicited by lender. Therefore, the most possible socioeconomic group to be invited by lender are the customers older than 32 and are of the lowest credit risk, and the least possible socioeconomic group to be invited by lender are the customers younger than 23 and of the highest credit risk.

The B2C online lending in China has been growing rapidly since 2010. Compared to the bank lending, the B2C online lending poses less requirement for borrowers, hence lenders are more subject to less credit worthy borrowers and the borrowers have more access to credit. The fast expansion has increased the lenders' risk exposure and the borrowers' debt obligation. In some extreme cases, there were exploitative activities on both the lending and borrowing sides. To regulate the market, the China Banking Regulatory Commission (CBRC) issued "the Interim Measures for the Administration of the Business Activities of Online Lending Information Intermediary Institutions" (the CBRC Act) on August 24, 2016. The CBRC Act is to protect all parties participating in online lending. It regulates the unsecured consumer lending activities. It requires the lenders to maintain responsible and fair business conduct. It requires the borrowers to disclose truthful information. Besides other requirements, it explicitly sets the limit on the maximum credit allowed in online lending. We find that after the passage of the CBRC Act, lender solicits more customers younger than 23 years old and with more credit worthiness.

Second, we find that lender charges lower interest rate for the selected customers, ceteris paribus. The interest rate is positively related to the credit unworthiness of the customers and negatively related to the age of the customers. The higher the credit risk, the higher the interest rate. Borrowers younger than 23 are charged significantly higher interest rates compared to other borrowers. Interestingly, for each more risky group, lender charges higher interest for the solicited customers. For each age group older than 23, lender charges more interest for the solicited customers. Moreover, after the passage of the CBRC Act, for each more risky group, lender charges more interest for the solicited customers compared to the non-solicited customers. After the passage of the CBRC Act, for each age group older than 23, lender charges less interest for the solicited customers compared to the non-solicited customers.

Third, we find that lender extends less credit for the selected customers, ceteris paribus. The credit limit is negatively related to the credit unworthiness of the customers. The higher the credit risk, the lower the credit limit. Interestingly also, for the higher default risk and the highest default risk customers, lender extends more credit limit for the solicited customers. For each age group older than 23, lender extends more credit limit for the solicited customers. Moreover, after the passage of the CBRC Act, for each age group older than 23, lender extends more credit limit for the solicited customers compared to the non-solicited customers. These results show that the unsecured consumer loan lender reduces the credit supply for *non-solicited* more risky borrowers, and in the meantime charges less for these borrowers. This demonstrates a trade-off between credit supply and fees across the socioeconomic groups of the borrowers for the lender. The CBRC Act exacerbated the trade-off explanation of the results.

Our paper is related to Ru and Schoar (2016) and Han, Keys, and Li (2018). Ru and Schoar (2016) show that credit card companies target less-educated customers with more heavily back-loaded hidden fees, especially more when the credit condition is more relaxed. In Ru and Schoar (2016), they demonstrate a *time-series* trade-off for the lender – short-term fee maximization versus long-term default using the back-loaded fees, by conducting a natural experiment that the less-educated customers become more credit-worthy due to the changes in state-level unemployment insurance. However, in our paper, we demonstrate a *cross-sectional* trade-off between credit supply and fees charged for borrowers – the *non-solicited* more risky borrowers are provided less credit limit and charged less current rate, while the *solicited* more risky borrowers are granted more credit limit and charged higher current rate. Han, Keys, and Li (2018) find that after the passing of the Credit Card Accountability Reliability and Disclosure (CARD) Act of 2009, the lenders reduced the credit supply of personal credit cards to the nonprime borrowers–borrowers with significant credit risk and/or limited payment ability. Our paper shows that after the passage of the CBRC Act, for each higher credit risk group, lender charges higher interest for the solicited customers compared to the non-solicited customers, and for the top two groups with highest default risk, lender extends more credit limit for the solicited customers compared to the non-solicited customers. After the passage of the CBRC Act, for each age group older than 23, lender charges lower interest and extends more credit limit for the solicited customers compared to the non-solicited customers. These results show that the CBRC Act exacerbated the trade-off explanation.

Fourth, the consumer loan default probability, arrears amount, and the time in arrears are lower for *solicited* customers, higher for more risk borrowers, higher for younger borrowers, and higher after the passage of the CBRC Act. This result is related to Agarwal, Driscoll, Gabaix, and Laibson (2009) which study life-cycle patterns in financial mistakes using a proprietary database that measures ten different types of credit behavior and find that financial mistakes follow a U–shaped pattern, with the cost-minimizing performance occurring around age 53-middle-aged adults make fewer financial mistakes than younger and older adults. In our paper, the highest age group is older than 45. So we would expect to see a downward sloping curve for borrowers making financial mistakes-having loans in arrears.

Fifth, we also find significant heterogeneity in the issuer's lending and consumers' defaulting activities across different geographic regions. The online retailer targets the customers from certain municipalities and provinces to lend strategically. The interest rate, the credit limit, the default probability, and the arrears amount all vary across different geographic regions. These differences are potentially related to the economic differences and cultural differences across China.

Our study contributes to a growing literature on consumer finance and household finance. Shui and Ausubel (2005) document that consumers prefer an introductory offer with a lower interest rate and shorter duration to one with a higher interest rate with a longer duration, even though they would benefit more from choosing the latter. Agarwal, Chomsisengphet, Liu, and Souleles (2015) had the similar findings that faced with a choice between two credit card contracts, one with an annual fee but a lower interest rate and one with no annual fee but a higher interest rate, on average consumers chose the credit contract that minimizes their costs, however, 40% still chose the suboptimal contract. Meier and Sprenger (2010) show that present-biased individuals are 15 percent more likely to have credit card debts. Conditional on borrowing, they borrow 25 percent more than dynamically consistent individuals. Agarwal, Skiba, and Tobacman (2009) find that most consumers borrowed on payday loans despite having substantial unused liquidity on their credit cards. Gabaix and Laibson (2006) show that firms want to hide some critical pricing information of the products to exploit myopic consumers, while sophisticated consumers can in turn exploit the firms.

Domowitz and Sartin (1999) compare the households declaring bankruptcy under both Chapters 7 and 13 of the Bankruptcy Code to the general population. They find that medical and credit card debt are the strongest contributors to bankruptcy. Fay, Hurst, and White (2002) show that the debtors strategically bankrupt. Households are more likely to file bankruptcy when their financial benefit from filing is higher. Gross and Souleles (2002) find that the propensity of personal bankruptcy is related to accounting–specific measures of risk and local economic conditions. Dobbie and Song (2015) find that Chapter 13 protection increases annual earnings by $5,562, decreases five-year mortality by 1.2 percentage points, and decreases five-year foreclosure rates by 19.1 percentage points.

Elul, Souleles, Chomsisengphet, Glennon, and Hunt (2010) show that both negative equity and illiquidity (the borrowers with high credit card utilization rates) are significantly associated with mortgage default. Guiso, Sapienza, and Zingales (2013) measure households' propensity to default on mortgages even if they can afford to pay them (strategic default in mortgage) when the value of the mortgage exceeds the value of the house. They find social determinants of strategic default in mortgage. Andersson, Chomsisengphet, Glennon, and Li (2013) show that consumers were eight times more likely to prioritize payments on mortgage debt over credit card payments. Avery and Turner (2012) introduces the general student loan markets. Yannelis (2017) provides empirical evidence of strategic student loan default. He shows that that bankruptcy protection would increase loan default by 18%, and eliminating administrative wage garnishment would increase default by 50%.

The remainder of this paper is organized as follows. Section 2 discusses the data and provides summary statistics. Section 3 presents empirical results. In Section 3.1, we present the empirical evidence that the B2C retailer strategically selects consumers to lend the loans, based on the characteristics of credit rating and age groups of the borrowers. Section 3.2 shows that the unsecured consumer loan lender reduces the credit supply for the *non-solicited* older than 23 and more risky borrowers, and in the meantime charges less current rate from them. Section 3.3 shows that the default patterns of the consumers of the B2C online retailer vary across the borrowers of different credit rating and age groups, and Section 3.4 demonstrates that there exists significant heterogeneity in this online retailer's lending and consumers' defaulting behaviors across geographic regions. Section 4 concludes the paper.

2 Dataset

Our dataset is a unique proprietary data set of about 3 million unsecured consumer loans of about 1.4 million loan borrowers from a representative sample of households provided by a Business-to-Consumer (B2C) online retailer in China. This retailer is one of the two largest B2C online retailers in China by transaction volume and revenue, and a member of the Fortune Global 500. The dataset contains the following data entries.

$LoanAccountNo$ records the account number of a loan. There are in total 2,998,627 loan observations. $LoanCustomerId$ is the customer ID of a loan. There are in total 1,394,502 unique borrowers in the sample. Panel A of Table 1 shows the loan borrowing frequency distribution of the unique borrowers. About 63.26% of the borrowers borrow the loans only once during the sample period. About 16.99% of the borrowers get the loans twice. 7.23% of the sample borrow the loans three times. About 10.05% of the borrowers borrow from four to nine times. The remaining 2.40% borrow for ten or more times.

$CustomerAreaLocation$ is the province where the customer is located. There are twenty-two provinces (not including Taiwan), five autonomous regions, four municipalities, and two special administrative regions–Hong Kong and Macau. Our sample covers the customers from all provinces, autonomous regions, and municipalities (thirty–one in total) except the two special administrative regions. Panel B of Table 1 shows the geographic distribution of the borrowers. There are significant heterogeneities in the geographic and economic distribution of the borrowers. Among four municipalities, Beijing Municipality has the highest number of borrowers (8.69%). The second largest number of borrowers (5.45%) come from Shanghai Municipality. Tianjin Municipality and Chongqing Municipality have similar percentage of borrowers which are 2.41% and 2.58% respectively. Among the twenty-seven provinces and autonomous regions, Guangdong Province (formerly named Canton) has the highest number of borrowers which is 14.49% of the sample. This is also higher than that of Beijing Municipality. Guangdong Province borders Hong Kong and Macau, and has the largest

GDP of China. The second largest number of borrowers (7.27%) are from Jiangsu Province. The third largest number of borrowers (6.96%) come from Sichuan Province. Compared to the highly populated area, the much less populated northwest and southwest bordering provinces of China have lowest percentage of the borrowers in the sample. For example, the lowest number of borrowers (0.05%) come from Tibet Autonomous Region. The second lowest number of borrowers (0.09%) come from Qinghai Province. The third lowest number of borrowers (0.22%) are from Ningxia Hui Autonomous Region. Xinjiang Uyghur Autonomous Region has 5th to the last number of borrowers while Inner Mongolia Autonomous Region has 7th to the last number of borrowers.

LoanStartDate is the origination date of the loans in our data sample. The starting dates of the loans in our data sample range from October 11, 2014 to October 31, 2016. Panel C reports the frequency distribution of the starting month of the loans which we obtain from daily *LoanStartDate*. About one half (48.12%) of the loans are originated in October 2016. The second largest amount of loans (14.70%) are originated in September 2016. The third largest amount of loans (8.27%) are originated in June 2016.

LoanEndDate is the maturity date of the loans in our data sample. The maturity dates of the loans in our data sample range from September 29, 2016 to October 31, 2018. Panel D reports the frequency distribution of the maturity month of the loans which we obtain from daily *LoanEndDate*. Approximately one third (32.87%) of the loans mature in November 2016. About 8.80% of the loans mature in December 2016. About two thirds of all the loans mature by the end of April, 2017.

CreditRating is the credit rating of the borrowers. There are four credit ratings for the loans. Rating 1 has the lowest default risk and Rating 4 has highest default risk. Panel E of Table 1 shows the frequency distribution of credit ratings. About 63.64% (close to 2 million) of the loans are rated 1 (the lowest default risk), 22.84% of the loans are rated 2 (the lower default risk), 10.25% of the loans are rated 3 (the higher default risk), and the remaining 3.26% of the loans are rated 4 (the highest default risk). The majority of the loans are of the lowest default risk. The most risky loans are about 3% of the whole sample.

LoanTerm is the loan term of the loans in the data samples in months. Panel F reports the frequency distribution of the terms of maturity *LoanTerm*. There are five categories for the terms of maturity: one month, three months, six months, twelve months (one year), and twenty-four months (two years). About 30% (29.63%) of the loans in the data sample mature in one month. About 10% (9.64%) of the loans mature in three months. 13.76% of the loans mature in six months. A little more than one quarter (26.73%) of the loans mature in one year. About one quintile (20.24%) of the loans mature in two years.

InArrearsIndicator is the indicator which shows whether or not the payment is behind schedule. Panel G of Table 1 shows the frequency distribution of *InArrearsIndicator*. Panel G shows that 13,418 loans are in arrears and 2,985,209 loans are not in arrears. Thus, the percentage of loans overdue after missing one or more required payments is only are 0.45% of the data sample. The vast majority of the loans are paid in time.

AgeBucket defines the age groups of borrowers. There are five categories from 1 to 5. "1" denotes "<=23" years old. "2" denotes "(23, 26]" years old. "3" denotes "(26, 32]" years old. "4" denotes "(32, 45]" years old. "5" denotes ">45" years old. Panel H of Table 1 shows the frequency distribution of age buckets. About 32.27% of the loans are borrowed by borrowers younger than 23. Approximately 17.60% of the loans are borrowed by age group from 23 to 26. About 28.43% borrowers are from 26 to 32 years old. About 19.93% borrowers are from 32 to 45 years old. The remaining 1.78% of borrowers are older than 45 years old. In summary, about one third of the borrowers are less than 23 years old, one half of the borrowers are younger than 26, a little more than three quarters of the borrowers are less than 32 years old, and about one quintile of the loans are borrowed by people 32 to 45 years old. Only less than 2% of the borrowers are older than 45.

CustomerChannel is the indicator to show whether the loan is *Not-solicited* or *Solicited* by lender. The *Not-solicited* borrowers initiate the loans through lender by themselves. The *Solicited* borrowers are initiated by lender. Lender selected these borrowers and invite them to use the lender' online B2C service. Panel I of Table 1 shows that 1,557,324 (51.93%) loans are the loans borrowed by the *Not-solicited* borrowers, and 1,441,303 (48.07%) loans are the loans borrowed by the *Solicited* borrowers.

Panel J of Table 1 is the two-way frequency distribution of customer channel and credit ratings. For all the groups of credit rating from the lowest default risk to the highest default risk, there are both *Not-solicited* borrowers and *Solicited* borrowers. In the lowest default risk group, the *Solicited* borrowers are 1.72 times more than the *Not-solicited* borrowers. However, in the other groups, there are far more *Not-solicited* borrowers compared to the *Solicited* borrowers. In the lower default risk group, the *Not-solicited* borrowers are 2.63 times more than the *Solicited* borrowers. In the higher default risk group and the highest default risk group, the *Not-solicited* borrowers are 6.18 and 35.26 times more than the *Solicited* borrowers, respectively. This shows that lender prefers to invite borrowers with higher credit ratings.

Panel K of Table 1 is the two-way frequency distribution of customer channel and loans in arrears. The distribution of the *Not-solicited* borrowers and *Solicited* borrowers in either of the loans-not-in-arrears and the loans in arrears is relatively even.

Panel L of Table 1 is the two-way frequency distribution of customer channel and age buckets. For all the age groups, there are both *Not-solicited* borrowers and *Solicited* borrowers. In the youngest age group (age<23), the *Not-solicited* borrowers are 2.74 times more than the *Solicited* borrowers. In the other age groups, the ratio of the *Solicited* borrowers to *Non-solicited* borrowers is between 1 and 1.76 (age group $(32, 45]$). This indicates that lender prefers to invite older borrowers.

Panel M of Table 1 is the two-way frequency distribution of customer channel and geographic distribution of the loans. The distribution of the *Not-solicited* borrowers and *Solicited* borrowers for most of the provinces is relatively even. Interestingly, for the municipalities, there are usually more *Solicited* borrowers than *Non-solicited* borrowers. Beijing, Shanghai, and Tianjin Municipalities have 1.75, 1.53, and 1.37 times more *Solicited* borrowers than

Non-solicited borrowers, respectively. Less populated regions such as Xinjiang Uyghur Auto Region, Tibet Autonomous Region, and Qinghai Province also have 1.90, 1.15 and 1.34 times more *Solicited* borrowers than *Non-solicited* borrowers, respectively. Guangdong Province has 1.25 times more *Solicited* borrowers than *Non-solicited* borrowers. For the provinces which there are far more *Non-solicited* borrowers than *Solicited* borrowers, the most notable two provinces are Shanxi Province and JiangXi Province where there are about 2 times more *Non-solicited* borrowers than *Solicited* borrowers. Shaanxi Province has 1.8 times more *Non-solicited* borrowers than *Solicited* borrowers. Anhui, Heilongjiang, and Jilin Provinces all have about 1.7 times more *Non-solicited* borrowers than *Solicited* borrowers. These indicates that JBDT prefer inviting the customers from more economically developed regions.

Panel N of Table 1 presents the summary statistics of $CurrentRate(\times 100)$, $CreditLimit$, $ArrearsAmount$ and $DaysInArrears$. All of these variables have positive skewness and kurtosis.

$CurrentRate(\times 100)$ is the service fee lender charges for customers.[2] For $CurrentRate(\times 100)$, the first rows are summary statistics for the whole sample, and the second rows are for the non-zero samples. For the whole sample, the average $CurrentRate(\times 100)$ is 0.27, the lowest decile, the lowest quartile, and the median are both 0.00, the standard deviation is 0.36, the highest quartile is 0.50, the highest decile is 0.98, and the maximum is 3.00. Across the whole sample, the $CurrentRate(\times 100)$ of 1,209,521 loans is non-zero. For these non-zero $CurrentRate(\times 100)$, the mean is 0.66, the median is 0.60, the standard deviation is 0.23, the lowest decile and the lowest quartile are both 0.50, the highest quartile is 0.90, the highest decile is 1.00, and the maximum is 3.00.

$CreidtLimit$ is the credit limit of the borrowers for the whole sample of 2,998,627 loans. The average credit limit is 8,347.73 yuan, the standard deviation is 4,280.59 yuan, the minimum credit limit is 0 cent, the lowest decile of the credit limit is below 3,589 yuan, the

[2]For example, suppose a customer owes 1,000 RMB to lender and decides to pay back in full over 3 months, if the current rate for the customer is 0.7%, then in each month, the service charge is $1,000 \times 0.7\% = 7$ RMB. In each month, Ming pays lender $\frac{1,000}{3} + 7 = 333.33 + 7 = 340.33$ RMB.

lowest quartile of the credit limit is below 5,485 yuan, the median credit limit is 8,000 yuan, the highest quartile of the credit limit is more than 10,543 yuan, the highest decile of the credit limit is 13,247 yuan, and the maximum credit limit is 218,191 yuan.

For $ArrearsAmount$ and $DaysInArrears$, the first rows are summary statistics for the whole sample, and the second rows are for the non-zero samples. For the whole sample, the average amount $ArrearsAmount$ is 0.86 yuan. The standard deviation of the amount paid behind schedule ia 33.46 yuan, the minimum, the lowest decile, the lowest quartile, the median, the highest quartile, and the highest decile of the amount in arrears are all 0 yuan, and the maximum amount in arrears is 11,846.20 yuan. Among all the 13,418 loans which are currently in arrears, the $ArrearsAmount$'s mean is 192 yuan. The standard deviation of the amount paid behind schedule ia 462.22 yuan, the minimum amount paid behind schedule is 51 cent, the lowest decile of the amount in arrears is 10.15 yuan, the lowest quartile of the amount in arrears is below 32.55 yuan, the median amount in arrears is 96.67 yuan, the highest quartile of the amount in arrears is more than 193.82 yuan, the highest decile of the amount in arrears is 368.62 yuan, and the maximum amount in arrears is 11,846.20 yuan.

$DaysInArrears$ is the number of days the loans are currently in arrears. For the whole sample, the average days of loans in arrears is 0.02 days. The standard deviation of the days of loans in arrears is 0.44 days, the minimum, the lowest decile, the lowest quartile, the median, the highest quartile, and the highest decile of days of loans in arrears are all 0 days, and the maximum days of loans in arrears is 35 days. Among all the 13,418 loans which are in arrears, the average days of loans in arrears is 4 days. The standard deviation of the days of loans in arrears is 5 days, the minimum days of loans in arrears is 1 days, the lowest quartile and the lowest decile of the days of loans in arrears are 1 day, the median days of loans in arrears is 2 days, the highest quartile of the days of loans in arrears is 5 days, the highest decile of the days of loans in arrears is 10 days, and the maximum days of loans in arrears is 35 days.

3 Empirical Analysis

In this section, we first present the empirical evidence that the B2C retailer's decisions to invite consumers are based on two factors: the characteristics of credit rating and age groups of the borrowers. We then present the evidence to show that the unsecured consumer loan lender reduces the credit supply for *non-solicited* borrowers with lower credit rating, but charges less for these borrowers. This demonstrates a trade-off between the credit supply and the rent. This trade-off phenomenon was exacerbated by the CBRC Act issued on August 24, 2016. Moreover, the unsecured consumer loan lender reduces the credit supply for *non-solicited* borrowers younger than 23, and charges less for these borrowers. We further show that the default patterns of the consumers vary across the borrowers of different credit rating and age groups. Finally, we demonstrate that there exists significant heterogeneity in this online retailer's lending and consumers' defaulting behaviors across geographic regions.

3.1 Customer Channel

Table 2 presents the results of panel Logit regressions of $D_{CustomerChannel}$ on the combination of the online lending Act dummy $D_{PostAct}$, dummies of $CreditRating$–$D^{LowerDefaultRisk}_{CreditRating}$, $D^{HigherDefaultRisk}_{CreditRating}$, and $D^{HighestDefaultRisk}_{CreditRating}$, and their interaction (Model (1)), the combination of the online lending Act dummy $D_{PostAct}$, dummies of $AgeBucket$–$D^{(23,26]}_{AgeBucket}$, $D^{(26,32]}_{AgeBucket}$, $D^{(32,45]}_{AgeBucket}$, $D^{>45}_{AgeBucket}$, and their interaction (Model (2)), and the comprehensive model (Model (3)), respectively. $D_{CustomerChannel}$ is 1 for the customer/borrower solicited by lender, 0 otherwise.[3] $D_{PostAct}$ is equal to one for days after August 24, 2016, 0 otherwise. This table shows that the likelihood of a customer being solicited by lender increases monotonically in credit worthiness and age, and after the passage of the CBRC Act, lender solicits more customers younger than 23 years old and with more credit worthiness.

Model (1) shows that the higher the credit risk of a borrower, the less likely the lender is willing to solicit the customer. This is intuitive as lender will face a higher chance of

[3]We use borrower and customer exchangeably in this paper.

defaulting from these high credit risk borrowers. The coefficients on the dummies of lower default risk, higher default risk, and highest default risk are -1.496, -2.072, and -3.628. These correspond to, prior to the passage of the CBRC Act, the odds of a lower, higher, and highest default risk customer being solicited by lender divided by the odds of a lowest default risk customer being solicited by lender are 0.224, 0.126, and 0.027, respectively. All results are significant at 1% level.

The coefficient on $D_{PostAct}$ is 0.668 with the standard error of 0.006. This means the odds ratio is 1.951. For the lowest default risk group, the odds of being solicited by lender is almost twice times more after the passage of the CBRC Act than before the Act. The coefficients on the interaction of $D_{CreditRating}^{LowerDefaultRisk}$, $D_{CreditRating}^{HigherDefaultRisk}$, and $D_{CreditRating}^{HighestDefaultRisk}$ with $D_{PostAct}$ are -0.023, -0.496, and -0.743, respectively. All results are significant at 1% level. These correspond to, the odds of being selected by lender after the passage of the CBRC Act (post-act) vs. prior to the passage of the CBRC Act (pre-act) for the lower, higher, and highest default risk customers, divided by the odds of being selected by lender after the passage of the CBRC Act (post-act) vs. prior to the passage of the CBRC Act (pre-act) for the lowest default risk customers, is 0.977, 0.610, and 0.476, respectively. All results are significant at 1% level. This means that the relative chance for lower, higher, and highest default risk customers (to the lowest default risk customers) being solicited by lender decreased after the passage of the Act.

The impact of the CBRC Act on whether or not a customer is selected by lender depends on the level of the default risk of the customers. For the lowest default risk customers, the impact of the CBRC Act is much higher than for the highest default risk customers. In particular, for the lowest default risk customers, the odds of being solicited by lender is almost twice times more after the passage of the CBRC Act than before the Act. By contrast, for the highest default risk customers, the odds of being solicited by lender is 0.923 ($=1.951 \times 0.476$) times more after the passage of the CBRC Act than before the Act. For the lower and higher default risk customers, the odds of being solicited by lender are respectively

1.906 (=1.951 × 0.977) and 1.190 (=1.951 × 0.610) times more after the passage of the CBRC Act than before the Act. After the Act, the largest increase in lender soliciting numbers is in the lowest default risk group and the second largest increase is in the lower default risk group. For the highest default risk group, lender solicits fewer customers post-Act compared to pre-Act.

Model (2) shows the interesting results that lender prefers more senior borrowers. If a customer is older than 32 years old, she is most likely to be solicited by lender. The coefficient on $D_{AgeBucket}^{(32,45]}$ is 1.780. The second most likely age group is from 26 to 32 years old. The coefficient on $D_{AgeBucket}^{(26,32]}$ is 1.626. If a customer is from 23 to 26 years old, she is less likely to be solicited by lender. The coefficient on $D_{AgeBucket}^{(23,26]}$ is 0.980. The least possible age group to be invited by lender to borrow are the borrowers younger than 23. These correspond to, prior to the passage of the CBRC Act, the odds of a customer in the age groups $(23, 26]$, $(26, 32]$ and $(32, 45]$ being solicited by lender divided by the odds of a customer in the age group younger than 23 being solicited by lender are 2.665, 5.085, and 5.927, respectively. All results are significant at 1% level. This is intuitive as borrowers older than 32 are at the peak of their income paths and hence can support more borrowing from lender.

The coefficient on $D_{PostAct}$ of Model (2) is 0.507 with the standard error of 0.009. This means that, for the age group younger than 23, the odds of being solicited by lender is 1.66 times more after the passage of the CBRC Act than before the Act. The coefficients on the interaction of $D_{AgeBucket}^{(23,26]}$, $D_{AgeBucket}^{(26,32]}$, and $D_{AgeBucket}^{(32,45]}$ with $D_{PostAct}$ are -0.126, -0.369, and -0.395, respectively. All results are significant at 1% level. These correspond to, the odds of being selected by lender after the passage of the CBRC Act (post-act) vs. prior to the passage of the CBRC Act (pre-act) for a customer in the age groups $(23, 26]$, $(26, 32]$, and $(32, 45]$, to the odds of being selected by lender after the passage of the CBRC Act (post-act) vs. prior to the passage of the CBRC Act (pre-act) for the age group younger than 23, is 0.882, 0.691, and 0.674, respectively. All results are significant at 1% level. Similar to the explanation of Model (1), the relative chance for customers older than 23 (to customers younger than 23) being solicited by lender decreased after the passage of the Act.

The impact of the CBRC Act on whether or not a customer is selected by lender depends on the age of the customers. For the age group younger than 23, the impact of the CBRC Act is much higher than for the age group $(32, 45]$. In particular, for the age group younger than 23, the odds of being solicited by lender is 1.66 times more after the passage of the CBRC Act than before the Act. By contrast, for the age group $(32, 45]$, the odds of being solicited by lender is 1.119 ($=1.660 \times 0.674$) times more after the passage of the CBRC Act than before the Act. For the age groups $(23, 26]$ and $(26, 32]$ customers, the odds of being solicited by lender are respectively 1.464 ($=1.660 \times 0.882$) and 1.147 ($=1.660 \times 0.691$) times more after the passage of the CBRC Act than before the Act. After the Act, the largest increase in lender soliciting numbers is in the age group younger than 23 and the second largest increase is in the age group $(23, 26]$.

Model (3) is the comprehensive model which confirms the findings of Models (1) and (2) and tells the consistent story that the more credit worthiness and the older the customers are, the more likely the customers are pre-selected by lender to borrow. And after the passage of the CBRC Act, lender solicits more customers younger than 23 years old and with more credit worthiness.

3.2 Strategic Lending

3.2.1 Current Rate

Table 3 presents the results of panel regressions of $CurrentRate$ (in basis points) on the combination of the online lending Act dummy $D_{PostAct}$, $D_{CustomerChannel}$, and their interaction (Model (1)), the combination of the online lending act dummy $D_{PostAct}$, $D_{CustomerChannel}$, their interaction, the dummies of $CreditRating$–$D_{CreditRating}^{LowerDefaultRisk}$, $D_{CreditRating}^{HigherDefaultRisk}$, and $D_{CreditRating}^{HighestDefaultRisk}$, the interactions of $D_{CustomerChannel}$ with the dummies of $CreditRating$, and the interactions of $D_{PostAct}, D_{CustomerChannel}$, and dummies of $CreditRating$ (Model (2)), and the combination of the online lending act dummy $D_{PostAct}$, $D_{CustomerChannel}$, their interaction, the dummies of $AgeBucket$–$D_{AgeBucket}^{(23,26]}$, $D_{AgeBucket}^{(26,32]}$, $D_{AgeBucket}^{(32,45]}$, $D_{AgeBucket}^{>45}$, the interactions of $D_{CustomerChannel}$ with the dummies of $AgeBucket$, and the interactions of $D_{PostAct}, D_{CustomerChannel}$, and dummies of $AgeBucket$ (Model (3)), respectively.

Model (1) shows that the coefficient on $D_{CustomerChannel}$ is -4.703 with 1% significance level. Ceteris paribus, the lender solicited borrowers enjoy in average 4.703 bps lower current rates compared to the lender non–solicited borrowers. Model (1) shows that the coefficient on $D_{PostAct}$ is 5.904 with 5% significance level. Ceteris paribus, lender raises current rates in average 5.904 bps after the passage of the CBRC Act. Model (1) also shows that the coefficient on the interaction item of $D_{CustomerChannel}$ with $D_{PostAct}$ is -8.921. For the selected customers, the current rate is 8.921 bps lower after the passage of the CBRC Act.

Model (2) shows that for the lender non–solicited borrowers' loans, compared to the group of the highest credibility (i.e., lowest default risk), the customer of the lower default risk has in average 9.705 bps more current rate; the customer of the higher default risk has in average 12.419 bps more current rate; and the customer of the highest default risk has in average 14.971 bps more current rate. All results are significant at the 1% level. There is a monotonic relationship between the current rate and the credit unworthiness of the customers.

Model (2) further shows that for the customer of the higher default risk, and the customer of the highest default risk, compared to lender non–solicited borrowers, the current rate of the lender–solicited borrowers are 3.582 bps more and 3.737 bps more respectively. All results are significant at the 1% level. Lender charges higher current rate to lender solicited customers than to lender non–solicited borrowers for more risky borrowers. This result is surprising. Table 2 shows that the customers solicited by lender to borrow have more credit worthiness and thus intuitively they should be charged less rate than lender non-solicited customers. However, when we turn to the analysis of credit limit, the trade-off between the credit supply and the rent (i.e., current rate) can well explain this result.

Model (2) also shows, for customers of the lower default risk, the higher default risk, and the highest default risk, the relative current rates charged for lender solicited borrowers (to lender non-solicited customers) are 4.377 bps more, 4.774 bps more, and 5.147 bps more, respectively, after the passage of the CBRC Act. All results are significant at the 1% level. This implies that the passage of the CBRC Act increased the relative current rate charged for lender solicited more risky borrowers (to lender non-solicited more risky borrowers), and then exacerbated the trade-off explanation of the results.

Model (3) shows that for the lender non–solicited borrowers' loans, compared to the group of the customers younger than 23, the customers who are older than 23 and younger than 26 have in average 6.941 bps less current rate; the customers who are older than 26 and younger than 32 have in average 5.840 bps less current rate; the customers who are older than 32 and younger than 45 have in average 5.827 bps less current rate; the customers who are older than 45 have in average 3.369 less current rate. All results are significant at the 1% level. There is an inverse relationship between the fee charged by lender and the age of the customers. Less current rate is charged for the customers older than 23. Agarwal, Driscoll, Gabaix, and Laibson (2009) observe the U-shape in age for credit card interest rates, auto loan interest rates, mortgage interest rates, and small business credit card interest rates with the age of peak performance around 53 years old. From 20 years old to 53 years old, there is a monotonically decreasing relationship in APR with respect to age. Our results are similar to Agarwal, Driscoll, Gabaix, and Laibson (2009) in observing the age effect in current rate.

Model (3) further shows that for the customers who are older than 23 and younger than 26, for the customers who are older than 26 and younger than 32, for the customers who are older than 32 and younger than 45, and for the customers older than 45, the current rates of the lender–solicited borrowers are higher than lender non–solicited borrowers by 3.148 bps, 2.845 bps, 3.701 bps, and 6.261 bps, respectively. All results are significant at the 1% level. Therefore, age plays an important role in determining the current rates for the customers, especially for the lender–solicited ones.

Model (3) also shows, for customers of who are older than 23 and younger than 26, who are older than 26 and younger than 32, who are older than 32 and younger than 45, and who are older than 45, the relative current rates charged for lender solicited borrowers (to lender non-solicited borrowers) are 8.052 bps less, 14.372 bps less, 18.395 bps less, and 21.950 bps less, respectively, after the passage of the CBRC Act. All results are significant at the 1% level. These results imply that the passage of the CBRC Act reduced the relative current rate charged for solicited older borrowers (to lender non-solicited older borrowers)

In summary, Table 3 shows that lender charges lower interest rate for the solicited borrowers, ceteris paribus. The interest rate is positively related to the credit unworthiness of the customers and negatively related to the age of the customers. The higher the credit risk, the higher the interest rate. Borrowers younger than 23 are charged significantly higher interest rates compared to other borrowers. For each credit risk group, lender charges more interest for the solicited customers. For each age group older than 23, lender charges more interest for the solicited customers. Given the same credit risk or age group, lender charges more interest for the solicited customers compared to the non-solicited customers. Moreover, after the passage of the CBRC Act, for more risky groups, lender charges more interest for the solicited customers compared to the non-solicited customers. After the passage of the CBRC Act, for each age group older than 23, lender charges less interest for the solicited customers compared to the non-solicited customers.

3.2.2 Credit Limit

Table 4 presents the results of panel regressions of $CreditLimit$ (in thousands) the combination of the online lending Act dummy $D_{PostAct}$, $D_{CustomerChannel}$, and their interaction (Model (1)), the combination of the online lending act dummy $D_{PostAct}$, $D_{CustomerChannel}$, their interaction, the dummies of $CreditRating$–$D_{CreditRating}^{LowerDefaultRisk}$, $D_{CreditRating}^{HigherDefaultRisk}$, and $D_{CreditRating}^{HighestDefaultRisk}$, the interactions of $D_{CustomerChannel}$ with the dummies of $CreditRating$, and the interactions of $D_{PostAct}, D_{CustomerChannel}$, and dummies of $CreditRating$ (Model (2)), and the combination of the online lending act dummy $D_{PostAct}$, $D_{CustomerChannel}$, their interaction, the dummies of $AgeBucket$–$D^{(23,26]}_{AgeBucket}$, $D^{(26,32]}_{AgeBucket}$, $D^{(32,45]}_{AgeBucket}$, $D^{>45}_{AgeBucket}$, the interactions of $D_{CustomerChannel}$ with the dummies of $AgeBucket$, and the interactions of $D_{PostAct}, D_{CustomerChannel}$, and dummies of $AgeBucket$ (Model (3)), respectively.

Model (1) shows that the coefficient on $D_{CustomerChannel}$ is -0.133 with 1% significance level. Ceteris paribus, the lender solicited borrowers are granted in average \$133 less credit limit compared to the lender non–solicited borrowers. Model (1) shows that the coefficient on $D_{PostAct}$ is -1.360 with 1% significance level. Ceteris paribus, lender lowers credit limits for borrowers in average \$1,360 after the passage of the CBRC Act. Model (1) also shows that the coefficient on the interaction item of $D_{CustomerChannel}$ with $D_{PostAct}$ is 0.925. It means that, for lender solicited borrowers, the credit limit is \$925 higher after the passage of the CBRC Act.

Model (2) shows that for the lender non–solicited borrowers' loans, compared to the group of the highest credibility, the customer of the lower default risk has in average \$1,664 less credit limit; the customer of the higher default risk has in average \$3,156 less credit limit; and the customer of the highest default risk has in average \$3,740 less credit limit. All results are significant at the 1% level. There is a monotonic decreasing relationship between the credit limit and the credit unworthiness of the customers.

Model (2) further shows that for the customers of higher and highest default risk, the lender–solicited borrowers are granted \$541 more and \$783 more credit limit respectively than lender non–solicited borrowers. All results are significant at the 1% level. Lender extends more credit limit to solicited borrowers than to non–solicited borrowers. In Model (2) of Table 3, we find that lender charges higher current rate to solicited borrowers with higher and highest default risk than to non–solicited borrowers with the same level of the risk. Putting them together, we find a trade-off between the credit supply and the rent (i.e., current rate) for solicited and non-solicited customers. If lender grants higher credit limit and charges higher current rate for non-solicited borrowers, the lender might face the borrowers who cannot pay their payments in the future. The lender in our paper balances the credit supply and the interest rate for borrowers with higher risk, where the credit card issuer in Ru and Schoar (2017) authorizes the same limit to all of customers but relies less on back-loaded fees for customers with higher risk.

Model (2) also shows, for the customers of the higher default risk, the relative credit limit for lender solicited borrowers (to lender non-solicited borrowers) is $211 more after the passage of the CBRC Act. The result is significant at the 1% level. This implies that the passage of the CBRC Act increased the relative credit limit for lender solicited customers with higher risk.

Model (3) shows for the customers who are older than 23 and younger than 26, for the customers who are older than 26 and younger than 32, for the customers who are older than 32 and younger than 45, and for the customers older than 45, the credit limits of the lender–solicited borrowers are higher than lender non–solicited borrowers by $98, $292, $231 and $482, respectively. All results are significant at the 1% level. Age also plays an important role in determining the credit limits for the customers, especially for the lender–solicited ones.

Model (3) further shows, for the lender selected customers of who are older than 23 and younger than 26, who are older than 26 and younger than 32, who are older than 32 and younger than 45, and who are older than 45, the relative credit limits for lender solicited borrowers are $116 more, $877 more, $1,075 more, and $1,009 more, respectively after the passage of the CBRC Act. All results are significant at the 1% level. This implies that the passage of the CBRC Act increased the relative credit limit for lender selected older customers.

In summary, Table 4 shows that lender extends less credit for the selected customers, ceteris paribus. The credit limit is negatively related to the credit unworthiness of the customers. The higher the credit risk, the lower the credit limit. Interestingly also, for the higher default risk and the highest default risk groups, lender extends more credit limit for the solicited customers. For each age group older than 23, lender extends more credit limit for the solicited customers. What's more, after the passage of the CBRC Act, for customers with higher default risk and older than 23, lender extends more credit limit for the solicited compared to the non-solicited customers.

These results of both Table 3 and Table 4 show that the unsecured consumer loan lender reduces the credit supply for *non-solicited* more risky borrowers, and in the meantime charges less for these borrowers. This demonstrates a trade-off across the socioeconomic groups of the borrowers for the lender. The CBRC Act exacerbated the trade-off explanation of the results.

3.3 Loans in Arrears

Table 5, Table 6, and Table 7 present the results of the panel Logit regressions of $InArrearsIndicator$, the panel Tobit regressions of $ArrearsAmount$, and the panel Tobit regressions of $DaysInArrears$ on the combination of the online lending act dummy $D_{PostAct}$, $D_{CustomerChannel}$ and their interaction (Model (1)), the combination of the online lending act dummy $D_{PostAct}$, $D_{CustomerChannel}$, their interaction, the dummies of $CreditRating$–$D^{LowerDefaultRisk}_{CreditRating}$, $D^{HigherDefaultRisk}_{CreditRating}$, and $D^{HighestDefaultRisk}_{CreditRating}$, and the interactions of $D_{CustomerChannel}$ with the dummies of $CreditRating$ (Model (2)), and the combination of the online lending act dummy $D_{PostAct}$, $D_{CustomerChannel}$, their interaction, the dummies of $AgeBucket$–$D^{(23,26]}_{AgeBucket}$, $D^{(26,32]}_{AgeBucket}$, $D^{(32,45]}_{AgeBucket}$, $D^{>45}_{AgeBucket}$, and the interactions of $D_{CustomerChannel}$ with the dummies of $AgeBucket$ (Model (3)), respectively. $InArrearsIndicator$ is 1 for the loan in arrears, 0 otherwise.

Models (1) of Table 5, Table 6, and Table 7 show that compared to the non–solicited customers, for the solicited customers, the loan is less likely to be in arrears, the arrears amount is smaller and there are fewer days in arrears. Models (1) also show that after the CBRC Act, the loan is more likely to be in arrears, the arrears amount is larger and there are more days in arrears.

Model (2) of Table 5 show that the higher the credit risk of a borrower, the more likely the loan is going to be in arrears. This is intuitive as the higher the credit risk of a borrower, the more likely the loan is going to default. The coefficients on the dummies of the lower default risk, the higher default risk, and the highest default risk are 0.555, 0.851, and 0.889, respectively. Model (2) of Table 6 show that the higher the credit risk of a borrower, the more arrears amount the loan has. The coefficients on $D^{LowerDefaultRisk}_{CreditRating}$, $D^{HigherDefaultRisk}_{CreditRating}$, and $D^{HighestDefaultRisk}_{CreditRating}$ are 0.145, 0.230, and 0.240, respectively. Model (2) of Table 7 show that the higher the credit risk of a borrower, the more days in arrears the loan has. The coefficients on $D^{LowerDefaultRisk}_{CreditRating}$, $D^{HigherDefaultRisk}_{CreditRating}$, and $D^{HighestDefaultRisk}_{CreditRating}$ are 2.654, 4.195, and 4.482, respectively. All three variables–$InArrearsIndicator$, $ArrearsAmount$ and $DaysInArrears$–are monotonically increasing with respect to the credit unworthiness. All results are significant at 1% level.

Model (3) of Table 5 show that the younger the borrower, the more likely the loan is going to be in arrears. This is intuitive as the younger the borrower, the less income the borrower has. The coefficients on $D^{(32,45]}_{AgeBucket}$ and $D^{>45}_{AgeBucket}$ are -0.332 and -0.398, respectively. Model (3) of Table 6 show that the younger the borrower, the more arrears amount the loan has. The coefficients on $D^{(32,45]}_{AgeBucket}$ and $D^{>45}_{AgeBucket}$ are -0.079 and -0.102, respectively. Model (3) of Table 7 show that the younger the borrower, the more days in arrears the loan has. The coefficients on $D^{(32,45]}_{AgeBucket}$ and $D^{>45}_{AgeBucket}$ are -1.616 and -2.016, respectively. All three variables–$InArrearsIndicator$, $ArrearsAmount$ and $DaysInArrears$–are decreasing with respect to the customer's age. All results are significant at 1% level.

In summary, Table 5, Table 6, and Table 7 show that the consumer loan default probability, arrears amount and the time in arrears are lower for *solicited* customers, higher after the CBRC Act, higher for more risk borrowers, and higher for younger borrowers. The more credit risk the borrower has, and the younger the customers are, the more likely the loans are in arrears, the more arrears amount the borrower has, and the more days in arrears for the borrower.

3.4 Geographic Heterogeneity

Finally, we find significant heterogeneity in the issuer's lending and consumers' defaulting activities across different geographic regions. The online retailer targets the customers from certain municipalities and provinces to lend strategically. The interest rate, the credit limit, the default probability, and the arrears amount all vary across different geographic regions. These differences are potentially related to the social economic differences and cultural differences across China.

Table 8 presents the results of panel regression of the following dependent variables on the dummies of the location of the customers: $CustomerChannel$ (Model (1)), $CurrentRate \times 100$ (Model (2)), $CreditLimit$ (Model (3)), $InArrearsIndicator$ (Model (4)), and $ArrearsAmount$ (Model (5)),. The omitted dummy stands for the Anhui province. All regressions cluster the standard errors by both loan borrowers and loan start date as in Petersen (2009). The omitted dummy stands for the Anhui province. Table 8 shows that these variables all demonstrate significant geographic heterogeneity.

Model (1) of Table 8 shows that the customers from the four municipalities are more likely to be solicited by lender. Compared to the Anhui province, the coefficients on Beijing, Shanghai, Chongqing and Tianjin are 1.11, 0.98, 0.32 and 0.86, respectively. The customers in the autonomous regions are also more likely to be solicited by lender. Compared to the Anhui province, the coefficients on Guangxi, Inner Mongolia, Ningxia Hui, Tibet and Xinjiang Uyghur autonomous regions are 0.42, 0.42, 0.38, 1.19 and 0.69, respectively. All results are significant at the 1% level.

Model (2) of Table 8 shows that the customers in Beijing and Shanghai municipalities are charged less fee compared to the customers in the Anhui province. The coefficients on Beijing and Shanghai are -0.02 and -0.03, respectively. The customers in Gansu, Guizhou and Qinghai provinces are charged more fee compared to the customers in the Anhui province– the coefficients are 0.16, 0.17 and 0.16, respectively. All results are significant at the 1% level.

Model (3) of Table 8 shows that the customers from the Anhui province have more credit limits ($CreditLimit$) than the vast majority of the customers in the other provinces. There are only seven municipalities or provinces whose customers have higher credit limits than those of the Anhui province. For example, the coefficients on Beijing, Shanghai, and Chongqing are 793.83, 702.66, and 54.57, respectively. The customers in the autonomous regions have less credit limits, compared to the Anhui province. For example, the coefficients on Guangxi, Inner Mongolia, Ningxia Hui, and Xinjiang Uyghur autonomous regions are -252.10, -601.63, -923.77, and -891.34, respectively. All results are significant at the 1% level. The similar results hold for $ApprovalAmount$ and $CurrentPrincipleBalance$.

Model (4) of Table 8 shows that compared to the customers in the Anhui province, the customers in the four municipalities are more likely to have loans in arrears. The coefficients on Beijing, Shanghai, Chongqing and Tianjin are 0.28, 0.26, 0.18 and 0.23, respectively. Compared to the customers in the Anhui province, the customers in the autonomous regions are even more likely to have loans in arrears. The coefficients on Guangxi, Inner Mongolia, Ningxia Hui, Tibet and Xinjiang Uyghur autonomous regions are 0.19, 0.53, 0.80, 1.16 and 0.29, respectively. All results are significant at the 1% level.

Model (5) of Table 8 shows that compared to the customers in the Anhui province, the customers in the four municipalities are higher arrears amount. The coefficients on Beijing, Shanghai, Chongqing and Tianjin are 76.41, 64.82, 44.32 and 54.93, respectively. Compared to the customers in the Anhui province, the customers in the autonomous regions have even higher arrears amount. The coefficients on Inner Mongolia, Ningxia Hui, Tibet and Xinjiang Uyghur autonomous regions are 137.73, 213.10, 316.41 and 80.97, respectively. All results are significant at the 1% level.

4 Conclusion

This paper explores the dynamic pricing strategies of an unsecured consumer loan issuer and the default patterns of the loans. We examine a unique proprietary data set of about 3 million unsecured consumer loans of about 1.4 million loan borrowers from a representative sample of households provided by a Business to consumer (B2C) online retailer in China. First, the likelihood of a customer being solicited by lender increases monotonically in credit worthiness and age. After the passage of the consumer finance policy of the China Banking Regulatory Commission (CBRC) Act (the CBRC Act) which regulates the unsecured consumer lending activities, the loans issuer solicits more customers younger than 23 years old and with more credit worthiness. Second, the loan issuer charges higher interest rate and grant less credit limit for more risky customers, however charges even higher interest rate and extends more credit limit for the *solicited* more risky customers. This phenomenon is exacerbated after the passage of the CBRC Act. Third, the loan issuer charges lower interest rate for older customers, but charges higher interest for the *solicited* older customers. This phenomenon is alleviated after the passage of the CBRC Act. These findings demonstrate a trade-off across borrowers. The unsecured consumer loan lender reduces the credit supply for the *non-solicited* more risky borrowers, and in the meantime charges less current rate from these borrowers. The CBRC Act exacerbated the trade-off explanation of the results. Fourth, the consumer loan default probability, arrears amount and the time in arrears are lower for *solicited* customers, higher after the CBRC Act, higher for more risk borrowers, and higher for younger borrowers. Fifth, we also find significant heterogeneity in the issuer's lending and consumers' defaulting activities across different geographic regions. We are the first to document these findings.

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Table 1: **Descriptive Statistics**

This table presents the summary statistics. Panel A shows the loan borrowing frequency distribution. Panel B shows the geographic distributions of the loans (the left three columns) and the borrowers (the right three columns) of *CustomerAreaLocation*. The first four rows are the municipalities. The next twenty-seven rows are the provinces and the autonomous regions with the descending order of frequency distribution of the borrowers. Panel C reports the frequency distribution of the origination month of the loans which we obtain from daily *LoanStartDate*. Panel D reports the frequency distribution of the maturity month of the loans which we obtain from daily *LoanEndDate*. Panel E reports the frequency distribution of credit ratings (*CreditRating*). Panel F reports the frequency distribution of the term of the loans in month (*LoanTerm*). Panel G reports the frequency distribution of the loans in arrears. Panel H reports the frequency distribution of age buckets (*AgeBucket*). Panel I reports the frequency distribution of customer channel (*CustomerChannel*). Panel J reports the two-way frequency distribution of *CustomerChannel* and *CreditRating*. Panel K reports the two-way frequency distribution of *CustomerChannel* and the loans in arrears. Panel L reports the two-way frequency distribution of *CustomerChannel* and *AgeBucket*. Panel M reports the two-way frequency distribution of *CustomerChannel* and *CustomerAreaLocation*. Panel N reports the summary statistics of $CurrentRate \times 100$ (the first line is for the whole sample, the second line is for the subsample for non-zero $CurrentRate \times 100$), *CreditLimit*, *ArrearsAmount* (the first line is for the whole sample, the second line is for the subsample for non-zero *ArrearsAmount*) and *DaysInArrears* (the first line is for the whole sample, the second line is for the subsample for non-zero *DaysInArrears*). The sample consists of 2,998,627 loan observations of 1,394,502 loan borrowers. The loan origination dates span from October 11, 2014 through October 31, 2016. The loan maturity dates span from September 29, 2016 to October 31, 2018.

Panel A: The Frequency Distribution of Loan Borrowing Frequency

Loan Borrowing Frequency	Number of Borrowers	Percent	Cumu. Perc.
1	882,145	63.26%	63.26%
2	236,967	16.99%	80.25%
3	100,788	7.23%	87.48%
4	53,947	3.87%	91.35%
5	32,502	2.33%	93.68%
6	20,902	1.50%	95.18%
7	14,515	1.04%	96.22%
8	10,469	0.75%	96.97%
9	7,825	0.56%	97.53%
>=10	34,442	2.40%	100.00%
Total	1,394,502	100.00%	

Panel B: The Geographic Distribution of the Loans and the Borrowers

CustomerAreaLocation	# of Loans	Percent	Cumu. Perc.	# of Borrowers	Percent	Cumu. Perc.
Beijing Municipality	260,715	8.69%	8.69%	130,011	9.32%	9.32%
Tianjin Municipality	72,265	2.41%	11.10%	34,566	2.48%	11.80%
Shanghai Municipality	163,437	5.45%	16.55%	83,813	6.01%	17.81%
Chongqing Municipality	77,448	2.58%	19.14%	34,259	2.46%	20.27%
Guangdong Province	434,549	14.49%	33.63%	224,912	16.13%	36.40%
Jiangsu Province	218,041	7.27%	40.90%	104,761	7.51%	43.91%
Sichuan Province	208,576	6.96%	47.86%	92,743	6.65%	50.56%
Shandong Province	155,334	5.18%	53.04%	71,473	5.13%	55.69%
Hubei Province	140,749	4.69%	57.73%	60,049	4.31%	59.99%
Shaanxi Province	128,025	4.27%	62.00%	49,799	3.57%	63.56%
Hebei Province	116,824	3.90%	65.90%	54,016	3.87%	67.44%
Liaoning Province	116,508	3.89%	69.78%	48,294	3.46%	70.90%
Henan Province	113,117	3.77%	73.55%	50,185	3.60%	74.50%
Zhejiang Province	103,361	3.45%	77.00%	52,914	3.79%	78.29%
Fujian Province	95,830	3.20%	80.20%	46,436	3.33%	81.62%
Anhui Province	91,539	3.05%	83.25%	37,396	2.68%	84.30%
Guangxi Zhuang Auto. Reg.	73,892	2.46%	85.71%	34,067	2.44%	86.75%
Hunan Province	68,992	2.30%	88.01%	30,345	2.18%	88.92%
Shanxi Province	60,949	2.03%	90.05%	25,083	1.80%	90.72%
Heilongjiang Province	53,433	1.78%	91.83%	20,609	1.48%	92.20%
Jiangxi Province	47,200	1.57%	93.40%	19,199	1.38%	93.58%
Jilin Province	41,079	1.37%	94.77%	16,308	1.17%	94.75%
Guizhou Province	31,057	1.04%	95.81%	13,550	0.97%	95.72%
Yunnan Province	30,225	1.01%	96.82%	13,937	1.00%	96.72%
Inner Mongolia Auto. Reg.	28,202	0.94%	97.76%	13,361	0.96%	97.68%
Gansu Province	24,827	0.83%	98.58%	10,468	0.75%	98.43%
Xinjiang Uyghur Auto. Reg.	17,105	0.57%	99.15%	9,566	0.69%	99.11%
Hainan Province	14,615	0.49%	99.64%	6,741	0.48%	99.60%
Ningxia Hui Auto. Reg.	6,504	0.22%	99.86%	3,284	0.24%	99.83%
Qinghai Province	2,770	0.09%	99.95%	1,574	0.11%	99.94%
Tibet Autonomous Region	1,459	0.05%	100.00%	783	0.06%	100.00%
Total	2,998,627	100%		1,394,502	100	

Panel C: The Frequency Distribution of the Origination Month of the Loans

Loan Start Month	Number of Loans	Percent	Cumu. Perc.
October, 2014	21	0.00%	0.00%
November, 2014	3,181	0.11%	0.11%
December, 2014	5,404	0.18%	0.29%
January, 2015	7,308	0.24%	0.53%
February, 2015	3,386	0.11%	0.64%
March, 2015	1,485	0.05%	0.69%
April, 2015	6,060	0.20%	0.90%
May, 2015	1,348	0.04%	0.94%
June, 2015	15,680	0.52%	1.46%
July, 2015	1,724	0.06%	1.52%
August, 2015	2,178	0.07%	1.59%
September, 2015	2,818	0.09%	1.69%
October, 2015	3,578	0.12%	1.81%
November, 2015	81,250	2.71%	4.52%
December, 2015	51,395	1.71%	6.23%
January, 2016	66,228	2.21%	8.44%
February, 2016	32,845	1.10%	9.53%
March, 2016	140,226	4.68%	14.21%
April, 2016	85,040	2.84%	17.05%
May, 2016	122,918	4.10%	21.15%
June, 2016	247,997	8.27%	29.42%
July, 2016	79,992	2.67%	32.08%
August, 2016	152,570	5.09%	37.17%
September, 2016	440,940	14.70%	51.88%
October, 2016	1,443,055	48.12%	100.00%
Total	2,998,627	100.00%	

Panel D: The Frequency Distribution of the Maturity Month of the Loans

Loan End Month	Number of Loans	Percent	Cumu. Perc.
September, 2016	4	0.00%	0.00%
October, 2016	2,438	0.08%	0.08%
November, 2016	985,574	32.87%	32.95%
December, 2016	263,784	8.80%	41.75%
January, 2017	242,403	8.08%	49.83%
February, 2017	72,478	2.42%	52.25%
March, 2017	215,218	7.18%	59.42%
April, 2017	191,944	6.40%	65.82%
May, 2017	73,037	2.44%	68.26%
June, 2017	131,282	4.38%	72.64%
July, 2017	24,924	0.83%	73.47%
August, 2017	39,830	1.33%	74.80%
September, 2017	88,907	2.96%	77.76%
October, 2017	113,622	3.79%	81.55%
November, 2017	49,642	1.66%	83.21%
December, 2017	3,745	0.12%	83.33%
January, 2018	7,714	0.26%	83.59%
February, 2018	7,075	0.24%	83.83%
March, 2018	15,521	0.52%	84.34%
April, 2018	16,678	0.56%	84.90%
May, 2018	22,900	0.76%	85.66%
June, 2018	18,717	0.62%	86.29%
July, 2018	36,031	1.20%	87.49%
August, 2018	32,720	1.09%	88.58%
September, 2018	169,346	5.65%	94.23%
October, 2018	173,093	5.77%	100.00%
Total	2,998,627	100.00%	

Panel E: The Frequency Distribution of Credit Ratings

Credit Rating	Number of Loans	Percent	Cumu. Perc.
1 (Lowest Default Risk)	1,908,405	63.64%	63.64%
2 (Lower Default Risk)	684,924	22.84%	86.48%
3 (Higher Default Risk)	307,466	10.25%	96.74%
4 (Highest Default Risk)	97,832	3.26%	100.00%
Total	2,998,627	100.00%	

Panel F: The Frequency Distribution of the Loan Terms

Loan Terms	Number of Loans	Percent	Cumu. Perc.
1 Month	888,433	29.63%	29.63%
3 Months	289,004	9.64%	39.27%
6 Months	412,653	13.76%	53.03%
12 Months	801,618	26.73%	79.76%
24 Months	606,919	20.24%	100.00%
Total	2,998,627	100.00%	

Panel G: The Frequency Distribution of the Loans In Arrears

In Arrears	Number of Loans	Percent	Cumu. Perc.
No	2,985,209	99.55%	99.55%
Yes	13,418	0.45%	100.00%
Total	2,998,627	100.00%	

Panel H: The Frequency Distribution of Age Buckets

Age Buckets	Number of Loans	Percent	Cumu. Perc.
<23	967,649	32.27%	32.27%
(23, 26]	527,640	17.60%	49.87%
(26, 32]	852,361	28.43%	78.29%
(32, 45]	597,634	19.93%	98.22%
>45	53,343	1.78%	100.00%
Total	2,998,627	100.00%	

Panel I: The Frequency Distribution of Customer Channel

Customer Channel	Number of Loans	Percent	Cumu. Perc.
Not Solicited by lender	1,557,324	51.93%	51.93%
Solicited by lender	1,441,303	48.07%	100.00%
Total	2,998,627	100.00%	

Panel J: The Two-Way Frequency Distribution of Customer Channel and Credit Ratings

Credit Rating	Not Solicited by lender	Solicited by lender	Total
1 (Lowest Default Risk)	701,167	1,207,238	1,908,405
2 (Lower Default Risk)	496,355	188,569	684,924
3 (Higher Default Risk)	264,668	42,798	307,466
4 (Highest Default Risk)	95,134	2,698	97,832
Total	1,557,324	1,441,303	2,998,627

Panel K: The Two-Way Frequency Distribution of Customer Channel and the Loans In Arrears

In Arrears	Not Solicited by lender	Solicited by lender	Total
No	1,549,620	1,435,589	2,985,209
Yes	7,704	5,714	13,418
Total	1,557,324	1,441,303	2,998,627

Panel L: The Two-Way Frequency Distribution of Customer Channel and the Age Buckets

Age Buckets	Not Solicited by lender	Solicited by lender	Total
<23	708,675	258,974	967,649
(23, 26]	274,321	253,319	527,640
(26, 32]	336,276	516,085	852,361
(32, 45]	216,195	381,439	597,634
>45	21,857	31,486	53,343
Total	1,557,324	1,441,303	2,998,627

Panel M: The Two-Way Frequency Distribution of Customer Channel and the Loans

CustomerAreaLocation	Not Solicited by lender	Solicited by lender	Total
Beijing Municipality	94,874	165,841	260,715
Tianjin Municipality	30,551	41,714	72,265
Shanghai Municipality	64,504	98,933	163,437
Chongqing Municipality	43,113	34,335	77,448
Guangdong Province	193,371	241,178	434,549
Jiangsu Province	109,888	108,153	218,041
Sichuan Province	109,734	98,842	208,576
Shandong Province	88,205	67,129	155,334
Hubei Province	79,491	61,258	140,749
Shaanxi Province	82,057	45,968	128,025
Hebei Province	65,150	51,674	116,824
Liaoning Province	66,594	49,914	116,508
Henan Province	69,153	43,964	113,117
Zhejiang Province	52,630	50,731	103,361
Fujian Province	53,037	42,793	95,830
Anhui Province	58,017	33,522	91,539
Guangxi Zhuang Auto. Reg.	39,345	34,547	73,892
Hunan Province	39,614	29,378	68,992
Shanxi Province	41,073	19,876	60,949
Heilongjiang Province	33,712	19,721	53,433
Jiangxi Province	31,140	16,060	47,200
Jilin Province	25,873	15,206	41,079
Guizhou Province	18,681	12,376	31,057
Yunnan Province	16,598	13,627	30,225
Inner Mongolia Auto. Reg.	14,990	13,212	28,202
Gansu Province	14,891	9,936	24,827
Xinjiang Uyghur Auto. Reg.	7,962	9,143	17,105
Hainan Province	7,865	6,750	14,615
Ningxia Hui Auto. Reg.	3,524	2,980	6,504
Qinghai Province	1,184	1,586	2,770
Tibet Autonomous Region	503	956	1,459
Total	1,557,324	1,441,303	2,998,627

Panel N: The Summary Statistics of $CurrentRate \times 100$, $CreditLimit$, $ArrearsAmount$ and $DaysInArrears$.

Variable	N	Mean	Std	Min	p10	p25	p50
$CurrentRate \times 100$	2,998,627	0.27	0.36	0.00	0.00	0.00	0.00
$CurrentRate \times 100$	1,209,521	0.66	0.23	0.01	0.50	0.50	0.60
$CreditLimit$	2,998,627	8,347.73	4,280.59	0.00	3,589.00	5,485.00	8,000.00
$ArrearsAmount$	2,998,627	0.86	33.46	0.00	0.00	0.00	0.00
$ArrearsAmount$	13,418	192.00	462.22	0.51	10.15	32.55	96.67
$DaysInArrears$	2,998,627	0.02	0.44	0.00	0.00	0.00	0.00
$DaysInArrears$	13,418	4.05	5.10	1.00	1.00	1.00	2.00

Variable	N	p75	p90	Max	Skewness	Kurtosis
$CurrentRate \times 100$	2,998,627	0.50	0.98	3.00	0.89	2.34
$CurrentRate \times 100$	1,209,521	0.90	1.00	3.00	0.34	2.07
$CreditLimit$	2,998,627	10,543.00	13,247.00	218,191.00	2.69	49.76
$ArrearsAmount$	2,998,627	0.00	0.00	11,846.20	122.15	21,984.84
$ArrearsAmount$	13,418	193.82	368.62	11,846.20	9.05	119.01
$DaysInArrears$	2,998,627	0.00	0.00	35.00	40.56	2,059.26
$DaysInArrears$	13,418	5.00	10.00	35.00	2.77	11.52

Table 2: **Customer Channel**

This table presents the results of panel Logit regressions of $D_{CustomerChannel}$ on the combination of the online lending act dummy $D_{PostAct}$ and the dummies of $CreditRating$ (Model (1))–$D^{LowerDefaultRisk}_{CreditRating}$, $D^{HigherDefaultRisk}_{CreditRating}$, and $D^{HighestDefaultRisk}_{CreditRating}$, and on the combination of $D^{PostAct}_{CreditRating}$, the dummies of $AgeBucket$ (Model (2))–$D^{(23,26]}_{AgeBucket}$, $D^{(26,32]}_{AgeBucket}$, $D^{(32,45]}_{AgeBucket}$, $D^{>45}_{AgeBucket}$ and their interactions, and the comprehensive model (Model (3)), respectively. $D_{CustomerChannel}$ is 1 for the customer/borrower solicited by lender, 0 otherwise. $D_{PostAct}$ is equal to one for days after August 24, 2016, 0 otherwise. All regressions cluster the standard errors by both loan borrowers and loan start date. The sample consists of 2,998,627 loan observations of 1,394,502 loan borrowers. The loan origination dates span from October 11, 2014 through October 31, 2016. The loan maturity dates span from September 29, 2016 to October 31, 2018. The numbers in parentheses are standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
$D_{PostAct}$	0.668***	0.507***	0.927***
	(0.006)	(0.009)	(0.010)
$D^{LowerDefaultRisk}_{CreditRating}$	−1.496***		−1.285***
	(0.011)		(0.011)
$D^{LowerDefaultRisk}_{CreditRating} \times D_{PostAct}$	−0.023**		−0.084***
	(0.011)		(0.011)
$D^{HigherDefaultRisk}_{CreditRating}$	−2.072***		−1.865***
	(0.017)		(0.018)
$D^{HigherDefaultRisk}_{CreditRating} \times D_{PostAct}$	−0.496***		−0.500***
	(0.017)		(0.018)
$D^{HighestDefaultRisk}_{CreditRating}$	−3.628***		−3.423***
	(0.053)		(0.054)
$D^{HighestDefaultRisk}_{CreditRating} \times D_{PostAct}$	−0.743***		−0.688***
	(0.058)		(0.058)
$D^{(23,26]}_{AgeBucket}$		0.980***	0.827***
		(0.014)	(0.015)
$D^{(23,26]}_{AgeBucket} \times D_{PostAct}$		−0.126***	−0.336***
		(0.014)	(0.015)
$D^{(26,32]}_{AgeBucket}$		1.626***	1.417***
		(0.012)	(0.013)
$D^{(26,32]}_{AgeBucket} \times D_{PostAct}$		−0.369***	−0.674***
		(0.012)	(0.013)
$D^{(32,45]}_{AgeBucket}$		1.780***	1.533***
		(0.014)	(0.015)
$D^{(32,45]}_{AgeBucket} \times D_{PostAct}$		−0.395***	−0.735***
		(0.013)	(0.014)
$D^{>45}_{AgeBucket}$		1.568***	1.347***
		(0.037)	(0.041)
$D^{>45}_{AgeBucket} \times D_{PostAct}$		−0.385***	−0.692***
		(0.037)	(0.040)
Constant	0.121***	−1.296***	−0.718***
	(0.006)	(0.009)	(0.011)
Pseudo R^2	15.00%	7.64%	17.96%

Table 3: **Current Rate and Customer Channel**

This table presents the results of panel regressions of *CurrentRate* (in basis points) on the combination of the online lending act dummy $D_{PostAct}$, $D_{CustomerChannel}$ and their interaction (Model (1)), the combination of the online lending act dummy $D_{PostAct}$, $D_{CustomerChannel}$, their interaction, the dummies of *CreditRating*–$D^{LowerDefaultRisk}_{CreditRating}$, $D^{HigherDefaultRisk}_{CreditRating}$, and $D^{HighestDefaultRisk}_{CreditRating}$, and the interactions of $D_{CustomerChannel}$ with the dummies of *CreditRating* (Model (2)), and the combination of the online lending act dummy $D_{PostAct}$, $D_{CustomerChannel}$, their interaction, the dummies of *AgeBucket*–$D^{(23,26]}_{AgeBucket}$, $D^{(26,32]}_{AgeBucket}$, $D^{(32,45]}_{AgeBucket}$, $D^{>45}_{AgeBucket}$, and the interactions of $D_{CustomerChannel}$ with the dummies of *AgeBucket* (Model (3)), respectively. $D_{CustomerChannel}$ is 1 for the customer/borrower solicited by lender, 0 otherwise. $D_{PostAct}$ is equal to one for days after August 24, 2016, 0 otherwise. All regressions cluster the standard errors by both loan borrowers and loan start date. The sample consists of 2,998,627 loan observations of 1,394,502 loan borrowers. The loan origination dates span from October 11, 2014 through October 31, 2016. The loan maturity dates span from September 29, 2016 to October 31, 2018. The numbers in parentheses are standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
$D_{CustomerChannel}$	−4.703***	−1.043	−5.297***
	(0.790)	(0.756)	(0.697)
$D_{PostAct}$	5.904**	4.644	15.388***
	(2.973)	(2.909)	(2.875)
$D_{CustomerChannel} \times D_{PostAct}$	−8.921***	−8.498***	−5.983***
	(0.947)	(0.905)	(0.739)
$D^{LowerDefaultRisk}_{CreditRating}$		9.705***	
		(0.381)	
$D_{CustomerChannel} \times D^{LowerDefaultRisk}_{CreditRating}$		0.015	
		(0.583)	
$D_{CustomerChannel} \times D^{LowerDefaultRisk}_{CreditRating} \times D_{PostAct}$		4.377***	
		(1.179)	
$D^{HigherDefaultRisk}_{CreditRating}$		12.419***	
		(0.651)	
$D_{CustomerChannel} \times D^{HigherDefaultRisk}_{CreditRating}$		3.582***	
		(1.203)	
$D_{CustomerChannel} \times D^{HigherDefaultRisk}_{CreditRating} \times D_{PostAct}$		4.774**	
		(2.017)	
$D^{HighestDefaultRisk}_{CreditRating}$		14.971***	
		(0.452)	
$D_{CustomerChannel} \times D^{HighestDefaultRisk}_{CreditRating}$		3.737**	
		(1.754)	
$D_{CustomerChannel} \times D^{HighestDefaultRisk}_{CreditRating} \times D_{PostAct}$		5.147**	
		(2.256)	
$D^{(23,26]}_{AgeBucket}$			−6.941***
			(0.689)
$D_{CustomerChannel} \times D^{(23,26]}_{AgeBucket}$			3.148***
			(0.515)
$D_{CustomerChannel} \times D^{(23,26]}_{AgeBucket} \times D_{PostAct}$			−8.052***
			(0.739)
$D^{(26,32]}_{AgeBucket}$			−5.840***
			(1.185)
$D_{CustomerChannel} \times D^{(26,32]}_{AgeBucket}$			2.845***
			(0.700)
$D_{CustomerChannel} \times D^{(26,32]}_{AgeBucket} \times D_{PostAct}$			−14.372***
			(1.106)
$D^{(32,45]}_{AgeBucket}$			−5.827***
			(1.310)
$D_{CustomerChannel} \times D^{(32,45]}_{AgeBucket}$			3.701***
			(0.654)
$D_{CustomerChannel} \times D^{(32,45]}_{AgeBucket} \times D_{PostAct}$			−18.395***
			(1.280)
$D^{>45}_{AgeBucket}$			−3.369**
			(1.357)
$D_{CustomerChannel} \times D^{>45}_{AgeBucket}$			6.261***
			(0.536)
$D_{CustomerChannel} \times D^{>45}_{AgeBucket} \times D_{PostAct}$			−21.950***
			(1.276)
Constant	28.148***	22.781***	30.934***
	(1.562)	(1.462)	(1.818)
R^2	2.54%	4.96%	6.57%

Table 4: **Credit Limit and Customer Channel**

This table presents the results of panel regressions of *CreditLimit* (in thousands) on the combination of the online lending act dummy $D_{PostAct}$, $D_{CustomerChannel}$ and their interaction (Model (1)), the combination of the online lending act dummy $D_{PostAct}$, $D_{CustomerChannel}$, their interaction, the dummies of *CreditRating*–$D^{LowerDefaultRisk}_{CreditRating}$, $D^{HigherDefaultRisk}_{CreditRating}$, and $D^{HighestDefaultRisk}_{CreditRating}$, and the interactions of $D_{CustomerChannel}$ with the dummies of *CreditRating* (Model (2)), and the combination of the online lending act dummy $D_{PostAct}$, $D_{CustomerChannel}$, their interaction, the dummies of *AgeBucket*–$D^{(23,26]}_{AgeBucket}$, $D^{(26,32]}_{AgeBucket}$, $D^{(32,45]}_{AgeBucket}$, $D^{>45}_{AgeBucket}$, and the interactions of $D_{CustomerChannel}$ with the dummies of *AgeBucket* (Model (3)), respectively. $D_{CustomerChannel}$ is 1 for the customer/borrower solicited by lender, 0 otherwise. $D_{PostAct}$ is equal to one for days after August 24, 2016, 0 otherwise. All regressions cluster the standard errors by both loan borrowers and loan start date. The sample consists of 2,998,627 loan observations of 1,394,502 loan borrowers. The loan origination dates span from October 11, 2014 through October 31, 2016. The loan maturity dates span from September 29, 2016 to October 31, 2018. The numbers in parentheses are standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
$D_{CustomerChannel}$	−0.133***	−0.913***	−0.300***
	(0.025)	(0.022)	(0.024)
$D_{PostAct}$	−1.360***	−0.964***	−1.773***
	(0.054)	(0.044)	(0.060)
$D_{CustomerChannel} \times D_{PostAct}$	0.925***	0.538***	0.665***
	(0.028)	(0.026)	(0.023)
$D^{LowerDefaultRisk}_{CreditRating}$		−1.664***	
		(0.030)	
$D_{CustomerChannel} \times D^{LowerDefaultRisk}_{CreditRating}$		−0.193***	
		(0.037)	
$D_{CustomerChannel} \times D^{LowerDefaultRisk}_{CreditRating} \times D_{PostAct}$		0.002	
		(0.029)	
$D^{HigherDefaultRisk}_{CreditRating}$		−3.156***	
		(0.030)	
$D_{CustomerChannel} \times D^{HigherDefaultRisk}_{CreditRating}$		0.541***	
		(0.045)	
$D_{CustomerChannel} \times D^{HigherDefaultRisk}_{CreditRating} \times D_{PostAct}$		0.211***	
		(0.052)	
$D^{HighestDefaultRisk}_{CreditRating}$		−3.740***	
		(0.04)	
$D_{CustomerChannel} \times D^{HighestDefaultRisk}_{CreditRating}$		0.783***	
		(0.10)	
$D_{CustomerChannel} \times D^{HighestDefaultRisk}_{CreditRating} \times D_{PostAct}$		0.186	
		(0.12)	
$D^{(23,26]}_{AgeBucket}$			0.267***
			(0.033)
$D_{CustomerChannel} \times D^{(23,26]}_{AgeBucket}$			0.098***
			(0.024)
$D_{CustomerChannel} \times D^{(23,26]}_{AgeBucket} \times D_{PostAct}$			0.116**
			(0.050)
$D^{(26,32]}_{AgeBucket}$			−0.138***
			(0.029)
$D_{CustomerChannel} \times D^{(26,32]}_{AgeBucket}$			0.292***
			(0.039)
$D_{CustomerChannel} \times D^{(26,32]}_{AgeBucket} \times D_{PostAct}$			0.877***
			(0.038)
$D^{(32,45]}_{AgeBucket}$			0.126***
			(0.040)
$D_{CustomerChannel} \times D^{(32,45]}_{AgeBucket}$			0.231***
			(0.054)
$D_{CustomerChannel} \times D^{(32,45]}_{AgeBucket} \times D_{PostAct}$			1.075***
			(0.039)
$D^{>45}_{AgeBucket}$			−0.125**
			(0.055)
$D_{CustomerChannel} \times D^{>45}_{AgeBucket}$			0.482***
			(0.071)
$D_{CustomerChannel} \times D^{>45}_{AgeBucket} \times D_{PostAct}$			1.009***
			(0.058)
Constant	8.184***	9.314***	8.147***
	(0.046)	(0.030)	(0.050)
R^2	3.07%	15.71%	4.70%

Table 5: **In Arrears Indicator**

This table presents the results of panel Logit regressions of $InArrearsIndicator$ on the combination of the online lending act dummy $D_{PostAct}$, $D_{CustomerChannel}$ and their interaction (Model (1)), the combination of the online lending act dummy $D_{PostAct}$, $D_{CustomerChannel}$, their interaction, the dummies of $CreditRating$–$D^{LowerDefaultRisk}_{CreditRating}$, $D^{HigherDefaultRisk}_{CreditRating}$, and $D^{HighestDefaultRisk}_{CreditRating}$, and the interactions of $D_{CustomerChannel}$ with the dummies of $CreditRating$ (Model (2)), and the combination of the online lending act dummy $D_{PostAct}$, $D_{CustomerChannel}$, their interaction, the dummies of $AgeBucket$–$D^{(23,26]}_{AgeBucket}$, $D^{(26,32]}_{AgeBucket}$, $D^{(32,45]}_{AgeBucket}$, $D^{>45}_{AgeBucket}$, and the interactions of $D_{CustomerChannel}$ with the dummies of $AgeBucket$ (Model (3)), respectively. $InArrearsIndicator$ is 1 for the loan in arrears, 0 otherwise. $D_{CustomerChannel}$ is 1 for the customer/borrower solicited by lender, 0 otherwise. $D_{PostAct}$ is equal to one for days after August 24, 2016, 0 otherwise. All regressions cluster the standard errors by both loan borrowers and loan start date. The sample consists of 2,998,627 loan observations of 1,394,502 loan borrowers. The loan origination dates span from October 11, 2014 through October 31, 2016. The loan maturity dates span from September 29, 2016 to October 31, 2018. The numbers in parentheses are standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
$D_{CustomerChannel}$	−0.297***	−0.117**	−0.334***
	(0.038)	(0.048)	(0.054)
$D_{PostAct}$	0.365***	0.270***	0.383***
	(0.028)	(0.029)	(0.023)
$D_{CustomerChannel} \times D_{PostAct}$	0.047	0.237***	0.022
	(0.044)	(0.050)	(0.047)
$D^{LowerDefaultRisk}_{CreditRating}$		0.555***	
		(0.035)	
$D_{CustomerChannel} \times D^{LowerDefaultRisk}_{CreditRating}$		0.328***	
		(0.077)	
$D^{HigherDefaultRisk}_{CreditRating}$		0.851***	
		(0.039)	
$D_{CustomerChannel} \times D^{HigherDefaultRisk}_{CreditRating}$		0.003	
		(0.147)	
$D^{HighestDefaultRisk}_{CreditRating}$		0.889***	
		(0.054)	
$D_{CustomerChannel} \times D^{HighestDefaultRisk}_{CreditRating}$		0.014	
		(0.506)	
$D^{(23,26]}_{AgeBucket}$			−0.036
			(0.056)
$D_{CustomerChannel} \times D^{(23,26]}_{AgeBucket}$			0.065
			(0.063)
$D^{(26,32]}_{AgeBucket}$			−0.084**
			(0.053)
$D_{CustomerChannel} \times D^{(26,32]}_{AgeBucket}$			0.165***
			(0.058)
$D^{(32,45]}_{AgeBucket}$			−0.332***
			(0.072)
$D_{CustomerChannel} \times D^{(32,45]}_{AgeBucket}$			0.099
			(0.067)
$D^{>45}_{AgeBucket}$			−0.398***
			(0.214)
$D_{CustomerChannel} \times D^{>45}_{AgeBucket}$			0.311*
			(0.174)
$Constant$	−5.537***	−5.918***	−5.488***
	(0.024)	(0.031)	(0.031)
$Pseudo\ R^2$	0.33%	1.09%	0.42%

Table 6: **Arrears Amount**

This table presents the results of panel Tobit regressions of $ArrearsAmount$ (in thousands) on the combination of the online lending act dummy $D_{PostAct}$, $D_{CustomerChannel}$ and their interaction (Model (1)), the combination of the online lending act dummy $D_{PostAct}$, $D_{CustomerChannel}$, their interaction, the dummies of $CreditRating$–$D^{LowerDefaultRisk}_{CreditRating}$, $D^{HigherDefaultRisk}_{CreditRating}$, and $D^{HighestDefaultRisk}_{CreditRating}$, and the interactions of $D_{CustomerChannel}$ with the dummies of $CreditRating$ (Model (2)), and the combination of the online lending act dummy $D_{PostAct}$, $D_{CustomerChannel}$, their interaction, the dummies of $AgeBucket$–$D^{(23,26]}_{AgeBucket}$, $D^{(26,32]}_{AgeBucket}$, $D^{(32,45]}_{AgeBucket}$, $D^{>45}_{AgeBucket}$, and the interactions of $D_{CustomerChannel}$ with the dummies of $AgeBucket$ (Model (3)), respectively. $D_{CustomerChannel}$ is 1 for the customer/borrower solicited by lender, 0 otherwise. $D_{PostAct}$ is equal to one for days after August 24, 2016, 0 otherwise. All regressions cluster the standard errors by both loan borrowers and loan start date. The sample consists of 2,998,627 loan observations of 1,394,502 loan borrowers. The loan origination dates span from October 11, 2014 through October 31, 2016. The loan maturity dates span from September 29, 2016 to October 31, 2018. The numbers in parentheses are standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
$D_{CustomerChannel}$	−0.075***	−0.027**	−0.087***
	(0.010)	(0.012)	(0.015)
$D_{PostAct}$	0.107***	0.083***	0.110***
	(0.009)	(0.008)	(0.011)
$D_{CustomerChannel} \times D_{PostAct}$	0.007	0.055***	0.002
	(0.012)	(0.013)	(0.013)
$D^{LowerDefaultRisk}_{CreditRating}$		0.145***	
		(0.011)	
$D_{CustomerChannel} \times D^{LowerDefaultRisk}_{CreditRating}$		0.090***	
		(0.021)	
$D^{HigherDefaultRisk}_{CreditRating}$		0.230***	
		(0.013)	
$D_{CustomerChannel} \times D^{HigherDefaultRisk}_{CreditRating}$		0.000	
		(0.040)	
$D^{HighestDefaultRisk}_{CreditRating}$		0.240***	
		(0.017)	
$D_{CustomerChannel} \times D^{HighestDefaultRisk}_{CreditRating}$		0.000	
		(0.141)	
$D^{(23,26]}_{AgeBucket}$			0.008
			(0.015)
$D_{CustomerChannel} \times D^{(23,26]}_{AgeBucket}$			0.020
			(0.017)
$D^{(26,32]}_{AgeBucket}$			0.019
			(0.014)
$D_{CustomerChannel} \times D^{(26,32]}_{AgeBucket}$			0.044***
			(0.016)
$D^{(32,45]}_{AgeBucket}$			−0.079***
			(0.019)
$D_{CustomerChannel} \times D^{(32,45]}_{AgeBucket}$			0.024
			(0.018)
$D^{>45}_{AgeBucket}$			−0.102***
			(0.055)
$D_{CustomerChannel} \times D^{>45}_{AgeBucket}$			0.075
			(0.047)
Constant	−2.166***	−2.261***	−2.155***
	(0.072)	(0.075)	(0.072)
Pseudo R^2	0.37%	1.14%	0.45%

Table 7: **Days In Arrears**

This table presents the results of panel Tobit regressions of $DaysInArrears$ on the combination of the online lending act dummy $D_{PostAct}$, $D_{CustomerChannel}$ and their interaction (Model (1)), the combination of the online lending act dummy $D_{PostAct}$, $D_{CustomerChannel}$, their interaction, the dummies of $CreditRating$–$D_{CreditRating}^{LowerDefaultRisk}$, $D_{CreditRating}^{HigherDefaultRisk}$, and $D_{CreditRating}^{HighestDefaultRisk}$, and the interactions of $D_{CustomerChannel}$ with the dummies of $CreditRating$ (Model (2)), and the combination of the online lending act dummy $D_{PostAct}$, $D_{CustomerChannel}$, their interaction, the dummies of $AgeBucket$–$D_{AgeBucket}^{(23,26]}$, $D_{AgeBucket}^{(26,32]}$, $D_{AgeBucket}^{(32,45]}$, $D_{AgeBucket}^{>45}$, and the interactions of $D_{CustomerChannel}$ with the dummies of $AgeBucket$ (Model (3)), respectively. $D_{CustomerChannel}$ is 1 for the customer/borrower solicited by lender, 0 otherwise. $D_{PostAct}$ is equal to one for days after August 24, 2016, 0 otherwise. All regressions cluster the standard errors by both loan borrowers and loan start date. The sample consists of 2,998,627 loan observations of 1,394,502 loan borrowers. The loan origination dates span from October 11, 2014 through October 31, 2016. The loan maturity dates span from September 29, 2016 to October 31, 2018. The numbers in parentheses are standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
$D_{CustomerChannel}$	−1.397***	−0.462***	−1.532***
	(0.171)	(0.209)	(0.244)
$D_{PostAct}$	1.663***	1.194***	1.807***
	(0.132)	(0.132)	(0.176)
$D_{CustomerChannel} \times D_{PostAct}$	0.118	0.984***	0.021
	(0.200)	(0.220)	(0.214)
$D_{CreditRating}^{LowerDefaultRisk}$		2.654***	
		(0.164)	
$D_{CustomerChannel} \times D_{CreditRating}^{LowerDefaultRisk}$		1.522***	
		(0.354)	
$D_{CreditRating}^{HigherDefaultRisk}$		4.195***	
		(0.190)	
$D_{CustomerChannel} \times D_{CreditRating}^{HigherDefaultRisk}$		0.100	
		(0.690)	
$D_{CreditRating}^{HighestDefaultRisk}$		4.482***	
		(0.264)	
$D_{CustomerChannel} \times D_{CreditRating}^{HighestDefaultRisk}$		−0.632	
		(2.348)	
$D_{AgeBucket}^{(23,26]}$			−0.208
			(0.253)
$D_{CustomerChannel} \times D_{AgeBucket}^{(23,26]}$			0.276
			(0.292)
$D_{AgeBucket}^{(26,32]}$			−0.470*
			(0.242)
$D_{CustomerChannel} \times D_{AgeBucket}^{(26,32]}$			0.730***
			(0.265)
$D_{AgeBucket}^{(32,45]}$			−1.616***
			(0.319)
$D_{CustomerChannel} \times D_{AgeBucket}^{(32,45]}$			0.512*
			(0.305)
$D_{AgeBucket}^{>45}$			−2.016***
			(0.937)
$D_{CustomerChannel} \times D_{AgeBucket}^{>45}$			1.412*
			(0.787)
$Constant$	−36.301***	−37.754***	−35.997***
	(0.444)	(0.472)	(0.447)
$Pseudo\ R^2$	0.24%	0.87%	0.32%

Table 8: **Geographic Heterogeneity**

This table presents the results of panel regression of the following variables on $CustomerAreaLocation$: $CustomerChannel$ (Model (1)), $CurrentRate \times 100$ (Model (2)), $CreditLimit$ (Model (3)), $InArrearsIndicator$ (Model (4)), and $ArrearsAmount$ (Model (5)),. The omitted dummy stands for the Anhui province. All regressions cluster the standard errors by both loan borrowers and loan start date as in Petersen (2009). The sample consists of 2,998,627 loan observations of 1,394,502 loan borrowers. The loan origination dates span from October 11, 2014 through October 31, 2016. The loan maturity dates span from September 29, 2016 to October 31, 2018. The numbers in parentheses are t-statistics. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)
	$CustomerChannel$	$Cur.Rate \times 100$	$CreditLimit$	$InArrears$ $Indicator$	$Arrears$ $Amount$
2 Beijing Municipality	1.11***	−0.02***	793.83***	0.28***	76.41***
	(138.77)	(−2.85)	(24.58)	(4.61)	(3.67)
3 Chongqing Municipality	0.32***	0.07***	54.57**	0.18**	44.32*
	(32.19)	(7.75)	(2.09)	(2.29)	(1.70)
4 Fujian Province	0.33***	−0.05***	58.57	0.23***	65.05***
	(35.34)	(−5.00)	(1.37)	(3.13)	(2.65)
5 Gansu Province	0.14***	0.16***	−702.48***	0.33***	88.88**
	(9.82)	(11.46)	(−17.01)	(3.19)	(2.25)
6 Guangdong Province	0.77***	0.01	18.90	0.19***	47.27**
	(102.47)	(1.51)	(0.72)	(3.20)	(2.35)
7 Guangxi Zhuang Auto. Reg.	0.42***	0.07***	−252.10***	0.19**	49.02*
	(41.55)	(7.33)	(−6.12)	(2.45)	(1.76)
8 Guizhou Province	0.14***	0.17***	−208.82***	0.18*	48.23
	(10.16)	(13.47)	(−6.40)	(1.74)	(1.31)
9 Hainan Province	0.40***	0.11***	−504.51***	0.27**	63.21
	(22.04)	(6.83)	(−10.27)	(2.03)	(1.36)
10 Hebei Province	0.32***	0.00	−368.84***	0.19***	42.73*
	(35.03)	(0.48)	(−11.57)	(2.70)	(1.80)
11 Henan Province	0.10***	−0.01	−260.23***	0.16**	41.64*
	(10.41)	(−1.47)	(−10.46)	(2.31)	(1.71)
12 Heilongjiang Province	0.01	0.15***	−206.64***	0.09	25.34
	(1.10)	(13.85)	(−6.01)	(1.05)	(0.85)
13 Hubei Province	0.29***	0.01	−63.63***	0.19***	47.15**
	(33.04)	(1.34)	(−2.74)	(2.75)	(2.08)
14 Hunan Province	0.25***	0.02**	−322.60***	0.12	28.33
	(24.20)	(2.09)	(−8.58)	(1.52)	(1.04)
15 Jilin Province	0.02	0.13***	−115.09***	0.13	34.02
	(1.38)	(10.64)	(−3.83)	(1.34)	(1.02)
16 Jiangsu Province	0.53***	0.01	196.62***	0.01	0.90
	(65.85)	(1.22)	(6.55)	(0.13)	(0.04)
17 Jiangxi Province	−0.11***	0.03***	−407.30***	0.21**	48.46
	(−9.55)	(2.90)	(−9.31)	(2.42)	(1.59)
18 Liaoning Province	0.26***	0.10***	−71.31**	0.20***	49.94**
	(28.72)	(11.49)	(−2.19)	(2.86)	(2.07)
19 Inner Mongolia Auto. Reg.	0.42***	0.15***	−601.63***	0.53***	137.73***
	(30.68)	(12.42)	(−15.06)	(5.64)	(4.13)
20 Ningxia Hui Auto. Reg.	0.38***	0.05***	−923.77***	0.80***	213.10***
	(14.75)	(2.75)	(−10.73)	(5.41)	(4.46)
21 Qinghai Province	0.84***	0.16***	−753.02***	0.32	72.09
	(21.55)	(6.86)	(−7.21)	(1.17)	(0.90)
22 Shaanxi Province	−0.03***	0.01	193.68***	0.19***	50.87**
	(−3.44)	(1.39)	(8.13)	(2.76)	(2.13)
23 Shandong Province	0.28***	0.00	−396.88***	0.23***	63.44***
	(32.18)	(0.47)	(−14.83)	(3.52)	(2.80)
24 Shanxi Province	−0.18***	−0.01	−211.11***	0.30***	78.25***
	(−16.07)	(−0.63)	(−7.87)	(3.79)	(2.86)
25 Shanghai Municipality	0.98***	−0.03***	702.66***	0.26***	64.82***
	(114.51)	(−3.38)	(25.03)	(3.93)	(2.95)
26 Sichuan Province	0.44***	0.07***	149.53***	0.27***	68.40***
	(54.53)	(8.70)	(7.31)	(4.20)	(3.17)
27 Tianjin Municipality	0.86***	0.09***	−99.56*	0.23***	54.93**
	(84.42)	(9.34)	(−1.79)	(3.03)	(2.10)
28 Tibet Auto. Reg.	1.19***	0.11**	−52.00	1.16***	316.41***
	(21.45)	(2.09)	(−0.38)	(4.65)	(2.72)
29 Xinjiang Uyghur Auto. Reg.	0.69***	0.08***	−891.34***	0.29**	80.97*
	(40.90)	(5.93)	(−16.90)	(2.39)	(1.91)
30 Yunnan Province	0.35***	0.13***	−422.68***	0.15	36.84
	(26.13)	(10.39)	(−12.15)	(1.46)	(1.11)
31 Zhejiang Province	0.51***	−0.07***	70.89**	0.14*	38.75
	(55.26)	(−7.62)	(2.35)	(1.85)	(1.60)
Constant	−0.55***	−0.14***	8,309.64***	−5.60***	−2,180.73***
	(−79.95)	(−20.39)	(124.68)	(−102.53)	(−30.05)