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Working Papers
RESEARCH DEPARTMENT

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WP 23-26

PUBLISHED
October 2023

FRB CFI
PHILADELPHIA

ISSN: 1962-5361

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DOI: https://doi.org/10.21799/frbp.wp.2023.26

Did Fintech Loans Default More During the COVID-19 Pandemic? Were Fintech Firms "Cream Skimming" the Best Borrowers?

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October 26, 2023

Abstract

A growing portion of consumer credit has recently been devoted to unsecured personal installment loans. Fintech firms have been active players in this market, with an increasing market share, while the market share of banks has declined. Studies of fintech lending have shown that their digital access and ability to leverage alternative data have increased accessibility in underserved areas, enabled consumers with thin credit files to obtain credit, and provided a lower cost alternative to long-term credit card financing. This paper exams three questions: (1) Do proprietary loan rating systems accurately predict the likelihood of default? (2) Can a proprietary loan rating system, leveraging alternative data, that was developed in a favorable economic period continue to perform well under adverse economic conditions (such as the COVID-19 pandemic)? (3) Have fintechs been "cream skimming," i.e., underpricing the cost of credit to top-tier customers? This study uses data from LendingClub, one of the largest fintech lenders in the personal loan market. We find that LendingClub's loan rating system is superior to traditional measures of credit risk when predicting the likelihood of default and that the loan rating system continued to perform well during the pandemic period. Finally, we find no evidence of cream skimming.

Keywords: Fintech, peer-to-peer (P2P), alternative data, financial inclusion, credit access, COVID-19, fintech loan default, cream skimming, fintech loan rate

JEL Classification: G21, G28, G18, L21

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I. Introduction

Fintech lending grew rapidly after the 2008 financial crisis. Access to these loans made it possible for some consumers, who would not have been able to qualify for credit from other sources, to obtain a loan and to do so at a rate lower than what their credit scores would suggest. Fintech lending continued to expand from unsecured personal installment loans to other loan products, including student loans, auto loans, mortgage loans, and small business loans. Jagtiani and Lemieux (2019) explore the roles of alternative data in enhancing credit access to those potentially underserved by traditional lenders. More than a decade of rapid growth in fintech lending led some to question during the COVID-19 pandemic (2020–2021) whether consumers may have been overleveraged and whether there would subsequently be more fintech loan defaults. In this paper, we investigate whether the comparative advantage of fintech firms (in their ability to more accurately price credit risk and predict future default) persisted in the unexpected economic environment that occurred during the pandemic period.

This paper may be considered an extension of Jagtiani and Lemieux (2019), who documented the roles of alternative data in enhancing accuracy in predicting the default risk of loans to nonprime consumers. Using data from LendingClub for unsecured personal installment loans originated from 2007 through 2015, they looked at the performance of LendingClub loan grades (LCLGs), a proprietary measure of credit risk that leverages alternative data. They found that LCLGs performed well in predicting loan performance during the two years after origination; that LCLGs were not highly correlated with FICO scores, a traditional measure of credit risk; and that LCLGs outperformed FICO scores in predicting loan defaults, thus allowing some nonprime consumers to access credit and at a lower interest rate than what they would have received through a traditional lending channel.[1]

We expand on Jagtiani and Lemieux (2019) by including the pandemic recessionary period and investigate whether LCLGs performed well during more adverse economic conditions and whether LCLGs and FICO scores still contained “different” information — i.e., would LCLGs continue to add a significant lift in default predictions during the pandemic? In this study, we also examine a finding by Di Maggio and Yao (2021) that fintechs, in general, charged customers with higher FICO scores lower rates than banks and thus “cream-skimmed” the best customers. The following

[1] References to FICO scores used for the analysis in this paper and in Jagtiani and Lemieux (2019) are associated with LendingClub data. The FICO scores in our analysis are not provided in the FRBNY Consumer Credit Panel/Equifax Data.

background information provides context for this research on the personal loan market, the pandemic, and LendingClub.

Personal Loan Market

The personal loan market is a subset of the nearly $5 trillion consumer loan market,[2] which includes revolving credit (primarily credit cards) and nonrevolving credit (which includes auto loans, education loans, and personal loans). Our study looks at loans originated between 2014 and 2019 and their performance during 2020 and 2021, the COVID-19 period. Latham (2023) reported that personal loan balances were $1.6 trillion as of yearend 2019 (based on data from TransUnion), up from $1.2 trillion on January 1, 2014. This represents over a 33 percent increase during the six-year period covered by our sample in this study. Fintechs represent growing competition for banks in this space. Latham (2023) found that, in 2014, fintechs represented 11 percent of the personal loan market. In 2019, fintechs' market share had risen to 42.6 percent of the growing market, while banks' market share had dropped from 39 percent to 26.6 percent during this same period.

The growth in fintech lending has generated questions about whether fintech lending is concentrated in any particular segment of consumers and how fintech loans are priced. Latham (2022) reported that, in 2019, only 15 percent of personal loan originations by banks were for customers with FICO scores lower than 660, while 26 percent of personal loan originations by fintechs went to customers with FICO scores lower than 660. At the other end of the spectrum, 60 percent of bank originations went to customers with FICO scores above 720, compared with 43 percent of fintech originations that went to this high-FICO group. These data indicate that, at the market level, banks target more creditworthy customers (with FICO scores above 720), while fintechs appear to target a broader range of customers. In this paper, we examine this issue and posit that LCLGs allow LendingClub to make finer distinctions among borrowers than is possible with traditional measures such as FICO scores. If this is the case, we would see borrowers with various FICO scores distributed across the loan grades assigned by LendingClub.

Another aspect of the market has been related to the interest rates that fintechs charge on their loans. Latham (2022), using data from SuperMoney, and Schulz (2022), using data from LendingTree, observe interest rates charged by these two fintech platforms. Both SuperMoney and LendingTree are peer-to-peer (P2P) lending platforms that connect potential borrowers to lenders. The papers analyzed loan offers made through their respective websites and looked at the dispersion of interest rates offered to potential borrowers with the same FICO score. Schulz (2022)

[2] Federal Reserve G.19, July 2023, available at www.federalreserve.gov/releases/g19/current/g19.pdf.

reported that the dispersion in interest rate annual percentage rates (APRs) averaged 7.1 percent for all borrowers, with the average being much higher for bottom-tier borrowers with FICO scores below 670. Latham (2022) found similar results, reporting that, for borrowers with FICO scores below 680, the spread between the highest and lowest interest rate APRs on personal loans offered by banks and those offered by fintechs was 13.67 percentage points. There are many potential reasons for this disparity, including the business model of the lender as well as their particular loan rating system. This paper sheds some light on how differences in loan rating systems can impact pricing for borrowers with similar FICO scores.

The COVID-19 Pandemic

The severe decline in economic activity due to the pandemic "lockdowns" caused unprecedented disruption in people's lives beginning in mid-March 2020. At the height of restrictions in late March 2020 and early April 2020, more than 310 million Americans were under directives ranging from "shelter in place" to "stay at home." According to the National Bureau of Economic Research (NBER), the economic contraction lasted only two months, from February 2020 to April 2020. Most of the COVID-19 restrictions were rolled back by the summer of 2021.[3] During 2020 and 2021, Congress authorized support that included extending unemployment benefits programs (including supplemental unemployment benefits), sending direct stimulus payments of $1,400 to eligible individuals, and developing supports for small businesses, among other measures.

Zabek and Larrimore (2020) reported that, before the pandemic, the Survey of Household Economics and Decisionmaking (SHED) found that the overall number of adults who said that they would pay an unexpected $400 expense with cash, savings, or a credit card paid off at the next statement was 63 percent in October 2019. The share who would pay a $400 emergency expense using cash or an equivalent increased from 64 percent in early April 2020 to 70 percent in July 2020, demonstrating the impact of the government support during the pandemic.

However, the pandemic impacted consumers unevenly. SHED also reported that, as of February 2020, 13 percent of all adults (20 percent of working adults) lost a job or were furloughed from March 2020 to the beginning of April 2020. Only 51 percent of respondents who had employment disruptions said that they were either doing okay or living comfortably in April. By contrast, 76 percent of respondents who had not experienced employment disruptions (either because they were working the same hours or because they were not working before the

[3] See the Business Cycle Dating Committee Announcement from July 19, 2021: www.nber.org/news/business-cycle-dating-committee-announcement-july-19-2021.

pandemic) said that they were doing at least okay financially. This highlights the differing impacts of the pandemic. For those who were able to continue working, their financial well-being did not suffer, but for those who lost their jobs, the impacts were more severe. Using tax filings data, Larrimore, Mortenson, and Splinter (2022) found that the share of all tax filings that suffered a decline in income of more than 10 percent increased significantly, from 26 percent in 2019 to 33 percent in 2020.

The overall consumer loan market dipped to $4.1 trillion in June 2020, down from $4.2 trillion at the beginning of that year. Using data from TransUnion, Schulz (2023) reported that the personal loan market also declined from $157 billion to $145 billion in 2020. To put this into perspective, the year-over-year growth of personal loan balances had been in the double digits since 2013, but it dropped to a negative 3 percent in 2020. TransUnion data also showed that, during the COVID period, originations of personal loans declined starting in 2019:Q3, but by 2021:Q3, originations exceeded 2019 levels. Personal loan volume rose to $167 billion in 2021 and $222 billion in 2022.

Federal Reserve data show that the delinquency rate for consumer loans at commercial banks rose from 2.32 percent in 2019:Q1 to 2.46 percent in 2020:Q1 and then fell to 1.69 percent in 2021:Q1.[4] These statistics show that the pandemic not only slowed the growth of the personal loan market but also reduced the size of the market. This may be driven by both consumers paying off existing loans and by a reduction in new originations. In this study, we look at how the pandemic period impacted LendingClub's portfolio and ask the following question: Did LCLGs continue to demonstrate superior performance (relative to traditional ratings) during these adverse economic conditions?

LendingClub

LendingClub has a history of being a pioneer from its beginning in 2007. It was the first P2P lender to register its offerings as securities with the Securities and Exchange Commission (SEC) and to offer loan trading on a secondary market. In 2014, LendingClub raised $1 billion in the largest U.S. technology initial public offering (IPO) that year.[5] LendingClub was viewed as one of the largest

[4] See "Charge-Off and Delinquency Rates on Loans and Leases at Commercial Banks" from the Board of Governors of the Federal Reserve System, available at www.federalreserve.gov/releases/Chargeoff/delallsa.htm.

[5] See "Lending Club IPO Tops $1 Billion After Exercise of Over-Allotment Option," from LendingClub (December 16, 2014), available at https://ir.lendingclub.com/news/news-details/2014/Lending-Club-IPO-Tops-1-Billion-After-Exercise-of-Over-Allotment-Option/default.aspx.

fintechs at that time, and in 2015, it reported that $15.98 billion in personal loans had been originated through its platform up to December 31, 2015.

During the sample period, LendingClub offered unsecured personal loans between $1,000 and $40,000 that were originated through a partner bank (WebBank in Salt Lake City, Utah). The standard loan period was three years, but the maximum term was five years. This is the loan product that is the focus of this study. Investors were able to search and browse the loan listings on LendingClub's website and select the loans that they wanted to invest in based on the information supplied about the borrower, the amount of loan, the loan grade, and the loan purpose. Investors made money from the interest on these loans. LendingClub made money by charging borrowers an origination fee and by charging investors a service fee.

Today, LendingClub is an insured depository institution, having received a bank charter in February 2021 with the consummation of its purchase of Radius Bank. Since becoming a bank, LendingClub has shut down its P2P lending program, but it continues to offer unsecured installment loans of up to $40,000 that typically have fixed interest rates and terms of three to five years. LendingClub Bank either sells consumer loans to institutional investors or retains them on its balance sheet. In its 2020 10-K report, the company describes the impact COVID-19 had on its operations.

> *As of the date of this Report, COVID-19 has had, and may continue to have, a number of adverse effects on our business and results of operations, including materially decreased demand for our products and negative pressure on overall platform returns, including as a result of increased credit risk of borrowers (including elevated delinquencies and charge-off rates) and the implementation of forbearance plans (pg. 27)*[6]

LendingClub reported that it adjusted its operations by adding customer support capacity, launching hardship/forbearance plans, waiving late fees, tightening underwriting, increasing interest rates on new loans, and laying off 30 percent of its workforce. As of December 31, 2020, repayment rates remained at pre-COVID-19 levels, and delinquency rates were lower than historical averages. LendingClub also reported that the credit and pricing policy changes made during 2019 and into 2020 resulted in a change in the mix of personal loan origination volume from higher-risk grades D through F to lower-risk grades A through C.[7]

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[6] See the report on the SEC Filings page of LendingClub's website, available at ir.lendingclub.com/financials/Docs/.

[7] There were no E-rated, F-rated, or G-rated loans originated in 2020. Of the 518,107 loans originated in 2019, a very small number were poorly rated: E-rated (3,397 loans, or 0.656 percent), F-rated (36 loans or 0.007 percent), and G-rated (17 loans or 0.003 percent).

II. Our Objectives and the Literature Review

This paper pursues three lines of inquiry. First, we ask whether proprietary loan rating systems more accurately predict the likelihood of default than the traditional risk matrix. Second, we ask whether a proprietary loan rating system that was developed in a favorable economic period, which leverages alternative data, would perform well under adverse economic conditions. We explore loan performance in a more recent period with a COVID shock and a sudden rise in interest rates, which are both exogeneous events that took place after the loans were originated. It is interesting to observe whether the artificial intelligence/machine learning (AI/ML) models and alternative data used by fintech lenders really worked when an unforeseen exogenous event hit the financial sector. Third, we explore whether fintech lenders (such as LendingClub) underprice the cost of credit to "better" customers? We test the following hypotheses (H1 to H3):

> ***H1****: Alternative data add value in predicting loan default. That is, alternative data (used in LendingClub's proprietary loan rating system) provide a lift in the accuracy of the predicted default rate.*
>
> ***H2****: The value added from alternative data continues to exist even during an unexpected, severe adverse economic environment. That is, the proprietary ratings assigned by LendingClub for loans that were originated during the pre-COVID period (favorable economic conditions) remained accurate during the COVID pandemic.*
>
> ***H3****: Fintech lenders do not compete with banks to cream-skim the best customers. That is, the interest rates charged by LendingClub on loans made to prime and super-prime consumers (using a few different thresholds for robust findings: a FICO score above 760, a FICO score above 780, and a FICO score above 800) are not lower than a "reasonable" rate.*

Research on fintech lending has increased with the availability of data. Allen, Gu, and Jagtiani (2021) present a comprehensive review of the literature on a wide range of topics related to fintechs. Their discussion of marketplace and P2P lending presents a growing body of literature that finds that alternative data — which refers to data outside of the traditional credit scores, requested loan amount, and current delinquencies — can be important in lenders' credit evaluations. White (2022), using data from Experian, reported that 62 million Americans have thin credit files, making it difficult or impossible for a lender to obtain a FICO score for those individuals. Having additional ways to assess the credit risk of a prospective borrower allows lenders to better assess the credit risk of the applicant.

Fintech lenders became a presence in the personal loan market in 2008, after the financial crisis. They generally do not have face-to-face interaction with loan applicants and have limited opportunity to leverage the traditional "soft information" that has been found to be important in bank relationship lending. However, fintech lenders have developed complex statistical methods using AI and ML techniques, along with (nontraditional) alternative data, to assess credit risk. Other studies have investigated various kinds of alternative data and found that they improve default prediction. Iyer, Khwaja, Luttmer, and Shue (2016); Hildebrandt et al. (2017); Lin et al. (2013); Gao et al. (2022); Dorfleitner et al. (2016); and Berg et al. (2020) found information on friendship and social networks, online footprints, and text-based analysis to be effective alternative data. Another source of alternative data is payments information. Square, PayPal, Stripe, Amazon, and Alibaba are real-world examples of lenders that make credit decisions based on proprietary payment data. Ghosh et al. (2022), using data from India, show that payments information predicts a higher likelihood of loan approval, a lower interest rate, and a higher loan amount for small businesses. These studies show that digital footprint variables complement, rather than substitute, the standard traditional information from consumer credit bureaus.

To date, several studies, such as Jagtiani and Lemieux (2019) and Croux et al. (2020), have shown that the fintech loan rating models perform well in the consumer lending space. In addition, in the small business lending space, Cornelli et al. (2023) show, using small business loan data from LendingClub and Funding Circle, that the delinquency rates predicted by fintech lenders are more precise than those predicted by traditional credit scores for small business loans as well. Cornelli et al. (2023) also find that actual default rates vary significantly within the same FICO segments for business loans. This further corroborates Jagtiani and Lemieux (2019), who found that there was a low correlation between LendingClub's internal proprietary scores in LCLG (which predict default) and FICO scores. Di Maggio et al. (2022) used data from the consumer lender Upstart and found strong evidence that loan rating systems that used alternative data provided broader credit access. Applicants with low credit scores and short credit histories benefited the most, and these selected low-score borrowers had a low likelihood of default.

In a recent study using personal loan data from a credit bureau from 2005 to 2019, Ueda, Zhang, and Zhao (2023) find that fintech firms' entry into the unsecured personal loan market brings lower costs for less risky borrowers. They also find that risky borrowers that are repeat fintech customers can borrow larger loans at lower rates, as fintech lenders incorporate their experience with the customer into that customer's rating. Johnson et al. (2023) found similar pricing disparities between fintechs and banks. They found that pricing (loan rates) relied heavily on conventional credit scores but found loan rates were not responsive to default risk. This seems to provide support to our hypothesis that alternative data are a factor in fintech loan pricing.

While the results of these studies are promising, none have looked at how these models perform under adverse economic conditions. Bao and Huang (2021) looked at the impact of the pandemic on fintech and traditional bank borrowers in China. They found that fintech firms were more likely to expand credit access to new and financially constrained borrowers after the start of the pandemic. However, the delinquency rate of fintech loans (fixed-rate installment loans) tripled after the outbreak, but there was no significant change in the delinquency of bank loans (line of credit, rather than installment, loans). A few studies have looked at Paycheck Protection Program (PPP) loans that fintechs made to businesses. Griffin et al. (2023) find that fintech PPP loans are six times more likely than loans from traditional banks to have an indicator that the loan is suspicious, and the misreporting rate increased over time. On a more positive side, Erel and Liebersohn (2020) find that fintech lenders increased access to the PPP by lending more in zip codes with fewer traditional banks, with lower incomes, and with higher minority percentages. Papers by Scharfstein and Chernenko (2022) and Howell et al. (2022) found that fintech PPP lending reached more diverse businesses than traditional bank PPP lending. In this paper, we will look at the impact of the pandemic on personal loans made by LendingClub, a U.S. fintech lender.

Another strand of fintech research has focused on the benefits of fintech lending in enhancing credit access for consumers who could not access credit from traditional banks — see Chava et al. (2021), Balyuk (2022), and Goldstein, Jagtiani, and Klein (2019). Jagtiani and Lemieux (2018) found that fintech lenders have penetrated areas that may be underserved by traditional banks. Similarly, Jagtiani et al. (2021) find that mortgage loans are more likely to be from fintech lenders in zip codes where there was a higher denial rate by traditional lenders. Di Maggio and Yao (2021), using marketwide data from TransUnion, constructed matched pairs of borrowers and found that, for similar borrowers, the terms offered by fintech lenders are better for borrowers with higher credit scores and that fintech loans are more likely to default. Matched pairs are determined by location, borrower demographics, and information contained in a credit file, including credit score, number of accounts, etc. Similarly, de Roure et al. (2022) find that fintech lenders are bottom fishing, especially when regulatory shocks create a competitive disadvantage for some banks. This paper will look at a related issue and focus on the question: Does LendingClub underprice the cost of credit to “better” customers?

III. The Data

Our analysis uses data on loans originated through an online alternative channel (loan-level data from the LendingClub consumer platform). In addition, economic factors are collected from the U.S. Census Bureau and the Haver Analytics database. Economic factors include state initial unemployment claims, the local unemployment rate, the local average household income, local business bankruptcies per thousand residents, and the local home price index. The economic factors are used at the most granular level associated with the borrower (the zip code, county, or state level). Finally, we also conduct some robustness testing, using credit card–level data from the Federal Reserve Bank of New York Consumer Credit Panel/Equifax Data (CCP), which contains tradeline (account-level) data for all credit cards — allowing us to compare LendingClub personal loan default with the overall consumer default on credit cards during the same time period, i.e., during the COVID-19 pandemic. Both the LendingClub and the CCP data sets are anonymized.

We recognize that these financial products are not identical, and that credit card default from the CCP versus installment personal loan default from LendingClub may not be directly comparable. However, we feel comfortable because any bias would occur in the direction that would underestimate the role of alternative data during the pandemic. It is more likely that people would choose to default on personal installment loan from LendingClub loan before they would choose to default on any line of credit (LOC), like credit cards. The literature shows that people would try to keep the LOC loan by keeping their cards current. In addition, the literature shows that about 90 percent of people who take a personal loan from LendingClub would use it to pay off their credit card balance, suggesting substitutability between credit cards and personal loan from LendingClub; see Jagtiani and Lemieux (2019).

Our analysis focuses on the performance of LendingClub loans made between 2014 and 2019. The sample consists of over 2.5 million loans, over 1 million of which were outstanding during the COVID-19 pandemic period (defined as March 2020 to November 2021). For each of the loans in this analysis, we collect the characteristics of the borrowers (FICO score at the time of loan application, LCLG at the time of loan origination, and zip code); the characteristics of the loan (loan rate in APR, loan maturity, and origination date); and the performance of each loan in the sample from the origination month to 24 months after origination.[8] The data set also includes information on loan performance over a two-year post-origination period for approximately 98.35 percent of all loans in the data set; the performance of the remaining 1.65 percent of loans was observed over a

[8] Note that references to FICO scores used for our analysis in this paper are associated with LendingClub data — in other words, these FICO scores are not provided in the CCP data set.

23-month post-origination period (because of data limitations). Following is a discussion of the data in relation to each of the questions we investigated.

(1) Do proprietary loan rating systems accurately predict the likelihood of default?

To answer this question, we explore the default rate on all loans originated by LendingClub during the period 2014–2020. Figures 1A–1D show the percentage of loan accounts that defaulted within 12 months and 24 months after origination by FICO score (Figures 1A and 1B) and by the proprietary LCLG (Figures 1C and 1D) — all by origination year. As expected, there is a positive relationship between defaults and loan ratings that increases with lower FICO scores and lower LCLGs for defaults within either 12 months or 24 months. The curves do shift a bit by origination year, possibly reflecting an adjustment in underwriting criteria, but the positive relationship remains. These graphs indicate that both the LCLGs and FICO scores are highly correlated with the probability of default (as expected) and that the correlation increases with increasing measures of risk.

More importantly, we note that, from Figures 1A and 1B, the highest default rate for the lowest FICO segment (below 680) was about 7 percent for the 12-month period after loan origination and was about 16 percent for the 24-month period. However, we observe a much higher default rate when looking at the highest default rate for the lowest LCLG segment (G-rated) in Figures 1C and 1D — in which the highest default rate was more than 20 percent for the 12-month period after loan origination and was more than 35 percent for the 24-month period. This demonstrates that the LCLG proprietary rating was able to identify risky borrowers on a more granular level than the FICO scores did. Further statistical analysis is presented in Table 1.

(2) Can a proprietary loan rating system that was developed in a favorable economic period and leverages alternative data perform well under adverse economic conditions?

To focus on the COVID period default, we include a subsample of loans that were included in the previous figures. Among all loans originated by LendingClub during the period 2014–2020, only those loans that were still active (outstanding) are included in this portion of the analysis. Figure A1 in the Appendix shows the ratio of loans originated in each year that remained active as of the beginning of the pandemic. About 90 percent of loans that LendingClub originated in 2019 remained outstanding as of the beginning of the pandemic period. Only less than 40 percent of loans that LendingClub originated in 2017 remained outstanding as of the beginning of the pandemic. Figure A2 in the Appendix presents the breakdown of these loans (that remained active as of the start of the pandemic) by LCLG. The plot shows, for example, that about 90 percent of A-rated loans that LendingClub originated in 2019 remained active as of the beginning of the pandemic. And, only about 65 percent of G-rated loans that LendingClub originated in 2019 was outstanding as of the beginning of the pandemic.

Figures 2A and 2B show the number of loans and the FICO distribution (as of origination) for LendingClub consumer loans that were outstanding during the COVID period — by year of origination and by loan age (as of the start of the COVID period), respectively. Similarly, Figures 2C and 2D show the number of loans and the LCLG distribution for loans that were outstanding during the COVID period — by year of origination and by loan age, respectively. From these figures, it is evident that a majority of LendingClub's customers fall within the 680 to 719 FICO band — often classified as *prime* borrowers. While it varies by year, TransUnion reports that approximately 20 percent of the U.S. population falls within this FICO band.[9] Similarly, it is also evident that the majority of LendingClub's borrowers fall in the top 3 LCLGs (A-rated, B-rated, and C-rated).[10] Despite the majority of LendingClub consumer loans being in the prime categories, there are significant number of loans that are in the below-prime or near-prime (a FICO score below 680 and LCLG below C-rated) classifications across all origination years. Previous research shows that fintech lenders in general are more willing than traditional banks to offer credit to below-prime consumers; see Dolson and Jagtiani (2023).

Since LendingClub loans have either a three-year maturity or a five-year maturity, loans that were originated before 2015 were no longer outstanding as of the COVID period.[11] This is consistent with the information in Figures 2B and 2D, in which the majority of loans were originated just one or two years before the start of the COVID-19 pandemic. Very few loans are four or five years old, as most loans have a three-year maturity.

In Figure 3A, the highest default rate is observed for loans that were originated in 2019, with an 8.5 percent average default rate for the lowest FICO segment (below 680). Figure 3B presents a similar default rate but by LCLG segments instead of by FICO segments. Once again, we find that the LCLG was able to identify high-risk borrowers at a more granular level. The highest default rate is observed in Figure 3B, with about a 14 percent average default rate for the lowest LCLG segments (G-rated, F-rated, and E-rated) and for loans originated in 2018 and 2019. The

[9] See "What Is a Good Credit Score?" from TransUnion, available at www.transunion.com/blog/credit-advice/whats-considered-a-good-credit-score.

[10] While these figures are plotted based on the number of accounts, the results are consistent with the plots in Figures A3 and A4 in the appendix, which plot the same FICO and LCLG distribution by loan amount (instead of by the number of loans).

[11] There were a small number of loans originated in 2014 that were still active during the pandemic. We conclude that these loans must have gotten extensions under special circumstances from LendingClub.

contribution of the alternative data embedded in the LCLGs seems to have continued to provide a lift in the default prediction accuracy even during the unforeseen adverse economic conditions of the pandemic period.

The increased accuracy in default prediction is evident from the FICO distribution within each LCLG segment, as presented in Figures 3A and 3B. Figure 4A shows that, for loans that LendingClub originated during the period 2014–2018, there are significant differences between the FICO scores and the proprietary LCLGs, as a significant portion of those loans that received the best ratings (A-rated and B-rated) were rated poorly based on FICO scores (below 680). Figure 4B shows the same distribution for loans that LendingClub originated in 2019 (just before the COVID period). We can see that LendingClub was more cautious in its credit decisions starting in 2019, when it stopped originating loans to those with the lowest ratings (F-rated and G-rated).[12] However, the differences between FICO scores and LCLGs continued to be present, and some of the top-rated loans (A-rated and B-rated) were given to those with FICO scores below 680. In addition, we also observe the reverse, in which some super-prime consumers based on traditional criteria (with a FICO score above 760) were classified as high risk and were assigned a low LCLG (C-ratings and D-ratings) by LendingClub.

The FICO composition of each of the LCLGs also demonstrates that LCLGs disaggregate the credit risk posed by borrowers in the FICO score below 680 segment and assign them ratings that range from A to G, the full range of LCLGs. Those borrowers with nonprime FICO scores (below 680) who were assigned top LCLG ratings were referred to in Jagtiani and Lemieux (2019) as the “Invisible Prime.” LendingClub uses the LCLG to estimate the probability of default and to price a loan. This means that customers with the same FICO score may receive loans that have very different rates, depending on the assigned LCLGs. Jagtiani and Lemieux (2019) show that the Invisible Prime consumers benefited, as they were able to access credit and did so at a lower interest rate than they would have otherwise. Additionally, some high-FICO consumers were subject to a higher loan rate when using a more forward-looking approach to default prediction using alternative data. Further examination of this, with loan-level regression analysis, is presented in Table 1. The correlation between the various LendingClub loan variables is presented in Table 2A for all loans originated in 2014-2019. The correlation coefficients presented in Table 2B are for a subset loans – only loans that remained active as of the beginning of the pandemic are included.

[12] Of the $8,533,442,875 of loans originated by LC in 2019, $49,981,075 (0.586 percent) were E-rated; $304,975 (0.004 percent) were F-rated; and $17,000 (0.0002 percent) were G-rated.

(3) Does LendingClub underprice the cost of credit to "better" customers?

We have shown that LendingClub borrowers with the same FICO score may be assigned different LCLGs and would therefore be charged different interest rates for their loans. This finding may be viewed as consistent with the claim that fintech lenders may have been "cream-skimming" to compete for the best customers from traditional lenders. That is, there have been claims that some super-prime borrowers might be getting lower interest rates from fintech lenders than they would from traditional lenders. Di Maggio and Yao (2021) find that, compared with traditional lenders, "fintech lenders" charge a higher interest rate (average 3 percent higher) on loans to lower-score borrowers and that they charge a lower interest rate (average 1.5 percent lower) on loans to high-score borrowers. We argue that it is important to look at the true default risk (rather than just FICO score) of the borrowers when analyzing whether fintech lenders were cream-skimming. It would be impossible to accurately analyze pricing by looking just at credit scores.[13] Focusing on data from LendingClub, the largest fintech personal lender, we find the opposite results.

We explore the FICO composition of each of the LCLGs for two time periods that roughly represent two different credit decisioning strategies — the pre-tightening period (2014–2018) and the tightening period (2019).[14] As shown in Figures 4A and 4B, LendingClub continued to grant credit to consumers in the nonprime segments (a FICO score below 680) even in the tightening period of 2019. The LCLGs disaggregate the credit risk posed by these borrowers in the nonprime FICO band and assign them ratings that range from A to G (the full range of the LCLGs) for loans originated in 2014–2018 (Figure 4A) and ratings that range from A to D for loans originated in 2019. Only the Invisible Prime consumers from the nonprime pool were able to get the loans in 2019 — Figure 4B shows a smaller ratio of loans from the nonprime FICO segment compared with that in Figure 4A.

Regarding the way LendingClub prices default risk, we investigate (1) whether LendingClub accurately estimate the risk of default across all FICO segments in its loan rating system? or (2) whether LendingClub "underpriced" the risk from a certain group (for high FICO bands). Figures 1B and 1D show that default rates are consistent, with an argument that loan risks are priced appropriately, although the LCLG seems to do a better job in pricing in a more granular risk bucket.

[13] It should also be noted that the term "fintech lenders" in Di Maggio and Yao (2021) is defined as those lenders "that operate exclusively online and do not have a brick-and-mortar presence, do not accept deposits, and are not regulated by the Federal Reserve or the Office of the Comptroller of the Currency (OCC)." Their definition of fintech lenders would naturally include traditional nonbank lenders that operate purely online (but do not utilize alternative data in their credit decisions), including some payday lenders.

[14] LendingClub stated that it changed its risk preference in 2019 and 2020 to fund more loans in the A-rated to D-rated LCLGs only.

We do not observe evidence of a "kink" in the default rate for high FICO segments (>720) or for high-rated LCLG (A-rated to C-rated) consumers from the plots below — consistent with an argument that LendingClub accurately estimated the risk of default across all FICO segments in its loan rating system.

In analyzing loan pricing, Figures 5A and 5B show that the interest rates charged by LendingClub are in line with the estimated default risk of the borrowers based on FICO scores and LCLGs, respectively. In Figure 5A, we re-segment the borrowers with high FICO scores (above 760) into more granular buckets: (1) FICO scores of 760–779, (2) FICO scores of 780–799, and (3) a FICO score of 800 or higher. These more granular FICO segments allow us to observe any potential special treatment to "better" borrowers. Our results in Figure 5A show evidence that borrowers with top FICO scores are, on average, not getting any special treatment and that they did not get unreasonably low interest rates from LendingClub. In addition, Figure 5B shows no evidence that A-rated or B-rated borrowers were charged disproportionately lower interest rates than other borrowers. We also observe increased interest rate spreads across all loan grades for loans that were originated in 2019 and 2020. Overall, we find no evidence of cream-skimming so far.

To further understand the spread behaviors, we examine the minimum and maximum spreads for each FICO bracket and for each LCLG bucket. Previous studies by Latham (2022), using data from SuperMoney, and Schulz (2022), using data from LendingTree, examine the dispersion of interest rates offered by these lenders to potential borrowers with the same FICO scores. Schulz (2022) reported that the dispersion in interest rate APRs averaged 7.1 percent for all borrowers, with the average being much higher for bottom tier borrowers with FICO scores below 670. Latham (2022) found similar results, reporting that, for borrowers with FICO scores below 680, the spread between the highest and lowest interest rate APRs offered on personal loans by banks and those offered by fintechs was 13.67 percentage points. Latham and Schulz reported similar results in their 2023 studies. There are many potential reasons for this disparity, including the business model of the lender as well as its proprietary loan rating system. Next, we explore and shed some light on the variations in LendingClub's loan pricing across borrowers with similar FICO scores.

Figure 6 shows the interest rate (defined as the rate charged by LendingClub over a similar risk-free Treasury rate with the same time to maturity) charged by LendingClub for loans that were originated during the period from 2007 to 2020 (the entire life of LendingClub as a fintech lender)[15]

[15] LendingClub became a bank holding company, LendingClub Bank, N.A., on February 1, 2021 — through an acquisition of Radius Bancorp and its wholly owned subsidiary, Radius Bank. Our sample includes only loans that were originated prior to the status change at LendingClub.

and for the more recent period from 2014 to 2019 — presented in terms of average, min, max, range, and percentile (25th, 50th, and 75th). Consistent with earlier studies, we find that the dispersion of the interest rate is wider for lower-rated (low-score) borrowers, especially when we focus on those with the same LGLG rating. For loans originated in 2007–2020, the dispersion is, on average, 8.49 percentage points for A-rated borrowers, but there is a much wider dispersion for G-rated borrowers, at 25.81 percentage points. The results hold, but are much weaker, when looking at the interest rate dispersion based on FICO segments, which are somewhat backward-looking compared with the LCLG ratings, which incorporate additional data for a more wholistic view of a borrower's financial condition. The A-rated borrowers are charged a maximum interest rate of 10.67 percentage points, while the rate of the highest FICO segment (above 800) of borrowers may be up to 26.72 percentage points. We find similar interest rates for loans originated in 2014–2019.

The results on interest rates overall indicate that the dispersion of interest rates is narrower for top-rated borrowers (A-rated and B-rated) and that the range of the rates is largest for the lowest-rated borrowers (F-rated and G-rated). In addition, when focusing on the dispersion of interest rates across rating grades or credit scores, the results show a much wider range of interest rates between A-rated and G-rated borrowers — from an average interest rate of 5.5 percent for A-rated borrowers to an average of 27 percent for G-rated borrowers, which is about a 21-percentage-point difference. In contrast, the difference between the average interest rate charged to the highest and lowest FICO segments is much smaller — only about 7 percentage point difference. Specifically, the average interest rate is 13.5 percent for borrowers with a FICO score below 680, but it is only about 6.5 percent for the best borrowers, with a FICO score above 800. This, again, demonstrates that the LCLG ratings are more precise in evaluating credit risk than the traditional credit scores. Most important, we find no evidence that the best borrowers (A-rated or B-rated) are getting disproportionately lower interest rates than other customers. This is further examined using the regression analysis in Tables 4, 5, and 6.

IV. The Empirical Analysis

Analysis of the data presented above indicates (1) that LendingClub's proprietary loan rating system does accurately predict the likelihood of default; (2) that LendingClub's proprietary loan rating system that was developed (leveraging alternative data) in a favorable economic period did continue to perform well under adverse economic conditions; and (3) that there is no evidence that LendingClub underpriced the cost of credit to "better" customers. The results are organized around the three research questions.

IV.1 Do Proprietary Loan Rating Systems Accurately Predict the Likelihood of Default?

We first repeat a similar analysis to that in Jagtiani and Lemieux (2019) but using a more recent data set including loans that were originated during 2014–2019.[16]

Table 1 presents the results of the regression analyses, in which the dependent variable is a binary variable that takes a value of 1 if the loan becomes delinquent within 24 months of origination and that takes a value of 0 otherwise. The sample includes all loans originated by LendingClub between 2014 and 2019. All equations also include a dummy variable for the year of origination, which accounts for any year-specific factors that could relate to the overall economy and/or to LendingClub's business strategy for that year. The regressions are generalized linear models with the logit link function. The six regressions represent specifications that examine the relationship between the dependent variable and (1) the FICO bands alone; (2) the local economic variables alone; (3) the FICO bands and the local economic factors; (4) the LCLGs alone; (5) the LCLGs and the local economic factors; and (6) the FICO bands, the LCLG ratings, and the local economic factors.

As expected, the coefficients of the FICO bands are positive, the coefficients of the FICO bands appear in rank order, and the FICO bands are statistically significant at the 1 percent significance level in Columns 1, 3, and 6 of Table 1. Likewise, the coefficients of LendingClub's rating grades are positive, the coefficients of the LCLGs appear in rank order, and the LCLGs are statistically significant at the 1 percent significance level in Columns 4, 5, and 6 of Table 1. Notably, there is no noticeable effect on the significance of the FICO bands or the significance of the LCLGs when the economic control factors are included in Columns 3 and 5, respectively. This suggests that local economic variables could supplement FICO scores or LCLGs to improve default prediction. When FICO bands and LCLGs are both included in the analysis, in Column 6, the coefficients of both sets of explanatory variables maintain their signs, rank order, and statistical significance. This suggests that while there is a portion of default risk that both the FICO bands and the LCLGs detect, some portion of the overall default risk can be detected exclusively by the FICO scores or by the LCLGs.

The dummy variables for the years of origination for 2015, 2016, 2017, and 2018 are positive and significant in all six equations, implying that defaults in these years were significantly greater than defaults in 2014. In equations (5) and (6), when both LCLGs and local economic factors are included, the dummy variable for the 2019 originations is not significant, and in equations 1–4, the coefficient is significantly negative. We understand from LendingClub statements that

[16] Jagtiani and Lemieux (2019) include loans that were originated in 2007–2015.

underwriting standards changed in 2019 and 2020, which could possibly be one explanation. Regardless, it does appear that there are factors that impact defaults that vary by year and that are not captured by FICO scores, LCLGs, or local economic conditions.

Most important, from Table 1, we find that there is a significant role for alternative data to play in boosting lenders' ability to accurately evaluate loan risk, as seen in the coefficients of each of the LCLG dummies being significantly positive and in rank order (with a higher default rate for lower LCLGs). This analysis further substantiates the graphical analysis and shows that the LCLG, which leverages alternative data, does add a significant lift in predicting loan default. Interestingly, it also shows that FICO scores and LCLGs seem to contain "different" information, as the coefficients are simultaneously significant.

Table 2 lists the correlation of all the variables. Similar to the findings of Jagtiani and Lemieux (2019) and Cornelli, Frost, Gambacorta, and Jagtiani (2023), the correlation between FICO scores and LCLGs is small.

To explore which specification is "better," we examine the receiver operating characteristic (ROC) curves for predicting delinquency within 24 months of origination, as presented in Figure 7**.** The ROC curves are plotted for the analyses in Columns (1), (3), (4), and (6) of Table 1. The results indicate that model (1), with only FICO bands, has the least predictive power (its ROC is closest to the 45-degree line). It is interesting to see that model (4), with only LCLGs, has much greater predictive power than model (3), which includes both FICO bands and local economic variables. The area under the curve (AUC) increased from 60.07 percent in model (3) to 67.77 percent in model (4). Last, model (6), with not only FICO bands and local economic variables but also LCLGs, has the strongest predictive power (its ROC is farthest from the 45-degree line); there is a very small improvement over model (4), which includes only the LCLGs. This implies that, although LCLGs are much better at predicting defaults, FICO bands and/or local economic conditions seem to capture some default risk not captured by LCLGs.

IV.2 Can a Proprietary Loan Rating System that Was Developed in a Favorable Economic Period and Leverages Alternative Data Perform Well Under Adverse Economic Conditions?

For this analysis, we repeat the analysis presented in Table 1 but only include loan observations that were still outstanding as of the beginning of the COVID period (March 2020) and observe their performance during the entire COVID period. The dependent variable is a binary variable that takes a value of 1 for loans that became 60 days past due during the COVID period (as opposed to loans that become 60 days past due within 24 months of origination, as was the case in Table 1) and that takes a value of 0 otherwise.

The results are presented in Table 3 for the same six specifications used in Table 1. The findings and conclusions are consistent with those reported in Table 1. Specifically, the coefficients of both the FICO bands and the LCLGs are positive, appear in rank order, and are statistically significant at the 1 percent significance level. Also, when the FICO bands and the LCLGs are simultaneously included in the analysis (in Column 6), they maintain their signs, rank order, and statistical significance. This repetition of the findings in Table 1 demonstrates that LCLGs continued to perform in a comparable manner during the COVID period, even though the LCLG ratings were assigned in a normal economic environment (during the pre-COVID period).

In this regression, because the dependent variable is defined as loans that defaulted during the COVID period, the year of origination represents the age of the loan. As expected, the results indicate that the oldest loans, those originated in 2015, have significantly lower rates of default during the COVID period. Since LendingClub states its maximum loan maturity is five years, loans originated in 2015 would have been close to maturity during the beginning of the COVID period. Thus, it is not surprising that the dummy variable is significantly negative. The local economic variables were all significant, except for the local unemployment rate. This is likely because of the enhanced unemployment benefits provided by the states during the pandemic. The coefficients for the loan grade variables increased with increasing risk, showing that loan defaults increased with risk.

Most important, both the FICO variables and the LCLG variables are significantly positive with the correct rank order, even when the economic factors are included, as shown in Column 6 — indicating that alternative data continued to contribute significantly in predicting default during the COVID period.

The ROC curves for this set of regressions are presented in Figure 8. These curves also lead us to a similar conclusion — LCLG models are superior at predicting default than models that include both FICO bands and local economic factors. This is particularly interesting, since the LCLGs were assigned during a totally different economic environment (the pre-COVID period). Again, we also find that LCLGs and FICO scores contain different information, especially during the COVID period. The additional local economic variables also improved the model performance of each of the specifications. It should be noted that the AUC, an indication of goodness-of-fit, is slightly lower for the COVID period regressions.

IV.3 Does LendingClub Underprice the Cost of Credit to "Better" Customers?

Graphical analysis, such as those in Figures 4A, 4B, 7, and 8, shows that LCLG ratings categorize applicants differently than FICO scores. Borrowers with FICO scores in a given category, such as prime borrowers, receive loan grades that run the entire range of the loan rating system — see Figures 4A and 4B. Loan ratings are an estimation of the probability of default (Figures 3A and 3B) and are used to price loans (Figures 5A and 5B). We test the hypothesis put forth by Di Maggio and Yao (2021) and de Roure et al. (2022) by observing how the price of default risk, i.e., interest rate on the loan, varied across the risk rating systems.

We conduct a regression analysis with the dependent variable being interest rate spread on the loans, in which the interest rate spread is defined as the interest rate charged by LendingClub minus the risk-free rate on Treasury securities with the same time to maturity.[17] The same set of independent variables used in Table 1 are included in the spread analysis — that is, FICO segments, LCLG ratings, economic factors, and year of origination dummies. For this interest rate analysis, we set an origination year of 2019 to be the base year (instead of omitting the origination year dummy for 2014). Therefore, the interpretation of the year variables is how pricing is different from pricing in 2019, holding the other variables constant. It should also be noted that the number of observations is reduced from about 2.5 million observations in Table 1 to about 1.6 million observations in the interest rate spread analysis. This is because interest rate spread cannot be calculated for some of the loan observations if the risk-free Treasury rate is not available for the same time to maturity. The results are presented in Table 4**.**

The results in Table 4 show that both the FICO scores and the LCLGs are important in risk pricing the loans, after controlling for economic factors and origination year. All the coefficients of the FICO bands and the LCLGs are significantly positive (at the 1 percent level), and they are in rank order, in which the interest rate spreads increase with the lower FICO scores and the lower LCLG rating grades. If there was any underpricing on the better loans, we would expect to observe one of the coefficients on one of the loan grades not being in rank order. So far, we find no evidence that

[17] The data on the constant maturity yields on U.S. Treasury Securities, specifically those with three- and five-year constant maturities, were sourced from Federal Reserve Economic Data (FRED) for all dates available between 2007 and 2020. These data represent the three- and five-year yields (respectively) on the most recently, relative to each observation's date, auctioned U.S. Treasury securities. These yields were then matched to LendingClub loans originated between 2007 and 2020 by loan origination date and by the loan maturity reported by LendingClub. We exclude loans for which yield data were not available. For those loans included in the loan interest rate spread analysis, each loan's spread was calculated by taking the difference between the loan's interest rate at origination and the matched Treasury security yield.

LendingClub may have underpriced the cost of credit to "better" customers, with FICO scores above 760.

To further explore this question, we assign a more granular grouping of the FICO scores by adding two more FICO segments into the analysis in Table 5 — a FICO score 800 or more (the base case), a FICO score of 780–799, and a FICO score of 760–779. The results continue to hold when we use more granular FICO segments, in which the coefficients of the FICO bands and the LCLG ratings are significantly positive (at the 1 percent level). They are also in rank order, in which the spreads increase with the lower FICO scores and the lower LCLG rating grades. Again, our results indicate that there is no evidence of cream skimming by fintech lenders (LendingClub, in this case).

To further explore the role of interest rate spreads, we note that there is an additional factor that goes into the risk pricing of LendingClub loans but that was not captured by either the FICO scores or the LCLG ratings. This additional factor could be captured in the error term — the so-called "spread residual." We estimate the spread residual using three different specifications in the regression analysis below.

Interest Rate Spread = a + b(Year Dummies) + c(FICO Dummies) + g(Economic Factors) + Spread Residual (1)

Interest Rate Spread = a + b(Year Dummies) + d(LCLG Dummies) + g(Economic Factors) + Spread Residual (2)

Interest Rate Spread = a + b(Year Dummies) + c(FICO Dummies) + d(LCLG Dummies) + g(Economic Factors) + Spread Residual (3)

In addition, we re-estimate the default probability analysis reported in Table 1 by adding an additional explanatory variable, the spread residual, and the results are reported in Table 6. The probability of loan default in Columns 1 to 3 is estimated without the spread residual variable. The same regressions are repeated in Columns (1'), (2'), and (3'), respectively, when the spread residual variable is also included. The spread residual variable used in Column (1') is a portion of the interest rate charged by LendingClub that is not captured by FICO score, economic factors, and year of origination. The spread residual in Column (2') is the portion of the interest rate that is not captured by LCLGs, economic factors, and year of origination. The spread residual in Column (3') is the portion of the interest rate that is not correlated with FICO score, LCLGs, economic factors, or year of origination.

In all columns in Table 6, the coefficients of the FICO dummies and the LCLG dummies are positive and significant at the 1 percent level, and they are in rank order. In addition, the coefficients of the spread residual in Columns (1'), (2'), and (3') are all positive and significant at the 1 percent level. The results indicate that the spread residual — the portion of the interest rate (charged by LendingClub) that is not explained by credit ratings (FICO score and LCLGs), economic factors, and the year of origination — is also significantly important in explaining loan default probability. In other words, our results in Table 6 confirm that the interest rate spreads charged by LendingClub are set based not only on the FICO score, the LCLGs, and the relevant economic factors but also on some unique factors that are not captured by the credit risk model but that are still important in determining a loan's default probability. This finding suggests that the "spread residual" could (at least partially) explain why some previous studies could have mistakenly misinterpreted the interest rate spread as potentially unfair pricing that favors a certain group of customers. We find no evidence of interest rate or risk mispricing in favor of top-rated consumers or any other groups of consumers.

V. Robustness Testing Using Data from the Federal Reserve Bank of New York Consumer Credit Panel/Equifax Data (CCP)

So far, our results based on personal loan data show that LendingClub's loan rating system (LCLG ratings) is superior in predicting the likelihood of default compared with traditional measures of credit risk and that the proprietary loan rating system, leveraging alternative data and developed in a favorable economic period, continued to perform well under adverse economic conditions (during the COVID-19 pandemic). However, this predictive ability was not as strong during the COVID period, as indicated by the flatter ROC curve for the COVID period regressions. Our results also indicate that the LCLGs and FICO scores contain some different information, and this was especially true during the COVID period. While the LCLG rating alone is superior to the traditional credit score in credit risk evaluation and pricing, the prediction could be improved when using both LCLG ratings and FICO scores, resulting in a slight lift in default prediction.

To shed more light on the difference in the performance of traditional loans (for which the credit decision is primarily based on traditional factors, such as credit score) and the performance of fintech loans (which use alternative data in the credit decision), we compare the performance of LendingClub personal loans with the overall consumer credit card performance for the same period, controlling for the risk characteristics of the consumer. To conduct this comparison, we use loan-level data from the FRBNY Consumer Credit Panel/Equifax Data (CCP), which contains information (including the type of credit card, the issuing date, the consumer's risk score, etc.) about each credit card held by each consumer and its delinquency status.

As described earlier, consumers in general would prioritize keeping credit card loans current and would choose to default on personal installment loans first, in order to maintain their line of credit. This would, therefore, likely result in a biased finding toward overestimating fintech loan default, compared with credit card loan default. For these reasons, our results of finding lower default rate on fintech loans would be robust findings.

The FRBNY Consumer Credit Panel/Equifax Data (CCP): We take a 1 percent random sample from the CCP data set.[18] The analysis includes only credit cards that were originated at the same time as the loans in this study — only those with an origination year from 2015 to 2019. Note that not all the cards that were originated in this period would remain active through the entire sample period. The default rate is calculated based on the number of defaulted cards in each year to number of credit cards in the sample that remain in active status in that year. The sample includes about 241,000 credit cards that were originated during 2015–2019.

The LendingClub data set contains 2,312,430 loans, all of which are installment loans originated between 2015 and 2019. The CCP data set contains 240,813 credit cards originated in the same period (between 2015 and 2019). Figures 9A and 9B show default rates on consumer credit cards based on the CCP and default rates on LendingClub consumer loans, respectively, by observation year (not necessarily origination year) and by credit scores (Equifax Risk Score for credit cards and FICO score for LendingClub loans). The Equifax Risk Score will be referred as the Risk Score throughout the paper.

Figure 9A shows that the annual default rate on credit cards in each year is significantly larger for consumers with a Risk Score below 680 than any other risk brackets — peaking at a 12 percent default rate in 2020 before it declined in 2021. The default rate on cards was very small (insignificant) in all years for consumers with a Risk Score above 760. It is not surprising that only nonprime consumers tend to default on their credit card loans.

From Figure 9B, unlike credit cards, the annual default rates on LendingClub personal loans always exhibit rank order. The overall default rates on LendingClub loans closely followed the default rates for those loans with FICO scores between 680 and 720 (the most common score ranges). As expected, the default rate was highest for consumers with FICO scores below 680, peaking at an 8 percent default rate in 2017 and declining to 5 percent or less in 2020 and 2021. While the overall default rates peaked at about 6 percent for both credit cards and LendingClub loans, the default rate for the low-score consumers (credit scores below 680) was much lower on

[18] The random sample is tied to the credit card tradeline not specific consumers. Thus, some credit cards for a given consumer may not be included. If the consumer has cards that were not in the random sample selected, those cards would not be included in our analysis here. In addition, if the consumer has more than one new credit card in the same month, those cards would share the same "Super-ID" on the FRBNY Consumer Credit Panel/Equifax Data (CCP). Those cards that were originated in the same month (and that share the same loan ID) are not included in our default analysis here, since we could not identify the performance of each individual card in this case.

LendingClub loans for the same period. Overall, fintech loans (originated by LendingClub) seem to default less than credit card loans (for all consumers, based on CCP), especially for nonprime borrowers.

When considering defaults during the COVID pandemic (defined as March 1, 2020, to November 30, 2021), we define the default rate as a ratio of the number of loans that defaulted (become at least 60 days past due) at any time during the pandemic period to the total number of unique loans that were outstanding during any part of the pandemic period. For this analysis, only loans that were originated during 2015–2019 (the pre-COVID period) are included in the sample. The percentage of accounts active during the pandemic period that were reported being more than 60 days past due during COVID period was 5.83 percent for LendingClub loans and higher default rate of 6.87 percent for credit card loans.[19]

Figures 10A and 10B show default rates on credit cards based on FRBNY Consumer Credit Panel/Equifax Data (CCP) and default rates on LendingClub consumer loans, respectively, by origination year and by credit scores (Equifax Risk Score for credit card loans and FICO score for LendingClub loans) as of credit card issuance or loan origination. The default can occur at any time during the pandemic period. In Figure 10A, once again, the credit card default rate was immaterial for top-score consumers with a Risk Score above 760. The credit card default rate for consumers with a Risk Score below 680, however, was much higher, peaking at above 16 percent for those cards that were issued in 2019. In Figure 10B, the default rates on LendingClub loans are in rank order and are much lower than the credit card default rates for low score consumers with FICO scores below 680, peaking at about 8.5 percent for loans that were originated in 2019. Our results so far show that, during the pandemic downturn, fintech loans (originated by LendingClub prior to the pandemic period 2015-2019) defaulted less than credit card loans (originated in the same period 2015-2019), controlling for consumer credit scores.

Overall, our results from comparing fintech loan (LendingClub loan) default with traditional loan (credit card loans) default indicate that, for nonprime consumers (with credit scores below 680), the default rate is much lower on fintech credit than it is on traditional credit. These results are robust, given that consumers would generally prioritize keeping their credit card loans current (to keep their LOC), which would have driven down default rate on credit card loans. We find the

[19] The FICO distribution for those LendingClub loans that were active during the pandemic period was as follows: FICO<680 (24.64 percent); FICO 680–719 (45.16 percent); FICO 720–759 (21.12 percent); and FICO>760 (9.09 percent). The Risk Score distribution for credit cards (from the FRBNY Consumer Credit Panel/Equifax Data (CCP) that were active during the pandemic period was as follows: Risk Score <680 (44.50 percent); Risk Score 680–719 (15.92 percent); Risk Score 720–759 (13.59 percent); and Risk Score >760 (25.98 percent).

opposite results -- credit card default rates are higher than that of LendingClub loans during the pandemic among nonprime borrowers. This is consistent with our earlier findings in Tables 1–6. Our findings overall show that fintech lenders are better able to identify good borrowers from the pool of nonprime consumers.

VI. Conclusions

Since the financial crisis, fintechs have forged an increasing market share of the growing personal loan market at the expense of commercial banks. Few fintechs are public companies, but research in this area has benefited from several of the largest fintech firms making their data available. This paper leverages data provided by LendingClub, one of the oldest and largest fintech personal lending platforms. We examine three research questions: (1) Do proprietary loan rating systems accurately predict the likelihood of loan default? (2) Can a proprietary loan rating system that was developed in a favorable economic period and that leverages alternative data continue to perform well under adverse economic conditions? And (3) does LendingClub underprice the cost of credit to "better" customers?

Previous research has shown that loan rating systems can accurately predict the likelihood of default. We find similar results over a more recent time period. We also find that default rates for nonprime consumers (with credit scores below 680) are much lower on LendingClub loans than on traditional personal loans (based on credit card default) during the same period, which is consistent with the important role of alternative data in identifying the Invisible Prime consumers from the nonprime pool. In addition, we extend the literature by looking at how well the LCLGs (assigned during the normal economic conditions in the pre-COVID period) performed during the COVID-19 pandemic period. The results demonstrate that the LCLGs continued to perform well during (unexpected) adverse economic conditions.

Overall, the analysis of default finds the following: (1) The proprietary loan rating system contained different information than the traditional measure of credit risk, FICO, in that the two measures have a low correlation, and the inclusion of both in the regression analysis improved the fit of the model; (2) the local economic variables that captured the economic environment of the borrower were significant in the default prediction model; and (3) there was additional variation in defaults that was picked up by a unique factor (unrelated to the proprietary LCLG rating, the FICO score, or the local economic factors), the so-called "spread residual" variable.

We also investigate the issue of differential pricing of risk. It is demonstrated in this paper how the proprietary loan rating system that leverages alternative data and artificial intelligence/machine learning (AI/ML) could disaggregate the risk beyond those measured by a traditional credit risk score (the FICO score). Fintech firms' loan pricing is determined by this finer disaggregation of risk so that loan applicants with similar FICO scores would receive pricing based on their "grade" in the proprietary loan rating system and thus receive loan offers with different interest rates.

Our regression results also show that some variations in the interest rate charged to consumers with similar LCLGs (the proprietary ratings) are also highly correlated with loan default, despite these variations being uncorrelated with credit scores, LCLGs, or economic factors. We argue that this unique factor, the "spread residual," which is not captured by the typical credit risk model but that is important in determining a loan's default probability, is likely a reason (at least partially) why some previous studies could have mistakenly misinterpreted the interest rate spread as potentially unfair pricing that favors a certain group of customers. We find no evidence of interest rate or risk mispricing in favor of top-rated consumers or any other groups of consumers — we reject the fintechs' cream-skimming hypothesis. There is no evidence of fintech lenders cream-skimming and offering unusually low interest rates on loans to "better" borrowers.

In terms of regulatory implications, in 2019, five federal agencies issued an interagency statement discussing the benefits and risks of using alternative data in credit decisions. It has been recognized by regulators that "using alternative data may enable consumers to obtain additional products and/or more favorable pricing/terms based on enhanced assessments of repayment capacity." Our results have confirmed that there are potential real benefits to consumers.

Fintech model developers should consider regulatory requirements when coding their algorithms with the use of alternative data. The Consumer Financial Protection Bureau (CFPB) has issued several statements about consumer protection concerns when using alterative data in credit decisions — highlighting issues associated with fair lending compliance.[20] There are also concerns related to the use of alternative data when traditional lenders use a proprietary risk rating mechanism (developed by third-party fintech vendors) without fully understanding their own credit decisioning process inside the "black box." Lenders must be able to demonstrate that their

[20] More details are available from these links: www.consumerfinance.gov/about-us/blog/using-alternative-data-evaluate-creditworthiness/ (general benefits and risks); www.consumerfinance.gov/compliance/circulars/circular-2022-03-adverse-action-notification-requirements-in-connection-with-credit-decisions-based-on-complex-algorithms/ (fair lending adverse action notice requirements); and www.consumerfinance.gov/compliance/circulars/circular-2023-03-adverse-action-notification-requirements-and-the-proper-use-of-the-cfpbs-sample-forms-provided-in-regulation-b/ (2023 update on fair lending adverse action notice requirements).

credit decisions are not biased against any protected class, regardless of whether the decisions are based on its proprietary risk rating systems that leverage alternative data and AI/ML.

Overall, our results indicate that there is a potential role for alternative data and AI/ML in enhancing credit access to nonprime consumers. We find no evidence of a fintech "cream-skimming" practice to offer unfair, favorable low-rate loans to better customers.

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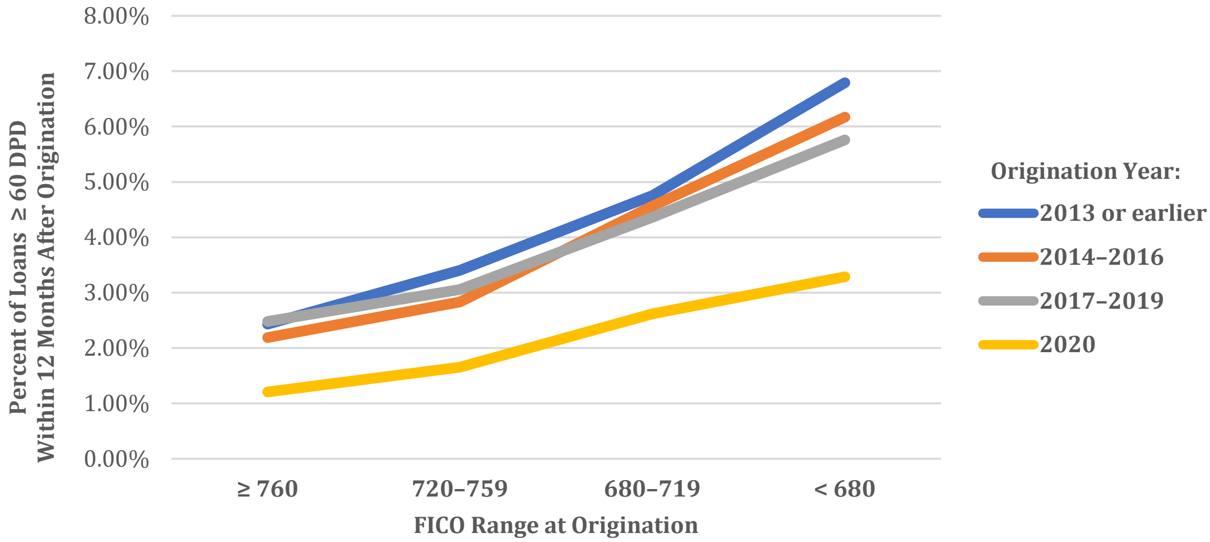
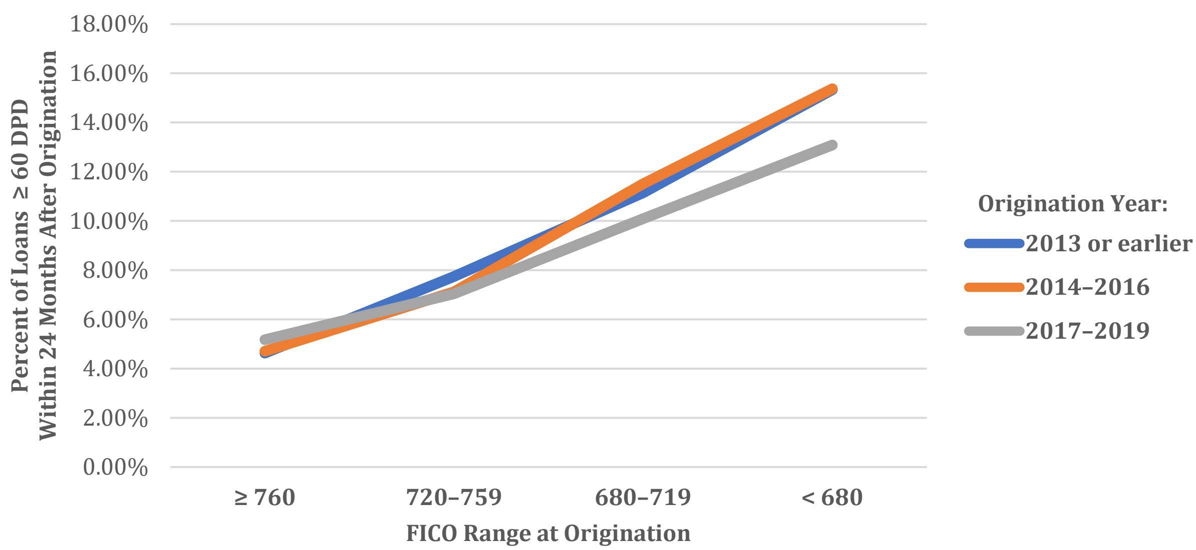
Figure 1A: Percent of Accounts that Became ≥ 60 DPD Within 12 Months After Origination — by FICO Score (at Origination) and by Origination Year



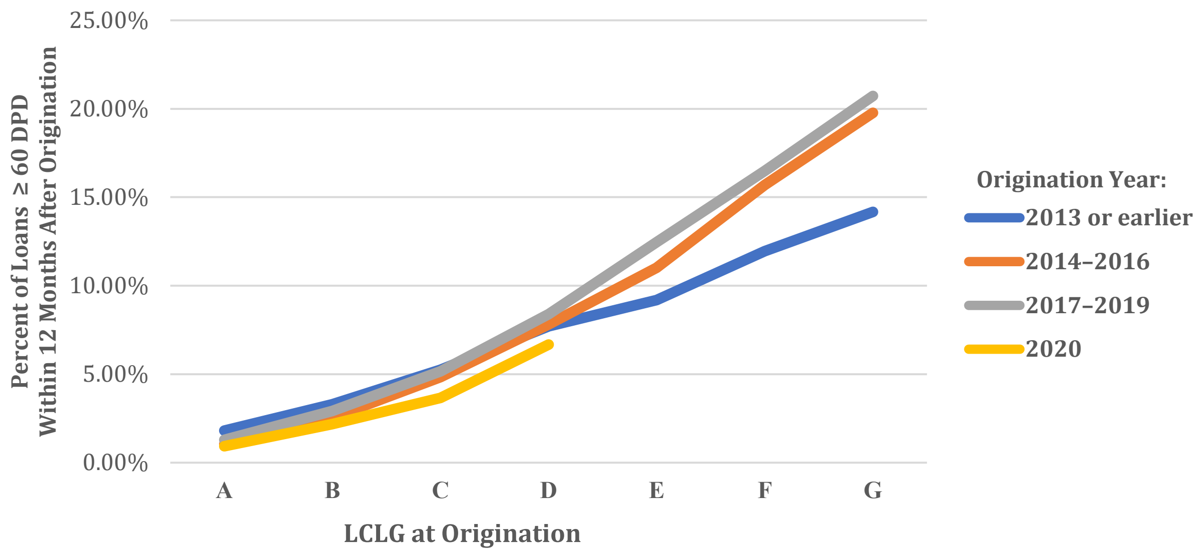
Source: Authors' calculations based on data from LendingClub.

Figure 1B: Percent of Accounts that Became ≥ 60 DPD Within 24 Months After Origination — by FICO Score (at Origination) and by Origination Year



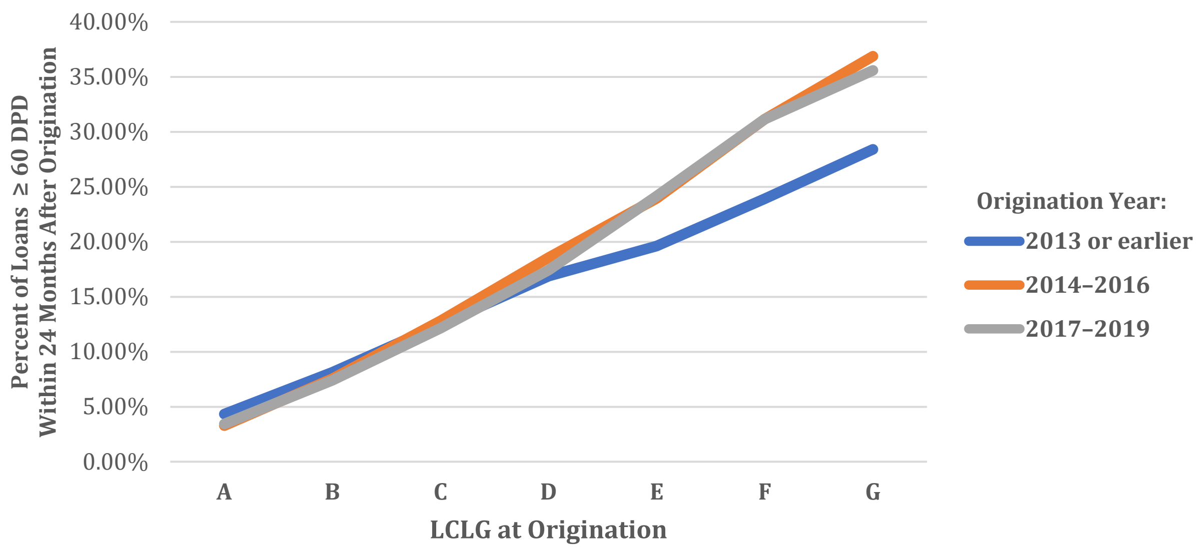
Note: The sample only includes loans with a 24-month observation window after origination.
Source: Authors' calculations based on data from LendingClub.

Figure 1C: Percent of Loans that Became ≥ 60 DPD Within 12 Months After Origination — by LCLG (at Origination) and by Origination Year



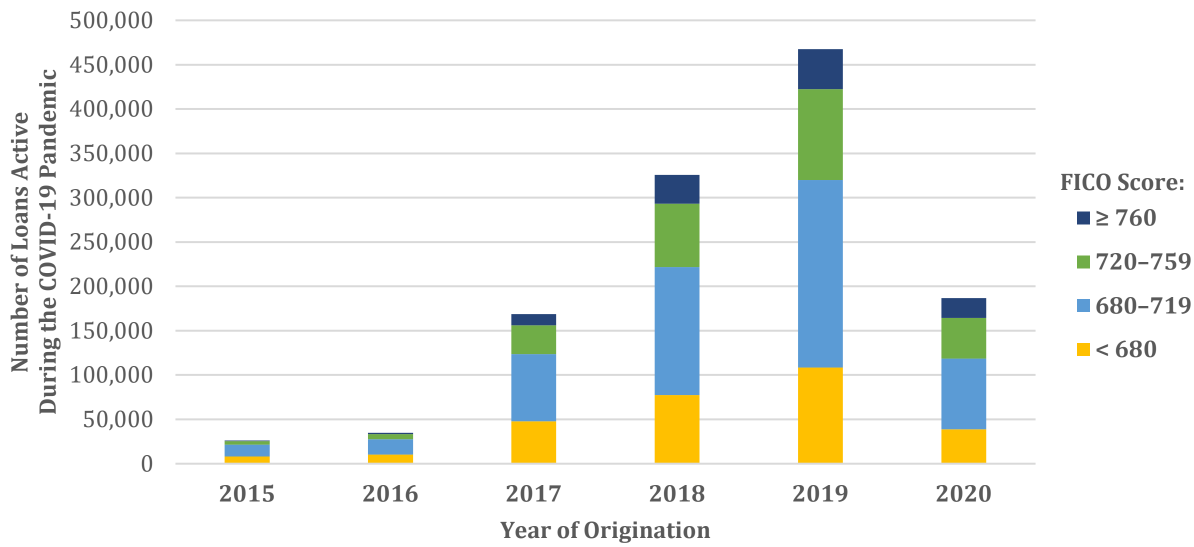
Source: Authors' calculations based on data from LendingClub.

Figure 1D: Percent of Accounts that Became ≥ 60 DPD Within 24 Months After Origination — by LCLG (at Origination) and by Origination Year



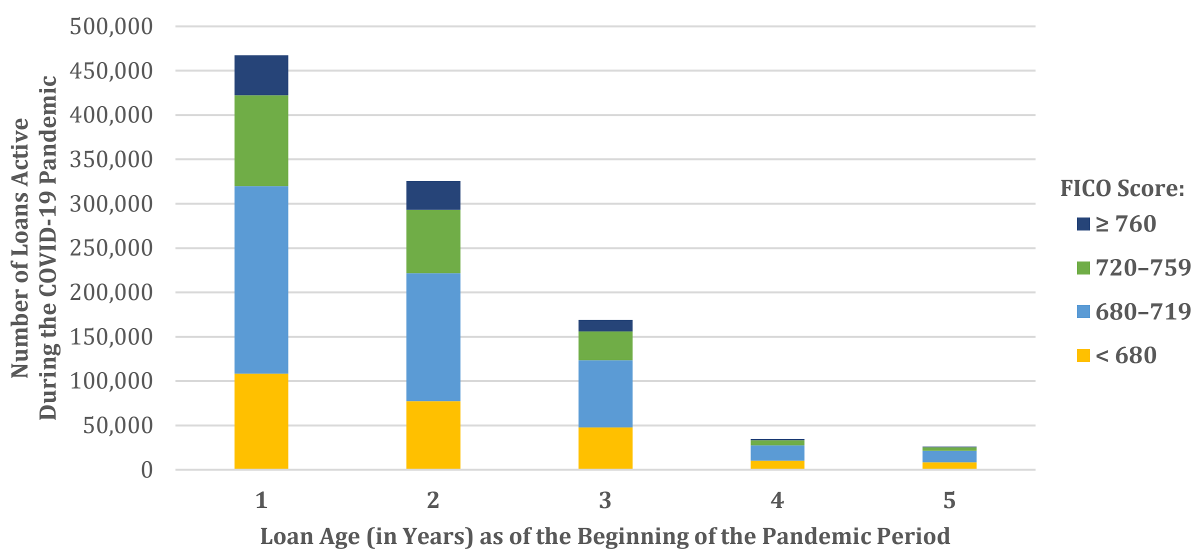
Note: The sample only includes loans with a 24-month observation window after origination.
Source: Authors' calculations based on data from LendingClub.

Figure 2A: Number of Loans Active During the COVID-19 Pandemic by Year of Origination and by FICO Score



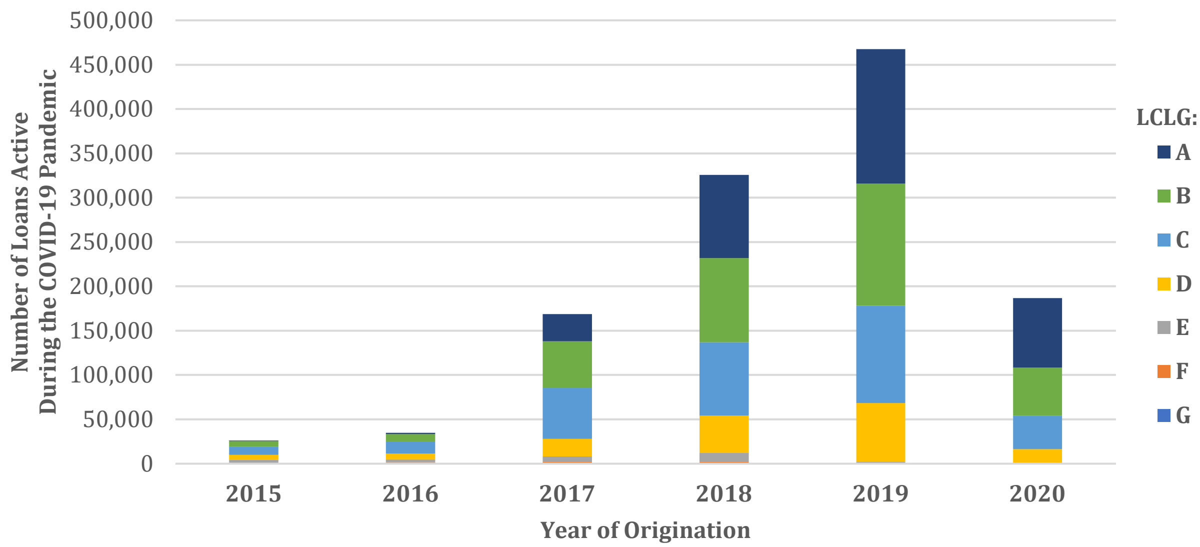
Source: Authors' calculations based on data from LendingClub.

Figure 2B: Number of Loans Active During the COVID-19 Pandemic by FICO Score and by Loan Age (in Years) as of the Start of the Pandemic



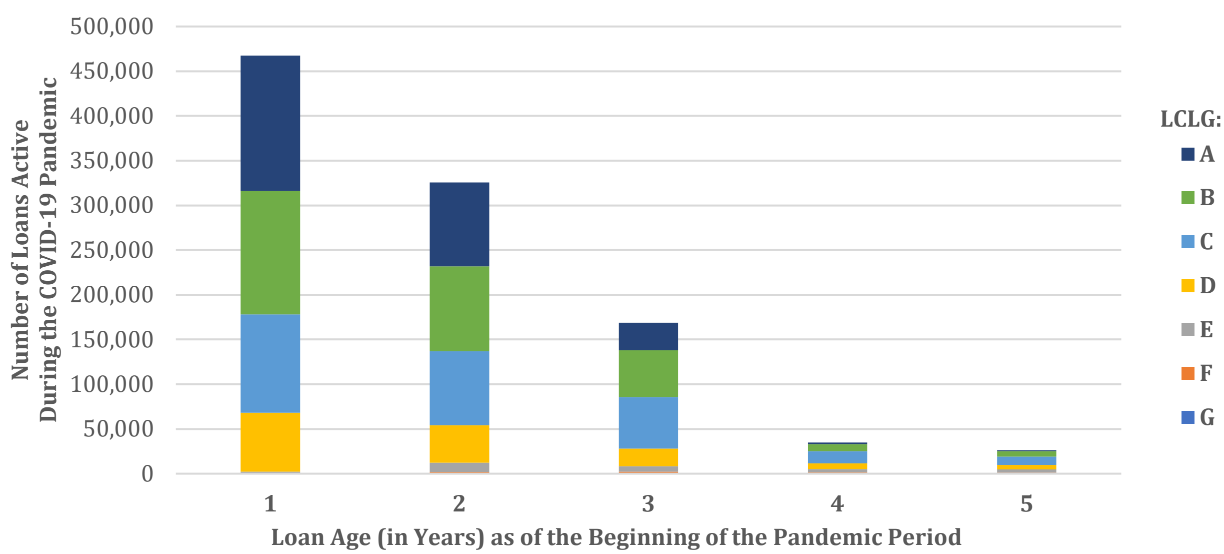
Source: Authors' calculations based on data from LendingClub.

Figure 2C: Number of Loans Active During the COVID-19 Pandemic by Year of Origination and by LCLG



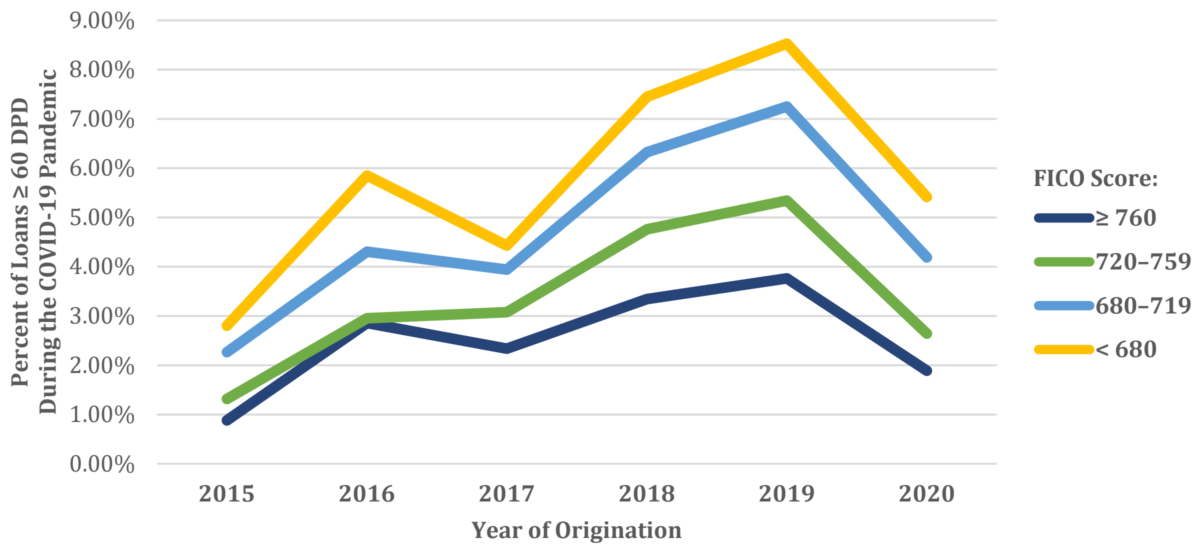
Source: Authors' calculations based on data from LendingClub.

Figure 2D: Number of Loans Active During the COVID-19 Pandemic by LCLG and by Loan Age (in Years) as of the Start of the Pandemic



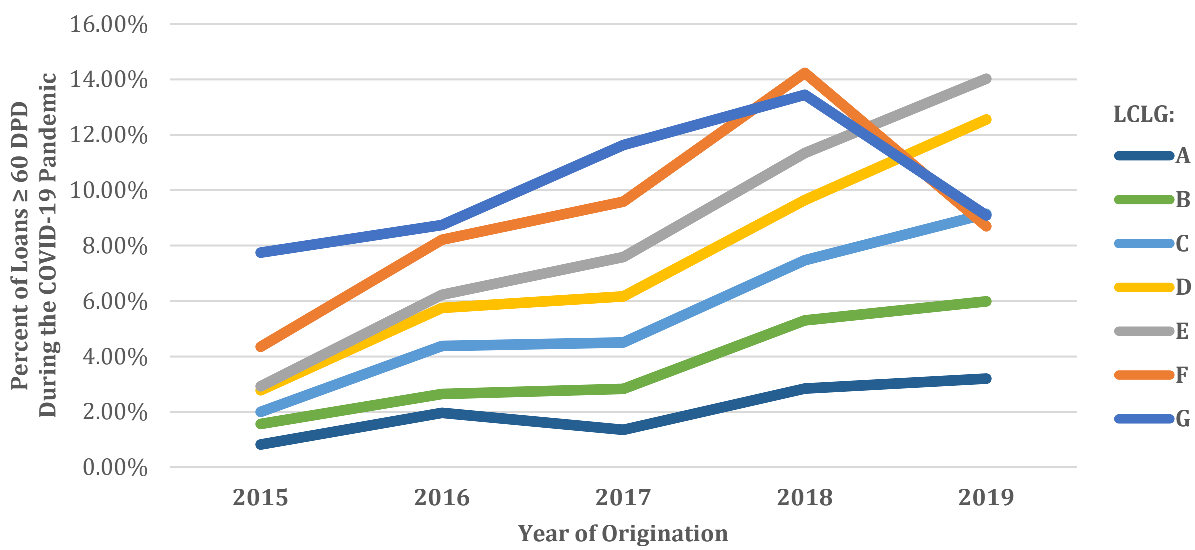
Source: Authors' calculations based on data from LendingClub.

Figure 3A: Percent of Loans that Became ≥ 60 DPD During the Pandemic by Origination Year and by FICO Score



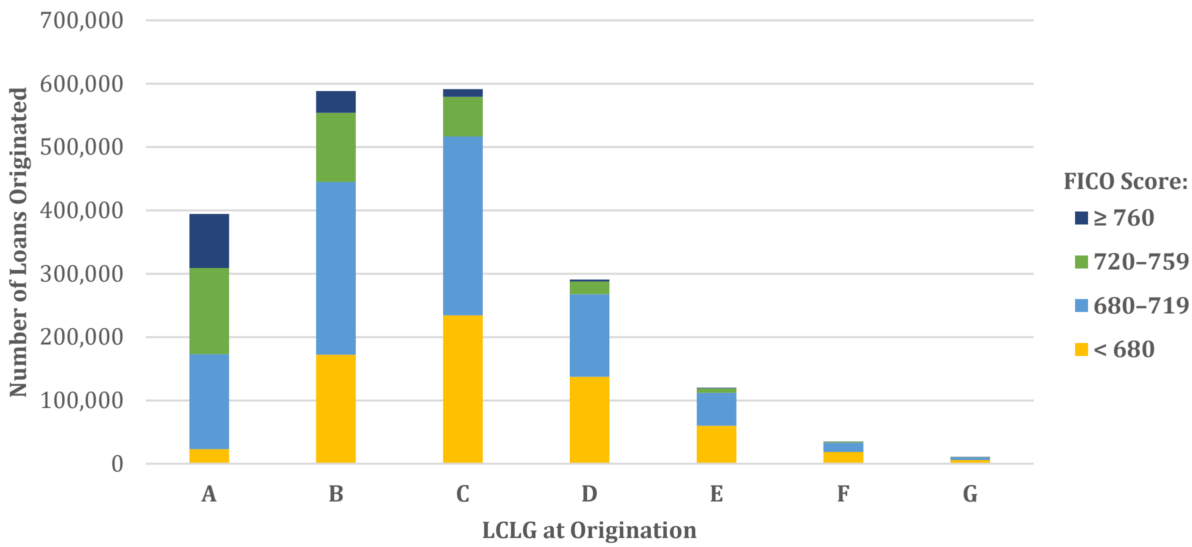
Note: The sample only includes loans that remained active during the pandemic.
Source: Authors' calculations based on data from LendingClub.

Figure 3B: Percent of Loans that Became ≥ 60 DPD During the Pandemic by Origination Year and by LCLG



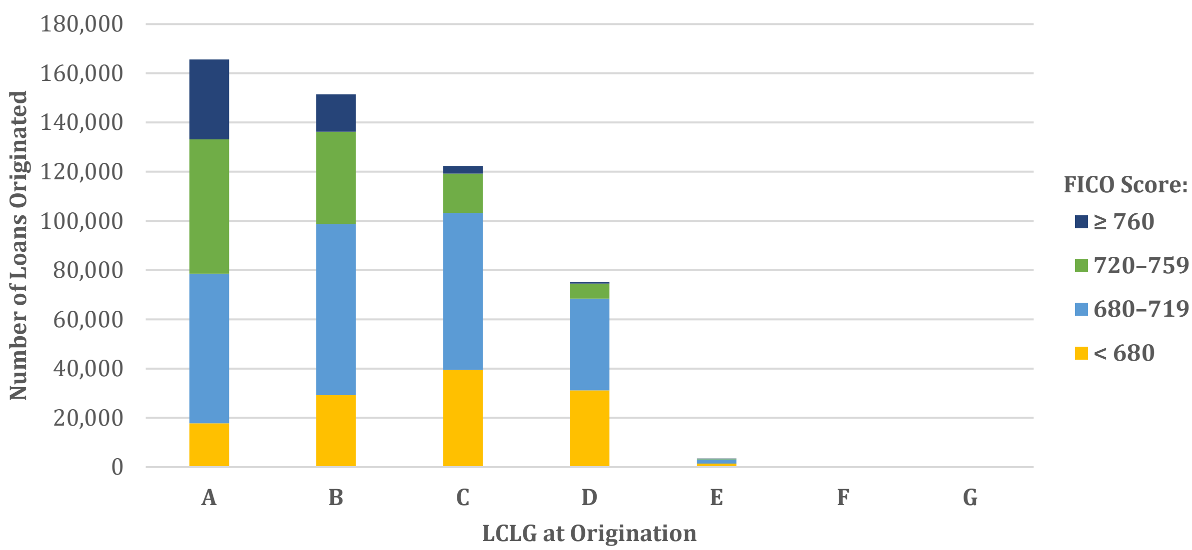
Note: The sample only includes loans that remained active during the pandemic.
Source: Authors' calculations based on data from LendingClub.

Figure 4A: Number of Loans Originated During the 2014–2018 Period by LCLG (at Origination) and by FICO Score (at Origination)



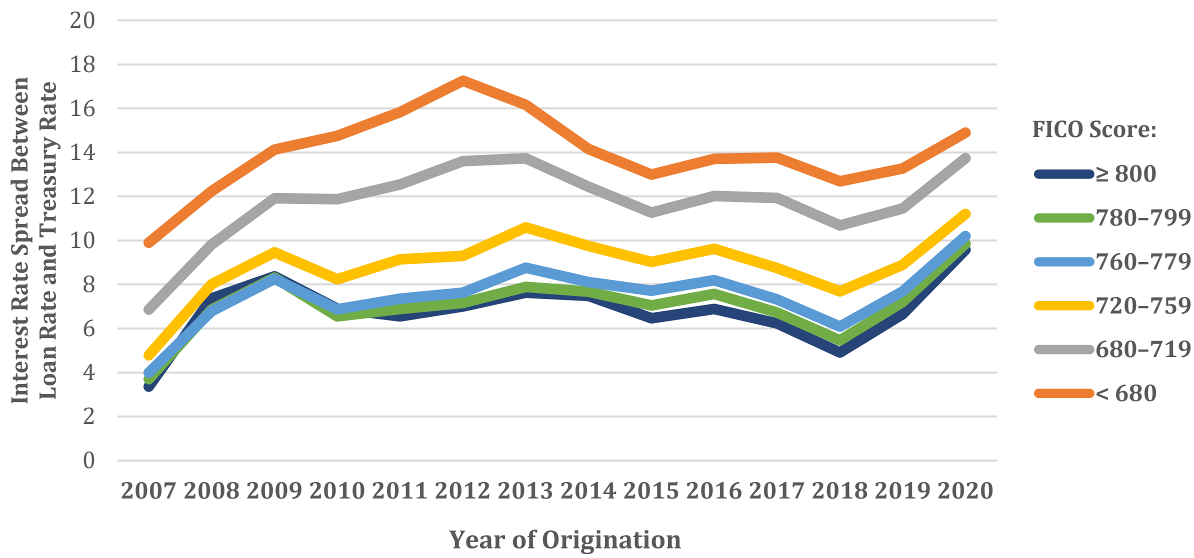
Source: Authors' calculations based on data from LendingClub.

Figure 4B: Number of Loans Originated in 2019 by LCLG (at Origination) and by FICO Score (at Origination)



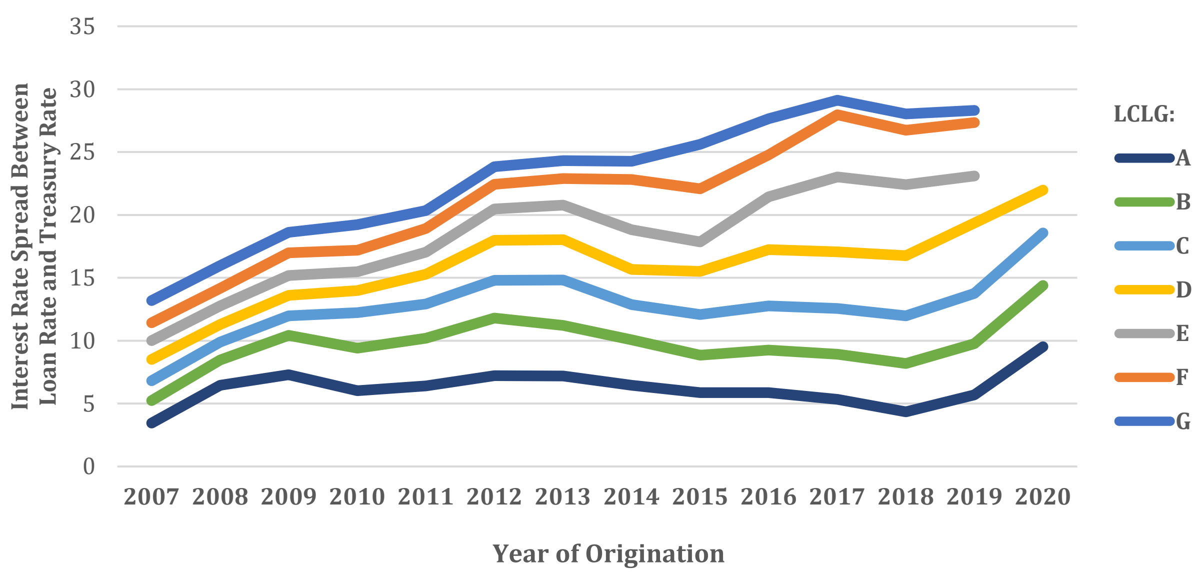
Source: Authors' calculations based on data from LendingClub.

Figure 5A: Interest Rate Spread on LendingClub Loans by FICO Score at Origination (2007–2020)



Source: Authors’ calculations based on data from LendingClub.

Figure 5B: Interest Rate Spread on LendingClub Loans by LCLG (2007–2020)



Source: Authors’ calculations based on data from LendingClub.

Figure 6: Interest Rate (Above Risk-Free Rate on Treasury Securities with the Same Time to Maturity) on LendingClub Loans — by FICO Segment and by LCLG Rating

By FICO Segments — Origination Year 2007 to 2020

FICO Segment	Min Interest Rate	Max Interest Rate	Max-Min	Average Interest[21]	25th Percentile	50th Percentile	75th Percentile
≥ 800	2.49	29.21	**26.72**	**6.43**	4.34	5.64	7.99
780–799	2.49	29.39	**26.90**	**6.98**	4.72	6.06	8.54
760–779	2.18	29.54	**27.36**	**7.54**	5.06	6.68	9.35
720–759	2.49	29.85	**27.36**	**8.98**	5.90	8.27	10.98
680–719	2.49	30.63	**28.14**	**11.79**	8.45	11.32	14.45
< 680	2.65	30.71	**28.06**	**13.65**	10.46	13.04	16.44

By LCLG Ratings — Origination Year 2007 to 2020

LCLG Rating	Min Interest Rate	Max Interest Rate	Max-Min	Average Interest	25th Percentile	50th Percentile	75th Percentile
A-Rated	2.18	10.67	**8.49**	**5.83**	4.74	5.71	6.54
B-Rated	3.04	15.94	**12.90**	**9.45**	8.25	9.41	10.40
C-Rated	3.04	20.60	**17.56**	**12.92**	11.75	12.69	13.78
D-Rated	3.04	30.71	**27.67**	**17.16**	15.66	16.81	18.15
E-Rated	3.04	26.72	**23.68**	**20.39**	18.30	20.38	22.38
F-Rated	3.13	29.75	**26.62**	**24.02**	22.29	23.49	26.14
G-Rated	4.27	30.08	**25.81**	**26.62**	24.48	27.13	29.00

By FICO Segments — Origination Year 2014 to 2019

FICO Segment	Min Interest Rate	Max Interest Rate	Max-Min	Average Interest	25th Percentile	50th Percentile	75th Percentile
≥ 800	2.49	29.21	**26.72**	**6.17**	4.24	5.47	7.31
780–799	2.49	29.39	**26.90**	**6.74**	4.42	5.88	8.16
760–779	2.49	29.54	**27.05**	**7.33**	4.91	6.45	8.96
720–759	2.49	29.85	**27.36**	**8.79**	5.71	7.98	10.85
680–719	2.49	30.08	**27.59**	**11.57**	8.17	11.01	14.12
< 680	2.65	30.00	**27.35**	**13.42**	10.16	12.69	16.16

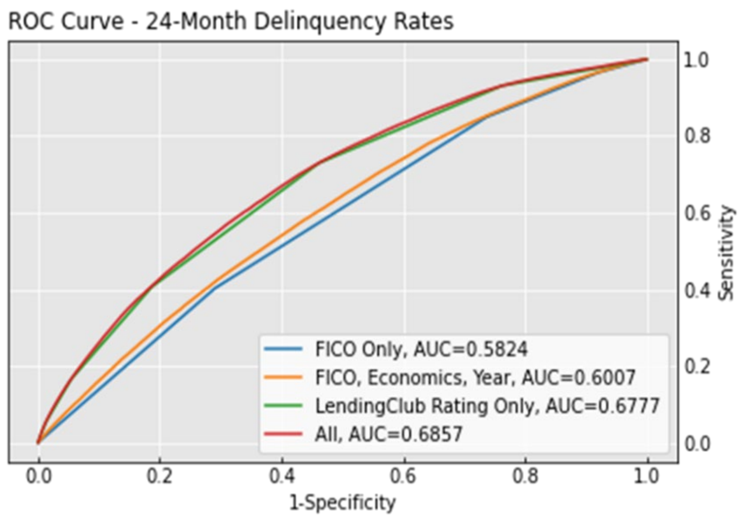
By LCLG Ratings — Origination Year 2014 to 2019

LCLG Rating	Min Interest Rate	Max Interest Rate	Max-Min	Average Interest	25th Percentile	50th Percentile	75th Percentile
A-Rated	2.49	8.04	**5.55**	**5.44**	4.52	5.57	6.34
B-Rated	3.04	12.13	**9.09**	**9.11**	8.18	9.13	10.07
C-Rated	3.04	16.23	**13.19**	**12.67**	11.69	12.52	13.57
D-Rated	3.04	27.29	**24.25**	**17.14**	15.63	16.65	18.06
E-Rated	3.04	26.72	**23.68**	**20.48**	18.29	20.46	22.60
F-Rated	3.13	29.75	**26.62**	**24.46**	22.41	24.05	26.71
G-Rated	4.27	30.08	**25.81**	**27.28**	25.72	27.75	29.06

Source: Authors' calculations based on data from LendingClub.

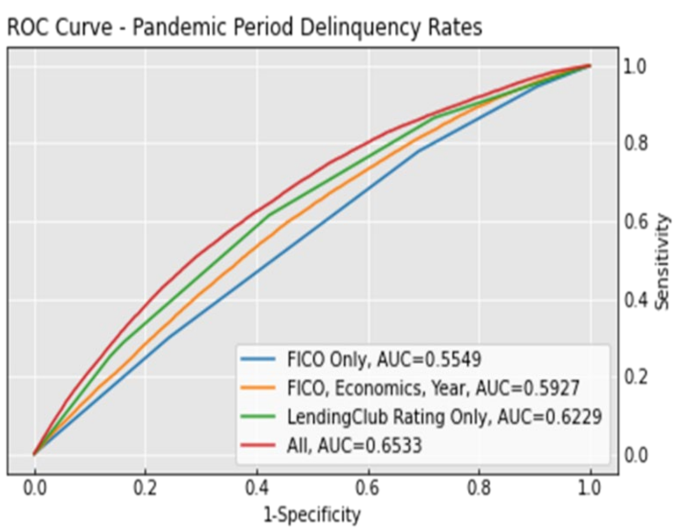
[21] Note that some of the low-FICO (e.g., <680) loans are rated highly (A-rated, B-rated, and C-rated) by LendingClub. The average interest rate would have been much higher (at least 18 percent) for all FICO brackets if those A-rated, B-rated, and C-rated loans were removed from the sample — e.g., the average interest rate for FICO<680 would be 18.71 percent for the loans originated during 2007–2020 and would be 18.69 percent for the loans originated during 2014–2019.

Figure 7: ROC Curves from Table 1 – Default Within 24 Months After Loan Origination



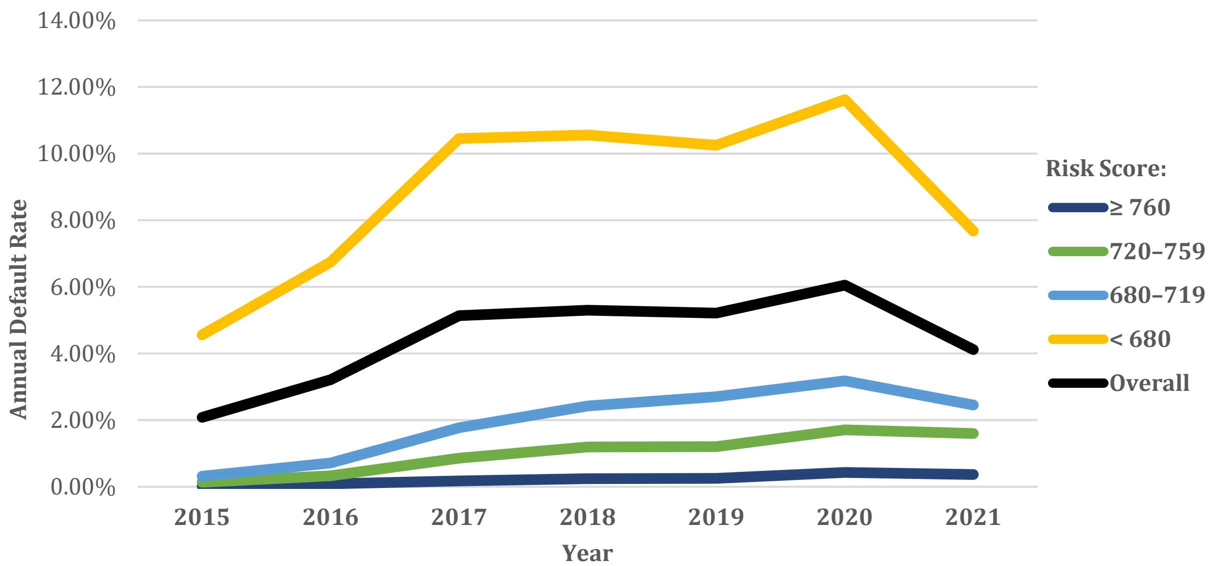
Note: Model (1) Blue = only FICO included; Model (3) Orange = FICO scores and economic factors included; Model (4) Green = only LCLG ratings included; and Model (6) Red = FICO scores, LCLG ratings, and economic factors included.
Source: Authors' calculations based on data from LendingClub, Haver Analytics, the U.S. Census Bureau.

Figure 8: ROC Curves from Table 3 – Default During the COVID Pandemic Period (March 2020 to November 2021).



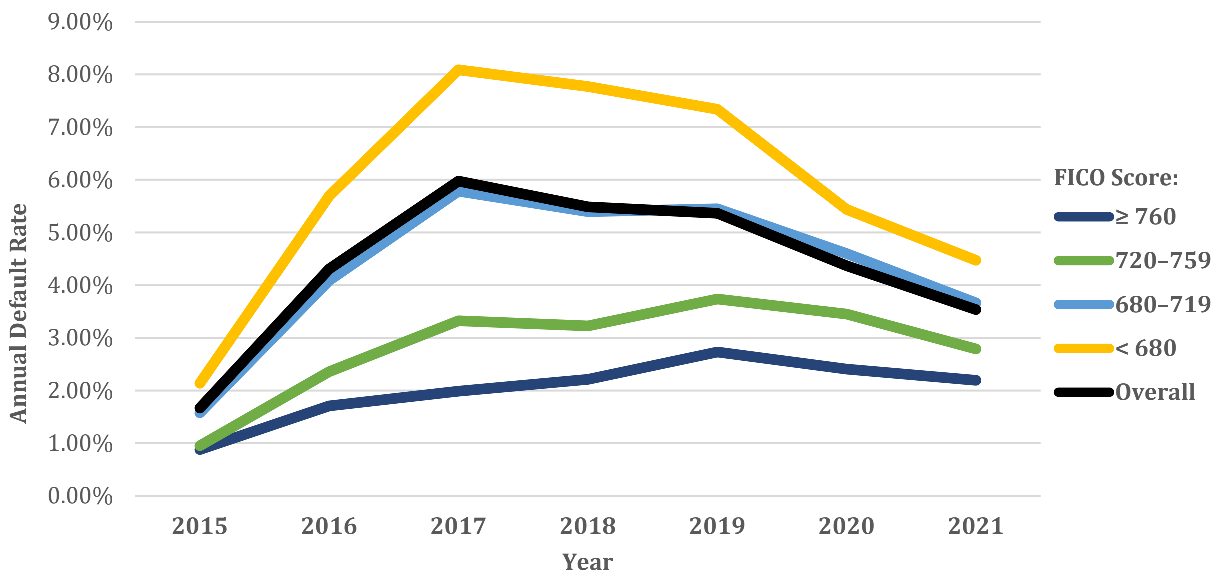
Note: Model (1) Blue = only FICO included; Model (3) Orange = FICO scores and economic factors included; Model (4) Green = only LCLG ratings included; and Model (6) Red = FICO scores, LCLG ratings, and economic factors included.
Source: Authors' calculations based on data from LendingClub, Haver Analytics, and the U.S. Census Bureau.

Figure 9A: Annual Default Rate of Consumer Card Loans from CCP by Year and by Risk Score (at Origination)



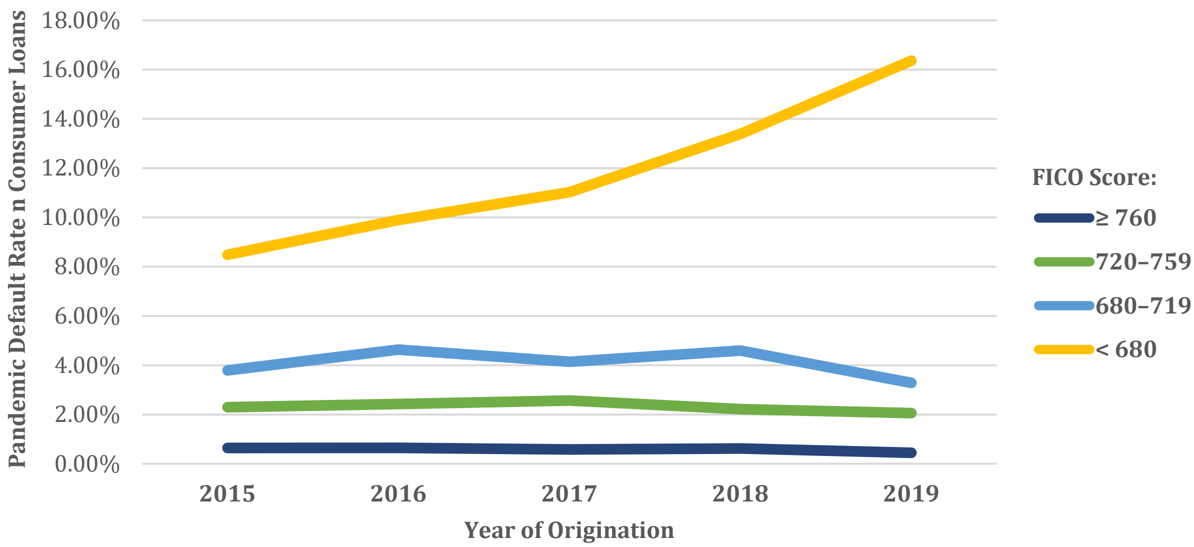
Source: Authors' calculations based on data from FRBNY Consumer Credit Panel/Equifax Data (CCP)

Figure 9B: Annual Default Rate of LendingClub Consumer Personal Loans by Year and by FICO Score (at Origination)



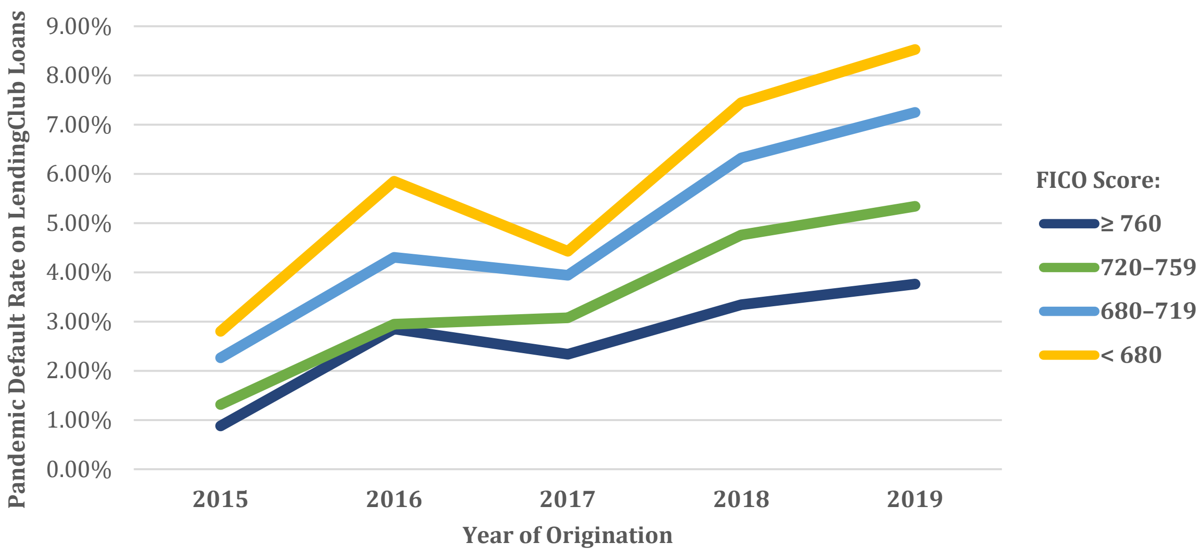
Source: Authors' calculations based on data from LendingClub.

Figure 10A: Default Rate of Consumer Card Loans During the Pandemic by Origination Year and by Risk Score as of Origination



Source: Authors' calculations based on data from FRBNY Consumer Credit Panel/Equifax Data (CCP)

Figure 10B: Default Rate of LendingClub Consumer Loans During the Pandemic by Origination Year and by FICO Score as of Origination)



Source: Authors' calculations based on data from LendingClub.

Table 1: Probability of LendingClub Loans Becoming ≥ 60 DPD Within 24 Months of Origination

The sample includes all loans originated by LendingClub between 2014 and 2019 for which a complete set of economic controls could be matched. The dependent variable is a binary variable that takes a value of 1 if the loan became delinquent (at least 60 DPD) within 24 months after origination and that takes a value of 0 otherwise. All equations include a dummy variable for the year of origination, which accounts for any year-specific factors that could relate to the overall economy and/or to LendingClub's business strategy for that year.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
FICO 720–759 at Origination	0.3504*** (28.83)	-	0.3498*** (28.78)	-	-	0.0565*** (4.56)
FICO 680–719 at Origination	0.7883*** (71.03)	-	0.7871*** (70.92)	-	-	0.1278*** (11.00)
FICO <680 at Origination	1.0955*** (97.89)	-	1.0933*** (97.68)	-	-	0.2276*** (19.18)
LCLG B-Rated at Origination	-	-	-	0.8109*** (93.30)	0.8102*** (93.20)	0.7623*** (85.46)
LCBG C-Rated at Origination	-	-	-	1.3722*** (165.17)	1.3717*** (165.06)	1.3019*** (148.65)
LCLG D-Rated at Origination	-	-	-	1.8143*** (210.11)	1.8142*** (210.01)	1.7326*** (188.84)
LCLG E-Rated at Origination	-	-	-	2.1594*** (212.80)	2.1598*** (212.74)	2.0768*** (195.61)
LCLG F-Rated at Origination	-	-	-	2.5112*** (180.16)	2.5114*** (180.09)	2.4255*** (169.61)
LCLG G-Rated at Origination	-	-	-	2.7369*** (125.75)	2.7377*** (125.73)	2.6489*** (120.30)
Home Price Index (3-Digit Zip Code)	-	+0.0000*** (5.28)	+0.0000*** (5.34)	-	0.0001*** (7.71)	0.0001*** (7.67)
Unemployment Rate (3-Digit Zip)	-	0.0125*** (5.58)	0.0092*** (4.07)	-	0.0068*** (2.95)	0.0063*** (2.73)
Business Bankruptcy (Per 1k Residents in 3-Digit Zip)	-	385.5858*** (7.14)	359.2669*** (6.62)	-	531.2382*** (9.66)	522.8338*** (9.50)
Median Household Income (3-Digit Zip)	-	-0.0000*** (-19.16)	-0.0000*** (-18.39)	-	-0.0000*** (-15.01)	-0.0000*** (-15.07)
Initial Unemployment Claims (State)	-	+0.0000*** (12.02)	+0.0000*** (12.10)	-	+0.0000*** (12.55)	+0.0000*** (12.57)
2015 Origination	0.0851*** (10.44)	0.0963*** (11.50)	0.1021*** (12.16)	0.1371*** (16.51)	0.1527*** (17.85)	0.1527*** (17.84)
2016 Origination	0.1509*** (18.73)	0.1605*** (18.77)	0.1791*** (20.87)	0.2325*** (28.30)	0.2575*** (29.43)	0.2598*** (29.68)
2017 Origination	0.0960*** (11.80)	0.0816*** (9.07)	0.1387*** (15.35)	0.1728*** (20.83)	0.2094*** (22.71)	0.2174*** (23.57)
2018 Origination	0.0214*** (2.63)	-0.0285*** (-3.03)	0.0791*** (8.37)	0.1609*** (19.39)	0.2102*** (21.81)	0.2250*** (23.30)
2019 Origination	-0.3099*** (-36.53)	-0.3497*** (-35.48)	-0.2426*** (-24.46)	-0.0709*** (-8.15)	-0.0153 (-1.51)	-0.0009 (-0.09)
Observations	2,527,856	2,527,856	2,527,856	2,527,856	2,527,856	2,527,856
Log-Likelihood	-8.44E+05	-8.54E+05	-8.43+05	-8.06E+05	-8.06E+05	-8.05E+05
Deviance	1.687E+06	1.707E+06	1.686E+06	1.612E+06	1.611E+06	1.610E+06
Pearson Chi-squared	2.530E+06	2.530E+06	2.530E+06	2.530E+06	2.530E+06	2.530E+06

Source: Authors' calculations based on data from LendingClub, Haver Analytics, and the U.S. Census Bureau.

Table 2A: Correlations Between Various LendingClub Variables, Origination Period 2014–2019

Variable	*≥ 60 DPD in 12 mo.*	*≥ 60 DPD in 24 mo.*	*HPI*	*Unemploy Rate*	*Business Bankruptcy*	*Med HH Income*	*Initial Unemploy Claims*	*D_2015*	*D_2016*	*D_2017*	*D_2018*	*D_2019*	*FICO 720–759*	*FICO 680–719*	*FICO <680*	*LCLG B-Rated*	*LCLG C-Rated*	*LCLG D-Rated*	*LCLG E-Rated*	*LCLG F-Rated*	*LCLG G-Rated*
≥ 60 DPD in 12 mo.	1.00	0.63	0.01	0.01	0.00	-0.01	0.01	0.01	0.01	0.00	0.00	-0.02	-0.03	0.00	0.05	-0.05	0.02	0.07	0.08	0.07	0.05
≥ 60 DPD in 24 mo.	0.63	1.00	0.00	0.03	0.01	-0.02	0.02	0.02	0.03	0.01	-0.01	-0.05	-0.06	0.00	0.08	-0.07	0.04	0.10	0.10	0.08	0.05
HPI	0.01	0.00	1.00	-0.18	0.16	0.52	0.61	-0.08	-0.04	0.01	0.06	0.10	0.02	0.00	-0.03	0.01	-0.02	-0.02	-0.03	-0.02	-0.01
Unemploy Rate	0.01	0.03	-0.18	1.00	0.02	-0.47	0.26	0.25	0.11	-0.07	-0.24	-0.33	-0.06	0.00	0.08	-0.01	0.03	0.02	0.07	0.05	0.02
Business Bankruptcy	0.00	0.01	0.16	0.02	1.00	0.20	0.17	0.07	0.01	-0.03	-0.08	-0.04	-0.01	0.00	0.02	0.00	0.00	0.00	0.01	0.01	0.00
Med HH Income	-0.01	-0.02	0.52	-0.47	0.20	1.00	0.18	-0.12	-0.08	0.00	0.08	0.17	0.03	0.00	-0.04	0.01	-0.02	-0.02	-0.04	-0.02	-0.01
Initial Unemploy Claims	0.01	0.02	0.61	0.26	0.17	0.18	1.00	0.04	0.02	0.00	-0.05	-0.06	-0.01	0.00	0.01	0.00	0.00	0.00	0.01	0.01	0.00
D_2015	0.01	0.02	-0.08	0.25	0.07	-0.12	0.04	1.00	-0.20	-0.20	-0.22	-0.23	-0.05	0.01	0.06	-0.01	0.01	0.01	0.07	0.04	0.01
D_2016	0.01	0.03	-0.04	0.11	0.01	-0.08	0.02	-0.20	1.00	-0.21	-0.22	-0.23	-0.04	0.00	0.05	0.02	0.02	-0.01	0.02	0.03	0.01
D_2017	0.00	0.01	0.01	-0.07	-0.03	0.00	0.00	-0.20	-0.21	1.00	-0.23	-0.23	0.00	-0.01	0.00	0.01	0.05	-0.02	-0.01	0.00	0.03
D_2018	0.00	-0.01	0.06	-0.24	-0.08	0.08	-0.05	-0.22	-0.22	-0.23	1.00	-0.25	0.05	-0.01	-0.07	-0.01	-0.03	-0.01	-0.02	-0.03	-0.02
D_2019	-0.02	-0.05	0.10	-0.33	-0.04	0.17	-0.06	-0.23	-0.23	-0.23	-0.25	1.00	0.06	0.00	-0.08	0.00	-0.05	0.00	-0.10	-0.06	-0.03
FICO 720–759	-0.03	-0.06	0.02	-0.06	-0.01	0.03	-0.01	-0.05	-0.04	0.00	0.05	0.06	1.00	-0.42	-0.31	0.04	-0.11	-0.11	-0.07	-0.04	-0.02
FICO 680–719	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	-0.01	-0.01	0.00	-0.42	1.00	-0.59	0.02	0.05	0.01	-0.01	-0.01	-0.01
FICO <680	0.05	0.08	-0.03	0.08	0.02	-0.04	0.01	0.06	0.05	0.00	-0.07	-0.08	-0.31	-0.59	1.00	-0.04	0.11	0.14	0.10	0.06	0.04
LCLG B-Rated	-0.05	-0.07	0.01	-0.01	0.00	0.01	0.00	-0.01	0.02	0.01	-0.01	0.00	0.04	0.02	-0.04	1.00	-0.40	-0.26	-0.14	-0.08	-0.04
LCLG C-Rated	0.02	0.04	-0.02	0.03	0.00	-0.02	0.00	0.01	0.02	0.05	-0.03	-0.05	-0.11	0.05	0.11	-0.40	1.00	-0.26	-0.14	-0.07	-0.04
LCLG D-Rated	0.07	0.10	-0.02	0.02	0.00	-0.02	0.00	0.01	-0.01	-0.02	-0.01	0.00	-0.11	0.01	0.14	-0.26	-0.26	1.00	-0.09	-0.05	-0.03
LCLG E-Rated	0.08	0.10	-0.03	0.07	0.01	-0.04	0.01	0.07	0.02	-0.01	-0.02	-0.10	-0.07	-0.01	0.10	-0.14	-0.14	-0.09	1.00	-0.03	-0.02
LCLG F-Rated	0.07	0.08	-0.02	0.05	0.01	-0.02	0.01	0.04	0.03	0.00	-0.03	-0.06	-0.04	-0.01	0.06	-0.08	-0.07	-0.05	-0.03	1.00	-0.01
LCLG G-Rated	0.05	0.05	-0.01	0.02	0.00	-0.01	0.00	0.01	0.01	0.03	-0.02	-0.03	-0.02	-0.01	0.04	-0.04	-0.04	-0.03	-0.02	-0.01	1.00

Source: Authors' calculations based on data from LendingClub and Haver Analytics.

Table 2B: Correlations Between Various LendingClub Variables for Loans Originated in 2014–2019 and Remained Active as of the Beginning of the Pandemic.

Variable	*≥ 60 DPD in Pandemic*	*HPI*	*Unemploy Rate*	*Business Bankruptcy*	*Med HH Income*	*Initial Unemploy Claims*	*D_2015*	*D_2016*	*D_2017*	*D_2018*	*D_2019*	*FICO 720–759*	*FICO 680–719*	*FICO <680*	*LCLG B-Rated*	*LCLG C-Rated*	*LCLG D-Rated*	*LCLG E-Rated*	*LCLG F-Rated*	*LCLG G-Rated*
≥ 60 DPD in Pandemic	1.00	0.01	-0.01	0.00	0.00	0.00	-0.03	-0.01	-0.04	0.00	0.04	-0.03	0.01	0.03	-0.02	0.04	0.07	0.02	0.01	0.01
HPI	0.01	1.00	-0.17	0.18	0.52	0.64	-0.06	-0.05	-0.04	0.01	0.07	0.00	0.00	-0.01	0.00	-0.02	-0.02	-0.02	-0.01	-0.01
Unemploy Rate	-0.01	-0.17	1.00	-0.07	-0.47	0.21	0.21	0.17	0.19	-0.02	-0.25	-0.02	0.00	0.03	-0.01	0.04	0.01	0.06	0.04	0.02
Business Bankruptcy	0.00	0.18	-0.07	1.00	0.22	0.17	0.03	0.02	0.02	-0.05	0.02	-0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Med HH Income	0.00	0.52	-0.47	0.22	1.00	0.23	-0.07	-0.06	-0.08	-0.02	0.13	0.01	0.00	-0.02	0.00	-0.03	-0.02	-0.03	-0.02	-0.01
Initial Unemploy Claims	0.00	0.64	0.21	0.17	0.23	1.00	0.02	0.01	0.03	-0.01	-0.02	0.00	0.00	0.00	0.00	0.00	-0.01	0.00	0.00	0.00
D_2015	-0.03	-0.06	0.21	0.03	-0.07	0.02	1.00	-0.03	-0.07	-0.11	-0.15	-0.03	0.02	0.03	-0.02	0.03	0.03	0.12	0.06	0.02
D_2016	-0.01	-0.05	0.17	0.02	-0.06	0.01	-0.03	1.00	-0.08	-0.13	-0.17	-0.02	0.02	0.02	-0.03	0.05	0.03	0.09	0.08	0.04
D_2017	-0.04	-0.04	0.19	0.02	-0.08	0.03	-0.07	-0.08	1.00	-0.30	-0.41	-0.02	0.00	0.04	0.02	0.07	-0.02	0.03	0.03	0.04
D_2018	0.00	0.01	-0.02	-0.05	-0.02	-0.01	-0.11	-0.13	-0.30	1.00	-0.63	0.02	-0.01	-0.02	0.00	-0.02	-0.02	0.03	0.00	-0.01
D_2019	0.04	0.07	-0.25	0.02	0.13	-0.02	-0.15	-0.17	-0.41	-0.63	1.00	0.02	0.00	-0.03	0.00	-0.07	0.01	-0.12	-0.07	-0.04
FICO 720–759	-0.03	0.00	-0.02	-0.01	0.01	0.00	-0.03	-0.02	-0.02	0.02	0.02	1.00	-0.47	-0.30	0.05	-0.12	-0.13	-0.06	-0.03	-0.02
FICO 680–719	0.01	0.00	0.00	0.01	0.00	0.00	0.02	0.02	0.00	-0.01	0.00	-0.47	1.00	-0.52	0.02	0.08	0.03	0.00	0.00	0.00
FICO <680	0.03	-0.01	0.03	0.00	-0.02	0.00	0.03	0.02	0.04	-0.02	-0.03	-0.30	-0.52	1.00	-0.06	0.12	0.17	0.08	0.04	0.02
LCLG B-Rated	-0.02	0.00	-0.01	0.00	0.00	0.00	-0.02	-0.03	0.02	0.00	0.00	0.05	0.02	-0.06	1.00	-0.39	-0.26	-0.10	-0.05	-0.03
LCLG C-Rated	0.04	-0.02	0.04	0.00	-0.03	0.00	0.03	0.05	0.07	-0.02	-0.07	-0.12	0.08	0.12	-0.39	1.00	-0.24	-0.10	-0.04	-0.02
LCLG D-Rated	0.07	-0.02	0.01	0.00	-0.02	-0.01	0.03	0.03	-0.02	-0.02	0.01	-0.13	0.03	0.17	-0.26	-0.24	1.00	-0.06	-0.03	-0.02
LCLG E-Rated	0.02	-0.02	0.06	0.00	-0.03	0.00	0.12	0.09	0.03	0.03	-0.12	-0.06	0.00	0.08	-0.10	-0.10	-0.06	1.00	-0.01	-0.01
LCLG F-Rated	0.01	-0.01	0.04	0.00	-0.02	0.00	0.06	0.08	0.03	0.00	-0.07	-0.03	0.00	0.04	-0.05	-0.04	-0.03	-0.01	1.00	0.00
LCLG G-Rated	0.01	-0.01	0.02	0.00	-0.01	0.00	0.02	0.04	0.04	-0.01	-0.04	-0.02	0.00	0.02	-0.03	-0.02	-0.02	-0.01	0.00	1.00

Source: Authors' calculations based on data from LendingClub and Haver Analytics.

Table 3: Probability of LendingClub Loans Becoming ≥ 60 DPD During COVID-19 Pandemic

The sample includes loans originated by LendingClub between 2014 and 2019 that were still in active status (outstanding) as of the beginning of COVID period (March 2020) and for which a complete set of economic controls could be matched. The dependent variable is a binary variable that takes a value of 1 if the loan becomes delinquent (at least 60 DPD) within 24 months after origination and that takes a value of 0 otherwise. All equations include a dummy variable for the year of origination, which accounts for any year-specific factors that could relate to the overall economy and/or to LendingClub 's business strategy for that year.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
FICO 720–759 at Origination	0.3564*** (17.02)	-	0.3561*** (17.01)	-	-	0.1527*** (7.21)
FICO 680–719 at Origination	0.6672*** (34.60)	-	0.6665*** (34.56)	-	-	0.1736*** (8.64)
FICO <680 at Origination	0.8427*** (42.40)	-	0.8411*** (42.32)	-	-	0.1838*** (8.74)
LCLG B-Rated at Origination	-	-	-	0.6580*** (46.31)	0.6582*** (46.31)	0.6364*** (44.05)
LCLG C-Rated at Origination	-	-	-	1.0905*** (79.43)	1.0904*** (79.39)	1.0537*** (72.68)
LCLG D-Rated at Origination	-	-	-	1.4181*** (97.43)	1.4185*** (97.41)	1.3773*** (88.48)
LCLG E-Rated at Origination	-	-	-	1.5538*** (61.11)	1.5532*** (61.07)	1.5110*** (57.96)
LCLG F-Rated at Origination	-	-	-	1.8273*** (37.36)	1.8278*** (37.36)	1.7851*** (36.23)
LCLG G-Rated at Origination	-	-	-	1.9549*** (23.12)	1.9528*** (23.09)	1.9102*** (22.54)
Home Price Index (3-Digit Zip Code)	-	0.0001*** (8.49)	0.0001*** (8.21)	-	0.0002*** (9.42)	0.0002*** (9.37)
Unemployment Rate (3-Digit Zip)	-	0.0074 (1.36)	0.0055 (1.01)	-	0.0033 (0.60)	0.0032 (0.57)
Business Bankruptcies (Per 1k Residents in 3-dDigit Zip)	-	728.4145*** (7.10)	699.2566*** (6.79)	-	782.8709*** (7.58)	778.2914*** (7.53)
Median Household Income (3-Digit Zip)	-	-0.0000*** (-11.20)	-0.0000*** (-11.05)	-	-0.0000*** (-9.61)	-0.0000*** (-9.65)
Initial Unemployment Claims (State)	-	-0.0000*** (-3.14)	-0.0000*** (-2.91)	-	-0.0000*** (-3.08)	-0.0000*** (-3.06)
2015 Origination	-1.2441** (-2.38)	-1.2820** (-2.46)	-1.2390** (-2.37)	-1.0472** (-2.00)	-1.0465** (-2.00)	-1.0464** (-2.00)
2016 Origination	-0.5184 (-0.99)	-0.5646 (-1.08)	-0.5064 (-0.97)	-0.3069 (-0.59)	-0.3016 (-0.58)	-0.2998 (-0.57)
2017 Origination	-0.6664 (-1.28)	-0.7303 (-1.40)	-0.6488 (-1.25)	-0.2530 (-0.48)	-0.2453 (-0.47)	-0.2453 (-0.47)
2018 Origination	-0.1596 (-0.31)	-0.2463 (-0.47)	-0.1351 (-0.26)	0.3166 (0.61)	0.3285 (0.63)	0.3298 (0.63)
2019 Origination	-0.0205 (-0.04)	-0.1000 (-0.19)	0.0102 (0.02)	0.5139 (0.98)	0.5293 (1.01)	0.5300 (1.01)
Observations	1,015,217	1,015,217	1,015,217	1,015,217	1,015,217	1,015,217
Log-Likelihood	-2.23E+05	-2.24E+05	-2.23E+05	-2.18E+05	-2.17E+05	-2.17E+05
Deviance	4.454E+05	4.481E+05	4.452E+05	4.351E+05	4.349E+05	4.348E+05
Pearson Chi-squared	1.020E+06	1.020E+06	1.020E+06	1.010E+06	1.010E+06	1.010E+06

Source: Authors' calculations based on data from LendingClub, Haver Analytics, and the Census Bureau.

Table 4: Interest Rates Charged by LendingClub

The sample includes all loans originated by LendingClub during the period 2014–2019 (the pre-COVID origination years) for which a complete set of economic controls could be matched. The dependent variable is interest rate spreads (the interest rate charged by LendingClub minus the risk-free rate on Treasury securities with the same time to maturity as the LendingClub loan). All equations include a dummy variable for the year of loan origination, which accounts for any year-specific factors that could relate to the overall economy and/or to LendingClub's business strategy for that year. The base year in this analysis is 2019.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
FICO 720–759 at Origination	1.8243*** (120.19)	-	1.8233*** (120.20)	-	-	0.3177*** (65.38)
FICO 680–719 at Origination	4.5360*** (328.64)	-	4.5335*** (328.64)	-	-	0.5803*** (126.51)
FICO <680 at Origination	6.3288*** (441.89)	-	6.3228*** (441.68)	-	-	0.6160*** (125.93)
LCLG B-Rated at Origination	-	-	-	3.7210*** (1181.46)	3.7205*** (1181.10)	3.5942*** (1103.81)
LCLG C-Rated at Origination	-	-	-	7.3062*** (2296.27)	7.3055*** (2295.12)	7.1268*** (2085.96)
LCLG D-Rated at Origination	-	-	-	11.7624*** (3115.79)	11.7615*** (3114.02)	11.5628*** (2865.92)
LCLG E-Rated at Origination	-	-	-	15.3263*** (2700.76)	15.3255*** (2700.00)	15.1283*** (2593.21)
LCLG F-Rated at Origination	-	-	-	19.2595*** (1981.78)	19.2586*** (1981.59)	19.0590*** (1948.74)
LCLG G-Rated at Origination	-	-	-	22.0002*** (1274.09)	21.9996*** (1274.05)	21.7952*** (1264.78)
Home Price Index (3-Digit Zip Code)	-	-0.0002*** (-9.55)	-0.0002*** (-10.31)	-	-0.0000 (-0.29)	-0.0000 (-0.94)
Unemployment Rate (3-Digit Zip)	-	0.0471*** (11.11)	0.0257*** (6.58)	-	-0.0036*** (-2.86)	-0.0045*** (-3.66)
Business Bankruptcy (Per 1k Residents in 3-Digit Zip)	-	-865.367*** (-8.76)	-1034.339*** (-11.37)	-	44.4616 (1.53)	17.4243 (0.60)
Median Household Income (3-Digit Zip)	-	-0.0000*** (-20.99)	-0.0000*** (-19.53)	-	-0.0000*** (-9.45)	-0.0000*** (-9.83)
Initial Unemployment Claims (State)	-	+0.0000 (0.65)	+0.0000 (1.24)	-	+0.0000*** (4.72)	+0.0000*** (5.04)
2014 Origination	0.8771*** (60.70)	1.4535*** (79.37)	0.7454*** (44.10)	-0.9397*** (-202.28)	-0.9428*** (-173.73)	-0.9700*** (-179.69)
2015 Origination	-0.2097*** (-17.98)	0.3409*** (24.44)	-0.3185*** (-24.71)	-1.5921*** (-424.06)	-1.5967*** (-385.26)	-1.6247*** (-393.85)
2016 Origination	0.5017*** (46.12)	1.0116*** (80.83)	0.4127*** (35.67)	-0.6809*** (-194.50)	-0.6851*** (-184.16)	-0.7070*** (-190.97)
2017 Origination	0.2810*** (25.19)	0.5310*** (43.02)	0.2237*** (19.67)	-0.8438*** (-234.94)	-0.8469*** (-231.29)	-0.8470*** (-232.72)
2018 Origination	-0.9197*** (-81.79)	-0.9493*** (-77.50)	-0.9506*** (-84.32)	-1.5859*** (-440.37)	-1.5876*** (-439.56)	-1.5770*** (-439.27)
Observations	1,670,528	1,670,528	1,670,528	1,670,528	1,670,528	1,670,528
Adjusted R-squared	0.174	0.025	0.175	0.916	0.916	0.917
AIC	9.740E+06	1.002E+07	9.738E+06	5.930E+06	5.930E+06	5.909E+06
BIC	9.740E+06	1.002E+07	9.739E+06	5.930E+06	5.930E+06	5.909E+06

Source: Authors' calculations based on data from LendingClub, Haver Analytics, the Census Bureau.

Table 5: Interest Rates Charged by LendingClub — Using More Granular FICO Segments

The sample includes all loans originated by LendingClub during 2014–2019 (the pre-COVID period) for which a complete set of economic controls could be matched. The dependent variable is the interest rate spread (the interest rate charged by LendingClub minus risk-free rate on Treasury securities with the same time to maturity as the LendingClub loan). All equations include dummy variables for year of loan origination (accounting for any year-specific factors that could relate to the overall economy and/or to LendingClub's business strategy for that year). The base year in this analysis is 2019.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
FICO 780–799 at Origination	0.5700***	-	0.5675***	-	-	0.1667***
	(15.50)		(15.44)			(14.27)
FICO 760–779 at Origination	1.1530***	-	1.1522***	-	-	0.2766***
	(34.64)		(34.64)			(26.14)
FICO 720–759 at Origination	2.5719***	-	2.5698***	-	-	0.5064***
	(87.95)		(87.93)			(54.26)
FICO 680–719 at Origination	5.2836***	-	5.2800***	-	-	0.7696***
	(185.05)		(185.02)			(83.54)
FICO <680 at Origination	7.0763***	-	7.0692***	-	-	0.8057***
	(245.65)		(245.54)			(85.92)
LCLG B-Rated at Origination	-	-	-	3.7210***	3.7205***	3.5909***
				(1181.45)	(1181.10)	(1102.21)
LCLG C-Rated at Origination	-	-	-	7.3062***	7.3055***	7.1236***
				(2296.27)	(2295.12)	(2084.13)
LCLG D-Rated at Origination	-	-	-	11.7624***	11.7615***	11.5598***
				(3115.79)	(3114.02)	(2864.61)
LCLG E-Rated at Origination	-	-	-	15.3263***	15.3255***	15.1252***
				(2700.76)	(2700.00)	(2592.70)
LCLG F-Rated at Origination	-	-	-	19.2595***	19.2586***	19.0558***
				(1981.78)	(1981.59)	(1948.68)
LCLG G-Rated at Origination	-	-	-	22.0002***	21.9996***	21.7919***
				(1274.09)	(1274.05)	(1264.81)
Home Price Index (3-Digit Zip Code)	-	-0.0002***	-0.0002***	-	-0.0000	-0.0000
		(-9.55)	(-10.44)		(-0.29)	(-1.05)
Unemployment Rate (3-Digit Zip)	-	0.0471***	0.0257***	-	-0.0036***	-0.0045***
		(11.11)	(6.58)		(-2.86)	(-3.66)
Business Bankruptcy (Per 1k Residents in 3-Digit Zip)	-	-865.367***	-1037.692***	-	44.4616	16.4962
		(-8.75)	(-11.41)		(1.53)	(0.57)
Median Household Income (3-Digit Zip)	-	-0.0000***	-0.0000***	-	-0.0000***	-0.0000***
		(-20.99)	(-19.42)		(-9.45)	(-9.75)
Initial Unemployment Claims (State)	-	0.0000	0.0000	-	0.0000***	0.0000***
		(0.65)	(1.27)		(4.72)	(5.07)
2014 Origination	0.8785***	1.4535***	0.7468***	-0.9397***	-0.9428***	-0.9694***
	(60.82)	(79.37)	(44.20)	(-202.28)	(-173.72)	(-179.62)
2015 Origination	-0.2077***	0.3409***	-0.3164***	-1.5921***	-1.5967***	-1.6240***
	(-17.81)	(24.44)	(-24.55)	(-424.06)	(-385.26)	(-393.75)
2016 Origination	0.5043***	1.0116***	0.4153***	-0.6809***	-0.6851***	-0.7061***
	(46.37)	(80.83)	(35.91)	(-194.50)	(-184.16)	(-190.75)
2017 Origination	0.2848***	0.5310***	0.2276***	-0.8438***	-0.8469***	-0.8457***
	(25.54)	(43.02)	(20.02)	(-234.94)	(-231.29)	(-232.40)
2018 Origination	-0.9167***	-0.9493***	-0.9474***	-1.5859***	-1.5876***	-1.5761***
	(-81.54)	(-77.50)	(-84.07)	(-440.37)	(-439.56)	(-439.10)
Observations	1,670,528	1,670,528	1,670,528	1,670,528	1,670,528	1,670,528
Adjusted R-squared	0.174	0.025	0.175	0.916	0.916	0.917
AIC	9.739E+06	1.002E+07	9.737E+06	5.930E+06	5.930E+06	5.908E+06
BIC	9.739E+06	1.002E+07	9.737E+06	5.930E+06	5.930E+06	5.909E+06

Source: Authors' calculations based on data from LendingClub, Haver Analytics, and the Census Bureau.

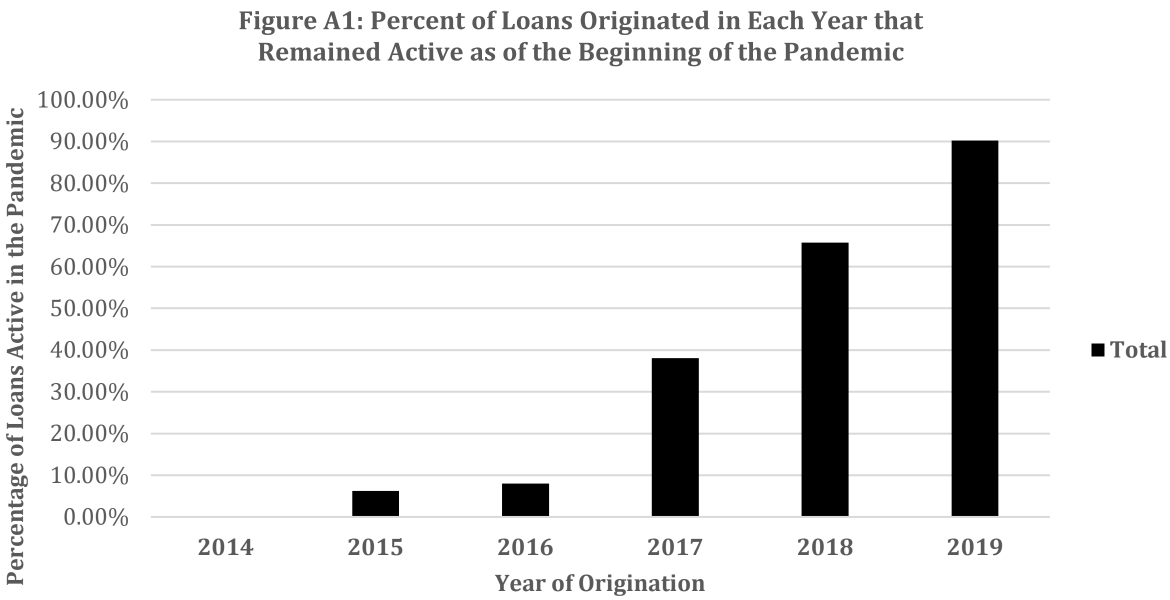
Table 6: The Role of Interest Rate Spread Residual in Determining Default Probability

The sample includes LendingClub loans that were originated during 2014–2019 for which a complete set of economic controls could be matched. The dependent variable is a binary variable that takes a value of 1 if the loan becomes at least 60 DPD within 24 months after origination and that takes a value of 0 otherwise. The Spread Residual (SR) used in Column (1) is the part of the interest rate charged by LendingClub that is not captured by FICO score, economic factors, and year of origination. The SR in Column (2) is not correlated with LCLGs, economic factors, and year. The SR in Column (3) is the part of the interest rate that is not correlated with FICO score, LCLGs, economic factors, or year.

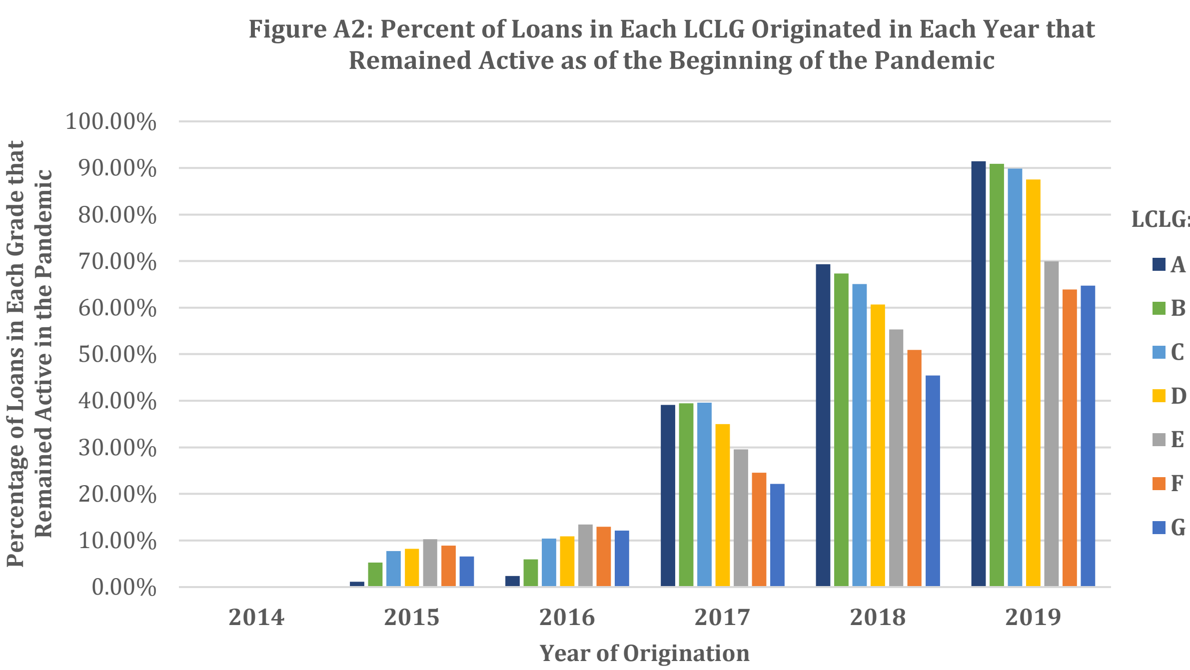
VARIABLES	(1)	(2)	(3)	(1')	(2')	(3')
FICO 720–759 at Origination	0.3556***	-	0.0609***	0.3217***	-	0.0616***
	(23.81)		(4.00)	(21.37)		(4.04)
FICO 680–719 at Origination	0.7929***	-	0.1345***	0.7420***	-	0.1347***
	(58.17)		(9.43)	(54.01)		(9.43)
FICO <680 at Origination	1.1026***	-	0.2383***	1.0648***	-	0.2369***
	(80.24)		(16.35)	(76.89)		(16.26)
LCLG B-Rated at Origination	-	0.8158***	0.7647***	-	0.8144***	0.7636***
		(76.29)	(69.65)		(76.18)	(69.58)
LCLG C-Rated at Origination	-	1.3728***	1.2994***	-	1.3712***	1.2982***
		(134.25)	(120.52)		(134.19)	(120.52)
LCLG D-Rated at Origination	-	1.8222***	1.7362***	-	1.8182***	1.7329***
		(171.34)	(153.65)		(171.07)	(153.46)
LCLG E-Rated at Origination	-	2.1565***	2.0697***	-	2.1386***	2.0531***
		(171.74)	(157.67)		(170.49)	(156.59)
LCLG F-Rated at Origination	-	2.5240***	2.4335***	-	2.5062***	2.4171***
		(148.37)	(139.40)		(147.18)	(138.36)
LCLG G-Rated at Origination	-	2.7389***	2.6463***	-	2.7277***	2.6362***
		(102.91)	(98.31)		(102.32)	(97.80)
Home Price Index (3-Digit Zip	+0.0000***	0.0001***	0.0001***	+0.0000***	0.0001***	0.0001***
Code)	(3.86)	(5.67)	(5.65)	(3.77)	(5.67)	(5.64)
Unemployment Rate (3-Digit	0.0084***	0.0054*	0.0049*	0.0083***	0.0053*	0.0048*
Zip)	(3.01)	(1.89)	(1.73)	(2.95)	(1.88)	(1.71)
Business Bankruptcies (Per	296.8013***	462.0375***	455.5369***	323.8872***	460.5209***	453.439***
1k Residents in 3-Digit Zip)	(4.46)	(6.84)	(6.74)	(4.78)	(6.81)	(6.71)
Median Household Income	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000***
(3-Digit Zip)	(-15.30)	(-12.44)	(-12.49)	(-15.57)	(-12.50)	(-12.55)
Initial Unemployment Claims	+0.0000***	+0.0000***	+0.0000***	+0.0000***	+0.0000***	+0.0000***
(State)	(11.73)	(12.09)	(12.10)	(12.23)	(12.10)	(12.12)
2015 Origination	0.1057***	0.1621***	0.1621***	0.1070***	0.1567***	0.1569***
	(9.74)	(14.65)	(14.66)	(9.73)	(14.23)	(14.25)
2016 Origination	0.1791***	0.2645***	0.2665***	0.1523***	0.2301***	0.2336***
	(16.67)	(24.14)	(24.32)	(13.97)	(21.02)	(21.33)
2017 Origination	0.1295***	0.2128***	0.2213***	0.0860***	0.1650***	0.1759***
	(11.29)	(18.17)	(18.88)	(7.37)	(14.07)	(14.99)
2018 Origination	0.0686***	0.2073***	0.2223***	0.0218*	0.1556***	0.1731***
	(5.63)	(16.68)	(17.87)	(1.76)	(12.50)	(13.89)
2019 Origination	-0.2382***	-0.0049	0.0100	-0.2855***	-0.0688***	-0.0513***
	(-19.01)	(-0.38)	(0.78)	(-22.44)	(-5.34)	(-3.98)
Spread Residual	-	-	-	0.1128***	0.0674***	0.0650***
				(223.22)	(42.30)	(40.65)
Observations	1,670,528	1,670,528	1,670,528	1,670,528	1,670,528	1,670,528
Log-Likelihood	-5.610+05	-5.362E+05	-5.359E+05	-5.368+05	-5.353E+05	-5.351E+05
Deviance	1.122E+06	1.072E+06	1.072E+06	1.074E+06	1.071E+06	1.070E+06
Pearson Chi-squared	1.670E+06	1.670E+06	1.670E+06	1.630E+06	1.670E+06	1.670E+06

Source: Authors' calculations based on data from LendingClub, Haver Analytics, and the U.S. Census Bureau.

Appendix

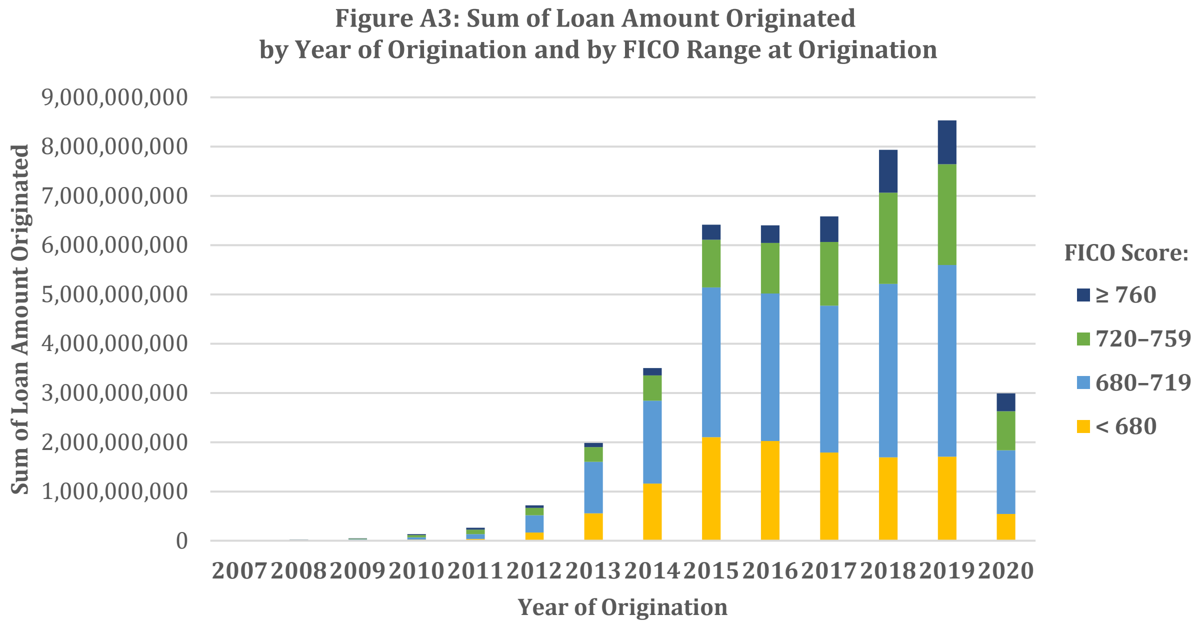


Source: Authors’ calculations based on data from LendingClub

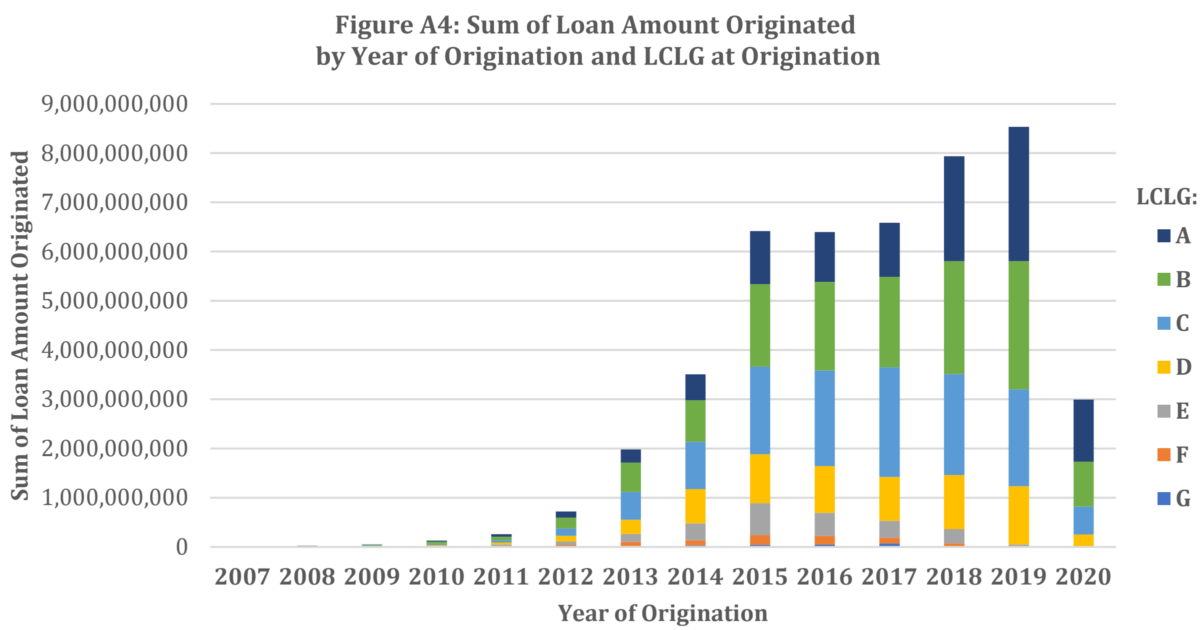


Note: The sample loans are the same for Figures A1 and A2. Figure A2 presents the breakdown of loans that remained active as of the start of the pandemic by LCLGs. The plot shows, for example, that about 90 percent of A-rated loans that LendingClub originated in 2019 were outstanding as of the beginning of the pandemic. And, only about 65 percent of G-rated loans that LendingClub originated in 2019 were outstanding as of the beginning of the pandemic.
Source: Authors’ calculations based on data from LendingClub

Figure A3: Sum of Loan Amount Originated by Year of Origination and by FICO Range at Origination



Source: Authors' calculations based on data from LendingClub.



Source: Authors' calculations based on data from LendingClub.