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Abstract

Small business lending (SBL) plays an important role in funding productive investment and fostering local economic growth. Recently, nonbank lenders have gained market share in the SBL market in the United States, especially relative to community banks. Among nonbanks, fintech lenders have become particularly active, leveraging alternative data for their own internal credit scoring. We use proprietary loan-level data from two fintech SBL platforms (Funding Circle and LendingClub) to explore the characteristics of loans originated pre-pandemic (2016–2019). Our results show that fintech SBL platforms lent more in zip codes with higher unemployment rates and higher business bankruptcy filings. Moreover, fintech platforms' internal credit scores were able to predict future loan performance more accurately than the traditional approach to credit scoring, particularly in areas with high unemployment. Using Y14M loan-level bank data, we also compare fintech SBL with traditional bank business cards in terms of credit access and interest rates. Overall, fintech lenders have a potential to create a more inclusive financial system, allowing small businesses that were less likely to receive credit through traditional lenders to access credit and to do so at lower cost.

JEL Classification: G18, G21, G28, L21

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1. Introduction

Small business lending (SBL) plays an important role in funding productive investment and fostering local economic growth (Beck and Demirgüç-Kunt, 2006). In the United States, community banks are known to have comparative advantages in SBL through their personal relationships with small business owners in their own local area. Until recently, the soft information that community banks have about their local small businesses and business owners were not easily accessible to outside lenders. Of the approximately 6,000 banks in the United States, about 90 percent are small local banks that exist to serve the people and businesses in their local community.

In the last several years, the financial landscape for SBL has changed significantly. Fintech lenders and other technology companies have shaken up the traditional ways of doing business. Lending by fintech and big tech firms has become increasingly important as a source of finance for both consumers and small businesses around the world; see Financial Stability Board (2019), Cornelli et al. (2019; 2020) and Ziegler et al. (2020). Soft information about businesses and entrepreneurs can now be obtained from nontraditional channels. For example, customer ratings and satisfaction about businesses may be available online. Information on the credibility and reputation of business owners is also available through several data aggregators and artificial intelligence (AI)/ machine learning (ML) vendors. In addition, through their use of digital platforms, some lenders can incorporate various types of alternative data, including those related to online footprints, phone and email history, location, etc. Digital platforms have allowed fintech lenders to serve borrowers that may otherwise be unserved or underserved by incumbent financial institutions, even in economies with relatively deep credit markets, like the United States.

While it seems that large U.S. banks have been increasing their SBL activities, this is true only when compared with the overall banking industry. The origination and funding of SBL overall has shifted dramatically over the past several years toward the nonbank ("shadow banking") sector. This is partly because of the increased regulatory burden since the financial crisis (eg, from the Dodd–Frank Act of 2010 and the rising cost of small loan origination). While nonbank lenders are subject to some consumer protection and other compliance requirements, they are not subject to the same rigorous supervisory examination as banks, allowing nonbank lenders to compete with banks in SBL.[1] At the same time, technological advances and the post-crisis pressure on bank business models may also be important drivers to the shift.

Fintech lenders have increasingly become an important part of the nonbank SBL sector. Funding Circle and LendingClub are examples of large fintech lenders that use big data and complex algorithms such as AI/ML models to evaluate the credit risk of small businesses and that of the business owners,[2] and to make lending decisions at a much faster speed than traditional lenders. Research has shown that fintech lenders are more efficient in making consumer loans than traditional lenders operating at the same scale. For instance, Hughes, Jagtiani, and Moon (2022) find LendingClub to be more efficient for consumer loans than traditional peer lenders of the same size. One

1 Nonbank lenders are, however, subject to significantly higher funding cost than banks since they do not have access to low-cost funding through insured deposits.

2 Fintech lenders, like Funding Circle and LendingClub, use AI/ML in developing the models that are ultimately presented in the form of traditionally structured logit regression models. Thus, they are not black-box models but using more complex algorithms and more data to achieve credit decisions that would be explainable to investors and potentially regulators.

factor that contributes to enhanced lending efficiency at fintech platforms is their ability to digitally collect and analyze nontraditional data, including what used to be referred to as soft information in relationship lending. This allows them to capture a more complete financial picture of the borrowers than traditional lenders can. This can improve access to credit. Jagtiani and Lemieux (2018, 2019) find that fintech lenders have helped some below-prime consumers to gain greater access to credit and at a lower cost, compared with what they would have been able to get through traditional channels.

Alternative data, which have been increasingly used by lenders to identify the "invisible prime" or "hidden prime" borrowers in consumer lending, have also been used to price credit risk in SBL. However, empirical evidence on fintech lending efficiency has so far focused on consumer credit. In this paper, we explore the roles of alternative data and the impact on credit access to small businesses.

In the United States, some fintech lenders have competed successfully with community banks. In addition, fintech lenders have also helped to fill the SBL credit gap in certain communities because of the SBL pullback and reduced market share by traditional banks. Fintech lenders often have access to their own proprietary big data from payment platforms that gives them a bird's-eye view of the business, industry, and location in which a firm operates. Several big tech payment platforms, such as Amazon, and fintech payment firms, such as Square[3] and PayPal, have also lent to business owners who may have thin credit files, but whose cash flows and payment transactions have been established through their payment platform. Other fintech SBL lenders, such as Kabbage, OnDeck, Funding Circle, and LendingClub use other alternative data in their lending decisions (Goldstein, Jagtiani, and Klein (2019)).[4]

The higher cost of originating small loans has been overcome through a digitized credit application and decision process, where the fixed cost of originating small short-term business loans has become trivial, relative to the cost incurred by traditional lenders. However, there have also been concerns about the potential impact of these disruptive business models on consumers, business owners, and financial stability, especially if the fintech credit scoring techniques do not prove to be valid in a different stage of the economic or financial cycle (such as a deep recession).

In this paper, we focus on fintech SBL, which is similar to SBL originated by traditional lenders, eg with comparable interest rates and loan maturities as those offered by banks. We explore the capacity of fintech firms to facilitate access to credit for small business owners who are headquartered in less financially developed areas and assess the subsequent performance of such loans. Specifically, we ask the following research questions. Has fintech lending enhanced credit access to small

3 In December 2021, Square rebranded itself and changed its name to "Block," as the group aims to emphasise business lines beyond its seller business (still branded as Square). Its ticker on the New York Stock Exchange will remain SQ at least for some periods of time. This rebranding is like that of other big-tech firms, such as Google that placed itself under the parent company Alphabet in 2015 and Facebook placing itself under parent company Meta in October 2021.

4 During the coronavirus Pandemic, several fintech SBL lenders (namely, Square, PayPal, Intuit Quickbooks, Funding Circle, and OnDeck) received approval by the U.S. regulators to originate Paycheck Protection Program (PPP) loans to small businesses under the CARES Act of March 2020. Other fintech platforms (which received the approval much later) worked with partner banks (such as Cross River Bank, Celtic Bank, Radius Bank, and Sunrise Banks) to assist with the PPP loan approval and origination in the first round of PPP.

business owners who are likely to be "underserved" by traditional lenders? Are there measurable differences in the information contents in credit scores assigned by fintech lenders versus those assigned by traditional credit rating agencies? What is the added value of alternative data in credit risk evaluation and lending decisions?

To do this, we use detailed microdata from Funding Circle's small business platform, and we compare this with the LendingClub SBL fintech platform, and then compare with traditional lending using data on (business) credit cards from Y-14M (submitted monthly to the Federal Reserve by CCAR banks for stress testing purposes). First, our results show that, also in the SBL space (in addition to consumer lending), fintech lenders can serve borrowers who were less likely to receive credit from traditional banks and that they employ alternative data to improve their credit risk evaluation and scoring. Second, more specifically, we find that fintech SBL platforms lent more in zip codes with higher unemployment rates and higher business bankruptcy filings. Third, our results confirm that fintech platforms' internal credit scores were able to predict future loan performance more accurately than the traditional approach to credit scoring (including both credit rating of the business owners and credit rating of the business itself). Fourth, we find that this enhancement – ie; the divergence of fintech scores from traditional credit scores and the improvement in predicting credit delinquencies – were particularly stronger in areas with high unemployment rate. Fifth, using Y-14M loan-level bank data (on traditional bank business cards) to compare with fintech SBL in terms of credit access and interest rates, our results confirm that fintech lenders provide credit to additional small business borrowers at lower cost.

It is important to note that our results in this paper, based on two specific fintech lenders, may not be applicable to the entire fintech lending industry. While these lenders played an important role in the fintech SBL market during the period of analysis, they may not be representative for the whole sector. Moreover, not all SBL products are the same, and they could have a dramatically different impact on borrowers and the economy overall. For example, some fintech lenders specialize in very small and short-term loans, with the intention to help business owners' deal with unexpected liquidity needs. Other fintech lenders specialize in longer-term loans like those provided and supported by the U.S. Small Business Administration (SBA). Within the fintech SBL space in the United States, loan products vary significantly in terms of loan amounts ($5,000 to $500,000), maturity (60 days to five years or longer), interest rates (7 percent to 200 percent annual percentage rate (APR)), and other features. Still, the use of proprietary data from two major fintech lenders, and a comparison with supervisory data from U.S. banks, allow for a more granular view of fintech credit than has been available in the past.[5] This represents one step in a broader research agenda.

The rest of the paper is organized as follows. Section II reviews the literature and discusses findings that are especially relevant to the roles of fintech in SBL. Section III describes the proprietary loan-level data from Funding Circle's small business lending platform. This section highlights stylized facts and presents summary statistics of the data. We compare some of these facts with aggregate data from the LendingClub SBL platform and from Y-14M bankcard data from the CCAR monthly submission, to evaluate differences. Section IV discusses the empirical findings related to the roles

[5] The two data sets (Funding Circle and LendingClub) used for this paper represent fintech lenders that offer interest rate in the lower end of the spectrum. Both also have their own self-imposed interest rate ceiling of 36 percent APR, with loan maturities ranging from one to five years.

of alternative data in fintech SBL and the impact on small business owners to access funding. Section V discusses conclusions and policy implications.

2. Related literature

There is a growing body of research on the drivers of fintech consumer credit, on the impact on credit access by consumers and on consumer privacy. However, the literature has been sparse on fintech SBL and how it impacts credit access by small businesses, small firm performance, local communities and the overall banking and economic outcomes. This section provides an overview.

A branch of the fintech literature has attempted to investigate the impact of fintech lending on credit access, and in some cases, asking if fintech lending is a substitute or complement to bank credit. For U.S. *consumer* credit markets, Jagtiani and Lemieux (2018) find that LendingClub consumer lending has penetrated areas underserved by traditional banks (eg, in highly concentrated markets and areas with fewer bank branches per capita). As for fintech mortgage lending, Jagtiani, Lambie-Hanson, and Lambie-Hanson (2021) find that mortgage loans are more likely to be originated by a fintech lender in areas in which there was a higher mortgage denial rate by traditional lenders in the previous period.

Similarly, for access to *business* credit, Erel and Liebersohn (2021) examine fintech lending to small businesses through the Paycheck Protection Program (PPP) in the U.S. during the pandemic. They find that fintech was disproportionately used in zip codes with fewer bank branches, lower incomes, and more minority households, and by small businesses with fewer banking relationships.[6] Another paper that examines the PPP program is Howell, Kuchler, Snitkof, Stroebel, and Wong (2022). They find that fintech SBL lenders had a higher minority share among the PPP loans and that fintech can reduce racial disparities among small business owners.

Regarding complementary or substitution, Dolson and Jagtiani (2021) find that, for both personal loans and mortgage loans, fintech lenders are more likely than other lenders (including both banks and other non-bank lenders) to reach out and offer credit to non-prime consumers, supporting the complementary hypothesis. Tang (2019) finds that online lending substitutes for bank lending by serving marginal borrowers in the United States, but it complements bank lending with respect to small loans. De Roure, Pelizzon, and Tasca (2016) use credit market data in Germany, and they show that fintech lenders serve the segment of riskier consumers who need small loans and are underserved by traditional banks. Thus, they conclude that fintech lenders substitute traditional banks for high-risk consumer loans. Much of the literature looks at the role of alternative data, including factors not traditionally considered to be closely related to the ability to pay (eg, digital footprints (Berg, Burg, Gombović, and Puri (2020)).[7]

Another strand of literature compares the behavior and pricing of fintech lenders with that of traditional banks. Buchak, Matvos, Piskorski, and Seru (2018) compare the pricing of online (fintech) lenders in the U.S. mortgage market with that of banks and

6 The PPP was created by the U.S. government as a response to the lockdown during the COVID-19 pandemic. It was intended to assist small business owners by giving out loans to small businesses to keep their employees on their payroll during the pandemic. The loans would be forgiven if they were used for the intended purposes.

7 See also Allen, Gu, and Jagtiani (2021) for a comprehensive literature survey of fintech research.

(non-fintech) shadow banks. They find that fintech lenders charge a premium of 14–16 basis points relative to bank mortgages. The reason is that fintech lenders use more comprehensive data about consumers to identify those who likely prioritize convenience and faster services and are willing to pay a premium. Jagtiani, Lambie-Hanson, and Lambie-Hanson (2021) find consistent results for conventional mortgages but point to the opposite findings when focusing only on Federal Housing Administration (FHA) loans. They conclude that conventional mortgage borrowers (who are generally well served in the financial system) tend to pay an interest rate premium to fintech lenders in exchange for convenience and faster services. FHA mortgage borrowers do not pay a premium rate but benefit from fintech lenders through increased funding access.[8] Fuster, Plosser, Schnabel, and Vickery (2018) find that fintech mortgage lenders process loan applications about 20 percent faster than traditional lenders. Like mortgage borrowers, Mach, Carter, and Slattery (2014) find that peer-to-peer lenders charge a premium (up to two times higher) for small business lending when compared with traditional sources. Gambacorta, Huang, Li, Qiu, and Chen (2020) find that big-tech credit in China is less sensitive to house prices than bank credit, as big data take the place of collateral in mitigating asymmetric information in the credit markets.

Traditional business lending could introduce biases based on a loan officer's perception of loan applicants, which affects loan approval and loan size. Carter, Shaw, Lam, and Wilson (2007) extract four criteria used by the loan officer and compare these with the sex of the loan applicant. Loan officers were more likely to assess female loan applicants on whether they had thoroughly researched the business, while male applicants were assessed more on whether they had thorough information about the business financial history, the business opportunity, and their personal characteristics. Bellucci, Borisov, and Zazzaro (2010) find that female entrepreneurs face tighter credit availability but do not differ in interest rates to their male counterparts. They also find that female loan officers restrict credit to unestablished borrowers more than their male colleagues. However, female loan officers are shown to ask female borrowers for collateral less often. Female loan officers are also more concerned with the applicants' marital status than male counterparts, as it may suggest financial responsibility; see Carter, Shaw, Lam, and Wilson (2007). Atkins, Cook, and Seamans (2021) explore the impact of race using data from the PPP during the pandemic and find evidence supporting the hypothesis that fintech could reduce racial disparity in SBL. While Black-owned businesses received smaller PPP loans than White-owned businesses, the racial impact became smaller and later disappeared as changes were made to allow for entry by fintech firms in the second round of the PPP.

Evidence of discrimination in SBL is apparent elsewhere, too. Borrowers at traditional lenders may be discouraged and simply not apply even if they need a further loan. Mijid and Bernasek (2013) calculate a 38 percent loan denial rate for minorities and 14 percent for Whites, where firm and owner characteristics can explain 24 percentage points of loan denial. Bates and Robb (2015) find that firms in minority neighborhoods that need credit but do not apply are more common than firms that do apply for bank loans. Han, Fraser, and Storey (2009) find evidence that discouragement is an effective self-rationing mechanism. Risky borrowers filter themselves based on demographics of the entrepreneur and business. However, Cole and Sokolyk (2016) find that for every three discouraged firms, one would have been

[8] FHA mortgage borrowers are more likely to be underserved, based on lower average income and lower average risk scores, and they generally receive lower interest rates.

approved for a loan had they applied. This represents a large inefficiency that fintech lending may help solve.

Literature on the use of small business credit scoring (SBCS) largely confirms that quantitative scoring has expanded credit availability to small businesses. Frame, Srinivasan, and Woosley (2001) find a positive relationship between the portfolio share of banks' SBL and the use of credit scoring models. Berger and Frame (2007) also associate SBCS with expanded credit quantities, but they find that SBCS leads to greater average risk, along with increased lending to low-income areas, over greater distances, and longer loan maturity. The introduction of SBCS aimed to give investors a better understanding of borrower creditworthiness but leaves out important information. Using only SBCS (ignoring a small business owner's personal credit risk) could lead to inaccuracies in loan decisions. Community banks are known to rely on soft information for lending decisions, and they tend to use SBCS to supplement their credit decisions when evaluating small business credit. Berger, Cowan, and Frame (2011) confirm that community banks use SBCS but also find that they tend to use consumer credit scoring more than SBCS to evaluate small business loans.

In addition, the use of alternative data and ML has been shown in several cases to improve credit assessments. Jagtiani and Lemieux (2019) find that rating grades from the LendingClub consumer platform (based on all available information including alternative data) perform well in predicting loan performance during the two years after loan origination date. The correlation between the rating grades and the FICO scores declined over time from 2007 to 2015. Frost, Gambacorta, Huang, Shin, and Zbinden (2019) show evidence that nontraditional data from Mercado Libre in Argentina help to predict defaults relative to the traditional credit bureau. Lu (2018) examines the credit assessment at Ant Financial Services Group (part of the Alibaba group, the largest fintech firm in China), which helps an online-based bank make a credit assessment in less than three minutes. MYbank (part of the Ant Financial Services) served over 20 million small businesses as of 2019. More than three-quarters of MYbank loan users had previously never received business loans from traditional banks. By using the Alibaba e-commerce network to track small business trading history, MYbank is able to predict borrowers' creditworthiness in minutes (with zero human interaction), while its competitors (mostly larger banks) refuse to lend to these small businesses due to their lack of sufficient credit information. Gambacorta, Huang, Qiu, and Wang (2019) find, with data from a Chinese fintech credit platform, that ML-based credit scoring was better able to predict default than traditional indicators after the 2017 regulatory shock in China.

Another strand of literature has looked at the impact of alternative data on credit access and firm performance. For example, Hau, Huang, Shan, and Sheng (2018) and Huang, Lin, Sheng, and Wei (2018) find that big-tech credit in China has reduced supply frictions in credit markets and that Chinese firms with access to big-tech credit experience higher performance than their small business firm peers. Dice and Liebersohn (2020) examine the response of fintech and nonbank lenders to financial services demand created by the introduction of the PPP during the COVID-19 pandemic. They find that online banks and nonbank financial institutions are disproportionately used by small businesses in areas with fewer banking services (measured by bank branches and businesses with little banking relationship) and that borrowers were more likely to get a fintech-enabled loan if they are in zip codes in which local banks were unlikely to originate PPP loans.

Overall, the efficiencies in digitizing various services by the banking industry can potentially improve upon or replace the traditional credit scoring and soft information at the center of relationship lending. By using big data on borrower demographics, nonbank lenders can implement advanced algorithms to quickly and effectively risk-rank applicants.

3. Data and stylized facts

Fintech loan-level data

We use proprietary data on fintech SBL from Funding Circle, and later LendingClub. The data set from Funding Circle contains loan-level data with a unique ID for each loan as well as characteristics of the loans and borrowers. This includes the credit rating of the business owner (FICO, VantageScore), the fintech credit rating of the business itself, firm-specific data (firm size, age, revenues, profitability, and number of employees), business funding needs (number of recent credit inquiries), and loan features (loan size, maturity, APR, fees, delinquency status, etc.). We then match local economic factors for each loan based on the zip code or county location of the loan.[9]

We also observe credit performance of each loan during the period of 24 months after its origination date. We flag the loan as being delinquent if it is at least 60 days past due (60+ DPD) within the first 24 months after the origination date. Note that loan maturities vary, and they are generally three to five years.[10]

One important characteristic of our data set is that we observe several risk ratings of each loan. First is the *Business Owner's Risk Score*, which comprises the FICO and Vantage scores (ranging from 300 to 850) for the business owner as of the loan application date. Second, we observe the *Business Risk Score*, which is Experian's Acquisition score assigned for the small business (rather than the small business owner). This scale looks different than the usual risk scores as the Acquisition Score is much more granular (from 100 to 100,000). Third, we observe the *Risk Rating Assigned by Funding Circle*, which ranges from A+ to D. We use dummy variables in the regressions to indicate that the loans are rated by Funding Circle as A-rated, B-rated, C-rated, or D-rated. The base case is the best rating assigned by Funding Circle, which is A+.

Bank-level and county-level SBL data

In addition, we collect SBL data from the Community Reinvestment Act (CRA) reports that banks file annually with federal regulators. Banks report the amount of SBL they

9 There are 41,683 zip codes in the United States, and 3,141 counties and equivalent entities. Thus, counties are generally larger. That said, zip codes can include parts of different counties; there is no one-to-one mapping.

10 Of the more than 15,000 small business loans we have from the Funding Circle platform, about 5 percent have a maturity of one year or less, and about 9 percent have a maturity of two years. The rest (about 86 percent of the loans) have a maturity of more than two years, with about 50 percent of all the loans being five-year loans. See Table A1 in the Appendix for more details. In general, Funding Circle loans have a longer maturity than loans from other SBL platforms. For LendingClub SBL, the majority of loans are small (less than $40,000), and almost all loans have a maturity of three years or less.

originate (or purchase) in each county and year. In addition to this flow data from the ***CRA reports***, we also collect stock data of outstanding SBL from the ***Call Reports***, which are filed on a quarterly basis by each bank with the federal regulators. Information on SBL originated by traditional banks is used to compute measures of SBL concentration at the county level.

Traditional small business credit (business credit cards) data

We use comparable business loan data (through credit cards) from the ***Federal Reserve's Y-14M reports.*** These data are reported monthly by bank holding companies with over $50 billion in assets. We use a 1 percent random sample of all business credit card accounts reported in the Y-14M data set. From this data set, we focus on those business card accounts that were open during the period 2016–2019 to match the small business loan data from Funding Circle and LendingClub.[11] For the most part, the Y-14M reports contain similar data on borrowers and other risk characteristics as those reported in the Funding Circle and LendingClub database (eg, origination date, origination amount, location of the borrowers, and borrowers' credit scores). We use data on business credit card loans from the Y-14M reports to compare with SBL originated by Funding Circle and LendingClub.

We start with 548,808 business card accounts. After screening out those charge cards (no credit limit) and those with missing business owner's FICO scores, we are left with 453,385 accounts. We then drop those business card accounts that were opened with missing APR data or with a promotional rate of 0 percent APR. Our final sample includes 275,024 business card accounts that were open during the period 2016–2019 that have data on business owners' FICO scores and interest rate in APR.[12]

Zip code (or county)-level economic factors

From the **FDIC Summary of Deposits**, we collect data on banking activity and the number of bank branches in each local community where fintech loans are made. Other general economic factors such as bankruptcy filings by businesses, market competition, house price indices, unemployment, etc. are collected from *Haver Analytics*, CoreLogic database, and other sources. We collect income data from the **American Community Survey (ACS) U.S. Census Bureau** (five-year estimates).

We then match the associated economic factors by the loan's zip code or at the county level (using the most granular level of data that is available). We have the house price index (HPI), unemployment rate, business bankruptcy filings, and degree of bank competition and market concentration at the county level, and we have median income of residents and population at the zip code level. The Herfindahl-Hirschman index (HHI) of market concentration is calculated in two different ways, based on the shares of banks in SBL and in total bank deposits in a county. For the HHI based on SBL share, the data on the share of SBL by each bank in a county come from the CRA reports for banks that submit CRA reports; and from Call Reports (in conjunction with FDIC Summary of Deposits reports) for small community banks that

[11] We note that these data are constrained by the limited number of reporters and, as such, may not represent the entire population of firms that issue business credit cards. However, Y-14M reporters do represent over 80 percent of all credit cards issued by commercial banks.

[12] The final sample from Y-14M reports includes 65,158 business card accounts originated in 2016, 64,538 in 2017, 67,340 accounts in 2018, and 77,988 accounts in 2019.

do not submit the CRA reports. Specifically, we apply the share of deposit-taking activities by each bank in each county to the amount of SBL from the bank's Call Reports for non-CRA reporters.

In addition to measuring market competition using the HHI based on SBL activities (by banks) in a county, we also measure the number of bank branches per capita and changes in bank branches at the zip code level. We estimate the number of bank branches per capita (per 100,000 people) using branching data from the FDIC Summary of Deposits reports and using population data (five-year estimates) from ACS as reported in 2018.

Table 1 summarizes the descriptive statistics of the variables used in the regressions. The database covers the period 2016–2019. The first panel summarizes the variables used in the regression that analyzes credit access. This is based on year and county or zip code level data, resulting in 9,688 observations. The Funding Circle SBL share is the ratio of its own SBL originated in each zip code in each year relative to the overall SBL that Funding Circle originated in all zip codes in each year. This share has an average of 0.04 and a maximum of 0.58, indicating that its loans are spread across a large number of zip codes although the loan may be quite concentrated in some specific areas in some years.

Local economic factors include the unemployment rate at the county level, the HPI at county level, business bankruptcy filing at county level, and median income at the zip code level. Local economic conditions are quite heterogeneous across counties or zip codes. For example, unemployment ranges from 1.6 percent to 19 percent, while median income ranges from nearly $9,000 to more than $243,000. As for the measure of SBL market concentration, we consider the HHI at the county level, based on SBL by banks in each county in each year. Even in this case, conditions are quite different across counties. In addition, we use market competition measures at the zip code level based on banking service activities: 1) the number of bank branches per capita in each zip code; 2) changes in the number of bank branches in each ZIP code from the previous year to the current year; 3) percent changes in the number of bank branches in each zip code from the previous year to the current year; and 4) a dummy indicator of whether the number of bank branches per capital in the zip code has declined from the previous year to the current year.

The second panel of Table 1 describes summary statistics for the variables used in our simple horse race models (described in the next section) that compare the FICO, VantageScore, and Funding Circle internal risk rating score (*FC risk scores*). This is based on loan-level data, resulting in 15,050 observations. The FC risk score is assigned using the company's proprietary model. We use dummy indicators for each loan considering the five categories, from A+-rated (lowest risk) to D-rated (highest risk). Additional information on loan contract maturity by Funding Circle risk bands is reported in **Table A1** in the Appendix. We define loans as being delinquent as of 24 months (or 12 months) after origination, if the borrower has a late payment (60+ days past due), as of 24 months (or 12 months) after origination, and zero otherwise.

Descriptive Statistics — Funding Circle

Sample includes loan-level data from Funding Circle SBL platform for the period 2016–2019 Table 1

	N	Mean	St. Dev.	Min	Max
	Credit Access Analysis				
Funding Circle SBL share[1]	9,688	0.04	0.04	0.00	0.58
County unemployment (%)	9,688	3.96	1.07	1.61	18.80
County HPI (in '00s)	9,688	1.96	0.51	0.89	3.91
County business bankruptcy filings per capita	9,688	0.0001	0.0001	0.0000	0.0006
Zip Median income (in $100,000s)	9,688	0.82	0.33	0.09	2.43
HHI: SBL concentration (in '000s)	9,688	0.82	0.53	0.29	6.87
Population (%)	9,688	0.04	0.03	0.00	0.25
Dummy, decrease in branches	9,688	0.22	0.41	0.00	1.00
Percentage decrease in branches	9,688	-0.03	0.07	-0.75	0.00
Percent change in branches	9,688	-0.02	0.10	-0.75	2.00
No new firms ('000s)	9,688	2.51	4.09	–1.27	20.17
County share of population above 65	9,179	15.36	3.87	7.42	41.24
	Defaults as predicted by FICO, VantageScore, FC risk grade				
12-month delinquency rate	15,040	0.04	0.19	0	1
24-month delinquency rate	15,040	0.07	0.25	0	1
FICO at origination	15,040	717	45	604	843
VantageScore	15,030	698	56	492	836
FC rating A	15,040	0.31	0.46	0	1
FC rating B	15,040	0.29	0.45	0	1
FC rating C	15,040	0.14	0.35	0	1
FC rating D	15,040	0.05	0.21	0	1
APR residuals	13,392	0.00	0.01	–0.07	0.19
	Default probability as of 24 months after origination				
Delinquent loan dummy[2]	11,640	0.07	0.26	0.00	1.00
Acquisition score	11,640	6332	13856	100	99900
FICO at origination	11,640	715	45	604	843
VantageScore at origination	11,635	697	56	492	836
FC rating A	11,640	0.31	0.46	0.00	1.00
FC rating B	11,640	0.28	0.45	0.00	1.00
FC rating C	11,640	0.14	0.35	0.00	1.00
FC rating D	11,640	0.05	0.21	0.00	1.00
Ln(profit)	11,640	10.81	1.34	1.39	15.16
Ln (gross revenue)	11,640	13.59	1.09	9.87	18.09
Ln (loan amount)	11,640	11.53	0.79	10.13	13.12
Loan maturity in months	11,640	47.11	14.72	6.00	60.00
County unemployment	11,640	3.62	0.95	1.56	16.98
County HPI	11,640	209	54	98	391
County business bankruptcy filings per capita	11,640	0.00008	0.00005	0.00000	0.00150

[1] Ratio of SBL loans originated (by Funding Circle SBL platform) in zip code *i* in year *t* relative to total SBL loans (in all zip codes) originated in year *t*. [2] Takes the value1 if the loan becomes delinquent (60+DPD) as of 24 months after origination; and zero otherwise.

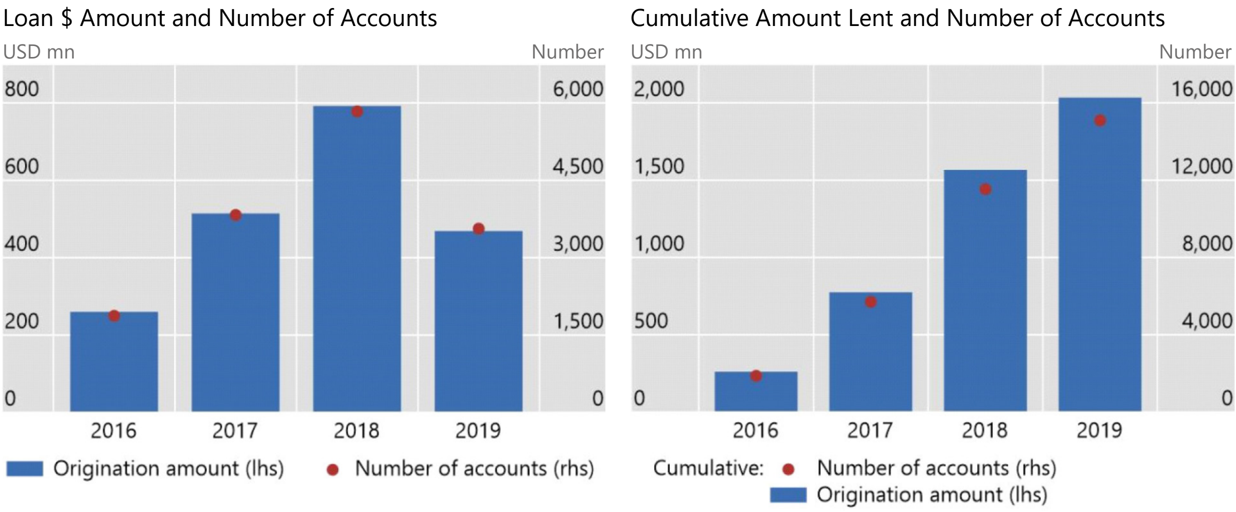
Sources: Funding Circle, CRA data, FDIC Summary of Deposits, Call Reports, Haver Analytics, and US Census.

The third panel of Table 1 includes the variables used in the regressions that model (in an exhaustive way) the probability of default on a loan. Here, we match loan-level data with various control factors including economic factors in the zip code where the loan is located, resulting in 11,640 observations. These models include not only the three different ratings on the borrower (FICO, Vantage, and FC risk scores) but also the business risk score from Experian, the so-called Acquisition Score.[13] Moreover, the models include local economic conditions, loan characteristics (eg, loan amount, loan maturity in months, loan APR, and year of origination) and borrower characteristics (such as business profits and business revenue). The pairwise correlations between Funding Circle loan characteristics and economic factors are presented in **Table A2** in the Appendix.

Some stylized facts

Funding Circle SBL activity increased in the period under investigation (see **Figure 1**). The data contain loans originated from 2016 to mid-2019; thus, the volume looks smaller in the last histogram rather than 2018 because it considers only six months (see left-hand panel). Our sample includes a total of 15,027 loans (about $2 billion total; see right-hand panel). The amount of SBL originated by Funding Circle in this period is quite remarkable, also considering other relevant platforms operating in the US. For example, in the period 2015–2018, the total of SBL originated by LendingClub was only $540 million.

Funding Circle SBL Activity (2016 to mid-2019) Figure 1



Source: Funding Circle.

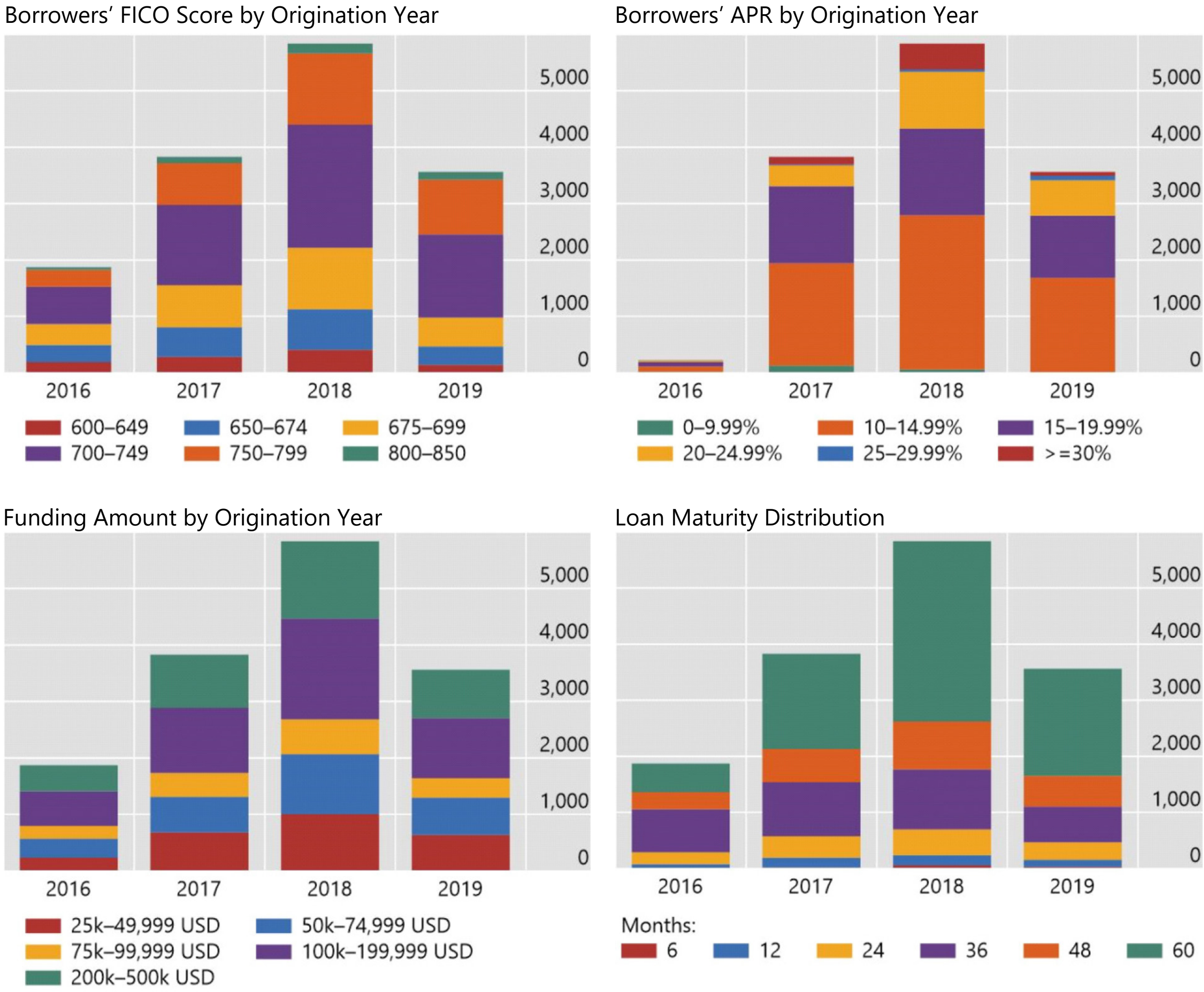
[13] Different lenders may have different products and attributes from vendors such as Experian and Dun & Bradstreet. Funding Circle uses the Experian Acquisition score (which is a rating for the business, rather than the small business owner). The scale looks different than other scores (such as FICO or Vantage Score), with a score of 7200 being in the 91st percentile. Unlike Funding Circle, the variable that measures business risk score (on the LendingClub SBL platform) is called an *IP Score*. This is comparable with the typical range used for FICO and other risk scores (from 300 to 850). Separately, for the measure of business owner's risk score, we have included the FICO scores and Vantage Score for business owners as of the loan application date.

The average loan originated by Funding Circle in the period under analysis is around $134,000, with a minimum of $25,000 and a maximum of $500,000. Just as a comparison, the average loan originated by LendingClub is about half this value, or around $56,000, with a minimum of $2,000 and a maximum of $600,000. Funding Circle loans are directed to firms with an average number of 12 employees and gross revenues of $1.5 million (compared with 11.6 employees and $1.1 million for LendingClub).

From the top panel of **Figure 2**, the FICO scores of the business owners range from 600 to 850 in each year, with a significant number of loans originated to below-prime business owners (red and blue in the upper-left panel, with a FICO score below 680). About half of the loans are associated with interest rates below 15 percent APR (green and orange in the upper-right panel). The bottom panels of Figure 2 show that the originated loan size ranges from $25,000 to $500,000 (bottom-left panel), with maturity ranging from one year to five years. About half of the loans in each rating grade are longer-term loans with a five-year maturity (bottom-right panel).

Funding Circle Loan Distribution: by FICO, APR, Amount, Maturity

Number of Loans | Figure 2



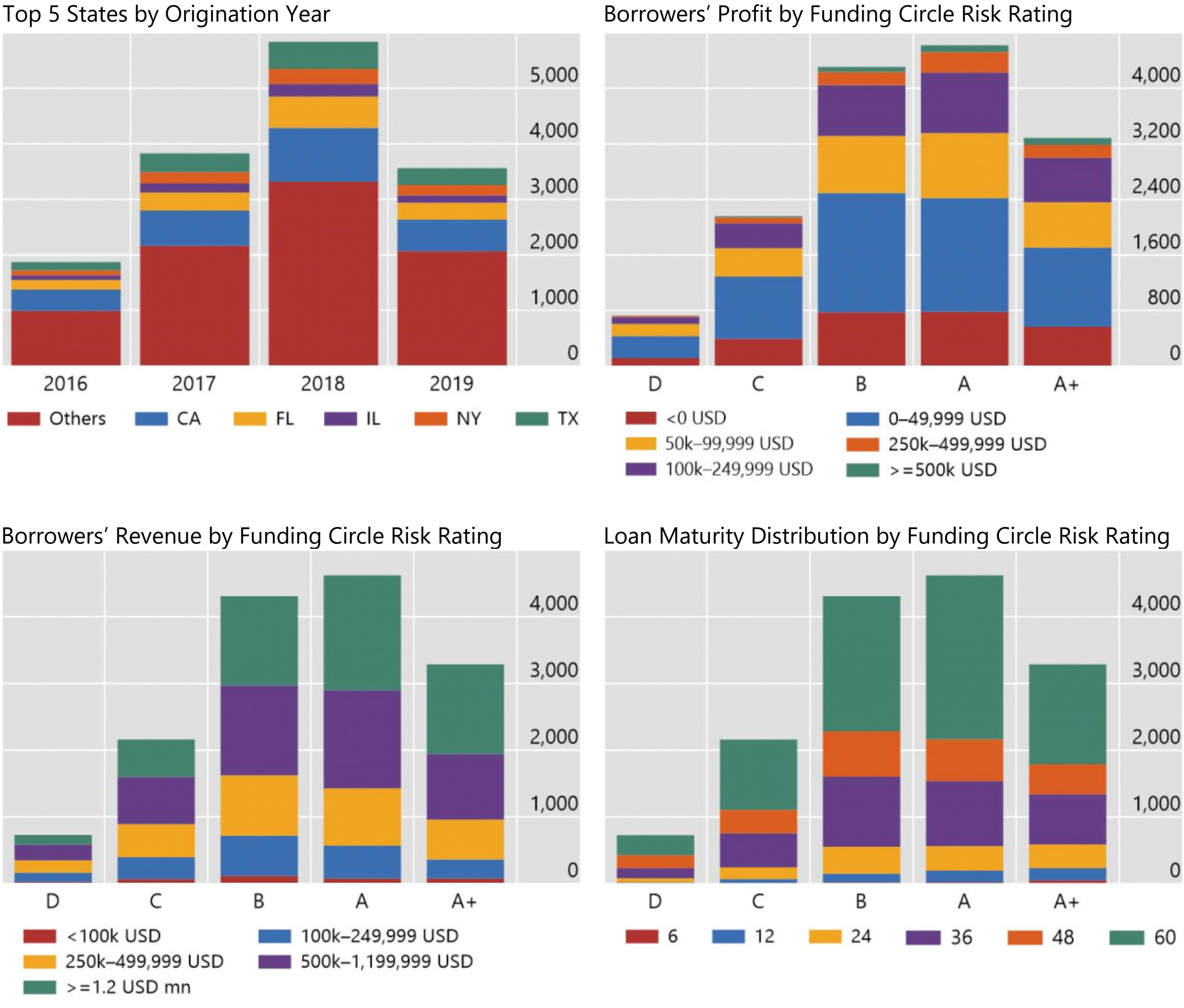
Source: Funding Circle.

Figure 3 shows that the top five states where loan are originated are the most populous: California (CA), New York (NY), Florida (FL), Texas (TX), and Illinois (IL), although these add to less than half of all the loan originations by Funding Circle (upper left-hand panel).[14] In the remaining panels of Figure 3, it is notable that there is heterogeneity in firm profitability, firm size (as measured by revenue), and loan maturity for each level of risk rating (A+ to D) assigned by Funding Circle.

Funding Circle Loan Distribution: by States; Profits, Revenue, and Maturity Across Credit Ratings

Number of Loans

Figure 3



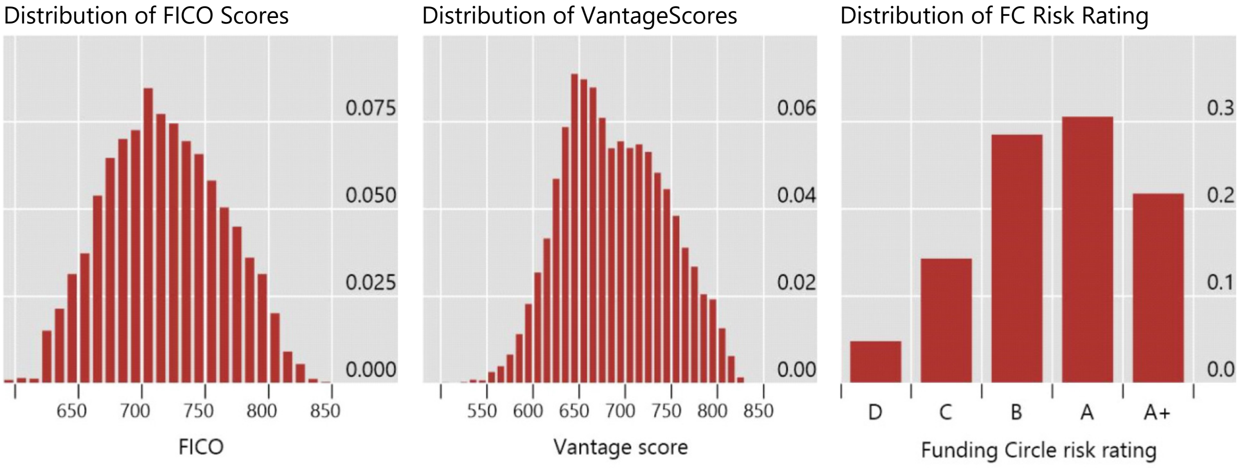
Source: Funding Circle.

[14] The full geographical distribution of SBL lending activity by state is reported in **Figure A1** of the Appendix. The distribution is not too different from that of LendingClub (see **Figure A2** in the Appendix). Just under half of LendingClub loans are to small businesses in the same five (most popular) states, but in a slightly different order: California, Florida, Texas, New York, and Illinois.

Funding Circle's own risk ratings are functionally comparable to FICO and VantageScores, but even *prima facie*, they exhibit notable differences. **Figure 4** compares the distribution of FICO scores, VantageScore, and Funding Circle's own ratings. The plots show that the mode (median) score is 710 (715) for FICO, 650 (693) for VantageScore; and A-rated for Funding Circle risk bands. About half of the loans received top ratings (A or A+) from Funding Circle, although they may not be highly rated based on the traditional credit scoring systems.

Loan Distribution by FICO, VantageScores, and Funding Circle's Rating Grades

Frequencies — Figure 4



Additional statistics on the distribution of credit scores: FICO: median score = 715; mean score = 717; VantageScore: median score = 693; mean score = 698; Funding Circle: a total of 15,096 loans, the median rating (at 7,548 position) is A-rated.

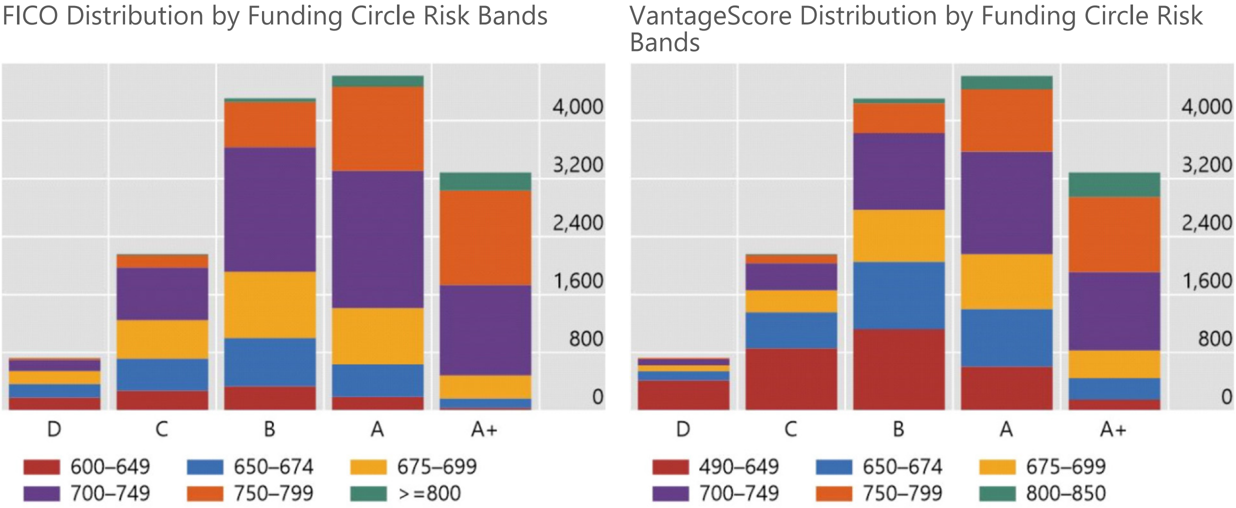
Source: Funding Circle.

Figure 5 shows that a significant number of loans that would traditionally be considered below prime, based on FICO score and VantageScore (red and blue histograms), are assigned much better ratings (A or A+) by Funding Circle. Indeed, as shown in **Figure A3** in the appendix, the correlation between the rating grades assigned by Funding Circle and the traditional credit ratings assigned by FICO or Vantage Score have been almost always below 50 percent over the sample.[15] Notably, this correlation is even lower when LendingClub credit rating is compared with FICO and Vantage Score. As shown in **Figure A3** in the Appendix, the correlation between the loan ratings assigned by LendingClub and the traditional scores is around 30 percent.

[15] This suggests that at least half of the variation in FC rating grades cannot be explained by traditional credit information that is incorporated in the FICO or VantageScore. The correlation is slightly higher for VantageScore than for FICO, probably because Vantage scores tend to account for some nontraditional data, such as utility and rent payments.

Funding Circle Loans: Credit Score Distribution by FC Rating Grades

Number of Loans | Figure 5

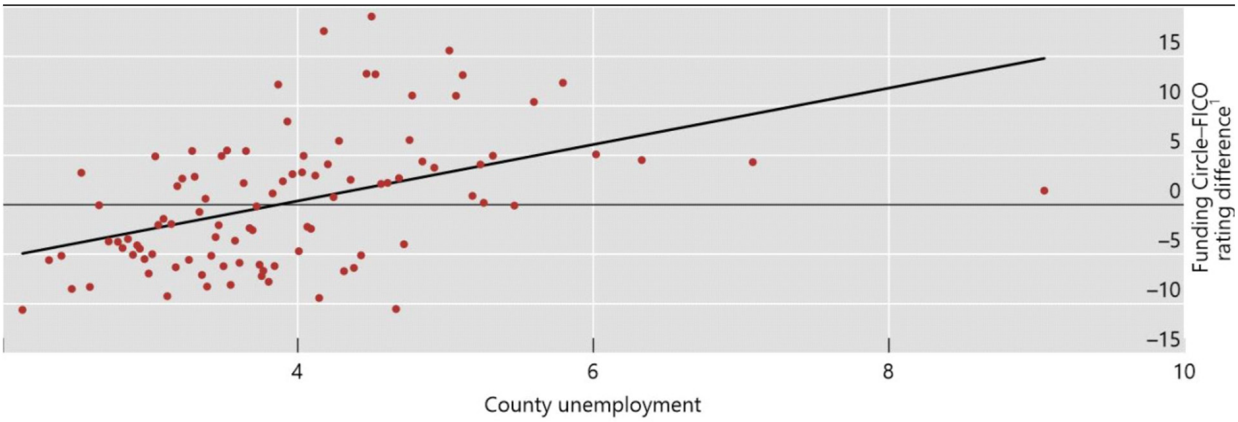


Source: Funding Circle.

The divergence between Funding Circle risk bands and traditional risk scores is not random. Indeed, as shown in **Figure 6**, it is even larger in U.S. counties with a higher unemployment rate. The scores also show *prima facie* differences in their predictive power.

Risk Assessments Diverge More in Areas with Higher Unemployment

Figure 6



[1] Funding Circle risk grades have been mapped to FICO scores based on the min-max range of the latter. The values have then been de-meaned.

Sources: Funding Circle, CRA data, FDIC Summary of Deposits, Call Reports, Haver Analytics.

Figure 7 presents delinquency rates for different combinations of Funding Circle risk ratings and the FICO or VantageScore ratings. This figure is divided into two panels: the left panel for FICO scores and the right panel for VantageScore. The size of the bubbles is proportional to the share of the firms in each rating distribution (ie, each combination of FC and FICO or VantageScore) based on the origination amount. On the vertical axis, the panel reports the delinquency rate (ie, the percentage of loans more than 60 days past due relative to the total number of loans). On the horizontal axis, it reports the risk matrix – with the Funding Circle credit rating compared with the traditional rating. As the FICO and VantageScore are continuous variables, we have segmented them into three different risk bands and then compared these with the five different Funding Circle risk ratings (D through A⁺).

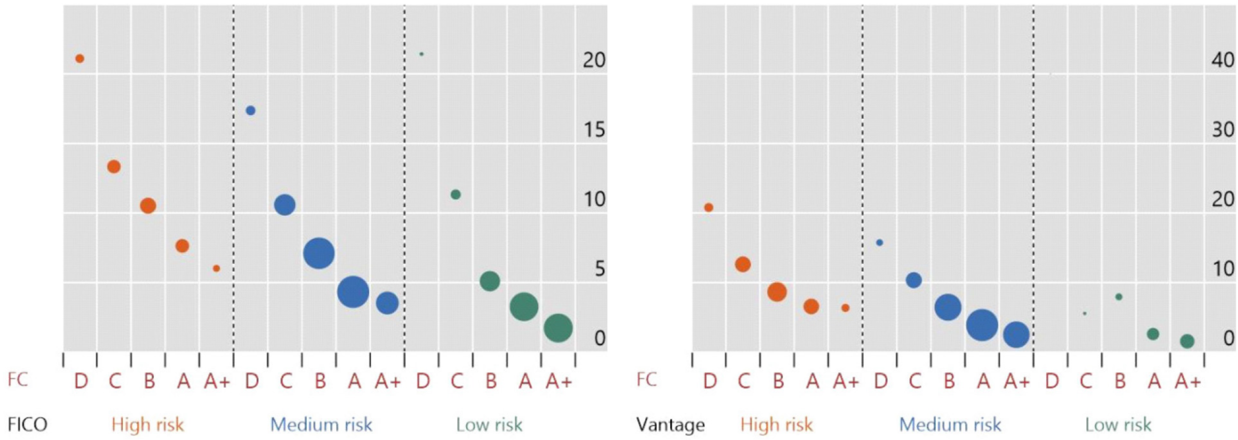
Delinquency Rates Decline Significantly for Higher FC Risk Bands, Controlling for FICO and VantageScore Bands

In Percent

Figure 7

Default Rate for FC Risk Band and FICO

Default Rate for FC Risk Band and VantageScore



This figure shows the delinquency rate (ie, the percentage of loans more than 60 days past due relative to the total number of loans). The plots are calculated based on a dummy that takes value 1 if the loan becomes delinquent (60+days-past-due) as of 24 months after origination and zero otherwise. The size of each bubble is proportional to the total origination amount.

Source: Funding Circle.

In the left panel, for a given FICO risk band (ie, high risk), the expected loss rate is strictly monotonic with the Funding Circle credit ratings (ie, the patterns of the dots show that the Funding Circle risk bands rank orders for expected loss). Conversely, given an internal rating (ie, B, C, or D), the delinquency rate is not strictly monotonic with the FICO score. For example, the dot associated with the D Funding Circle risk bands for the low-risk FICO band indicates a higher risk than the corresponding D rating in the medium-risk FICO band. Moreover, the Funding Circle risk bands have a narrow range of default for each rating grade: high-default rates for D-rated and low-default rates for A-rated. In contrast, the range of default rate is broader based on FICO or Vantage scores, ranging from delinquency rates of 1.7 percent to 21.4 percent for the low-risk FICO band. Most importantly, by using its proprietary scoring model, Funding Circle has been able to make credit available to those high-risk borrowers (based on FICO scores).

Table 2 presents a matrix of delinquency rate for loans in the various risk buckets, based on Funding Circle risk bands versus the traditional risk bands (FICO scores). The last column of Table 2 presents the portfolio share by FICO risk bands. As shown, 12.6 percent of the portfolio of loans originated by Funding Circle would fall into the high-risk FICO cluster. Banks use a mix of FICO score information and soft information from loan officers, but in general, they would not lend to these borrowers in the U.S.[16] With its more granular scoring model, Funding Circle can offer credit and in turn help these borrowers gain access to the SBL market.

[16] Anecdotally, many U.S. banks use a cutoff and do not lend to borrowers with FICO credit scores below 580.

Delinquency Rate by Funding Circle Rating Grades and FICO Scores								Table 2
		Funding Circle Risk Grades					Total FICO	Portfolio Share
		D	C	B	A	A+		
FICO Band	Low Risk	21.4%	11.3%	5.1%	3.3%	1.7%	3.6%	36.3%
	Medium Risk	17.4%	10.6%	7.1%	4.3%	3.5%	6.7%	51.1%
	High Risk	21.1%	13.3%	10.5%	7.6%	6.0%	11.8%	12.6%
Total FC Risk Grade		19.3%	11.5%	7.3%	4.3%	2.6%	6.5%	
Portfolio Share		3.1%	12.3%	27.5%	33.8%	23.3%		

Delinquency rates are defined as the share in the total number of outstanding loans 60 days or more past due, divided by the total number of loans. These are shown for different ranges of FICO scores and Funding Circle risk bands, over the period 2016–2019. The (discrete) Funding Circle credit ratings at origination are divided into five different risk groups (A+ through D), while the (continuous) scores of the FICO credit bureau are divided into three corresponding to risk level: Low Risk (FICO>739); Medium Risk (FICO between 670–739); and High Risk (FICO<670).

Source: Authors' calculations based on data from Funding Circle.

Table 3 reports the APR by Funding Circle rating grades and by FICO buckets. There is little variation of interest rates across Funding Circle risk grades. For example, for loans with Funding Circle D-rated, the associated APRs are almost the same regardless of their FICO scores, ranging from 31.0 percent APR for the low-risk FICO band to 31.3 percent APR for the high-risk FICO band. In contrast, we observe a wide variation of APR across FICO buckets. For example, for the high-risk FICO bucket, interest rates range from 11.5 percent APR to 31.3 percent APR. This characteristic is similar but less pronounced compared with the same distribution for LendingClub SBL platform (see **Table A3** in the Appendix).

APR by Funding Circle Rating Grades and FICO Scores								Table 3
		Funding Circle Risk Grades					Total FICO	Portfolio Share
		D	C	B	A	A+		
FICO Band	Low Risk	31.0%	23.1%	18.9%	13.9%	11.2%	14.4%	36.3%
	Medium Risk	31.1%	23.1%	18.8%	14.0%	11.4%	17.4%	51.1%
	High Risk	31.3%	23.1%	18.9%	14.3%	11.5%	20.4%	12.6%
Total FC Risk Grade		31.2%	23.1%	18.9%	14.0%	11.3%	16.9%	
Portfolio Share		3.1%	12.3%	27.5%	33.8%	23.3%		

This table shows APRs for different ranges of FICO score and Funding Circle risk grades, for loans that were originated on the Funding Circle SBL platform during the period 2015–2019. The (discrete) Funding Circle credit ratings at origination are divided into five different risk groups (A+ through D), while the (continuous) scores of the FICO credit bureau are divided into three corresponding to risk level: Low Risk (FICO>739); Medium Risk (FICO between 670 and 739); and High Risk (FICO<670).

Source: Authors' calculations based on data from Funding Circle.

These simple statistics indicate that the internal rating system of Funding Circle differentiates between borrowers more than the traditional credit ratings like FICO scores, thus allowing Funding Circle to extend loans to borrowers who would otherwise be excluded from credit markets. However, two aspects remain to be assessed. First, we need to verify whether Funding Circle lending improves financial inclusion in underserved areas of the country. Second, we need to test whether the Funding Circle rating system based on ML techniques and big data outperform (ex post) the more traditional rating/scoring in predicting defaults. We perform this analysis in the next section.

4. Empirical analysis

Credit access and financial inclusion

In the first step of the empirical analysis, we want to assess where fintech SBL is more extensive, to shed light on its role to improve credit access and thus financial inclusion of previously underserved businesses and geographies. The estimation is specified as follows:

$$FC\ SBL\ ratio_{zct} = \beta Unemployment_{ct} + \gamma HPI_{ct} + \delta BBF_{ct} + \theta Income_{zct} + \vartheta HHI_{ct} + \\ + \mu Population_{zct} + \alpha_s + \varepsilon_{ct} \quad (1)$$

where z, c, t stand for zip code, county, and time, respectively. Our dependent variable, $FC\ SBL\ ratio_{zct}$ is the ratio of SBL loans originated by the Funding Circle SBL platform in zip code z, in county c in year t relative to total SBL loans originated by Funding Circle in year t. To control for time-invariant state characteristics (such as state-specific unemployment benefits, property taxation, or corporate rules), we include state fixed effects (α_s).[17]

The unemployment rate ($Unemployment$), house price index (HPI), and level of business bankruptcy filings in the last 24 months (BBF) are calculated at the county level, while the median level of income ($Income$) is at the zip code level. These variables capture economic factors that could influence the development of fintech SBL in a specific geographic location. The HHI measures the level of market concentration and is calculated as the sum of the squared share of SBL lending by each bank in each county. To control for demographic factors, we also include the percentage share of population in each zip code ($Population$) as more loans are expected to be granted in an area with a larger population. The results are presented in **Table 4**.

As a first-pass analysis, in the first column (Model 1) of Table 4, we correlate the FC SBL ratio with a simple model that includes only the $Population$ share. This model can explain 7.4 percent of the variability of the FC SBL ratio.

In the second column (Model 2) of Table 4, we include the other (time varying) county/zip code characteristics. The unemployment rate in a county is positively correlated with FC's lending share in that area. A one standard deviation increase in the unemployment ratio can be associated with an increase in the FC SBL share by 0.002 percentage points in a specific zip code (1.07*0.002). This is economically relevant as it represents 5 percent of Funding Circle credit in an average zip code.

[17] We do not include origination year fixed effects because we want to focus on whether loans go into more underserved areas — overall — rather than comparing within each origination year. We include origination year fixed effects in the analysis at the loan level.

Credit Access Analysis Table 4

	Funding Circle SBL Share						
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
County unemployment		0.00197***	0.00199***	0.00197***	0.00197***	0.00153***	0.00196***
		(0.000422)	(0.000423)	(0.000422)	(0.00042)	(0.00040)	(0.00044)
County HPI (in '00s)		0.000124	0.000142	0.000122	0.00011	-0.00367***	0.00027
		(0.00132)	(0.00132)	(0.00132)	(0.00132)	(0.00139)	(0.00141)
County business bankruptcy filings per capita		48.29***	48.01***	48.32***	48.27***	41.23***	52.95***
		(7.092)	(7.070)	(7.091)	(7.09599)	(7.16031)	(7.75989)
Median income (in '00,000s)		0.0118***	0.0118***	0.0118***	0.0118***	0.0118***	0.0116***
		(0.00131)	(0.00131)	(0.00131)	(0.00131)	(0.00131)	(0.00134)
SBL concentration (in '000s)		0.00106	0.00108	0.00105	0.00107	0.00179**	0.00155
		(0.000829)	(0.000829)	(0.000829)	(0.00083)	(0.00083)	(0.00103)
Population (%)	0.289***	0.293***	0.290***	0.292***	0.292***	0.288***	0.281***
	(0.0170)	(0.0180)	(0.0181)	(0.0180)	(0.01802)	(0.01807)	(0.01892)
Dummy, decrease in branches			0.00209**				
			(0.000963)				
Percentage decrease in branches				0.00293			
				(0.00465)			
Percent change in branches					0.00347		
					(0.00323)		
No new firms ('000s)						0.00081***	
						(0.00015)	
County share of population above 65							-0.00026**
							(0.00012)
Model	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Observations	10,279	9,688	9,688	9,688	9688	9688	9179
R^2	0.074	0.085	0.085	0.085	0.085	0.089	0.083

***/**/* denotes results that are significant at the 1%/5%/10% levels, respectively. The sample is based on loan-level data from Funding Circle SBL Platform for the period: 2016 Q1–2019 Q2. All regressions include constant and state-level dummy indicators. Dependent variable is Funding Circle SBL Share, which is defined as the ratio of SBL loans originated (by Funding Circle SBL platform) in zip code *i* in year *t* relative to total SBL loans (in all zip codes) originated in year *t*.

Sources: Funding Circle, CRA data, FDIC Summary of Deposits, Call Reports, Haver Analytics, and US Census.

An increase in house prices is positively correlated with the FC SBL share, but the effect is not statistically significant. This may reflect the fact that fintech SBL is not typically collateralized (see also Gambacorta et al., 2020). By contrast, the effect of the median income (calculated at the zip code level) is positive and statistically significant, reflecting changes in demand conditions for firms that translate into higher demand for credit by firms. A one standard deviation increase in median income is associated with a rise in the FC SBL share by 0.004 percentage points (0.33*0.012). This is also economically relevant as it represents around 10 percent of Funding Circle credit in an average zip code.

Interestingly, fintech SBL origination is positively associated with a higher rate of business bankruptcy filings (BBF), supporting our hypothesis that fintech SBL lenders could expand credit access to more small business owners (especially those with little track record) through their use of alternative data. The effect is economically relevant. A one standard deviation increase in BBF is associated with a rise in the FC SBL share of 0.005 percentage points (0.0001*48.29). This represents around 12 percent of Funding Circle credit in an average zip code. Market competition (based on the share of SBL lending by each bank in each county) does not affect the FC SBL ratio.[18]

The three columns (Models 3 to 5) of Table 4 control for changes in the structure of bank branches. In particular, the third column (Model 3) considers a dummy that takes the value of 1 for those counties that experienced a decrease in bank branches from the previous year, and zero elsewhere. We find that in these counties, the FC SBL share is significantly higher. However, the effect is positive but not statistically significant when considering the *percentage* decrease in bank branches (Model 4) and the *percent change* in branches (Model 5). The last two columns of Table 4 (Models 6 and 7) control for the number of new firms in a county, calculated as the change in the number of firms from year *t* to year *t-1* plus the number of firm deaths in year *t-1*, and the share of county population above 65 years of age. The results indicate that more new firms are associated with greater credit access (Model 6). This could result from these being areas with many firm entries and exits, and potentially to greater credit demand, all else equal.[19] Finally, the results from model 7 suggest that there is less lending where there share of county population over 65 is higher.

Economic Contribution of Factors in the Credit Access Analysis

Table 5

	Model 2		Model 3		Model 4		Model 5		Model 6		Model 7	
Regressor	Shapley Value	Percent	Shapley Value	Percent	Shapley Value	Percent	Shapley Value	Percent	Shapley Value	Percent	Shapley Value	Percent
Country unemployment	0.00353	4.17%	0.00354	4.16%	0.00353	4.17%	0.00353	4.17%	0.00293	3.31%	0.00363	4.4%
County HPI (in ’00s)	0.00365	4.31%	0.00368	4.32%	0.00364	4.30%	0.00364	4.30%	0.00298	3.37%	0.00396	4.79%
County business bankruptcy filings per capita	0.00622	7.35%	0.00617	7.25%	0.00622	7.36%	0.00621	7.34%	0.00532	6.02%	0.00628	7.6%
Median income (in ’00,000s)	0.00792	9.37%	0.00785	9.23%	0.0079	9.34%	0.0079	9.33%	0.00782	8.83%	0.00746	9.02%
SBL concentration (in ’000s)	0.00033	0.39%	0.00033	0.39%	0.00033	0.39%	0.00033	0.39%	0.00035	0.4%	0.00014	0.17%
Population (%)	0.04645	54.94%	0.04596	54.03%	0.04643	54.89%	0.04643	54.85%	0.04496	50.79%	0.04233	51.23%
Dummy, decrease in branches			0.00096	1.12%								
Percentage decrease in branches					0.00011	0.13%						
Per cent change in branches							0.00018	0.21%				
No new firms ('000s)									0.00981	11.08%		
County share of population above 65											0.00279	3.37%
State-level dummies	0.01645	19.46%	0.01658	19.49%	0.01642	19.41%	0.01642	19.40%	0.01434	16.2%	0.01605	19.43%

The economic contributions refer to the econometric models reported in Table 4. The sample includes loan-level data from Funding Circle SBL Platform for the period: 2016–2019.

Sources: Funding Circle, CRA data, FDIC Summary of Deposits, Call Reports, Haver Analytics, and US Census**.**

18 Similar results are obtained using the share of deposit-taking activities by each bank in each zip code for non-CRA reporters to estimate their SBL as a measure of market concentration (see **Table A4** in the Appendix).

19 The results are qualitatively similar when we control for the number of new firm establishments instead of the number of new firms.

In **Table 5**, we show the Shapley value decomposition of the statistical contribution to explain the FC SBL share. This indicates that the population share and state fixed effects capture, respectively 55 percent and 19 percent of the FC SBL share variability. Median income at the zip code level explains 9 percent, while unemployment and bankruptcy filings explain a total of 12 percent, taken together. These last two variables represent a good proxy for the overall contribution of financial inclusion factors that can be associated with FC SBL share.

Ex-post default performance

As a second step of the analysis, we assess whether the Funding Circle rating system based on ML techniques and big data outperforms (ex post) the more traditional rating scoring in predicting defaults.

First, we compare the performance of the Funding Circle credit scoring model versus traditional FICO and Vantage scores. Specifically, our goal is to assess whether the fintech credit scoring model (based on ML plus big data) is better able to predict borrowers' defaults than traditional credit scoring models. The analysis is performed at the (more granular) loan level.

We start by estimating the following model to predict defaults:

$$p(D_{i,t}) = \Phi\left(\alpha Credit\ Scoring_{i,t} + \mu_S + \mu_T + \varepsilon_{i,t}\right) \tag{2}$$

where $p(D_{i,t})$ indicates the probability for the loan not to be repaid (and to generate a loss). The credit scoring refers to borrower i at time t. We consider — one at the time — the FICO score, the VantageScore, and the Funding Circle risk grades. The FICO and Vantage scores are continuous variables, while the Funding Circle rating grade is organized into buckets. The model includes state (μ_S) and time origination (μ_T) fixed effects.

The results are presented in the first three columns of **Table 6**. Panel (a) considers delinquency as of 12 months from origination, while Panel (b) analyzes the effects as of 24 months after origination. All estimates use a Logit regression model. Credit scores are always a highly significant predictor of delinquency. However, the pseudo R^2 of the model that uses FC risk grades (column 3) is significantly higher than that obtained using the FICO score (column 1) and the VantageScore (column 2). The results are similar for both considering a 12-month and 24-month delinquency horizon. Results are also consistent when adding APR residuals (see final column and below).

Table 7 compares the performance of the three different credit scoring approaches. The table is divided into two panels, with two different delinquency rate horizons (12 months and 24 months after origination). Each panel reports the area under the receiver operating characteristics curve (AUROC) for every credit scoring method. The AUROC is a widely used metric for judging the explanatory power of credit scores. The AUROC ranges from 50 percent (purely random prediction) to 100 percent (perfect prediction). The formal test on the difference in performance across the models can be done comparing the 95 percent confidence interval reported in the last two columns of Table 7, with significant improvement in predictive ability when moving from either FICO or Vantage scores to Funding Circle rating grades.

PD as Predicted by FICO, VantageScore, and Funding Circle Risk Grades Table 6

	Panel A: 12-Month Delinquency Rates			
	(1)	(2)	(3)	(4)
FICO Score	-0.00943***			
	(0.00101)			
VantageScore		-0.00706***		
		(0.000795)		
FC Risk Grades				
A			0.575***	0.573***
			(0.182)	(0.194)
B			1.188***	1.235***
			(0.172)	(0.182)
C			1.830***	1.837***
			(0.175)	(0.186)
D			2.361***	2.392***
			(0.191)	(0.200)
APR residuals				2.957
				(4.639)
Observations	15,017	15,007	15,017	13,337
Pseudo R^2	0.0689	0.0670	0.104	0.109
	Panel B: 24-Month Delinquency Rates			
	(I)	(II)	(III)	(IV)
FICO Score	-0.0104***			
	(0.000809)			
VantageScore		-0.00774***		
		(0.000638)		
FC Risk Grades				
A			0.601***	0.622***
			(0.134)	(0.143)
B			1.178***	1.227***
			(0.127)	(0.137)
C			1.748***	1.736***
			(0.133)	(0.143)
D			2.271***	2.279***
			(0.150)	(0.159)
APR residuals				2.862
				(3.688)
Observations	14,961	14,951	14,961	13,281
Pseudo R^2	0.0916	0.0889	0.118	0.118

The table reports the estimates for a logit regression analysis. All regressions include state dummies and origination year dummies.

Source: Funding Circle

Area Under the Receiver Operating Characteristic (ROC) Curves — Table 7

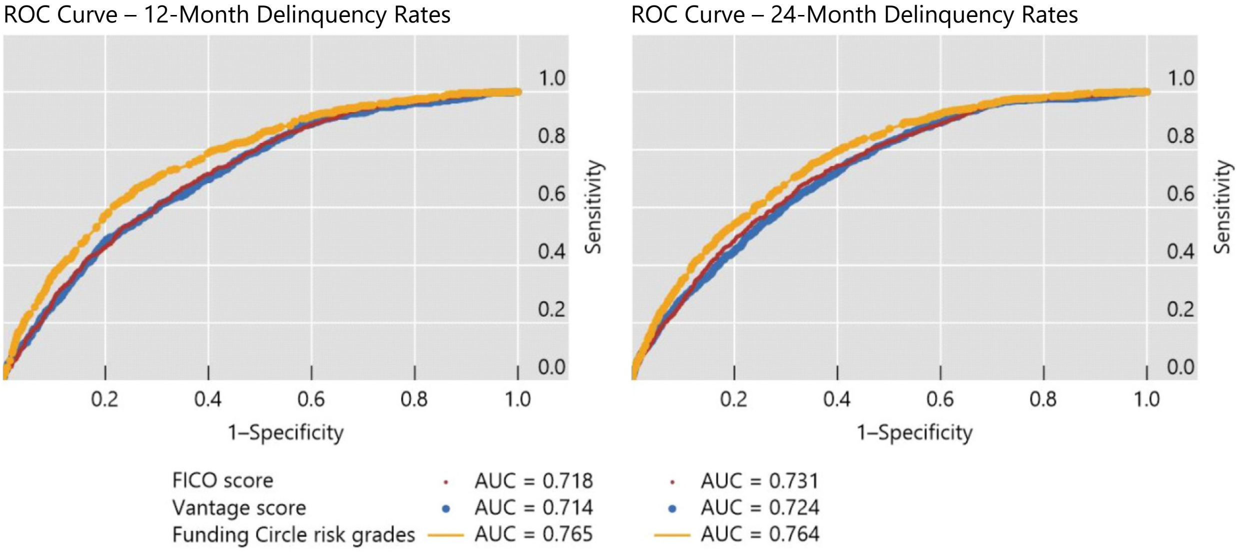
	Panel A: ROC Curves — 12-Month Delinquency Rates				
	Observations	AUROC	Std. Err.	95% Confidence Interval	
FICO Score	13,337	0.7176	0.0107	0.6967	0.73853
VantageScore	13,337	0.7136	0.0109	0.69228	0.73487
FC Risk Grades	13,337	0.7645	0.0102	0.74455	0.7844
FC Risk Grades and APR Residuals	13,337	0.7676	0.0101	0.74778	0.78733
	Panel B: ROC Curves — 24-Month Delinquency Rates				
	Observations	AUROC	Std. Err.	95% Confidence Interval	
FICO Score	13,281	0.7312	0.0084	0.71482	0.74764
VantageScore	13,281	0.7243	0.0084	0.70783	0.74086
FC Risk Grades	13,281	0.7643	0.0079	0.74883	0.77981
FC Risk Grades and APR Residuals	13,281	0.7665	0.0079	0.75102	0.78206

The table reports the estimates for the logit regression, which include state- and origination year-level dummies, as reported in Table 6.

Source: Funding Circle.

Figure 8 shows the receiver operating characteristics (ROC) curve for each credit scoring. The ROC curve is created by plotting the true positive rate (TPR) against the false positive rate (FPR) at various threshold settings. The TPR is also known as *sensitivity*. The FPR is also known as the *fall-out* or *probability of false alarm* and can be calculated as (1 − specificity).

Predictive Power of FICO, VantageScore, and Funding Circle Risk Grades — Figure 8



The x-axes show the fraction of false positives, whereas the y-axes show the fraction of true positives. The higher the curve the stronger the performance of the model. Based on the models in Table 6.

Source: Funding Circle.

The left-hand panel of Figure 8 reports the results for the three different credit scores searching for unpaid loans as of 12 months after origination, while the right-hand panel repeats the analysis for a 24-month performance window after origination. In both cases, the results show that the Funding Circle risk grades perform better than the other two rating approaches. The difference between the FICO and the Vantage scores is marginal, with the first one performing slightly better. The three models are statistically different at the 5 percent level, as formally verified by inspection of the last two columns of Table 7.

We conduct four additional tests with a view of shedding further light on the informational advantage of the FC rating grades. *First*, as the FICO and the Vantage scores are continuous variables while the FC rating grade is expressed in dummies, we have rerun all the results using similar risk buckets for all three approaches. We divide the FICO score and the VantageScore into five different buckets, to be comparable with the FC rating grades A to D. The results, reported in **Figure A5** (in the Appendix), indicate that the FC rating grade has always a greater explanatory power than the FICO score and the Vantage score.

Second, we perform a similar test by adding to the model the information content of the interest rates. If interest rates are simply assigned based on the credit scores, they should add no additional information. However, it is possible that in some cases interest rates may be assigned based on additional pieces of information other than the credit ratings. We find that the APR is closely linked to the Funding Circle risk band (see the left-hand panel of **Figure A6** in the Appendix), but there is still some residual variability. For this reason, we have included in the last column of **Table 6** a regression that includes the residual of a regression of the interest rate on FC rating grades. The test aims to control for the fact that the interest rate could contain additional information that is not already included in Funding Circle rating grades. The coefficient on the APR residual in last column of Table 6 is not statistically significant and the AUROC improves just marginally (see that last row of Panel A and B of **Table 7**). This indicates that adjustments to APRs are not systemically in one direction (to riskier or less risky borrowers) and/or that all relevant information available to Funding Circle is already included in the FC rating grade.

Third, to assess how the improvement in predictive power varies by geography, we compare the improvement in the AUROC of the FC rating grade in areas with unemployment that is above the median with areas where it is at or below the median. **Table 8** shows that the improvement in the AUROC is 7.5 percentage points in high-unemployment areas, versus only 2.4 percentage points in low-unemployment areas, over a 12-month horizon. This complements our results on credit access, showing that the FC risk bands outperform traditional scores especially in underserved areas.

Improvement in Receiver Operating Characteristic (ROC) Curves — Table 8

	Increase in AUROC (FICO Vs FC risk grades)		
	Unemployment above median	Unemployment at or below median	Without unemployment breakdown
12-Month Delinquency Rates	7.46%	2.36%	4.69%
24-Month Delinquency Rates	4.74%	2.11%	3.31%

The table reports the increase in the area under the ROC curve (AUROC) for the logit regression, which include state- and origination year-level dummies, as reported in Table 6.

Source: Funding Circle.

Default Probability as of 24 Months After Origination

Table 9

	Delinquent Loan Dummy — as of 24 Months After Origination		
	(1)	(2)	(3)
Acquisition score	-0.00001*	-0.00001**	-0.00001**
	(0.000005)	(0.000004)	(0.000004)
FICO at origination	-0.00727***		-0.00526***
	(0.00121)		(0.00124)
VantageScore	-0.00418***		-0.000370
	(0.000970)		(0.00101)
FC rating A		0.609***	0.494***
		(0.150)	(0.152)
FC rating B		1.245***	1.044***
		(0.143)	(0.152)
FC rating C		1.852***	1.589***
		(0.151)	(0.164)
FC rating D		2.497***	2.165***
		(0.173)	(0.189)
Ln (profit)	-0.0460	-0.0216	-0.0300
	(0.0306)	(0.0317)	(0.0318)
Ln (gross revenue)	-0.217***	-0.214***	-0.201***
	(0.0525)	(0.0528)	(0.0533)
Ln (loan amount)	0.547***	0.572***	0.606***
	(0.0734)	(0.0760)	(0.0771)
Loan maturity in months	0.00402	0.00537*	0.00466
	(0.00299)	(0.00307)	(0.00310)
Unemployment	0.0493	0.0207	0.0235
	(0.0377)	(0.0388)	(0.0388)
County HPI	0.00177	0.000936	0.00121
	(0.00125)	(0.00128)	(0.00129)
County business bankruptcy	-1,358*	-1,551*	-1,487*
filings per capita	(798.9)	(802.2)	(808.4)
Observations	11,580	11,585	11,580
Pseudo R^2	0.110	0.140	0.144

***/**/* denotes results that are significant at the 1%/5%/10% levels, respectively. The table reports the estimates for a logit regression which include a constant, state dummies, and origination-year dummy indicators. The sample includes loan-level data from Funding Circle SBL platform for the period: 2016–2019. Dependent variable is a binary variable that takes the value of 1 if the loan becomes delinquent (60+DPD) as of 24 months after origination and zero otherwise.

Sources: Funding Circle, CRA data, FDIC Summary of Deposits, Call Reports, and Haver Analytics.

Fourth, we consider how much the Funding Circle rating grade adds to a complete model that includes the FICO score, the VantageScore and a set of further traditional variables. The rationale of this test is to verify the contribution of Funding Circle's own rating above and beyond what could be captured by traditional credit ratings. **Table 9** presents the analysis of default probability as of 24 months after origination.[20] The first column reports the result including the FICO, the VantageScore and a set of traditional variables. The second column reports the results including the Funding Circle rating grade and the same set of the traditional variables. In both columns, we also include the Acquisition score that is assigned to the specific business, rather than the small business owner. Interestingly, moving from the first column to the second column, the R^2 increases by 3 percentage points, from 11.0 percent to 14.0 percent. In the final column, we consider a model with all the credit scoring approaches and the set of traditional variables, and the R^2 increases further to 14.4 percent. By comparing the R^2 in the first and the third column, we can infer that the Funding Circle rating grade explains almost one third of the delinquency behavior in this more saturated model.

To wrap up, **Figure 9** shows a comparison between small business loans originated by the two fintech lenders and the traditional credit source through credit cards issued by large banks (data at account level from Y-14M). There is evidence supporting our earlier findings that fintech lenders have the potential to move toward a more inclusive financial system where small business owners who are considered below prime could get access to business funding and could do so at a lower cost than otherwise.

Panel A of Figure 9 compares FICO distribution for loans that were originated in 2016–2019. It is interesting to note that borrowers who chose fintech lenders include those with relatively high FICO scores as well as those below-prime business owners. About half of fintech lenders' SBL portfolios, from Funding Circle and LendingClub, are small business loans made to business owners with FICO scores 700 or higher. However, this is still a much smaller portion compared with bank loans. About 80 percent of bank business cards were issued to business owners with FICO scores above 700, and more than half of all business card holders have FICO scores above 750.

Panel B of Figure 9 compares the funding costs faced by business owners when borrowing from the specific fintech lenders in our sample vs. through small business credit cards. About 50 percent of small business loans originated by Funding Circle in each year have an APR below 15 percent and a substantial share of borrowers with FICO below 675 also received loans from Funding Circle with an APR below 15 percent.[21] For LendingClub, a substantial share of borrowers with FICO below 675 received an APR below 20 percent. For bank business cards (Y-14M data), only a small portion of business cards were issued to business owners with FICO scores below 675, and the (contractual) interest rates charged to these business owners were mostly above 20 percent APR.

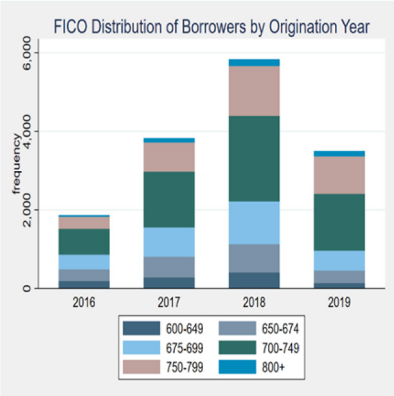
[20] We also find consistent results when we observe delinquency within a shorter window of 12 months after origination. The test is reported in Table A5 of the Appendix.

[21] As mentioned earlier, not all fintech lenders are the same. These findings based on Funding Circle and LendingClub may not be applicable to other fintech SBL platforms.

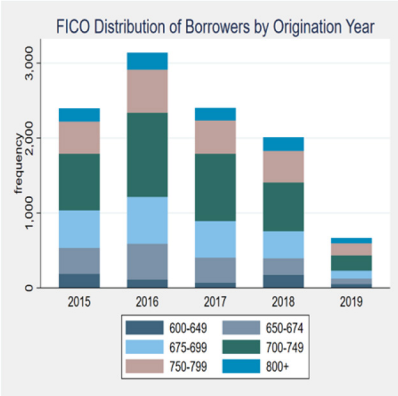
Comparing Interest Rates on SBL Originated by Fintech Lenders vs. Traditional Banks (Controlling for Business Owners' Credit Scores) Figure 9

Panel A: FICO Distribution by Origination Year (2016–2019)

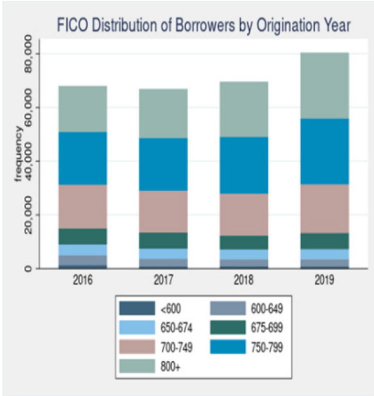
Funding Circle SBL



Lending Club SBL



Banks (Business Cards)

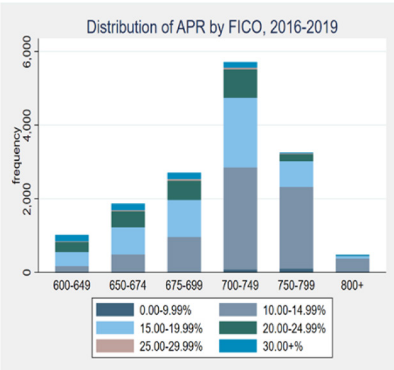


Borrowers from fintech lenders include those with relatively high FICO scores and those below prime. Many creditworthy SBL owners also choose to take out loans from fintech lenders. About half of fintech lenders' SBL portfolios, from Funding Circle and LendingClub, are small business loans made to business owners with FICO scores of 700 or higher. In contrast, about 80 percent of bank business cards were issued to business owners with FICO score above 700, and more than half of all business card holders have FICO above 750.

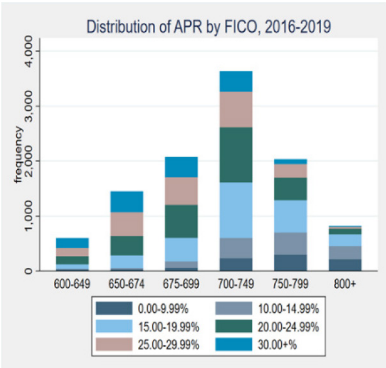
Sources: Funding Circle, LendingClub, and Y-14M.

Panel B: APR Distribution by Business Owners' FICO Scores and Origination Year

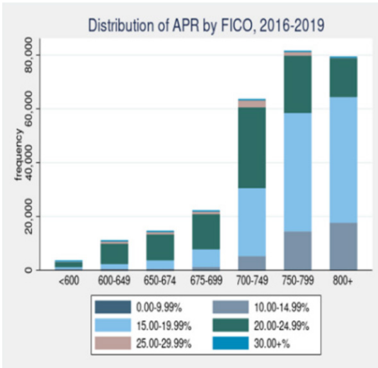
Funding Circle SBL



Lending Club SBL



Banks (Business Cards)



About 50 percent of small business loans originated by Funding Circle in each year have an APR below 15 percent (not shown here) and a significant amount of SBL with FICO below 675 also received an APR below 15 percent. For LendingClub, a significant amount of SBL with FICO below 675 received an APR below 20 percent. For bank business cards (Y-14M data), a small portion of business cards were issued to business owners with FICO below 675, and the (contractual) interest rates charged to these business owners were mostly above a 20 percent APR.

Sources: Funding Circle, LendingClub, and Y-14M.

5. Conclusions

Our analysis, based on a unique proprietary data set of two large fintech SBL platforms and additional proprietary data on comparable bank lending over the period 2016–2019, supports the hypothesis that fintech lenders have been able to expand credit access to those underserved small business owners who are not likely to receive funding from traditional lenders. This may be particularly relevant for those small business owners with a short credit history and those in areas that face a higher local unemployment rate and a higher rate of business bankruptcy filing. We indeed find that Funding Circle lent to many small business firms that, because of the owner's FICO score, would not have had access to bank loans, and that it lent more in areas with higher unemployment and business bankruptcies, controlling for other risk characteristics.

Our results also suggest that alternative data about the small businesses and their owners can play an important role in allowing fintech SBL platforms to expand credit access. We find that the ratings that Funding Circle assigns to each loan were important in explaining the future credit performance of the loans over the 24-month period after loan origination. The information used by Funding Circle (in its process to risk rank each loan) is superior to the information content of traditional credit risk measures such as the FICO and Vantage scores. The contribution of these alternative data increased further in areas with a high unemployment rate. In a saturated model that includes the business credit rating by rating agencies (ie; the business owner's credit rating by FICO or Vantage scores), the general characteristics of the loan terms (maturity, origination date, loan amount), and the local economic conditions where the businesses are located, our results indicate that Funding Circle's credit rating contributes significantly and explains about one-third of the variation in a loan's default probability. This finding is consistent with previous studies for fintech personal lending, and it provides support for the use of alternative data in small business lending as well.

These findings have relevance for the role of fintech lenders going forward. Outside our period of analysis, fintech lenders also played a role in facilitating loans to small mom-and-pop shops that did not have established banking relationship during the COVID-19 pandemic, which began in February/March 2020. When funding supply mostly dried up during the lockdown, most fintech SBL lenders refocused their loan originations toward the U.S. PPP loans, and many partnered with banks. While most banks had to prioritize their existing business customers in processing PPP loan applications, leaving smaller businesses exposed to bankruptcy risk, fintech lenders entered the space to fill the credit gap. Fintech partnerships with community banks during the pandemic made it possible for partnered banks to reach new customers, allowing small banks as a group to originate a larger share of PPP loans than their share of banking assets.[22]

While offering similar loan products as banks, fintech lenders have been subject to a different set of regulations. All consumer loans from banks and nonbanks are generally subject to some consumer protection laws, but nonbank lenders are not subject to the periodic onsite examinations to which the banks are subject. However, through recent partnerships with banks, some fintech platforms have also been subject to examination (as a significant banking service provider) or are indirectly subject to the rigorous standards that banks must comply. Several fintech platforms have recently become a bank either through acquisition or being granted a banking charter, allowing them to access low-cost funding through insured deposits. Banks have also been investing and partnering with fintech vendors to access today's technology. Bank loans and fintech loans are likely to become more alike as this trend continues.

It is important to remember that fintech lenders are not all the same; thus, the results found in this paper may not necessarily apply to other fintech SBL platforms.

22 As an example, about 65 percent of PPP loans that were originated by Funding Circle during the pandemic were new customers with no prior business relationship.

Most important, we have demonstrated the potential of what the fintech platforms and their use of alternative data could do to move us toward a more inclusive financial system. As collaboration and partnerships grow among traditional banks and fintech firms, they would become more efficient in utilizing borrowers' data using today's technology and likely to work together in enhancing financial inclusion and the overall economic performance.

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Appendix

Distribution of Loan Maturity by FC Risk Bands

Table A1

FC Risk Band Loan Maturity in Months	A+	A	B	C	D	Total
6	0.34%	0.15%	0.13%	0.06%	0.01%	0.68%
12	1.20%	1.15%	0.87%	0.39%	0.13%	3.73%
24	2.35%	2.44%	2.67%	1.17%	0.40%	9.04%
36	4.99%	6.45%	6.96%	3.37%	1.03%	22.80%
48	2.97%	4.16%	4.49%	2.33%	1.26%	15.21%
60+	9.91%	16.24%	13.43%	6.98%	1.99%	48.54%
Total	21.76%	30.59%	28.54%	14.30%	4.82%	100%

Source: Funding Circle.

Funding Circle SBL — Pairwise Correlations — Funding Circle SBL Loan Characteristics and Local Economic Factors

Table A2

	Loan amount	Loan maturity in months	Acquisition score	Loan APR	FICO at origination	VantageScore	12-month del’cy dummy[1]	24-month del’cy dummy[2]	FC rating A+	FC rating A	FC rating B	FC rating C	FC rating D	Origination year 2016	Origination year 2017	Origination year 2018	Origination year 2019	Ln (profit)	Ln (gross revenue)	Unemployment	HPI
Loan maturity in months	**0.16**	1																			
Acquisition score	**-0.06**	-0.01	1																		
Loan APR	**-0.14**	**0.02**	**-0.02**	1																	
FICO at origination	**0.15**	**-0.03**	**0.03**	**-0.41**	1																
VantageScore	**0.15**	**-0.03**	**0.02**	**-0.46**	**0.72**	1															
12-month delinquency dummy[1]	**0.02**	0.00	**-0.02**	**0.15**	**-0.09**	**-0.08**	1														
24-month delinquency dummy[2]	**0.04**	**0.02**	**-0.03**	**0.15**	**-0.12**	**-0.12**	**0.74**	1													
FC rating A+	**0.05**	**-0.07**	**0.02**	**-0.58**	**0.32**	**0.35**	**-0.07**	**-0.08**	1												
FC rating A	**0.08**	**0.05**	-0.01	**-0.36**	**0.10**	**0.11**	**-0.06**	**-0.06**	**-0.35**	1											
FC rating B	**-0.03**	0.00	0.00	**0.23**	**-0.14**	**-0.16**	0.01	**0.02**	**-0.33**	**-0.42**	1										
FC rating C	**-0.07**	**0.02**	-0.01	**0.48**	**-0.21**	**-0.23**	**0.08**	**0.08**	**-0.22**	**-0.27**	**-0.26**	1									
FC rating D	**-0.10**	0.00	-0.01	**0.63**	**-0.19**	**-0.21**	**0.11**	**0.12**	**-0.12**	**-0.15**	**-0.14**	**-0.09**	1								
Origination year 2016	0.01	**-0.13**	-0.01	-0.01	**-0.08**	**-0.05**	**0.04**	**0.09**	**-0.08**	0.00	**0.07**	0.01	**-0.03**	1							
Origination year 2017	0.00	**-0.05**	0.01	**-0.09**	**-0.04**	**-0.04**	0.00	**0.06**	**0.16**	-0.01	**-0.06**	**-0.08**	**-0.03**	**-0.22**	1						
Origination year 2018	0.01	**0.09**	-0.01	**0.08**	-0.01	**-0.02**	**0.05**	0.00	**-0.07**	0.01	**-0.04**	**0.06**	**0.12**	**-0.30**	**-0.46**	1					
Origination year 2019	**-0.02**	**0.05**	0.01	0.01	**0.12**	**0.11**	**-0.09**	**-0.13**	**-0.02**	0.00	**0.06**	0.01	**-0.08**	**-0.21**	**-0.32**	**-0.44**	1				
Ln (profit)	**0.34**	**-0.05**	**-0.03**	**-0.08**	**0.04**	**0.06**	0.00	0.00	**0.05**	**0.03**	**-0.03**	**-0.04**	**-0.05**	**0.04**	0.02	**-0.03**	**-0.02**	1			
Ln (gross revenue)	**0.60**	**-0.09**	**-0.10**	**-0.15**	**0.15**	**0.14**	-0.01	-0.01	**0.09**	**0.06**	**-0.05**	**-0.08**	**-0.08**	**0.09**	**0.02**	**-0.06**	**-0.02**	**0.40**	1		
Unemployment	-0.01	**0.02**	0.01	0.00	-0.01	0.01	0.01	0.01	0.01	**-0.02**	0.01	0.00	0.00	**0.04**	0.01	0.00	**-0.05**	-0.01	0.00	1	
HPI	**0.07**	**-0.05**	0.01	-0.01	**0.05**	0.01	0.01	0.00	-0.01	0.00	0.00	0.00	0.00	0.00	-0.01	0.00	**0.02**	**0.05**	**0.07**	**-0.04**	1
County business bankruptcy filings per capita	**0.03**	-0.01	0.01	-0.01	0.01	0.01	0.01	-0.01	-0.01	**0.02**	0.00	**-0.02**	0.00	0.01	0.00	-0.01	0.00	**0.03**	0.01	**-0.07**	**0.12**

Bold figures indicate statistical significance at the 5 percent level. The sample includes loan-level data from Funding Circle SBL Platform for the period 2016–2019.

[1] Takes the value of 1 if loan becomes delinquent (60 days past due) as of 12 months after origination and zero otherwise. [2] Takes the value of 1 if loan becomes delinquent (60 days past due) as of 24 months after origination and zero otherwise.

Sources: Funding Circle and Haver Analytics.

LendingClub SBL — APR by LendingClub Rating and FICO Scores in the U.S.

Table A3

		LendingClub Risk Rating					Total FICO	Portfolio share
		D	C	B	A	A+		
	Low risk	24.0%	22.5%	21.3%	17.0%	12.5%	17.6%	42.0%
FICO score	Medium risk	27.2%	26.7%	24.4%	18.8%	13.6%	22.5%	46.6%
	High risk	29.0%	28.7%	25.2%	19.6%	14.6%	25.7%	11.4%
Total LC Risk Rating		27.2%	26.2%	23.8%	18.2%	13.0%	21.4	
Portfolio share		6.9%	19.4%	26.5%	26.6%	20.7%		

This table shows APRs for different ranges of FICO score and LendingClub risk ratings, for loans that were originated on the LendingClub SBL platform during the period 2015–2019. The (discrete). LendingClub risk ratings at origination are mapped into five different risk groups (A+ for categories R1–R2 or C1–C3, A for R3–R4 or C4–C7, B for R5–R6 or C8–C11, C for R7–R8 or C12–C15, and D for R9–R10 or C16–C20). The (continuous) scores of the FICO credit bureau are divided into three segments corresponding to risk level (low, for scores higher than 739; medium, for scores between 670 and 739; and high, for scores below 670).

Source: Authors' calculations based on data from LendingClub.

Credit Access Estimations

Table A4

	Funding Circle SBL Lending Ratio1.				
	(I)	(II)	(III)	(IV)	(V)
County unemployment		0.00197***	0.00199***	0.00197***	0.00197***
		(0.000421)	(0.000422)	(0.000421)	(0.000421)
County HPI (in '00s)		0.000159	0.000178	0.000157	0.000144
		(0.00132)	(0.00132)	(0.00132)	(0.00132)
County business bankruptcy		48.21***	47.95***	48.24***	48.19***
filings per capita		(7.098)	(7.077)	(7.097)	(7.102)
Median income (in '00,000s)		0.0118***	0.0118***	0.0118***	0.0118***
		(0.00131)	(0.00131)	(0.00131)	(0.00131)
SBL concentration (in '000s)		0.00110	0.00114	0.00109	0.00109
based on non-CRA report		(0.000839)	(0.000839)	(0.000839)	(0.000839)
Population (%)	0.289***	0.292***	0.290***	0.292***	0.292***
	(0.0170)	(0.0180)	(0.0180)	(0.0180)	(0.0180)
Dummy, decrease in branches			0.00210**		
			(0.000963)		
Percentage decrease				0.00289	
in branches				(0.00465)	
Percent change in branches					0.00343
					(0.00322)
Observations	10,279	9,688	9,688	9,688	9,688
R2	0.074	0.085	0.085	0.085	0.085

***/**/* denotes results that are significant at the 1%/5%/10% levels, respectively. The dependent variable is the ratio of SBL loans originated (by Funding Circle SBL platform) in zip code i in year t relative to total SBL loans (in all zip codes) originated in year t. The regressions include a constant and state-level dummies. The sample is based on loan-level data from Funding Circle SBL platform for the period 2016:Q1– 2019:Q2.

Sources: Funding Circle, CRA data, FDIC Summary of Deposits, Call Reports, and Haver Analytics.

Default Probability as of 12 months After Origination

Table A5

	Delinquent Loan Dummy — 12 Months After Origination		
	(I)	(II)	(III)
Acquisition score	-0.000012	-0.000010*	-0.000009*
	0.000008	0.000005	0.000005
FICO at origination	-0.00603***		-0.00342**
	(0.00149)		(0.00151)
VantageScore	-0.00358***		0.000815
	(0.00125)		(0.00131)
FC rating A		0.580***	0.533***
		(0.203)	(0.206)
FC rating B		1.210***	1.128***
		(0.194)	(0.207)
FC rating C		1.886***	1.781***
		(0.199)	(0.217)
FC rating D		2.583***	2.451***
		(0.218)	(0.241)
Ln (profit)	0.00561	0.0287	0.0240
	(0.0407)	(0.0424)	(0.0424)
Ln (gross revenue)	-0.281***	-0.271***	-0.264***
	(0.0630)	(0.0634)	(0.0635)
Ln (loan amount)	0.454***	0.502***	0.519***
	(0.0903)	(0.0942)	(0.0949)
Loan maturity in months	-0.00339	-0.00282	-0.00313
	(0.00364)	(0.00377)	(0.00379)
Unemployment	0.0742	0.0546	0.0529
	(0.0461)	(0.0472)	(0.0471)
County HPI	0.00247	0.00168	0.00178
	(0.00151)	(0.00153)	(0.00153)
County business bankruptcy	-622.6	-555.4	-532.0
filings per capita	(1,028)	(1,023)	(1,024)
Observations	11,625	11,630	11,625
Pseudo R^2	0.0808	0.121	0.123

***/**/* denotes results that are significant at the 1%/5%/10% levels, respectively. The table reports the estimates for a logit regression including a constant, state dummies, and origination-year dummies. The dependent variable takes the value of 1 if loan is the loan becomes delinquent (60+DPD) as of 12 months after origination and zero otherwise. The sample includes loan-level data from Funding Circle SBL Platform for the period 2016–2019.

Sources: Funding Circle, CRA data, FDIC Summary of Deposits, Call Reports, and Haver Analytics

(a) ROC Curves – Unemployment above the Median

Table A6

	Panel A: ROC Curves — 12-Month Delinquency Rates				
	Observations	AUROC	Std. Err.	95% Confidence Interval	
FICO Score	6,153	0.679	0.0162	0.64736	0.71073
VantageScore	6,153	0.6768	0.0165	0.64445	0.7092
FC Risk Grades	6,153	0.7536	0.0148	0.72457	0.78264
FC Risk Grades and APR Residuals	6,153	0.7605	0.0146	0.73193	0.78905
	Panel B: ROC Curves — 24-Month Delinquency Rates				
	Observations	AUROC	Std. Err.	95% Confidence Interval	
FICO Score	6,123	0.7003	0.0125	0.67572	0.72482
VantageScore	6,123	0.698	0.0126	0.67335	0.72274
FC Risk Grades	6,123	0.7477	0.0115	0.72514	0.77019
FC Risk Grades and APR Residuals	6,123	0.7533	0.0114	0.73091	0.77564

(b) ROC Curves – Unemployment at or below the Median

	Panel A: ROC Curves — 12-Month Delinquency Rates				
	Observations	AUROC	Std. Err.	95% Confidence Interval	
FICO Score	6,482	0.7567	0.0142	0.72886	0.78456
VantageScore	6,482	0.7493	0.0144	0.72117	0.77744
FC Risk Grades	6,482	0.7803	0.014	0.75293	0.8077
FC Risk Grades and APR Residuals	6,482	0.7804	0.0139	0.75225	0.80678
	Panel B: ROC Curves — 24-Month Delinquency Rates				
	Observations	AUROC	Std. Err.	95% Confidence Interval	
FICO Score	6,386	0.7685	0.0115	0.74592	0.79105
VantageScore	6,386	0.7589	0.0116	0.7361	0.78168
FC Risk Grades	6,386	0.7896	0.011	0.76808	0.81108
FC Risk Grades and APR Residuals	6,386	0.79	0.011	0.76851	0.81154

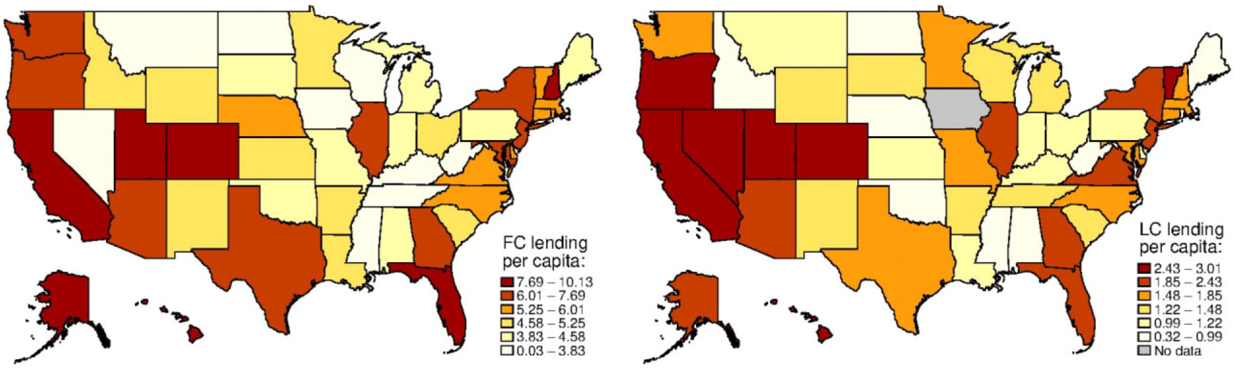
The table reports the estimates for the logit regression, which include state- and origination year-level dummies, as reported in Table 6. The sample includes only zip codes with an unemployment rate above the median in panel (a) and below the median in panel (b).

Source: Funding Circle.

SBL Lending Activity by State

In U.S. Dollars per capita | Figure A1

Funding Circle (2016–2019) | LendingClub (2015–2019)



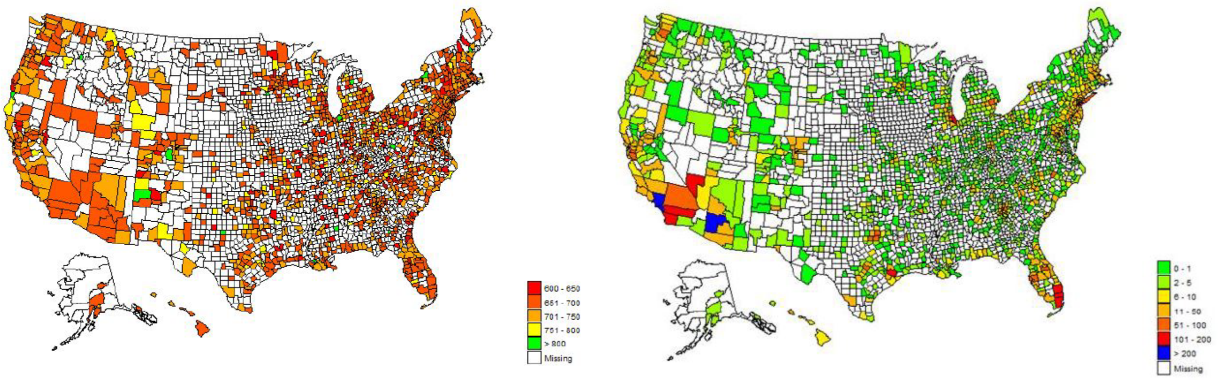
The graphs show the total amount lent in each state by each of the two fintech firms over the period indicated divided by the 2019 population in each State.

Sources: Funding Circle, LendingClub, U.S. Census Bureau, authors' calculations.

LendingClub Credit Portfolio by County

Figure A2

Average VantageScore by County[1] | Total Number of Loans per County[2]

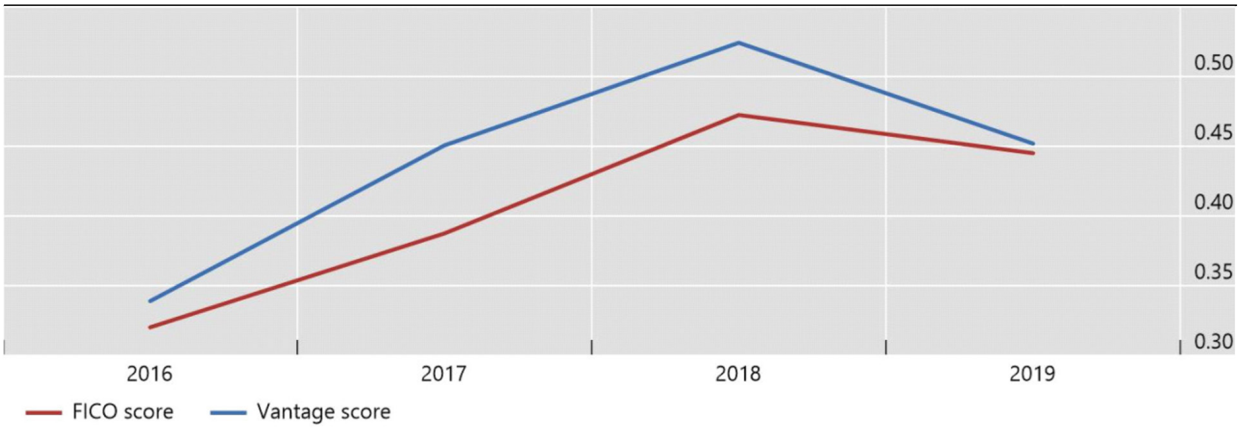


[1] Average VantageScore of LendingClub SBL Platform's small business borrowers in each county. [2] Average number of SBL loans originated by LendingClub SBL Platform in each county.

Sources: LendingClub, authors' calculations.

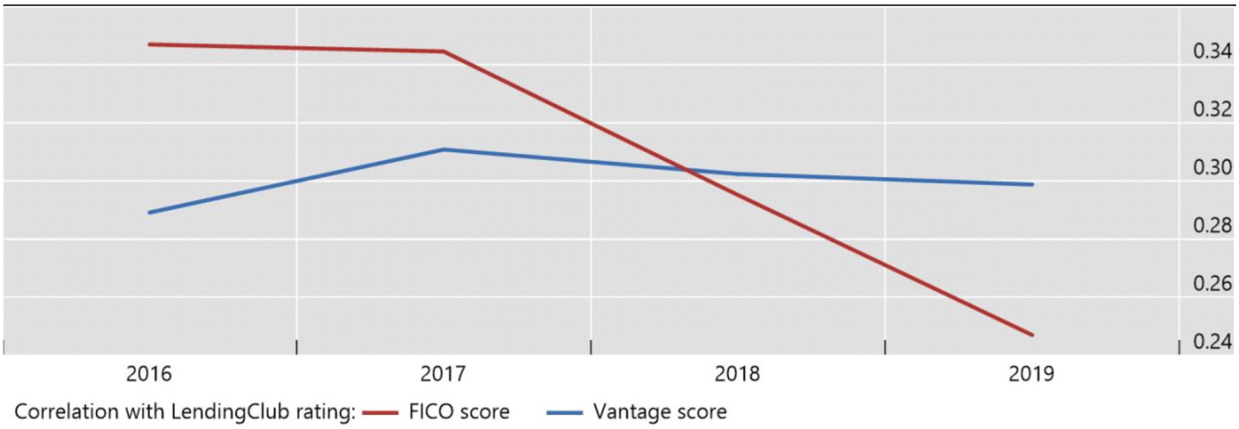
Correlation Between Funding Circle's Risk Bands and Traditional Credit Scores (FICO and VantageScore)

Correlation Coefficient | Figure A3



Source: Funding Circle.

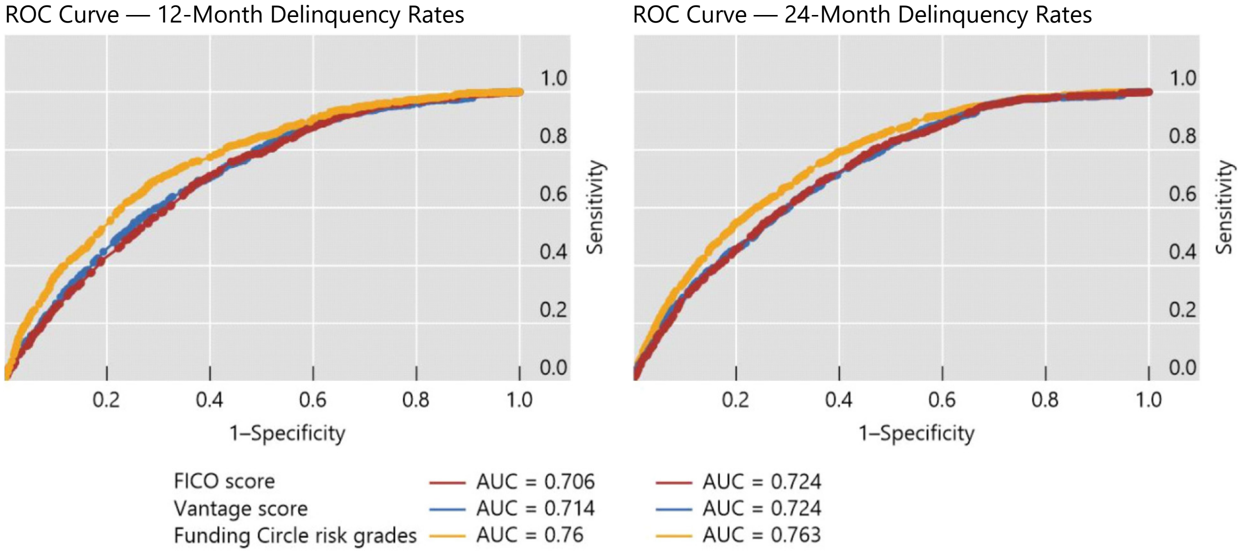
Correlation Between LendingClub Rating Grades and FICO and VantageScore | Figure A4



Source: LendingClub.

Predictive Power of FICO, VantageScore, and Funding Circle Risk Grades

Figure A5

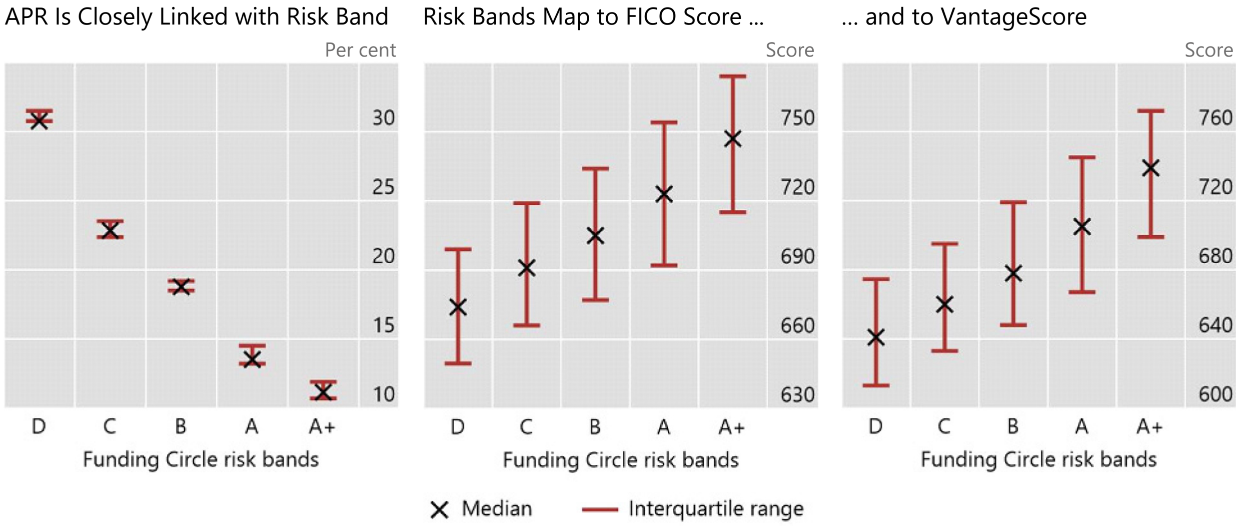


Note: Based on estimates for a logit regression including state- and origination year-level dummies. All credit scores are divided in 5 buckets. The FICO scores are divided into five buckets – Poor (FICO<580), Fair (FICO between 581 and 670), Good (FICO between 671 and 740), Very Good (FICO between 741 and 800), and Exceptional (FICO>800). The VantageScore is also divided into five buckets: Very Poor (scores <550), Poor (scores between 551 and 650), Fair (scores between 651 and 700), Good (scores between 701 and 750), and Excellent (scores >750). The x-axes show the fraction of false positives, whereas the y-axes show the fraction of true positives. The higher the curve the stronger the performance of the model.

Sources: Funding Circle; What Is a Good Credit Score? – Forbes Advisor.

Funding Circle Risk Bands Are Functionally Similar to Other Risk Scores

Figure A6



Source: Funding Circle.