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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 business bankruptcy filings and higher unemployment rates. Moreover, fintech platforms' internal credit scores were able to predict future loan performance more accurately than the traditional approach to credit scoring. Using Y-14M 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.

Keywords: fintech credit, peer-to-peer (P2P) lending, marketplace lending, small business lending (SBL), Funding Circle, LendingClub, alternative data, credit access, credit scoring,

JEL Classification: G18, G21, G28, L21

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I. 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) 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, this is true only when compared with the overall banking industry. The origination and funding of SBL overall has shifted dramatically over the past few years toward the nonbank (“shadow banking”) sector. This is partly because of the increased regulatory burden since the financial crisis (e.g., 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 be important drivers to the shift.

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

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/machine learning (ML) models to evaluate the credit risk of small businesses and 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 than traditional peer lenders (for consumer loans) of the same size. One 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 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 “invisible 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 Square³ 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,

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.

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 period 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.

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 digitised 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 similar to SBL originated by traditional lenders with loan terms that are longer (typically three years or longer) and with interest rates that are comparable with 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 the subsequent performance of such loans. Specifically, we ask the following research questions: Has fintech lending enhanced credit access to small business owners who are likely to be “underserved” by traditional lenders? Are there measurable differences in fintech credit scores with respect to other traditional credit scores? What is the value of alternative data in credit risk evaluation and credit decisions?

To do this, we use detailed microdata from Funding Circle’s small business platform, and we compare this with the LendingClub SBL platform and traditional (business) credit cards data from Y-14M (submitted monthly to the Federal Reserve by CCAR banks for stress testing purposes). Our results show that, also in the SBL space, fintech lenders can serve borrowers who were less likely to receive credit from traditional banks and that they employ alternative data to improve credit scoring. Specifically, we find that fintech SBL platforms lent more in zip codes with higher business bankruptcy filings and higher unemployment rates. Moreover, fintech platforms’ internal credit scores were able to predict future loan performance more accurately than the traditional approach to credit scoring. The Y-14M loan-level bank data allow us to compare fintech SBL with traditional bank business cards in terms of credit access and interest rates. We confirm that fintech lenders provide credit to additional borrowers at lower cost.

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 (Kabbage, Fundera, Lendio, Brex, Fundbox, Bluevine, and Nav) work with partner banks (such as Cross River Bank, Celtic Bank, Radius Bank, and Sunrise Banks) to assist with the PPP loan approval and origination.

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. The reason is that 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 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 consumer 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 (e.g., in

⁵ The two data sets used for this paper — Funding Circle and LendingClub — both offer interest rate in the lower end and with their own self-imposed ceiling of 36 percent APR, with loan maturities ranging from one to five years.

highly concentrated markets and areas with fewer bank branches per capita). Similarly, 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. 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.

For both personal loans and mortgage loans, Dolson and Jagtiani (2021) find that 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. 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 (e.g., 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 (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.

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 businesses 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.

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 from 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 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

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 rates.

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 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 as 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

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.

months after the origination date. Note that loan maturities vary, and they are generally three to five years.¹⁰

One important characteristic of our dataset 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 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

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 other platforms. For example, the majority of the SBL originated by LendingClub are small loans (less than \$40,000), and almost all loans have a maturity of three years or less.

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 (e.g., 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 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 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 do not submit the CRA reports.

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.

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 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. The Funding Circle SBL share has an average of 0.04 and a maximum of 0.58, indicating that the macroeconomic relevance of such loans is generally small, such credit is less than 1 percent of total SBL in the most served zip code.

Local economic factors include 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 FICO, VantageScore, and the Funding Circle internal risk rating score (FC risk scores). The FC risk score is assigned using the company's proprietary model. We use dummy indicators for each loan considering 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.

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. 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 (e.g., 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 has 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.

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. FC 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).

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 VantageScore for business owners as of the loan application date.

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).

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.

Figure 4 shows that 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. 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.¹⁵ The correlation is slightly higher for VantageScore than for FICO. Notably, this correlation is even lower when LendingClub credit rating is compared with FICO and VantageScore. 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.

Figure 5 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. In addition, **Figure 6** 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.

Figure 7 presents the relationship between Funding Circle risk rating and the FICO/Vantage Score ratings. This figure is divided into two panels: the left panel for FICO scores and the right panel for Vantage scores. The size of the bubbles is in proportion to the share of the firms in each

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.

¹⁵ Specifically, at least half of the variations in FC rating grades cannot be explained by traditional credit scores (FICO and Vantage scores in this case). However, some of the variation in FC rating grades may be explainable by the same credit-related information that are used in the traditional credit-scoring process, but they are used in a different way by fintech lenders.

rating distribution based on origination amount. Each of the panels presents a risk matrix with Funding Circle credit rating compared with the two traditional ratings one at the time. On the vertical axis, the panels report the delinquency rate (i.e., the percentage of loans more than 60 days past due relative to the total number of loans). As the FICO and the Vantage scores 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+).

In the left panel, for a given FICO risk band (i.e., high risk), the expected loss rate is strictly monotonic with the Funding Circle credit ratings (i.e., the patterns of the dots show that the Funding Circle risk bands rank orders for expected loss). Conversely, given an internal rating (i.e., 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 important, 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 the 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.

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

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

similar but less pronounced compared with the same distribution for LendingClub SBL platform (see **Table A3** in the Appendix).

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

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.

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 6 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 SBL share. 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.

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 statistically positive and 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, 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 last 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

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).

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).

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:

$$p(D_{i,t}) = \Phi(\alpha \text{Credit Scoring}_{i,t} + \mu_S + \mu_T + \varepsilon_{i,t}) \quad (2)$$

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 models are estimated using 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.

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.

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 $(1 - \text{specificity})$.

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 column of Table 7

We conduct three 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 A4** (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 A5** 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, 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 8** presents the analysis of default probability as of 24 months after origination.¹⁹ 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 see 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

¹⁹ We also find consistent results when we observe delinquency within a shorter window of 12 months after origination. The test is reported in Table A4 of the Appendix.

credits. 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.²⁰ 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.

5. Conclusions

Our analysis, based on a unique proprietary data set of two large fintech SBL platforms and further data on comparable bank lending over 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 higher rate of business bankruptcy. We indeed find that Funding Circle lent to many 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.

Our results also suggest that alternative data about the small businesses and their owners could 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) are superior to the information content of traditional credit risk measures such as the FICO and Vantage scores. In a saturated model that includes the business credit rating by rating agencies, 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

²⁰ 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.

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 to assist with fraud, identity, and know your customer (KYC)/ anti-money laundering (AML) work. 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.²¹

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. In addition, new types of bank/fintech partnership have emerged as regulators attempted to move cryptocurrency activities under the banking regulation umbrella. Fintech platforms increasingly partner with banks to provide the technology needed to issue stablecoins for faster business-to-business (B2B) payments among businesses that have an account with banks in the network. Financial authorities continue to adapt their supervisory process to remain effective in the new financial landscape. Previous research has documented unintended consequences and the interplay among banking

²¹ 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.

regulations.²² In addition, coordination and collaboration among financial regulators across agencies and across jurisdictions would be important in designing effective fintech regulations.

There have been concerns about a potential systemic impact of fintech failure on overall financial stability. Unlike traditional lenders, fintech lenders that follow a P2P strategy (matching borrowers and lenders directly) more strictly were not subject to default risk during the pandemic recession, as they did not fund their loans on the balance sheet. Some fintech platforms that carried SBL loans on their balance sheet faced significant losses, and some were acquired by banks during the pandemic; for example, OnDeck and Kabbage were acquired by Enova and American Express, respectively.

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. 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. Overall, banks and fintech lenders are becoming more alike over time, and they are partnering more. In this way, they could potentially work together to rebuild the economy during the recovery period, thereby enhancing financial inclusion and the overall economic performance.

²² Jagtiani, Vermilyea, and Wall (2018) discusses basic third-party vendor risk exposure and the new supervisory guidelines on third-party risk management. Allen, Gu, and Jagtiani (2021 and 2022) discuss the impact of fintech and cryptocurrency activities on consumers and the financial system, as well as the current status on fintech regulations. See also Financial Stability Board (2017), Allen, Goldstein, and Jagtiani (2018), and Jagtiani and John (2019) for discussion on fintech and financial stability.

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Table 1: Descriptive Statistics — Funding Circle

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

	Observations	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
Defaults as predicted by FICO, Vantage Score, 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

Footnote:

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 value 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.

Table 2: Delinquency Rate by Funding Circle Rating Grades and FICO Scores

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 and 739); and High Risk (FICO<670).

	Funding Circle Risk Grades					Total FICO	Portfolio Share
	D	C	B	A	A+		
Low Risk	21.4%	11.3%	5.1%	3.3%	1.7%	3.6%	36.3%
FICO Band 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%		

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

Table 3: APR by Funding Circle Rating Grades and FICO Scores

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 and 739); and High Risk (FICO<670).

	Funding Circle Risk Grades					Total FICO	Portfolio Share
	D	C	B	A	A+		
Low Risk	31.0%	23.1%	18.9%	13.9%	11.2%	14.4%	36.3%
FICO Band 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%		

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

Table 4: Credit Access Analysis

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 .

	Funding Circle SBL Share				
	Model 1	Model 2	Model 3	Model 4	Model 5
County unemployment		0.00197*** (0.000422)	0.00199*** (0.000423)	0.00197*** (0.000422)	0.00197*** (0.000422)
County HPI (in '00s)		0.000124 (0.00132)	0.000142 (0.00132)	0.000122 (0.00132)	0.000109 (0.00132)
County business bankruptcy filings per capita		48.29*** (7.092)	48.01*** (7.070)	48.32*** (7.091)	48.27*** (7.096)
Median income (in '00,000s)		0.0118*** (0.00131)	0.0118*** (0.00131)	0.0118*** (0.00131)	0.0118*** (0.00131)
SBL concentration (in '000s)		0.00106 (0.000829)	0.00108 (0.000829)	0.00105 (0.000829)	0.00107 (0.000828)
Population (%)	0.289*** (0.0170)	0.293*** (0.0180)	0.290*** (0.0181)	0.292*** (0.0180)	0.292*** (0.0180)
Dummy, decrease in branches			0.00209** (0.000963)		
Percentage decrease in branches				0.00293 (0.00465)	
Percent change in branches					0.00347 (0.00323)
Model	OLS	OLS	OLS	OLS	OLS
Observations	10,279	9,688	9,688	9,688	9,688
R ²	0.074	0.085	0.085	0.085	0.085

Note: ***/**/* denotes results that are significant at the 1%/5%/10% levels, respectively.

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

Table 5: Economic Contribution of Factors in the Credit Access Analysis

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.

Regressor	Model 2		Model 3		Model 4		Model 5	
	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%
County HPI (in '00s)	0.00365	4.31%	0.00368	4.32%	0.00364	4.30%	0.00364	4.30%
County business bankruptcy filings per capita	0.00622	7.35%	0.00617	7.25%	0.00622	7.36%	0.00621	7.34%
Median income (in '00,000s)	0.00792	9.37%	0.00785	9.23%	0.0079	9.34%	0.0079	9.33%
SBL concentration (in '000s)	0.00033	0.39%	0.00033	0.39%	0.00033	0.39%	0.00033	0.39%
Population (%)	0.04645	54.94%	0.04596	54.03%	0.04643	54.89%	0.04643	54.85%
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%
State-level dummies	0.01645	19.46%	0.01658	19.49%	0.01642	19.41%	0.01642	19.40%

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

Table 6: Probability of Defaults as Predicted by FICO, Vantage Score, and Funding Circle Risk Grades

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

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*** (0.182)	0.573*** (0.194)
B			1.188*** (0.172)	1.235*** (0.182)
C			1.830*** (0.175)	1.837*** (0.186)
D			2.361*** (0.191)	2.392*** (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*** (0.134)	0.622*** (0.143)
B			1.178*** (0.127)	1.227*** (0.137)
C			1.748*** (0.133)	1.736*** (0.143)
D			2.271*** (0.150)	2.279*** (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

Source: Funding Circle

Table 7: Receiver Operating Characteristic (ROC) Curves

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

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

Source: Funding Circle.

Table 8: Default Probability as of 24 Months After Origination

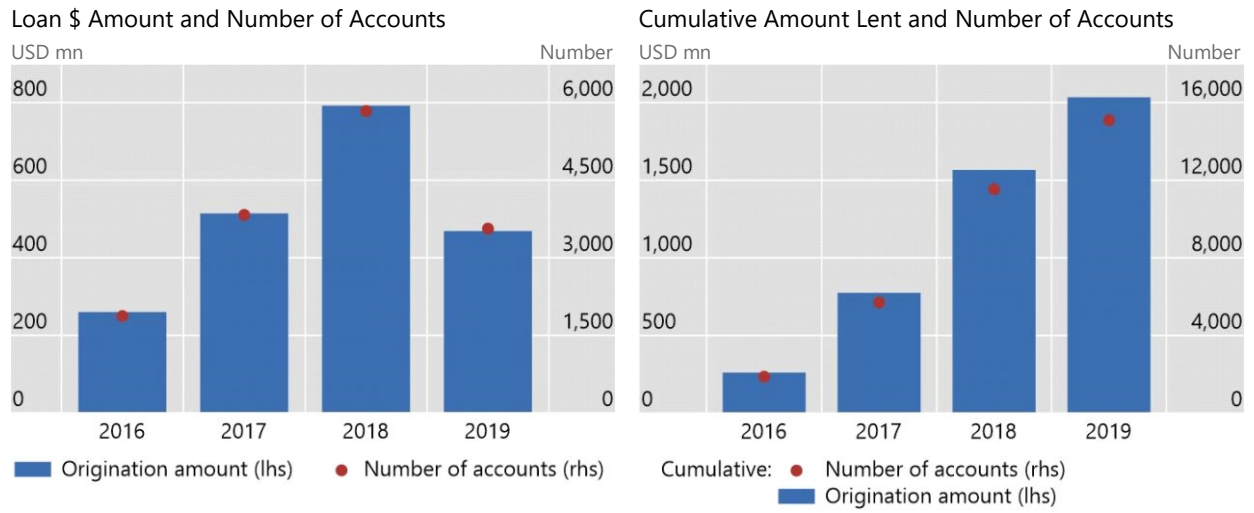
The table reports the estimates for a logit regression which include a constant, state dummies, and origination-year dummy indicators. The sample includes loan-level data from Funding Circle SBL platform for the period: 2016–2019. Dependent variable is a binary variable that takes the value of 1 if the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

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

Note: ***/**/* denotes results that are significant at the 1%/5%/10% levels, respectively.

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

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

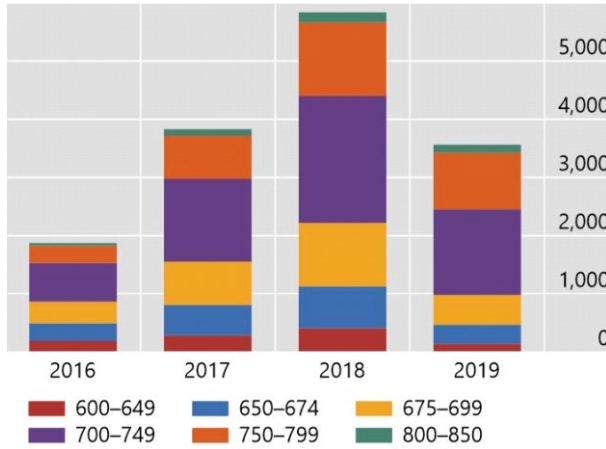


Data Source: Funding Circle.

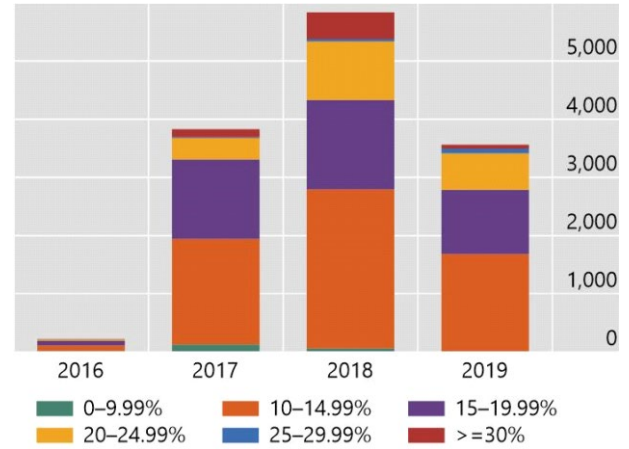
Figure 2: Funding Circle Loan Distribution: by FICO, APR, Amount, Maturity

Number of Loans

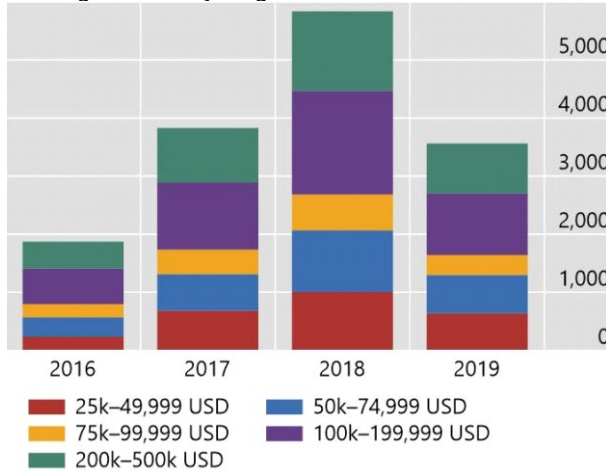
Borrowers' FICO Score by Origination Year



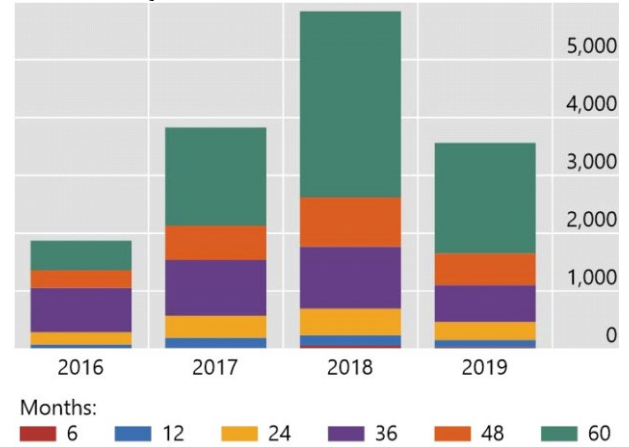
Borrowers' APR by Origination Year



Funding Amount by Origination Year



Loan Maturity Distribution

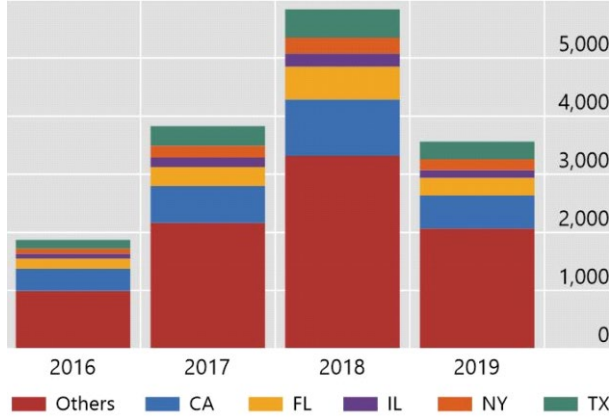


Data Source: Funding Circle.

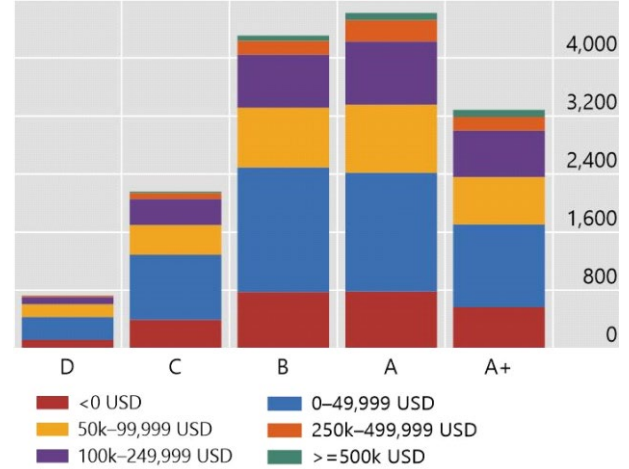
Figure 3: Funding Circle Loan Distribution: by States; Profits, Revenue, and Maturity Across Credit Ratings

Number of Loans

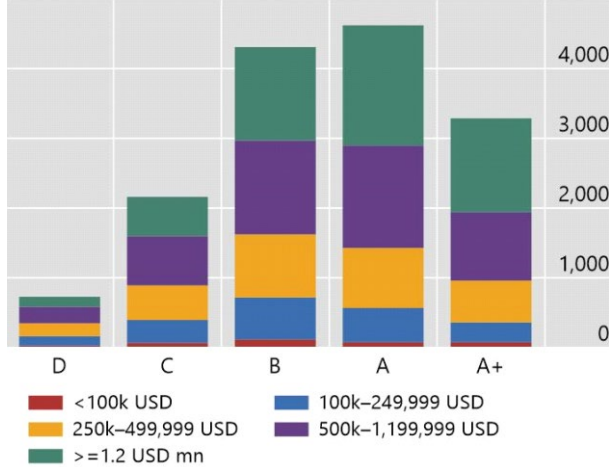
Top 5 States by Origination Year



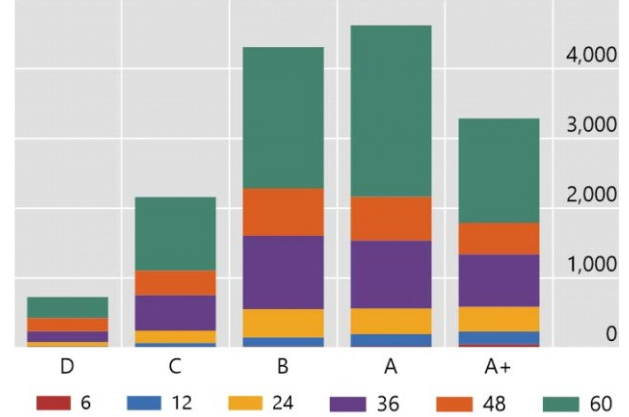
Borrowers' Profit by Funding Circle Risk Rating



Borrowers' Revenue by Funding Circle Risk Rating



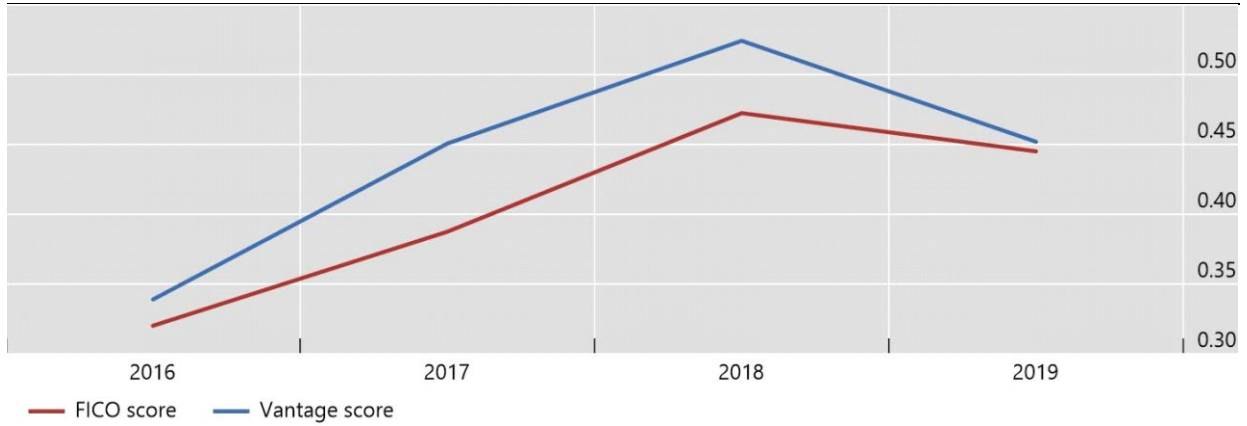
Loan Maturity Distribution by Funding Circle Risk Rating



Data Source: Funding Circle.

Figure 4: Correlation Between Funding Circle's Risk Bands and Traditional Credit Scores (FICO and VantageScore)

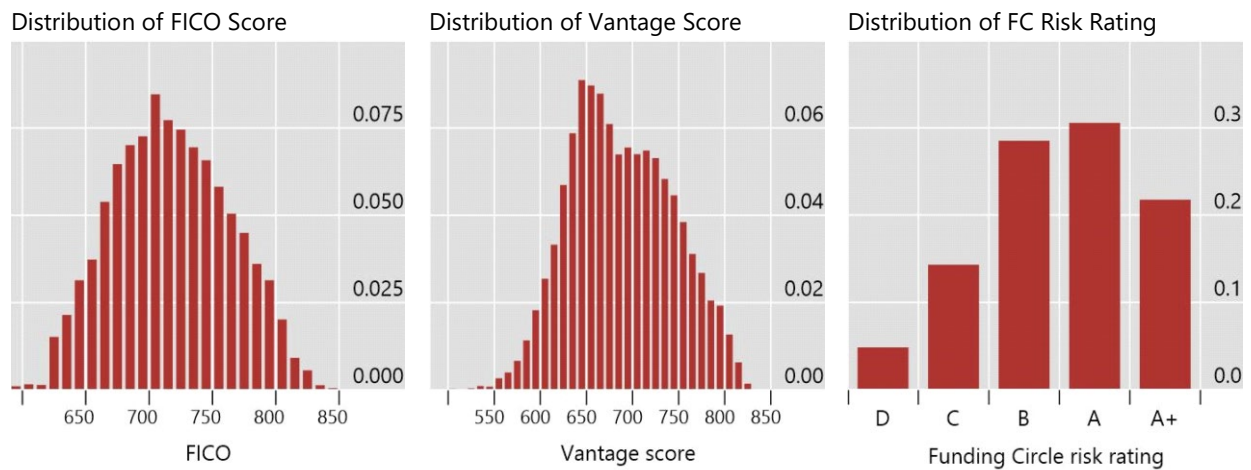
Correlation Coefficient



Data Source: Funding Circle.

Figure 5: Funding Circle Loan Distribution by FICO vs. VantageScore vs. Funding Circle Own Ratings

Frequencies



Note: Additional statistics on the distribution of credit scores:

FICO: median score = 715; mean score = 717

VantageScore: median score = 693; mean score = 698

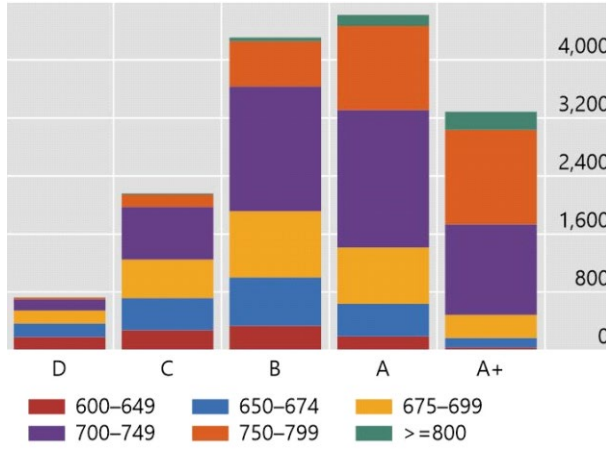
Funding Circle: a total of 15,096 loans, the median rating (at 7,548 position) is A-rated.

Data Source: Funding Circle.

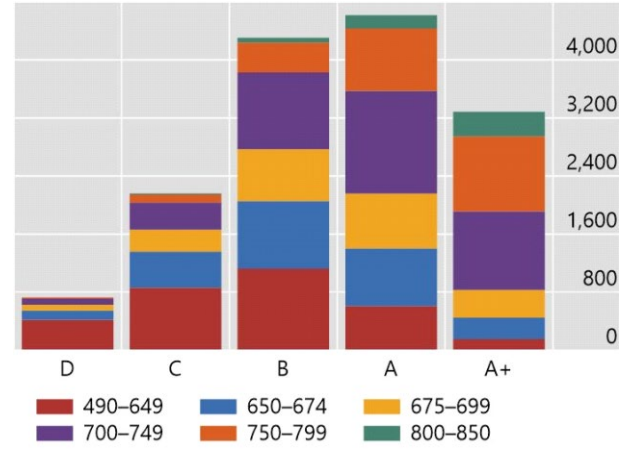
Figure 6: Funding Circle Loan: Credit Score Distribution by Funding Circle's Own Rating Grades

Number of Loans

FICO Distribution by Funding Circle Risk Bands



VantageScore Distribution by Funding Circle Risk Bands

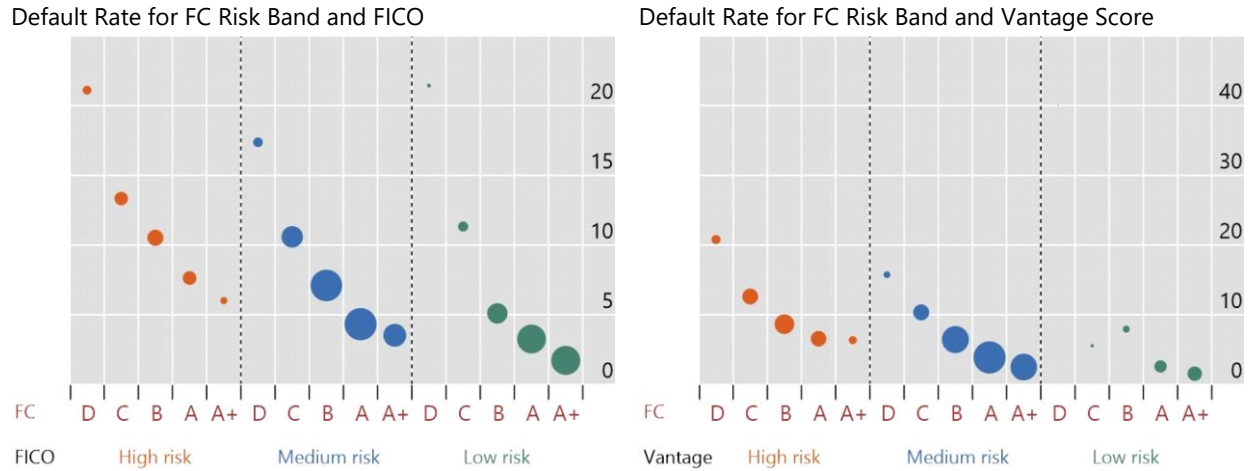


Data Source: Funding Circle.

Figure 7: Delinquency Rates Decline Significantly for Higher FC Risk Bands, Controlling for FICO and VantageScore Bands

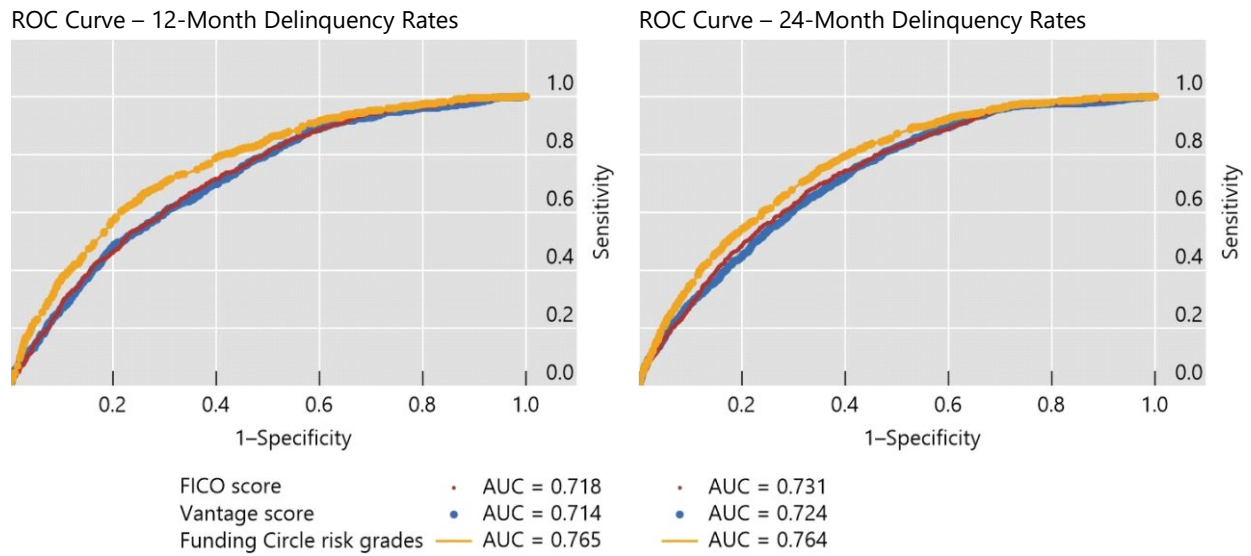
This figure shows the delinquency rate (i.e., the percentage of loans more than 60 days past due relative to the total number of loans). The plots are calculated based on a dummy that takes value 1 if the loan becomes delinquent (60+days-past-due) as of 24 months after origination and zero otherwise.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

In Percent



Data Source: Funding Circle.

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

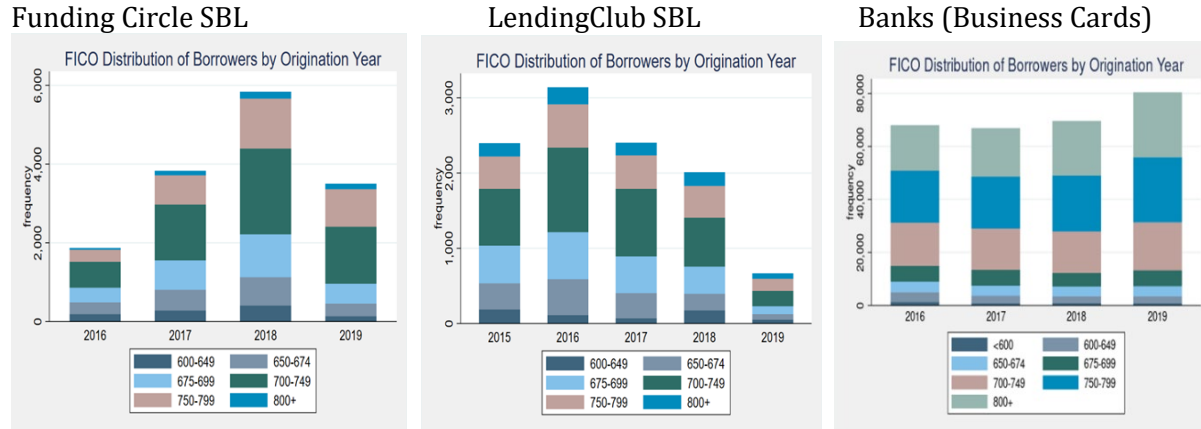


The x-axes show the fraction of false positives, whereas the y-axes show the fraction of true positives. The higher the curve the stronger the performance of the model. Based on the models in Table 6.

Data Source: Funding Circle.

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

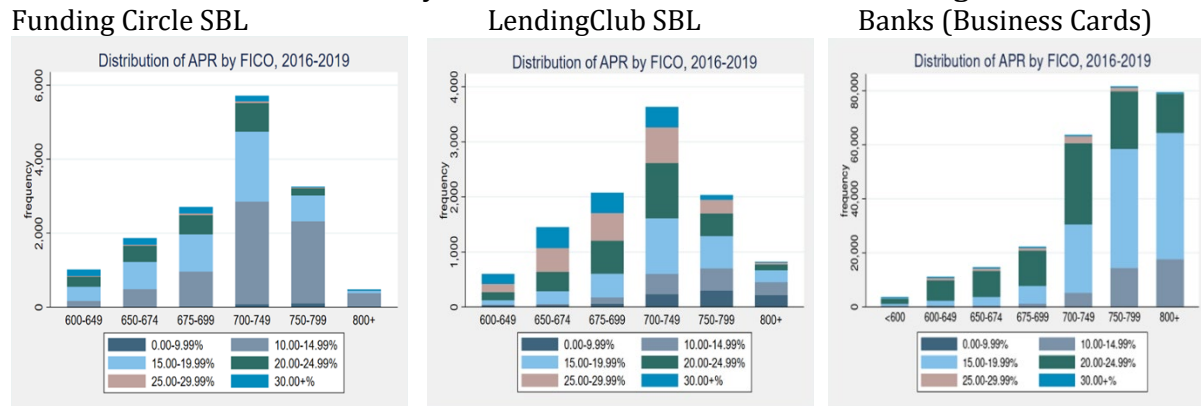
Panel A: FICO Distribution by Origination Year (2016–2019)



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

Note: 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.

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



Source: Funding Circle, LendingClub, and Y-14M

Note: 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.

Appendix

Table A1: Distribution of Loan Maturity by FC Risk Bands

FC Risk Band	A+	A	B	C	D	Total
Loan Maturity in Months						
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%

Data Source: Funding Circle.

Table A2: Funding Circle SBL — Pairwise Correlations — Funding Circle SBL Loan Characteristics and Local Economic Factors

The sample includes loan-level data from Funding Circle SBL Platform for the period 2016–2019

	Loan amount	Loan maturity in months	Acquisition score	Loan APR	FICO at origination	Vantage Score	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	

Note: Bold figures indicate statistical significance at the 5 percent level.

Footnotes:

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.

Data Sources: Funding Circle and Haver Analytics.

Table A3: LendingClub SBL — APR by LendingClub Rating and FICO Scores in the U.S.

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.

	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%		

Note:

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.

Table A4: Credit Access Estimations

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.

	Funding Circle SBL Lending Ratio¹.				
	(I)	(II)	(III)	(IV)	(V)
County unemployment		0.00197*** (0.000421)	0.00199*** (0.000422)	0.00197*** (0.000421)	0.00197*** (0.000421)
County HPI (in '00s)		0.000159 (0.00132)	0.000178 (0.00132)	0.000157 (0.00132)	0.000144 (0.00132)
County business bankruptcy filings per capita		48.21*** (7.098)	47.95*** (7.077)	48.24*** (7.097)	48.19*** (7.102)
Median income (in '00,000s)		0.0118*** (0.00131)	0.0118*** (0.00131)	0.0118*** (0.00131)	0.0118*** (0.00131)
SBL concentration (in '000s) based on non-CRA report		0.00110 (0.000839)	0.00114 (0.000839)	0.00109 (0.000839)	0.00109 (0.000839)
Population (%)	0.289*** (0.0170)	0.292*** (0.0180)	0.290*** (0.0180)	0.292*** (0.0180)	0.292*** (0.0180)
Dummy, decrease in branches			0.00210** (0.000963)		
Percentage decrease in branches				0.00289 (0.00465)	
Percent change in branches					0.00343 (0.00322)
Observations	10,279	9,688	9,688	9,688	9,688
R ²	0.074	0.085	0.085	0.085	0.085

Note: ***/**/* denotes results that are significant at the 1%/5%/10% levels, respectively.

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

Table A5: Default Probability as of 12 months After Origination

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.

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

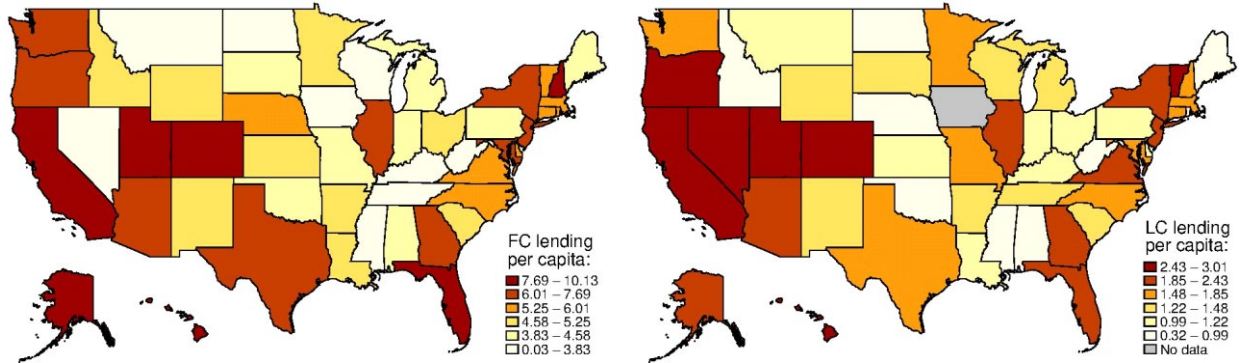
Note: The ***/**/* denotes results that are significant at the 1%, 5%, 10% levels, respectively. Sources: Funding Circle, CRA data, FDIC Summary of Deposits, Call Reports, and Haver Analytics.

Figure A1: SBL Lending Activity by State

In U.S. Dollars

Funding Circle (2016–2019)

LendingClub (2015–2019)



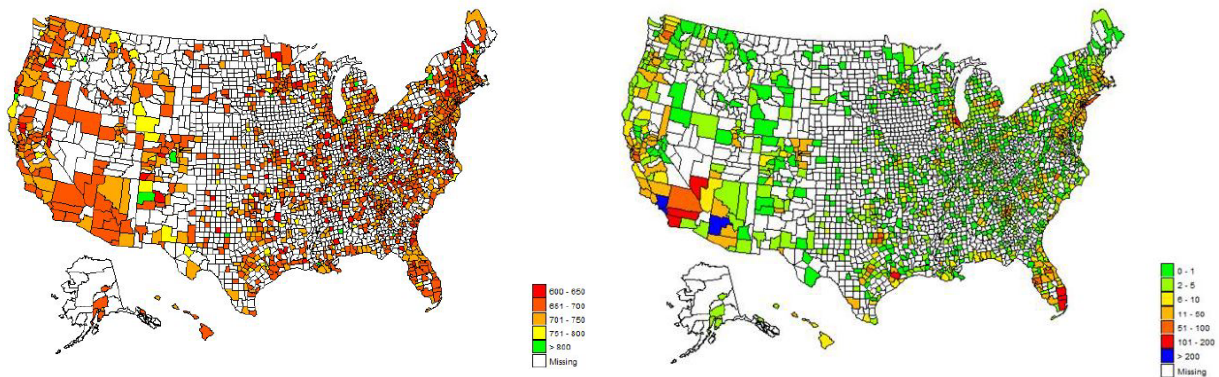
The graphs show the ratio of the total amount lent in each state by each of the two fintech firms over the period indicated divided by the 2019 population in each State.

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

Figure A2: LendingClub Credit Portfolio by County

Average VantageScore by County¹

Total Number of Loans per County²



Footnotes:

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.

Figure A3: Correlation Between LendingClub Rating Grades and FICO and VantageScore

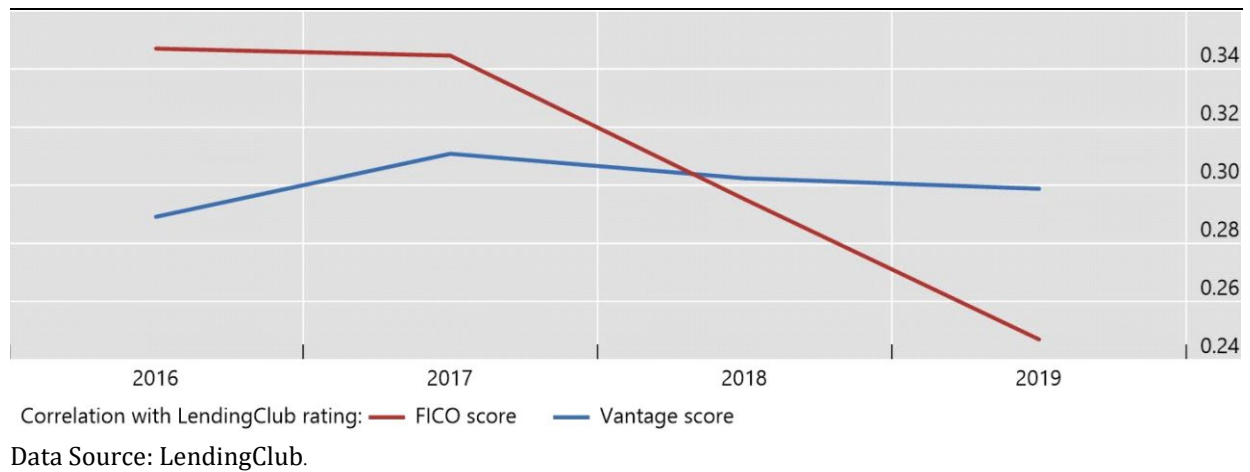
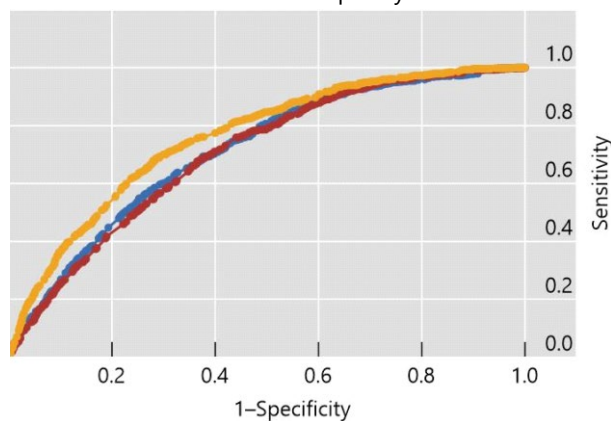


Figure A4: Predictive Power of FICO, VantageScore, and Funding Circle Risk Grades

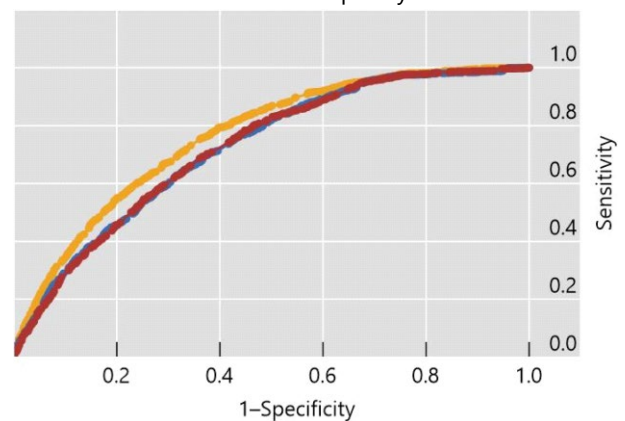
Based on estimates for a logit regression including state- and origination year-level dummies. All credit scores are divided in 5 buckets. The FICO scores are divided into five buckets – Poor (FICO<580), Fair (FICO between 581 and 670), Good (FICO between 671 and 740), Very Good (FICO between 741 and 800), and Exceptional (FICO>800). The Vantage Score 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).

ROC Curve — 12-Month Delinquency Rates



FICO score — AUC = 0.706
 Vantage score — AUC = 0.714
 Funding Circle risk grades — AUC = 0.76

ROC Curve — 24-Month Delinquency Rates



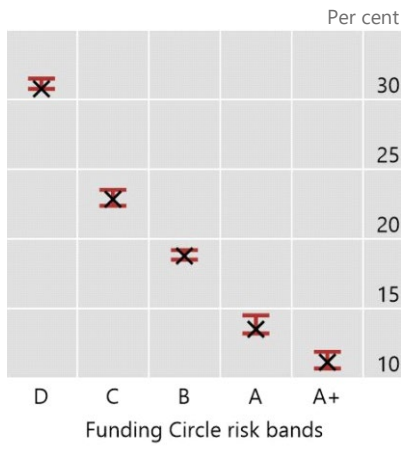
FICO score — AUC = 0.724
 Vantage score — AUC = 0.724
 Funding Circle risk grades — AUC = 0.763

Note: 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.

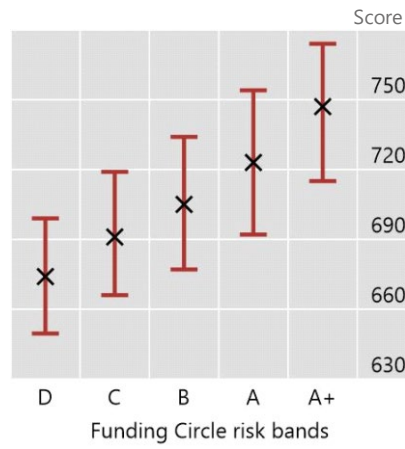
Sources: Funding Circle, [What Is a Good Credit Score? – Forbes Advisor](#).

Figure A5: Funding Circle Risk Bands Are Functionally Similar to Other Risk Scores

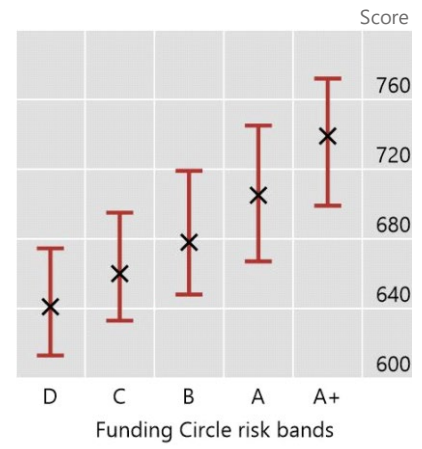
APR Is Closely Linked with Risk Band



Risk Bands Map to FICO Score ...



... and to VantageScore



× Median — Interquartile range

Data Source: Funding Circle.