CFS Working Paper Series

No. 706

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The Performance of Marketplace Lenders*

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20 May 2022

We analyze the performance of marketplace lending using loan cash flow data from the largest platform, Lending Club. We find substantial risk-adjusted performance of about 40 basis points per month for the entire loan portfolio. Other loan portfolios grouped by risk category have similar risk-adjusted performance. We show that characteristics of the local bank sector for each loan, such as concentration of deposits and the presence of national banks, are related to the performance of loans. Thus, marketplace lending has the potential to finance a growing share of the consumer credit market in the absence of a competitive response from the traditional incumbents.

Keywords: Marketplace lending, household finance, financial intermediation, financial innovation, competition

JEL Codes: G12, G21

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We thank Gregory Connor, Robin Greenwood, Julapa Jagtiani, Christos Koulovatianos, Clemens Sialm, Ulf von Lilienfeld-Toal, Laurent Weill, Brian Wolfe, and seminar participants at the Dublin Conference on Fintech and Financial Risk Management, the Fourteenth Annual Financial Intermediation Research Society Finance Conference, the Second Toronto FinTech Conference, the Seventh Luxembourg Asset Management Summit, and the Workshop on Fintech Adoption and Economic Behavior at the University of Strasbourg for their helpful comments. The views expressed in this paper are those of the authors and do not reflect the positions of Mandatum.

I. Introduction

Several companies have redesigned the complex process of household lending by linking borrowers and lenders more directly via online platforms. We refer to these online platforms as marketplace lending platforms and to the related activity as marketplace lending. This innovation led to the emergence of new intermediaries offering competitive financial services. These financial intermediaries have the potential to play a significant role in household finance.

We analyze the performance of consumer loans originated through Lending Club (LC), the largest marketplace lending platform in the United States (US).[1] To the best of our knowledge, this paper is the first to analyze the performance characteristics for this asset class using payment data for individual loans. Our findings indicate that the LC loan portfolio has an average internal rate of return (IRR) of 40 basis points per month across vintage months. This average IRR is approximately 5% on an annualized basis. For comparison, the average annualized 1-month Treasury Bill rate is about 0.2%, the average 1-year Treasury Constant Maturity Rate is about 0.5%, and the average 1-year LIBOR is about 1.4% during the sample period. Thus, the average IRR for the typical portfolio of LC loans issued in a given month is much higher than benchmark interest rates.

We construct a monthly loan index return to measure risk-adjusted performance. This index is designed to measure the performance of the entire LC loan portfolio during a specific month for loans issued at different points in time, rather than the total performance until maturity of the set of loans issued in a particular month. Our baseline specification for the index is based on a marked-to-market valuation approach that incorporates changes in the yield for a value-weighted portfolio of credit card asset-backed securities (ABS). The changes in this yield reflect the changes in credit market conditions and default expectations for consumer loans that cannot be directly observed for LC loans after origination. This approach ensures that the performance of the loan index reflects both the cash flow from the underlying loan portfolio as well as market's changing valuation of securities with similar exposure to consumer credit risk. We also utilize several permutations of the valuation approach to verify that our findings do not depend critically on any one aspect of our technique. This monthly index has an average risk-adjusted monthly return of about 39 basis points

[1] Lending Club started operating as a Facebook application in May 2007 by utilizing the existing trust among interlinked individuals of the social network (VentureBeat, 2007). By the end of 2007, Lending Club became an independent platform. During our sample period, from December 2007 until March 2017, Lending Club facilitated more than $20 billion in loans while paying more than $3 billion in interest to the independent lenders.

(approximately 4.8% annualized) and this risk-adjusted performance estimate is quite close to the difference between the average IRR and the average 1-month Treasury Bill rate. These consumer loans are fixed income securities, and therefore, this performance is associated with low volatility compared to typical equity portfolios. The systematic exposure of the LC loan index to the stock market is near zero. This should not be particularly surprising. The stocks of investment banks are exposed to equity risk while the exposure of a corporate bond portfolio to equity risk much more limited. Similarly, the systematic risk of the stock for Lending Club is much more risky than the actual LC loan portfolio. The monthly Sharpe ratio of the LC portfolio return is 0.86, which is much higher than the monthly Sharpe ratio of 0.16 for the US stock market for the same time period. Even the Sharpe ratio of 0.28 for a US Corporate 1-3 Year Index, an investment grade bond portfolio with similar duration, is considerably lower than the Sharpe ratio for LC loans during this period.[2]

The typical risk factors for the equity market as well as commonly used aggregate liquidity factors do not explain a substantial portion of the expected return for this loan portfolio. While the factors reflecting credit risk, and to a lesser extent interest rate risk, in the corporate bond market do have significant explanatory power for the return to the LC loan portfolio, the inclusion of these risk factors does not have a noticeable impact on the estimated risk-adjusted return. Thus, the high average return for the LC loan portfolio is associated with very favorable risk properties and this new asset class may be of considerable interest to a wide range of investors.

Of course, other asset classes such as private equity and crypto-currencies have exhibited high realized returns for a decade or more. Realized performance is not necessarily an indication of high risk-adjusted expected returns. However, these other asset classes hold securities whose valuations are based on potentially volatile expectations of distant and uncertain future performance. This explanation for any difference between realized returns and expected returns is less plausible in the context of LC loans because these securities are essentially 36 month fixed income instruments for which default risk over a limited duration is the dominant source of risk.

Lending Club is attracting more institutional investors, presumably due to the historical performance of the loan portfolio. According to Lending Club's 10-K filings, the percentage of LC loans held by institutional investors (i.e., whole loans purchased by qualified investors) was

[2] Data for ICE Bank of America Merrill Lynch US Corp 1-3yr Total Return Index is available from the Federal Reserve Bank of St. Louis website (FRED).

approximately 1% in 2012 and this percentage increased to 48% by 2015. Marketplace lending is a rapidly growing business with a loan volume during 2017 of $26 billion in the US. Nevertheless, there remains tremendous capacity for expansion because the credit card debt of US households financed by commercial banks was about $790 billion at the end of 2017 and the most common purpose for LC loans is consumer debt consolidation.[3]

If this level of superior performance is expected to persist, then it will eventually attract significantly more capital. Indeed, in the case of Lending Club, it appears that institutional investors are now willing to fully finance the entire LC loan portfolio. More generally, it may be the case that retail investors eventually become unnecessary participants in marketplace lending.[4] The analogous pattern in which high risk-adjusted initial fund performance generates additional capital for subsequent funds has already been established in private equity (Metrick and Yasuda, 2010). The related expansion of private equity funds, particularly venture capital funds, has changed how firms access capital. If more capital enters marketplace lending in response to performance, then a new equilibrium is likely to develop, changing how consumers access debt markets. Tang (2019) finds that marketplace lending via Lending Club is a substitute for bank lending for most borrowers. Therefore, the probability that marketplace lending gains substantial market share depends on whether these platforms continue to offer borrowers competitive rates while providing high loan portfolio returns to the investors holding the loans. The analysis of loan portfolios available on marketplace platforms is of critical relevance because this alternative approach to financial intermediation seeks to displace the incumbent providers.

We use a dataset of monthly loan payments for all LC loans from December 2007 until March 2017. The data set of monthly observations on the loan payments include more than 23 million records and is matched to loan details and borrower characteristics known at the time of loan issuance. Borrower characteristics include FICO ratings, employment status, income, home ownership, stated purpose of loan, and geographic area. Given such detailed information, investors can screen potential borrowers on the Lending Club platform to build customized portfolios.

[3] Data for credit card debt originated by commercial banks is available from the Federal Reserve Bank of St. Louis website (FRED).

[4] We note that in the fourth quarter of 2020, Lending Club announced the decision to close the platform for individual investors to buy small increments of loans originated by Lending Club. This closure of the retail platform, implemented at the end of 2020, likely reflected the interaction of two patterns. First, Lending Club has become increasingly successful in attracting institutional investors based on the performance of its loan portfolio. Second, the demand for consumer loans through Lending Club and the creditworthiness of potential borrowers has changed substantially during the ongoing Covid-19 pandemic.

During the sample period, investors could also set mechanical rules to allocate capital to many loans within a category. According to Vallee and Zeng (2018), the decision to screen or to follow mechanical rules is dependent on investor sophistication. In this sense, our performance analysis based on all loans in a category is likely a lower bound for the performance of sophisticated institutional investors during our sample period.

Previous research regarding marketplace lending has focused on two topics. First, marketplace lending received considerable attention in the context of financial intermediation, addressing questions such as the role of marketplace lending and how it changes the lending business for traditional providers of household credit (Berger and Gleisner, 2009; De Roure et al., 2016; Michels, 2012; Miller, 2015; Wei and Lin, 2016). The second research area is the behavior of agents participating in marketplace lending. This research analyzes the selection process of loans by individual lenders and the loan characteristics associated with eventual default (Dorfleitner et al., 2016; Hertzberg et al., 2018; Herzenstein et al., 2011; Iyer et al., 2015; Lin et al., 2013; Lin and Viswanathan, 2015; Zhan and Liu, 2012). Online financial intermediation allows many potential lenders to assess the detailed characteristics of individual borrowers. It is certainly possible that disseminating the same information to several independent lenders leads to improved accuracy in the decision to finance the loan. However, institutional investors began purchasing securitized products based on diversified portfolios of LC loans in 2017. This approach to financing these loans indicates that institutional investors are willing to purchase these portfolios without carefully screening each loan using a variety of individual borrower characteristics.

It is clear from subsequent loan performance that Lending Club is able to assess the probability of loan default with considerable precision. For instance, Serrano-Cinca et al. (2015) show that there is a strong relationship between the credit risk category assigned to loans and the probability of default using publicly available data from Lending Club. We confirm this pattern for LC credit categories. Moreover, we find that the risk-adjusted return for the loans in each credit risk category are virtually identical across most of the different credit categories. This relation across categories indicates that the higher interest rates for loans deemed more risky are largely offset by higher default rates for these loans.

The approximate equivalence of risk-adjusted performance across most credit categories implies that diversified investors are largely indifferent when allocating capital between credit categories. Since origination fees collected by Lending Club are proportional to the loan volume and the losses associated with default are largely borne by the independent lenders, Lending Club has a strong incentive to generate this indifference so that most loans receive financing. While the profitability of banks is also related to loan volume, the extent to which banks retain a substantial portion of these consumer loans may force them to allocate limited capital to the more profitable lending opportunities and to forgo other opportunities. Essentially, banks must rank potential loans by profitability to allocate limited resources, but Lending Club and other marketplace platforms are capable of originating all lending opportunities that independent investors view as profitable. This may be one key innovation that allows marketplace lending to compete effectively with banks for personal loans.[5]

There is an extensive literature analyzing the industrial organization of the banking sector in the United States. The general assessment is that banks, as the traditional providers of consumer credit, possess market power. However, this evidence often depends on the particular type of the loan and the competitive structure of the local market. For instance, Kahn et al. (2005) find that a more concentrated local market for banks is associated with higher consumer loan rates. However, this pattern does not hold for automobile loans, presumably because the captive finance subsidiaries of manufacturers provide additional competition. In addition, the collateralized nature of the automobile loan requires much less borrower-specific information acquisition by banks. Rice and Strahan (2010) find that the decreased competition between banks increases interest rates for small firms. They use state level regulatory changes regarding the expansion of bank branch networks across state boundaries to show that small firms located in states with tighter restrictions regarding bank entry face higher interest rates than otherwise identical firms.

More recent evidence from Schwert (2020) regarding syndicated bank loans indicates that these loans typically embed an interest rate premium compared to bond yields for the same companies. This result is interpreted as suggestive evidence of market power because the premium is not related to the size of the loan as it would be in a competitive environment with fixed costs and the syndicated loan market is dominated by a few large participants. Moreover, the findings in Erel (2011) indicate that bank mergers lower interest rates for commercial loans, presumably because improved efficiency more than offsets other considerations. However, for the subset of

[5] For instance, such competitive advantage for Lending Club does not exist in the US residential mortgage market. Most mortgages originated by banks are already quickly sold to other investors, and so, there is much less bank exposure through loan retention.

these mergers that substantially increase market power due to a high geographical overlap in operations, interest rates on commercial loans increase significantly after the merger. Butler et al. (2017) examine the impact of the local banking sector on consumer interest rates from a different perspective. They find that prospective borrowers in a local environment with better access to bank finance report a lower maximum willingness to pay in terms of interest rates on Prosper, another marketplace lending platform.

The presence of market power in the banking sector indicates that there are barriers to entry of some form. These barriers might include the high fixed costs of regulatory compliance, such as Dodd-Frank and capital adequacy requirements, as well as the costs of supporting a network of branches or ATM locations. In many respects, this situation corresponds well to the structure of the ride hailing industry. As Cramer and Krueger (2016) discuss, taxicab companies have local market power created by the municipal medallion system, jurisdiction restrictions, and the regulation of fares. In addition, taxicab companies usually own and maintain a fleet of automobiles. Ride hailing services, such as Uber and Lyft, have been able to enter this industry by avoiding these barriers to entry. These new entrants utilize unregulated drivers as contract workers and each driver's personal car as capital. In an analogous manner, marketplace lending platforms circumvent many of the regulatory costs and capitalization requirements in the traditional banking sector. The originated loans are distributed quickly to a diffuse set of investors, and so, marketplace platforms avoid the regulatory compliance and network infrastructure associated with retail banking, deposit taking and capital reserves. At this point, the main difference between these two industries is that new entrants in ride hailing have captured large market shares, while marketplace lending still has a very small share of the consumer loan market (Milne and Parboteeah, 2016).

The risk-adjusted performance of the entire LC loan portfolio provides one important indicator of the potential for substantial displacement of traditional banks in the future. We also investigate how characteristics of the local banking environment are associated with the performance of marketplace loans. The extent to which the performance of LC loans is related to the local characteristics of the banking sector suggests that the high risk-adjusted performance of the loan portfolio is correlated with the presence of barriers to entry. Lending Club can be viewed as a disruptive entrant using an alternative lending technology that largely avoids various potential barriers to entry. For instance, small banks are better able to utilize soft information according to Berger et al. (2005). It may be possible that some aspect of Lending Club's approach allows marketplace lending to enter local markets largely served by small banks because large banks may be at a competitive disadvantage.

We use two variables to describe the local banking environment: 1) the concentration ratio of the largest five banks based on deposits in the locality to measure local bank competition, and 2) the fraction of branches in the locality belonging to the five largest national banks to measure local access to national credit providers with diversified loan portfolios. Our findings indicate that the performance of the LC loan portfolio is significantly higher in localities with relatively high local bank concentration and relatively low national bank presence. This evidence suggests that marketplace lending platforms are able to undercut the market power of traditional creditors that stems from local barriers to entry. Of course, correlation is not necessarily proof of causation. Nevertheless, these patterns do provide clear evidence that loans in these localities are more profitable due to whatever local conditions are correlated with higher barriers to entry. Lending Club, as well as marketplace lending more generally, may find that targeted marketing in localities with these characteristics is highly beneficial.

The remainder of this paper is organized as follows. The next section discusses the data, provides summary statistics, and presents an initial IRR analysis of loan performance. Section III describes the methodology used to construct the monthly loan portfolio index return. Section IV presents the risk-adjusted performance results for the LC loan portfolio. Section V analyzes the interaction between traditional banks, as measured by the characteristics of local banking environment, and the performance of LC loans. Section VI concludes.

II. Data and summary statistics

Our data includes 23 million monthly payment records for all LC loans that were financed between December 2007 and March 2017. These records are matched to loan details and borrower characteristics measured at the time the loan is financed. Personal identifiers are not included. This monthly payment information for each individual loan is provided by RiverNorth, a closed-end fund specialized in marketplace lending. This data set includes the entire spectrum of consumer loans issued by Lending Club, without any selection bias. To verify the completeness of the loan histories, we compare the number of issued loans and aggregate loan volume calculated from payment data provided by RiverNorth with the publicly available summary statistics from Lending

Club in Appendix Table 1. These statistics match perfectly, and therefore, we have the full population of loans issued by Lending Club.

The initial balance of a LC consumer loan ranges from \$1,000 to \$40,000. An individual can have as a maximum two distinct loans at the same time. Investors only decide what fraction of the specific loan to finance because the loan terms are set by Lending Club. Each loan is segmented into \$25 notes, thus investors may form diversified loan portfolios with relatively small amounts of capital. For instance, a \$5,000 investment can be used to form a loan portfolio including notes from 200 different loans. This type of marketplace lending can be interpreted as a particular type of crowdfunding as in Morse (2015). For large loan portfolios, the lack of segmentation below this \$25 threshold is completely irrelevant to investors. Accredited investors, e.g., institutions, can purchase whole loans. If investors on the platform do not finance a posted loan request, then the loan does not get issued.[6] A loan request remains active until it is fully funded or for a maximum of 14 days. Origination fees for these loans range between 1% and 6% of the loan amount, due to the credit rating and other items used for credit risk assessment. The monthly payment obligations begin within 30 days of origination and include the standard components: the principal and the interest based on the borrower's risk profile.

The data set combines information on monthly payments received, loan details (interest rate, maturity, funded amount), loan status updates (current, late, charged off, or fully paid), and the risk profile of the borrower at the time of the loan application such as the FICO score of the borrower. Cash flows on a monthly basis for each loan are absolutely essential to the calculation of an accurate IRR for each loan portfolio. This detailed information is also critical for the construction of the monthly portfolio index returns. The data set includes socioeconomic variables such as employment history, purpose of the loan, home ownership, and open credit lines. Our analysis of loan portfolio performance uses the payment information as well as the interest rate and credit risk category of each loan. Lending Club assigns its own credit risk category to every loan: Each capital letter ranging from A (lowest risk category) through G (highest risk category) represents a credit category. The classification procedure further divides loans within each category into more narrow subcategories. For instance, category A includes subcategories A1

[6] If a loan does not get fully financed, borrowers can reapply for the remaining part within 30 days. If granted, the total loan is considered as one application.

through A5. At the specific point in time, all of the loans within each of these subcategories receive the same interest rate. There are 35 different credit risk subcategories present in the data.

Table 1 provides the summary statistics of the 36-month maturity loans by broad credit risk category assigned by Lending Club and issue year.[7] Loans in the broad credit risk categories E, F, and G are included in the All category reflecting all loans, but these loans are not reported in separate groups because the sample size is very small and the categories themselves became obsolete. Several patterns emerge from these summary statistics. First, the number of loans has increased rapidly in each of the credit categories and this rapid expansion took place later for the more risky loan categories. Second, the average loan size has typically increased within each credit category, although this increase has been much more modest than the increase in the number of loans. These two patterns indicate that the number of borrowers, rather than the size of the loan, is the main source of growth for this marketplace lending platform. Third, the average interest rate has remained stable or decreased for the less risky credit categories, while the average interest rate for more risky categories has slowly increased. Lastly, the vast majority of loans, by number and by dollar volume, are issued to relatively safe borrowers.

A thorough performance analysis of a loan portfolio begins with a monthly payment history for each issued loan after subtracting the LC servicing fee (1% of each payment).[8] Note that this 1% servicing fee based on each monthly payment is different from the loan origination fee of 1% to 6% of the initial loan amount charged by Lending Club when the loan is funded. Before considering risk-adjusted performance using a monthly loan portfolio index return generated from cash flows, estimated changes in loan yields, and assumptions about the probability of default, we start with a more basic analysis of performance using IRR calculations. We form a portfolio containing all loans with a stated maturity of 36 months issued in a particular month, the vintage month. To ensure that we capture the vast majority of payments after the stated maturity of 36 months, we include an additional six months of payments on these loans. Thus, we sum all of the

[7] We consider issued loans with 36 months until maturity for our analysis even though loans with 60 months until maturity also exist. The issuance of loans with 60-month maturities did not begin until June 2010. Given the start date and the increased time to maturity, we only have complete payment information for these loans if they were issued between June 2010 and March 2012. This would be an extremely restrictive time frame for any performance analysis. Nevertheless, in unreported results the performance of loans with 60 months to maturity appears to be even more favorable than the performance of loans with 36 months to maturity.

[8] The retail investors on the LC platform typically pay a servicing fee of 1% of each payment received from the borrower. However, Lending Club does list alternative fee structures in its IPO prospectus. The performance results reported in this paper are not sensitive to which fee structure is utilized.

payments, net of fees, to investors for each of the 42 months following issuance. Given the 42 months of payment data and the combined loan balance at the time of issue, we calculate the monthly internal rate of return of the loan portfolio for that vintage month.

We implement this procedure for each issue month in our data set for which we have at least 42 months of subsequent payment information in the sample period. We present the summary statistics for the resulting time series of monthly IRRs for the LC loan portfolios in Panel A of Table 2. We follow the same approach to evaluate the performance of portfolios for each issue month separately for each of the broad credit risk categories. Based on the first column in Panel A of Table 2, the average monthly IRR across portfolios formed by issue month is 0.40%, that is, approximately 5% on an annual basis. The average 1-year Treasury Constant Maturity Rate is about 0.5% during the sample period. Similarly, the average of 1-year LIBOR is about 1.4% on an annualized basis for the same period. We note that the average IRR for the typical portfolio of LC loans is much higher than these benchmark interest rates.

If compensation for systematic risk explains the high average IRR of these loan portfolios, then systematically risky loans in the LC portfolios should have a higher average IRR compared to the relatively safe loans in these portfolios. Subdividing the issue month loan portfolio by credit category, we observe a threefold increase in the volatility of loan portfolio IRR between category A and category D. The IRR for each issue month exhibits considerable volatility within a credit category. Indeed, we find negative IRRs for several issue months during the 2008-2009 financial crisis. Since the financial crisis occurs at the beginning of the sample period and is a rare event historically, the average IRRs in Table 2 may be lower than the expected IRRs for loan portfolios in the future. If anything, the exposure of these loans to systematic risk during the financial crisis is higher than it would be in a typical recession. Since the weight of each issue month in these summary statistics is equal, the relatively low number of loans in months near the beginning of the sample period does not reduce the impact of the financial crisis on the performance metrics.

Because we require at least 42 months of subsequent payment information for a loan to be included in this basic IRR analysis, this approach relies more heavily on the performance of loans issued near the beginning of the sample period. However, in the subsequent section using a LC loan portfolio index this restriction to loans with at least 42 months of data in the sample period is eliminated. This alternative approach addresses concerns about the representativeness of the loans issued near the beginning of the sample period. For both the entire sample period and for the 2013-

2017 sub-period, the analysis of this alternative portfolio index metric generates quantitatively similar results to the basic IRR analysis presented in Table 2.

Panel B of Table 2 shows that the interest rates are about twice as large for the risky credit categories compared to the relatively safe credit categories. Since the average IRR is approximately unchanged across credit categories, the more risky credit categories must also have much higher loan default rates to offset the strong monotonic pattern for interest rates. However, the differences in volatility and loan default rates between categories are only associated with a very modest increase in average performance. The relatively risky loan portfolios tend to have slightly higher average IRRs compared to relatively safe portfolios. The average monthly IRR for category A is 0.40% and the average monthly IRR for category D is 0.44%, but this difference is not statistically significant.

It is certainly possible that the relatively risky loan portfolios have greater exposure to systematic risk. In this context, the rate of loan defaults, especially during the financial crisis, should be correlated with the systematic risk exposure of the loan portfolio. While Lending Club typically waits until a loan is at 120 days past due to charge off the loan, employing this definition would delay the realization of default by several months. Instead, we use two consecutive missed loan payments as our main proxy for loan default to ensure that the timing of the measured default rate is approximately correct.[9] Panel A of Figure 1 shows the percentage of all loans that miss two consecutive payments during each quarter. We note that this percentage increases dramatically during the financial crisis. This pattern of default is also visible for the percentage of the outstanding loan balance owed by borrowers that miss two consecutive payments. Thus, loan default appears to be systematically risky.

More importantly, the different loan credit risk categories have different levels of exposure to this measure of systematic risk. For example, Panel B of Figure 1 shows that both category C and category D have much greater rates of loan defaults, especially during the financial crisis, compared to category A. Nevertheless, the average IRR for category C and for category D are only a few basis points higher than the IRR for category A. This difference in average IRRs is not economically important or statistically significant. The cross-sectional variation in average IRR

[9] In Table 3 in Section III, we confirm that this definition is highly correlated with the eventual failure of the borrower to make any subsequent payments, that is, loan default. Alternative definitions of default using one missed payment or three missed payments generate similar patterns.

for the different loan portfolios is not tightly linked to the variation in the exposure to systematic default risk for the credit categories. Thus, this measure of systematic risk appears to be virtually unrelated to the average IRR of the loan portfolios across credit categories. We conduct a formal analysis of risk-adjusted performance for LC loan portfolios constructed using credit risk categories in Section IV and confirm that the performance across credit categories is not explained by the typical equity or bond risk factors.

The apparent absence of a relation between IRR performance and systematic risk proxies across credit categories brings attention to an important topic. In a perfectly competitive loan market, the expected return for a loan portfolio would be related to its systematic risk exposure. However, in this particular implementation of marketplace lending, Lending Club sets the interest rate. Borrowers and lenders only accept or reject the specific opportunity. To the extent that Lending Club has market power, there is a range of interest rates that both borrowers and lenders would be willing to accept. Moreover, any market power may itself depend on the riskiness of the loan. Consequently, the absence of a strong trade-off between systematic risk and IRR may be less surprising in this context.

III. Monthly loan portfolio index return

To construct a monthly loan portfolio index return for the estimation of risk-adjusted performance, it is necessary to infer the intermediate valuation of existing loans every month using the data set containing the complete payment history for each issued loan. The return index is designed to measure the performance for an investor that holds a value-weighted portfolio of all loans issued by Lending Club. Of course, the typical institutional investor might hold a diversified portfolio of loans without holding a small amount of every loan. Nevertheless, this loan index provides a very useful benchmark that is similar in spirit to the CRSP value-weighted index for the US stock market. We use this payment history to identify the timing of both missing and partial payments. These payment irregularities increase the probability of loan default considerably and we use this information to estimate each loan's value every month.

Table 3 shows the relevant statistics. Panel A focuses on the probability that borrowers fail to make any subsequent payments, i.e., loan default, after a given pattern of missed payments or partial payments. Column 2 of Panel A presents the transition probability that a loan switches from current status to not making any subsequent payments in a given month by credit rating category.

Unsurprisingly, the probability of switching status is monotonically increasing from 0.0014 for credit category A to 0.0073 for credit category D. It is important to note that these monthly transition probabilities are not the cumulative probabilities that LC loans in a given category stop making subsequent payments at any point before the loan is fully repaid. Of course, this cumulative probability of default would be much higher than the transition probability. The analogy in life insurance is that the probability of an insured person dying in a particular year is different from, and much lower than, the probability of the insured person dying at some point during the next ten years.

For each credit category, it is clear that the probability that the borrower does not make any subsequent loan payments increases with each consecutive missed payment. Conditional on missing even one payment, the probability of loan default is approximately 70% and this probability is virtually identical across credit categories. Rather than using Lending Club's definition for a loan charge-off, in our construction of monthly loan index returns, we set the return for a particular constituent loan in the index to -1 at the end of the month following two consecutive missed payments because the probability of loan default is more than 85%. This assumption will slightly understate loan portfolio performance in our tests because about 14% of these loans with two consecutive missed payments do eventually make at least one subsequent payment. Waiting until there are three consecutive missed payments before setting the loan return to -1 does not change the risk-adjusted performance estimates substantially, but it would delay the entry of information into the index about the very high likelihood of default.[10] Using this alternative definition of loan default, the percentage of loans that make any subsequent payments after exhibiting this pattern is less than 7%.

Panel B of Table 3 shows the probability of each loan status within each credit category. Unsurprisingly, the probability of missing a payment in a given month increases monotonically from 0.0024 for category A to 0.0128 for category D. The probability of missing two consecutive payments is also monotonically increasing across the credit categories. Missing loan payments are much more common than partial loan payments. Interestingly, a second consecutive partial loan payment is associated with a substantial decrease in the probability that there are no subsequent loan payments, that is, a loan default is not particularly likely in the last column of Panel A. Of

[10] In unreported results, we show that this change would increase risk-adjusted performance by about 5 basis points per month compared to the baseline specification.

course, it is still the case that a loan default is more likely following one partial payment or two consecutive partial payments compared to loans that are current. We take into account the increased default probability based on any payment irregularity. As soon as we detect a partial payment or a missed payment, we revalue the remaining scheduled payments using the market-based approach described below. These loans will use an elevated interest rate until the borrower returns to the original payment schedule.

Next, we explain how to construct the monthly loan portfolio return index. Since we do not observe market prices, we must estimate the present value of the remaining scheduled payments to reflect changes in the term structure and default probabilities. To ensure that the results do not depend on the stability of Lending Club assigned interest rates, the present value of the remaining scheduled payments uses discount rates that reflect the changing yield on credit card asset backed securities (ABS). Panel A of Figure 2 depicts the yield for a value-weighted index of portfolios of credit card ABS available from Datastream. This yield series reflects credit market conditions and default expectations for consumer loans because the yields on these fixed income instruments are based on market prices for consumer debt. Clearly, the yield for credit card ABS moves considerably during the financial crisis, but new interest rates set by Lending Club are much more stable. In this formulation, we use changes in the yield for credit card ABS along with the original LC interest rate at issuance to calculate the appropriate discount rate for subsequent scheduled payments. While this approach does not provide a perfect public market, it is an approximation that does reflect market expectations.

To calculate the portfolio returns of LC loans, we start with the following equation:

$$R_{L,t+1} = \frac{\sum_{i=1}^{N}\left(CF_{i,t+1} + V_{i,t+1}\right)}{\sum_{i=1}^{N} V_{i,t}}, \tag{1}$$

where $CF_{i,t+1}$ is the loan payment for loan i just before the beginning of period $t+1$ (net of the LC fee of 1%), $V_{i,t}$ is the value of the remaining scheduled loan payments for loan i at the beginning of period t based on data available at time t, and $V_{i,t+1}$ is the value of the remaining scheduled loan payments for loan i at the beginning of period $t+1$ based on data available at time $t+1$. This equation is the value-weighted return for any portfolio of securities. The difficulty in our context is that we do not observe the value of the loan at the beginning and at the end of every month from market prices or market-based yields.

We implement our analysis with three different proxies for the unobserved market-based yield of each loan. It may be the case that the interest rates set by Lending Club do not reflect changing market conditions and default probabilities in the consumer loan market. To address this possibility, we set the discount rate in the present value calculation for loan *i* as follows:

$$y_{i,t} = y_{i,0} + (y_{ABS,t} - y_{ABS,0}), \tag{2}$$

where $y_{i,0}$ is the LC interest rate set at origination, and $y_{ABS,t} - y_{ABS,0}$ is the change in the yield for credit card ABS since the loan origination. The yield for credit card ABS is based on several indices aggregated using market capitalization. This approach embeds the time series variation in the default spread for credit card lending to discount the cash flows of LC loans. This variation is critical during the financial crisis when credit card ABS yields spiked even though Lending Club did not substantially increase interest rates for new consumer loans. Presumably, the high default rates on existing LC loans during this time period would indicate that the unobserved market yield for LC loans would increase in a manner more consistent with credit card ABS yields.

The value of loan *i* at time *t* is then calculated accordingly as

$$V_{i,t} = \sum_{j=1}^{T} \frac{C_{t+j}}{\left(1+y_{i,t}\right)^{j}}, \tag{3}$$

where C_{t+j} is the scheduled payment at $t+j$, and $y_{i,t}$ is the discount rate for scheduled payment given by Equation (2), that is, the LC interest rate at origination plus the change in the yield for credit card ABS since loan origination. Hence, the present value of the loan could increase due to a significant fall in interest rates even though the outstanding balance decreases with each loan payment.

If the loan is not current, that is, there have been partial payments or missing payments that have not been rectified, then $y_{i,t}$ is the interest rate on the all loans in the worst narrow credit category with the same month of origination, the category with the highest interest rate at the same approximate time of origination, plus the change in the yield for credit card ABS since loan origination. If loan *i* has two consecutive missed payments, then we set $V_{i,t+1}$ to zero and $CF_{i,t+1}$ is zero due to the missed payment, and therefore, the net return for the loan in this month is -1. Based on the index methodology, this loan is then removed from the loan portfolio index in subsequent months. Our approach for default implies that the calculated return for the loan portfolio understates the performance to a limited extent because a small fraction of these loans with two missed payments do subsequently recover.[11] However, using this definition of default preserves the approximate timing for the entry of default information into the loan index much better than waiting for several more months to verify that there are no subsequent payments. In unreported results, alternative definitions of default using more missed payments have a negligible impact in the subsequent analysis of performance.

Second, we also consider an alternative approach to our preferred market-based valuation. Instead of incorporating changes in the yield of credit card ABS, we assume that the yield to maturity for newly originated LC loans is the correct discount rate for the remaining scheduled payments for all current loans in the same specific credit category. This interest rate for newly originated loans is determined by market conditions to some extent because many borrowers and lenders agree to these terms each month. In this alternative calculation, we update the discount rate to be equal to the interest rate of newly issued LC loans with the same sub-credit category (e.g., A4) for loans that are current. As soon as we detect a partial payment or a missed payment, we revalue the remaining scheduled payments using the highest interest rate for all newly issued LC loans. If there are two consecutive missed payments, we set the return for a particular constituent loan in the index to -1 at the end of the month. This benchmark should reflect the changes in market conditions to some extent and also changes in credit category-specific credit spread forecast by Lending Club. Panel B of Figure 2 displays the average interest rate for each credit category over time. The interest rates for LC loans are remarkably stable within each credit category, especially during the financial crisis period. This pattern emphasizes the possibility that the interest rates for each credit category assigned by Lending Club may reflect other strategic considerations beyond the fundamental risk properties of the loans in the category.

[11] We note that the IRR analysis does not require any assumptions about default. Since the average monthly IRR without default assumptions that is reported in Table 2 and the average monthly portfolio index return reported in Table 4 in Section IV are virtually identical (0.40% per month), this assumption about default is not substantially altering performance in general.

Lastly, we confirm that the use of the time variation in credit card ABS yields or LC interest rates are not the source of our findings. We remove the influence of variation in credit conditions by assuming that the discounted value of the loan is the outstanding loan balance. Implicitly, this approach assumes that the original interest rate is the correct discount rate for the remaining scheduled payments even though lending conditions, such as monetary policy and average loan default probabilities, may have changed. For completeness, this exercise is reported in Appendix Table 3.

IV. Results

We find that the risk-adjusted performance of our monthly return index for LC loans is large and statistically significant. Before investigating risk-adjusted performance, Table 4 presents the basic statistics for the monthly return index. In addition to high average returns, we also observe a low return volatility. The average monthly return for the entire loan portfolio is 0.43%. The average monthly return for each credit category varies between 0.44% and 0.50%. Since the loans in the broad credit risk categories E, F, and G are included in the All category, but these loans are not reported in any of the separate risk groups, the average across the reported categories does not match the average for all loans. The monthly volatility for the entire loan portfolio is 0.47%; it increases monotonically from 0.46% for risk category A to 0.66% for category D.

We note that the summary statistics for the monthly portfolio index return provided in Table 4 are not directly comparable to the average IRR statistics reported in Table 2 because the sample period for Table 2 is 42 months shorter due to the data requirements for calculating the IRR for all loans issued in a vintage month. Consequently, the financial crisis has a larger impact on the IRR summary statistics compared to the monthly loan portfolio index return summary statistics. Nevertheless, the average IRR across observed vintages of 0.40% is only slightly lower than the average monthly index return of 0.43%.

According to Table 4, the Sharpe ratio for all LC loans based on the monthly return index is 0.86. This ratio is more than 5 times larger than the monthly Sharpe ratio of 0.16 for the US stock market during the sample period.[12] It is also about 3 times larger than the monthly Sharpe ratio of 0.28 for the US Corporate 1-3 Year Index for the same time period. While the average return across credit categories does not exhibit a particular pattern, the Sharpe ratio associated with

[12] The Sharpe ratio for the US stock market from 1926 until 2017 is 0.12 instead of 0.16 for the sample period.

the performance of each credit category decreases substantially with credit risk. For instance, the ratio for category A is 0.93 and the ratio for category D is 0.63. It is remarkable that this ratio for the most risky credit category of LC loans is still at least three times as high as than the Sharpe ratio of the stock market.

The monthly return index for all LC loans is a very useful gauge of performance, but we also investigate the performance properties of investors holding randomly selected portfolios of LC loans. We simulate the performance of this type of investor 1,000 times using random selection to choose a subset of LC loans. For each simulation, $25 is invested in 100 different loans randomly selected from all loans originating in a month.[13] The loans at origination are sampled without replacement within each simulation and this investment selection approach is repeated using the newly originated loans in each month during the sample period. Essentially, this approach creates an equal-weighted portfolio at origination. For each simulation, the loans purchased are held from origination through complete repayment or default. The loan index for each simulation, and the associated index return, is constructed following the approach outlined in Section III using the baseline intermediate valuation methodology incorporating the changing yield of credit card ABS.

Figure 3 presents the distribution of the average monthly index return from the 1,000 simulations using randomly selected loans. The average (and median) across simulations of the average monthly index return using random selection and equal-weighting is 0.37%. This average is modestly lower than the average return of 0.43% for the value-weighted index for the entire LC loan portfolio. The two standard deviation confidence interval for the average across simulations of the average monthly index return ranges from 0.34% per month to 0.40% per month. Thus, the favorable properties of the LC loan portfolio can be obtained using nothing more sophisticated than a modestly diversified portfolio of these LC loans.

In Table 5, we utilize the monthly portfolio index return series to estimate risk-adjusted performance and assess how much of this performance can be explained by various factor models. Since LC loans are fixed income securities, investors holding LC loans should be exposed primarily to two basic risks: interest rate risk and default risk. These two risks are usually

[13] We note that there are 100 or fewer loans issued during the two months near the beginning of the sample period, August 2008 and September 2008. This implies that each simulation invests $25 in all of the originated loans during these two months rather than selecting a random subset.

correlated with a variety of macroeconomic conditions that also affect the equity market and the bond market. We include commonly used factors from the equity market and the fixed income market in our specifications. The factors used in the regressions include the value-weighted CRSP stock market index return in excess of the risk-free rate (MKT), the size (SMB), value (HML), profitability (RMW), and investment factors (CMA), the momentum factor (MOM), the bond market factor (BM), and the credit spread factor (CS). The risk-free rate, R_f, is the one-month Treasury bill rate. The five equity factors and the risk-free rate are obtained from Kenneth French's data library. The two bond factors are calculated using data available at the St. Louis FRED website following the definitions provided by Fung and Hsieh (2004). The bond market factor is defined as the change in the yield on 10-year Treasury bonds and the credit spread factor is defined as the change in the yield spread between 10-year Treasury bonds and Moody's Baa bonds.

The first six columns in Table 5 use the 1-factor, 3-factor model, and 5-factor model, respectively. Two of these six specifications are augmented with the momentum factor. The last two specifications, columns 7 and 8, include the two bond factors. The results in Table 5 show that the risk-adjusted performance of LC loans is not driven by any particular specification of the typical risk factor model. The relatively low R^2 for these regressions indicate that the traditional risk factors for the equity market and the bond market only explain a modest fraction of the performance of marketplace loans. The estimates of risk-adjusted performance range from 0.39% per month to 0.44% per month, depending on the model specification. Each of the performance estimates is significantly different from zero with a *t*-statistic greater than 5.[14]

Table 5 indicates that the only significant coefficient estimates are for the credit spread, value, and momentum factors, depending on the specification. The significance of the credit spread factor and the negative sign for the coefficient should not be at all surprising given the incorporation of the change in the yield for credit card ABS in the construction of the return index. Since an increase in the credit spread is likely to be highly correlated with an increase in the yield of credit card ABS, the higher credit spread should lower the contemporaneous monthly index return. The significance of momentum seems to be partly driven by its exceptionally low performance in the year 2009, when LC loans also experienced higher default rates. Unreported

[14] The *t*-statistics are calculated using Newey-West standard errors with a lag length of 12. Unreported calculations indicate that the strong statistical significance of the risk-adjusted performance estimates does not depend on the lag length selected, that is, selecting any lag length from 0 to 36 produces qualitatively similar patterns.

results indicate that the estimate for momentum falls by about 50% and the estimates are not statistically significant if observations before 2010 are excluded from the sample period. It is interesting that the momentum factor is not statistically relevant once the credit spread factor is also included in the specification. The coefficient on the value factor is marginally significant in two specifications and strongly significant in one specification. All other coefficients are insignificant at conventional levels. In general, the explanatory power of these factor models is low and the highest R^2 is only 0.35.

In Table 6 we analyze the performance of the LC loan portfolio index from 2013-2017 to verify that the high risk-adjusted return estimates for the LC index are not an artefact of the realized returns for loans issued near the beginning of sample period or the realization of risk factors during the financial crisis and the immediate recovery. According to Table 1, LC loan issuance was very low during the first few years of the sample period. In addition, the model used by LC to determine the credit categories, and consequently, the interest rates was subsequently refined. By limiting the sample period in this manner, loans issued later in the sample period dominate the return calculation for the LC portfolio index. The risk-adjusted performance estimates for the specifications in Table 6 are all modestly higher than the corresponding estimates of abnormal performance in Table 5. This pattern suggests that the small number of loans issued near the beginning of the sample period is not responsible for the observed abnormal performance results. Moreover, the few statistically significant factor loadings in Table 5 are no longer significant in Table 6. This may be due to lower power to reject the null associated with the more limited sample size, but it may also be the natural consequence of removing the highly volatile period of financial from the sample.

LC loans may be deemed illiquid assets for a variety of reasons. Even without identifying a particular source of liquidity risk, we can still investigate whether the typical liquidity risk factors explain the performance of the LC loan portfolio. The model specifications in Table 7 augment the baseline risk-adjustment specifications in Table 5 with factors related to different aspects of liquidity risk according to the literature. The TED factor is the change in the TED spread used by Boyson et al. (2010). The P&S factor is from WRDS and is based on Pastor and Stambaugh (2003). The short-term reversal factor, ST REV, is obtained from Kenneth French's website. The consideration of the short-term reversal, ST REV, as a liquidity factor follows from Nagel (2012).

Each of the first three columns of Table 7 includes one measure of liquidity risk in addition to the typical equity factors. None of the coefficient estimates for each of these liquidity factors are statistically significant. More importantly, the estimate of monthly risk-adjusted performance is virtually identical in all three of these specifications. The fourth column includes all three measures of liquidity risk because each measure by itself may not fully capture liquidity risk. However, this combined model specification using the three measures of liquidity risk together does not alter the risk-adjusted estimate of performance for the LC loan portfolio. Whatever the source of this risk-adjusted performance, it does not appear to be strongly related to liquidity risk. The next four columns of Table 7 revisit this exercise using the market, the baseline bond factors in Table 5, and the same liquidity factors. While the coefficients for two liquidity factors are not statistically significant, the TED factor is statistically significant in Column 5 and marginally significant in Column 8. In spite of this statistical relation, the risk-adjusted performance estimates for the LC portfolio remain largely unchanged at slightly more than 40 basis points per month. While the underlying loans may be illiquid assets, the returns to the LC return index does not appear to be sufficiently correlated with aggregate liquidity risk for this risk to explain the historically high returns.

In Table 8, we revisit selected specifications while using alternative bond factors constructed from various Bank of America Merrill Lynch US Corporate Bond indices available from the St. Louis FRED website. The credit return factor (CR) is the difference between the BBB index return and the AAA index return, the term return factor (TR) is the difference between the 7 to 10 year index return and the 1 to 3 year index return, and the matched maturity factor (MM) is the 1 to 3 year index return minus the 1-month Treasury bill rate. In particular, the matched maturity factor is designed to capture the performance of fixed income securities with similar duration, limited liquidity, and moderate default risk. First, the coefficient estimates for two of these alternative bond factors, the credit return factor and the matched maturity factor, are significant in these specifications. These factors are likely correlated with the changes in the ABS yield used in the market-based valuation approach for the loan portfolio index return. Second, the estimates of risk-adjusted performance are only slightly lower than those found in Table 5 and Table 7. So, loan performance is systematically risky based on these bond factors, but these risk exposures are not large enough to explain the high risk-adjusted performance of the LC loan portfolio.

The significant coefficient estimates for the credit spread factor, or alternatively the credit return factor, is not surprising. These loans are clearly exposed to systematic default risk based on the time series of defaults in Figure 1. The increased risk of systematic default for corporate bonds, captured by the credit spread factor, or alternatively the credit return factor, should be correlated with the same macroeconomic conditions that would generate movements in systematic default probabilities for consumer loans.

Table 9 analyzes risk-adjusted performance separately for each credit category. Our results show that risk-adjusted performance is between 0.44% per month and 0.50% per month across the four credit categories. However, the modest differences in risk-adjusted performance between the loan categories are not statistically significant. The credit spread factor and the value factor are statistically significant for all of the credit categories. The statistical significance of a few risk factor loadings varies to some extent depending on the credit category. For example, the coefficient for the momentum factor is only significant for credit category A.

The close similarity of risk-adjusted performance across almost all of the credit categories implies that diversified investors are not motivated to concentrate capital in only one or two of the credit categories. Setting interest rates so that investors are approximately indifferent across loans in the different credit risk categories is probably an important consideration for Lending Club because profitability is generated from origination fees and subsequent payments that are approximately proportional to loan volume. At the same time, the costs of loan default are largely absorbed by the independent lenders. Therefore, Lending Club has a strong incentive to ensure that as many loans as possible receive financing from the independent lenders subject to the constraints imposed by the reputational cost of poor loan portfolio performance on the provision of capital by investors to finance subsequent loans. This incentive structure may be quite different from that of banks. Since banks retain some portion of the underlying loans and also maintain capital reserves, they may be forced to allocate limited capital to the most profitable lending opportunities. The direct distribution model, in which default risk is held by independent investors, may provide Lending Club with a competitive advantage that offers borrowers lower interest rates for a given level of credit risk and also allows more loan origination.

Table 10 presents the regression results using the loan portfolio index return series in which each loan value is estimated based on the yield-to-maturity of newly originated LC loans in the same credit category instead of the change in the yield for credit card ABS following LC loan issuance. This alternative methodology is described more completely in Section III. Our results show similar, albeit slightly lower, risk-adjusted performance for each credit category compared to the specifications in Table 9. These findings confirm that the estimates of this performance are not a consequence of the specific assumption utilized to value LC loans each period. Most of the risk factors are not statistically significant at conventional levels. The coefficients for the momentum factor are always positive and significant in some specifications.

Notably, the coefficient for the credit spread factor is not significant using this alternative construction of the LC portfolio index return. This is not at all surprising because the interest rates for new loans each month set by Lending Club and the yields or returns for corporate bonds appear to be mostly unrelated. This decoupling may be quite relevant if Lending Club sets interest rates in a much more stable manner for strategic reasons that are not strongly linked to the default risk of the loans themselves.

Lastly, we confirm that the volatility of the yield on credit card ABS or the volatility of LC interest rates does not explain our findings. We remove the variation in credit conditions from the valuation procedure by setting the discounted value of the loan to the outstanding loan balance. This approach assumes that the original interest rate is the correct discount rate for the remaining scheduled payments even though the appropriate interest rate may have changed. Of course, the variation in the time series of the default rate for LC loan defaults is still captured by the loan portfolio index return. For completeness, we report these results in Appendix Table 3. We find similar risk-adjusted performance results of approximately 0.40% per month. We note that most of the risk factors are unrelated to the performance of the LC loan portfolio. For this loan valuation approach, only the coefficient estimate for the momentum factor is significant using conventional critical values. The coefficient estimates for the market factor and the credit spread factor are marginally significant in several specifications, but the explanatory power of the factor model remains low.

The analysis in this section indicates that the risk-adjusted performance of the LC loan portfolio is positive and highly significant. This finding is not due to a particular intermediate valuation methodology or based on a specific construction of the bond factors. The typical equity and bond factors used to benchmark the traditional asset classes explain a small proportion of the variation in LC loan portfolio performance. These findings indicate that marketplace lending is an attractive investment.

V. Characteristics of local banks and loan performance

The evidence in the preceding sections indicates that the LC loan portfolio has very favorable performance characteristics. The high risk-adjusted performance of the LC loan portfolio indicates that the typical equity factors and bond risk factors used in cross-sectional asset pricing do not explain the high average returns of LC loans. This section provides evidence that supports an alternative explanation for this superior performance. Essentially, Lending Club is able to undercut the interest rates for consumer loans within the traditional banking sector and then distribute these loans, along with any favorable performance properties, to investors. Since the interest rates set by traditional banks may reflect substantial market power in many settings, the performance of LC loans will be high when the gap between the cost of capital and interest rates for traditional banks in a particular region is large. To the extent that LC loan performance is related to the market power of traditional banks, it should be possible to detect this pattern using an analysis of LC loan performance and local banking characteristics, and thus, provide a partial explanation for the high risk-adjusted performance of the LC loan portfolio.

To analyze whether the local banking environment is correlated with the performance of LC loans, we merge loan level observations to information characterizing the local banking environment. We use the Summary of Deposits (SOD) survey conducted by the FDIC as of June 2007 before the beginning of the sample period for LC loans. This timing is important to avoid the possibility that the introduction of loans from Lending Club affected local conditions in the traditional banking sector. The SOD data set contains branch location and deposit information for banks serving each locality. Since the borrower location information for each LC loan only includes the borrower's state and the first three digits of the borrower's zip code, we aggregate measures of the local banking environment at the same location level.

First, we measure local bank competition using the concentration ratio of the largest five banks based on deposits in the locality, defined as a particular state and truncated zip code combination. This variable is the sum of deposits held by all branches in the locality associated with the five largest local banks divided by deposits for all banks in the locality. In this context, the concentration ratio will typically capture whether access to traditional loans in a locality is dominated by a few banks or if there is extensive competition between many traditional providers of loans. Second, we measure national bank presence using the fraction of branches in the locality belonging to the five largest national banks determined by the number of national branch locations.[15] This variable is the total count of branches belonging to the five largest bank branch networks in the locality divided by the total number of bank branches in the locality. While this measure is imperfect, it is designed to capture whether the bank branches in the locality are exposed largely to local or regional conditions or whether the branches are associated with banks holding diversified portfolios of loans held in many locations across the country through a large national network. Indeed, the absence of geographic diversification for a local bank might explain why banks choose to finance 38% of the LC loan portfolio in 2018 according to the quarterly report.

To analyze whether the performance of LC loans is correlated with local bank competition, we begin by sorting LC loans for each vintage month in each credit risk category into two sub-portfolios based on whether the loan is in a location with a local bank concentration ratio greater than the median. We calculate the IRR of the loan portfolio characterized by the combination of vintage month, credit risk, and median split based on the local bank concentration ratio. In columns 1 through 3 of Table 11, we regress this portfolio performance outcome on an indicator variable for above median concentration ratio, that is, the variable is equal to 1 when local bank competition is low, and on various controls. In column 1, we find that loan portfolios for localities with above median concentration ratios, that is, less local bank competition, have a significantly higher performance. The estimated difference of 6 basis points per month does not change in column 2 when risk category fixed effects are introduced or in column 3 when both risk category and issuance (vintage) month fixed effects are included. Consequently, it does seem that one source of the high performance of LC loans stems from entering a local bank environment that is not fully competitive, that is, access to loans financed by bank branch deposits in these localities is controlled to a greater degree by the five largest local banks operating in that particular locality.

This finding of different performance for LC loans related to local bank competition is almost entirely associated with the performance of LC loans in the high credit risk categories. In columns 4 through 6 of Table 11, we include the indicator for low local bank competition, an indicator for loan portfolios for high credit risk categories, and the interaction between the indicator for low bank competition and the indicator for a high credit risk loan portfolio. We note

[15] In June 2007, at the time of the survey, the five largest national banks by number of bank branches in descending order were Bank of America, Wells Fargo, JP Morgan Chase, Wachovia, and US Bank.

that the coefficient estimate for low local bank competition (uninteracted) is essentially zero in these three columns. This estimate indicates that for LC loan portfolios with low credit risk (credit categories A and B), there is no change in LC loan performance associated with differences in local bank competition. Instead, the coefficient for the interaction term shows that we observe significantly higher performance for LC loans in localities with low local bank competition only for the subset of loans in the high credit risk categories (categories C and D). This pattern is consistent with a traditional banking sector that tends to allocate more capital to safer lending opportunities and requires a higher profit margin for more risky loan opportunities or often avoids them altogether.

Next, we analyze whether the performance of LC loans is related to national bank presence. We follow an analogous approach by sorting the LC loans within each vintage month and each credit risk category portfolio into two sub-portfolios based on whether the loan is issued in a location with high national bank presence. We calculate the IRR of the loan portfolio characterized by the combination of vintage month, credit risk, and median split based on the fraction of branches in the locality belonging to the five largest national banks. We regress the IRR performance outcome for each portfolio on an indicator variable for below median national bank presence that is, the variable is equal to 1 when the presence of national banks is low and zero otherwise. We report our findings in Table 12 about the estimated performance difference between LC loans in localities with low national bank presence and high national bank presence.

The results in Table 12 show that this estimated difference in performance is 6 basis points per month and is also statistically significant. This difference remains significant in the specification augmented with risk category fixed effects as well as in the specification including risk category and issuance month fixed effects. In columns 4 through 6, we investigate the interaction between low national bank presence and high credit risk. Unlike the evidence for local bank competition, the role of national bank presence is not significantly related to the credit category of the loans. Instead, there is a marginally significant impact of low national bank presence for all loan risk categories. Essentially, we find a relatively high presence of national banks in the locality is associated with a reduction in the risk-adjusted performance of the LC loan portfolio. Presumably, this pattern is related to greater consumer access to large banks with a lower cost of capital.

The results in Table 13 indicate that the measure of bank competition and the measure for presence of national banks do not really capture the same characteristics of the locality. The indicator for a high concentration ratio is statistically significant in all specifications and the indicator for low national bank presence is marginally significant or conventionally significant, depending on the particular specification. The estimated coefficient for the interaction term between the two measures is negative and significant. This pattern indicates that the cumulative role of these characteristics is not simply the sum of two distinct forces.

Both characteristics of the local banking sector, local bank competition and the local presence of national banks, are significantly related to the performance of LC loan portfolios. The distinct role of each of these characteristics suggests that the high risk-adjusted performance of LC loans is partially explained by how Lending Club competes for consumers within a local market dominated by the traditional banking sector.

VI. Conclusion

This paper analyzes the performance of the consumer loan portfolio issued by Lending Club, the largest marketplace lending platform in the US. Based on the monthly loan portfolio index, the average risk-adjusted return of the entire LC loan portfolio is 0.39% per month. The monthly Sharpe ratio of this aggregate LC loan portfolio is more than 5 times higher than the market during the same time period The high average return coupled with very advantageous risk properties indicates that this new asset class should be viewed favorably by most investors. While the analysis based on the loan portfolio index return uses assumptions about discount rates and default status, the average of the IRR for each vintage month of 0.40% is also consistent with this assessment of performance.

In addition, we find that the risk-adjusted return for the portfolio of loans in each credit risk category is about equal for most of the different credit risk categories. This pattern of risk-adjusted performance for the different categories implies that diversified investors should be largely indifferent when allocating capital between the various credit categories. Lending Club has an incentive to maintain this indifference so that capital moves between credit categories and most loans in each category receive financing. Since fees collected by Lending Club are roughly proportional to loan volume and the losses associated with default are borne almost entirely by the independent lenders, Lending Club would like to maximize volume subject to the willingness of investors to finance the loans. In contrast, traditional providers might face situations in which the most favorable lending opportunities are originated but other profitable opportunities are rejected due to the shadow cost of capital imposed by reserve requirements.

Our analysis indicates that the strong performance of LC loans is related to the market power and national network of traditional banks. The high performance of LC loans is associated with participation in local bank environments that exhibit more market power and are largely detached from national bank networks, as measured by the concentration ratio for the five largest local banks and the presence of large national banks, respectively. Furthermore, this significantly higher performance of these loans in the context of high market power is only due to the subset of loans in the high credit risk categories (categories C and D). The findings support our hypothesis that marketplace lenders effectively compete in situations where traditional lenders would tend to set higher interest rates due to local conditions, reflecting the interaction between market power and the cost of capital for banks in these localities.

The likelihood that marketplace lending acquires considerable market share depends on whether Lending Club, and other platforms, can continue to attract borrowers while still offering high loan portfolio returns to the investors. The performance of loans issued by marketplace lending platforms provides a valuable forecast regarding the eventual success or failure of this innovation. Given the structure of this alternative form of financial intermediation, marketplace lending can only displace the traditional incumbents if investors are willing to purchase the loans on a much larger scale.

Since Lending Club has not yet captured a large share of the market, the structure of the new equilibrium with traditional providers and marketplace lenders is far from obvious. The substantial fraction of LC loans held by banks suggests that many banks may find it at least as profitable to finance LC loans rather than develop a competing platform. At the same time, Goldman Sachs developed a competing online platform in late 2016 called Marcus. This platform provides consumer loans with a similar loan structure to Lending Club, including a fixed interest rate and a fixed term length. If marketplace lending platforms acquire substantial market power, then these platforms may extract some of this risk-adjusted performance from investors by raising origination or payment fees. Alternatively, if marketplace lending eventually becomes the dominant consumer loan form with many different providers, then we might anticipate even lower interest rates to attract borrowers. However, the very modest changes in market share induced by marketplace lending thus far suggest that any transformation of the banking sector is not likely to be particularly rapid. Therefore, high average risk-adjusted returns on marketplace lending platforms are likely to persist in the near future.

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Table 1. Summary statistics for Lending Club loans

This table shows the summary statistics for Lending Club loans with 36 months until maturity. The reported statistics are number of loans, average loan size, and average interest rate by broad credit risk category and issue year. The broad credit risk categories, such as A, B, C and D are determined using a proprietary assessment of creditworthiness of each loan by Lending Club. This assessment uses variables including FICO score, employment status, home ownership, and geographic area (first 3 digits of the zip code). Loans in the credit risk categories E, F, and G are included in the All category reflecting all loans, but these loans are not reported in separate groups because the sample size is very small and the categories became obsolete. The interest rate for each loan is assigned by Lending Club and is directly linked to the more narrow credit grades within each broad credit category, such as subcategories A1 through A6 within the broad credit risk category A.

Category		All			A			B			C			D	
Issue Year	N	Loan size	Interest rate	N	Loan size	Interest rate	N	Loan size	Interest rate	N	Loan size	Interest rate	N	Loan size	Interest rate
2008	2,393	8,347	12.1%	318	5,974	8.4%	594	8,440	10.4%	580	8,315	11.8%	419	8,588	13.4%
2009	5,281	9,811	12.4%	1,203	7,232	8.6%	1,445	10,851	11.8%	1,348	9,750	13.3%	817	10,642	14.9%
2010	9,156	9,559	11.3%	2,567	8,044	7.2%	2,805	10,112	10.7%	2,070	9,126	13.5%	1,253	10,816	15.2%
2011	14,101	9,399	10.6%	5,579	8,923	7.1%	4,722	9,545	11.0%	2,203	9,010	13.9%	1,261	10,567	16.2%
2012	43,470	11,679	12.6%	10,753	11,117	7.6%	16,805	11,006	12.1%	9,902	11,516	15.2%	5,088	13,849	18.2%
2013	100,422	12,667	13.4%	17,057	15,172	7.7%	40,313	12,878	11.8%	24,693	12,265	15.4%	14,505	10,549	18.7%
2014	162,570	12,586	12.5%	35,333	14,397	7.5%	53,460	12,653	11.2%	44,042	11,994	14.1%	20,510	11,532	17.0%
2015	283,173	12,807	11.3%	70,132	14,473	6.9%	91,783	12,520	10.0%	77,457	11,895	13.2%	32,740	12,304	16.6%
2016	323,495	12,768	11.9%	66,862	13,953	6.9%	114,783	12,091	10.3%	92,317	12,463	13.7%	36,707	13,450	18.1%

Table 2. Basic performance statistics for Lending Club loans

Panel A of this table presents the monthly internal rate of return (IRR) statistics of Lending Club loans. The IRR for each loan portfolio by vintage and credit risk category is calculated using the monthly cash flows aggregated by issue month and by credit risk category. There are 70 issue months with sufficient time after issuance to calculate the IRR of the loan portfolio. The reported statistics are based on the 70 observations for each category. Panel B shows (monthly) interest rate statistics of Lending Club loans for the same sample of months. The credit risk categories are determined using a proprietary assessment of creditworthiness of each loan by Lending Club. This assessment uses variables including FICO score, employment status, home ownership, and geographic area (first 3 digits of the zip code). Loans in the credit risk categories E, F, and G are included in the All category reflecting all loans, but these loans are not reported in separate groups because the sample size is very small and the categories became obsolete.

Panel A: Monthly internal rate of return statistics

	All loans	A	B	C	D
Average	0.40%	0.40%	0.42%	0.44%	0.44%
Median	0.46%	0.40%	0.49%	0.51%	0.53%
Min	-0.44%	-0.42%	-1.15%	-0.51%	-1.11%
Max	0.62%	0.67%	0.83%	0.77%	1.04%
Std. Dev.	0.22%	0.14%	0.27%	0.29%	0.39%

Panel B: Monthly interest rates

	All loans	A	B	C	D
Average	1.00%	0.65%	0.94%	1.14%	1.32%
Median	1.00%	0.63%	0.95%	1.13%	1.27%
Min	0.79%	0.53%	0.78%	0.90%	1.04%
Max	1.16%	0.77%	1.03%	1.31%	1.57%
Std. Dev.	0.09%	0.05%	0.07%	0.11%	0.16%

Table 3. Missed payments, partial payments and default

Panel A of this table shows the probability that a borrower does not make any subsequent loan payments in spite of an outstanding loan balance for each credit risk category and specific loan status, such as number of consecutive missed payments or consecutive partial payments. The loan status of Current indicates that there are no delinquent payments. Panel B shows the frequencies of each loan status, such as number of consecutive missed payments and partial payments. The credit risk categories are determined using a proprietary assessment of creditworthiness of each loan by Lending Club. This assessment uses variables including FICO score, employment status, home ownership, and geographic area (first 3 digits of the zip code). Loans in the credit risk categories E, F, and G are included in the All category reflecting all loans, but these loans are not reported in separate groups because the sample size is very small and the categories became obsolete.

Panel A: Probability that a borrower does not make any subsequent loan payments conditional on loan status

Loan Status	All	Current	First missed payment	Second consecutive missed payment	Third consecutive missed payment	First partial payment	Second consecutive partial payment
All loans	0.0183	0.0040	0.7038	0.8655	0.9349	0.5911	0.1340
A	0.0063	0.0014	0.6995	0.8648	0.9301	0.5827	0.1561
B	0.0136	0.0030	0.7009	0.8627	0.9317	0.5826	0.1208
C	0.0238	0.0052	0.7065	0.8684	0.9366	0.6006	0.1469
D	0.0342	0.0073	0.7053	0.8656	0.9370	0.5957	0.1313

Panel B: Probability of each loan status

Loan Status	Current	First missed payment	Second consecutive missed payment	Third consecutive missed payment	First partial payment	Second consecutive partial payment
All loans	0.9800	0.0069	0.0051	0.0041	0.0016	0.0003
A	0.9932	0.0024	0.0018	0.0014	0.0005	0.0001
B	0.9851	0.0052	0.0038	0.0030	0.0012	0.0002
C	0.9743	0.0089	0.0067	0.0053	0.0020	0.0003
D	0.9624	0.0128	0.0096	0.0077	0.0030	0.0007

Table 4. Summary statistics for the monthly index return for Lending Club loan portfolios

This table provides the summary statistics for the monthly index return for Lending Club. The credit risk categories are determined using a proprietary assessment of creditworthiness of each loan by Lending Club. This assessment uses variables including FICO score, employment status, home ownership, and geographic area (first 3 digits of the zip code). Loans in the credit risk categories E, F, and G are included in the All category reflecting all loans, but these loans are not reported in separate groups because the sample size is very small and the categories became obsolete. The construction of the loan portfolio index is described in Section III using a market-based intermediate valuation approach that incorporates changes in the yield for credit card ABS. The risk-free rate, R_f, used to calculate the Sharpe ratio is the one-month Treasury bill rate. For comparison purposes, we also report the analogous performance statistics for the stock market using the value-weighted CRSP stock market index and for corporate bonds using the Bank of America Merrill Lynch US Corporate Bond 1 to 3 year index available from the St. Louis FRED website. The sample period is from January 2008 to March 2017.

	All loans	A	B	C	D	Stock Market	Corporate Bonds
Average Return	0.43%	0.44%	0.50%	0.48%	0.44%	0.75%	0.26%
Standard Deviation	0.47%	0.46%	0.47%	0.50%	0.66%	4.63%	0.85%
Minimum Return	-1.80%	-2.11%	-1.75%	-1.67%	-3.44%	-17.15%	-4.75%
Maximum Return	1.84%	2.17%	2.60%	1.85%	1.88%	11.35%	3.05%
Median Return	0.50%	0.41%	0.55%	0.55%	0.54%	1.29%	0.22%
Sharpe ratio	0.86	0.93	1.00	0.90	0.63	0.16	0.28

Table 5. Risk-adjusted performance of the Lending Club loan portfolio

This table shows the results of regressions in which the monthly index return for all Lending Club loans in excess of the risk-free rate, R_L-R_f , is regressed on various sets of risk factors. The construction of the loan portfolio index is described in Section III using a market-based intermediate valuation approach that incorporates changes in the yield for credit card ABS. The factors used in the regressions include the value-weighted CRSP stock market index return in excess of the risk free rate (*MKT*), the size (*SMB*), value (*HML*), profitability (*RMW*), and investment factors (*CMA*), the momentum factor (*MOM*), the bond market factor defined as the change in the yield on 10-year treasury bonds (*BM*), and the credit spread factor defined as the change in the yield spread between 10-year Treasury bonds and Moody's Baa bonds (*CS*). The risk-free rate, R_f, is the one-month Treasury bill rate. The five equity factors and the risk free rate are from Kenneth French's data library. The two bond factors are calculated using data available at the St. Louis FRED website. The *t*-statistics based on Newey-West standard errors with a lag length of 12 are shown in parentheses below the coefficients. The sample period is from January 2008 to March 2017. The asterisks *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Category	All	All	All	All	All	All	All	All
Alpha	0.0042***	0.0040***	0.0039***	0.0039***	0.0042***	0.0042***	0.0042***	0.0044***
	(6.16)	(5.66)	(5.36)	(5.03)	(7.53)	(6.99)	(6.54)	(7.74)
MKT		0.0201	0.0321	0.0272	0.0223	0.0188	-0.0133	-0.0072
		(1.07)	(1.29)	(1.19)	(1.30)	(1.13)	(-1.62)	(-0.82)
SMB			-0.0092	-0.0082	-0.0183	-0.0184		-0.0249
			(-0.86)	(-0.79)	(-1.41)	(-1.42)		(-1.59)
HML			-0.0512	-0.0612*	-0.0440	-0.0565*		-0.0429***
			(-1.62)	(-1.78)	(-1.47)	(-1.72)		(-2.71)
MOM				-0.0157**		-0.0143**		-0.0042
				(-2.52)		(-2.18)		(-0.70)
RMW					-0.0586	-0.0590		-0.0468
					(-1.30)	(-1.30)		(-1.31)
CMA					-0.0297	-0.0181		-0.0176
					(-0.76)	(-0.49)		(-0.46)
BM							-0.0402	0.0216
							(-0.14)	(0.09)
CS							-0.9982***	-0.8986***
							(-3.03)	(-3.44)
N	111	111	111	111	111	111	111	111
R^2		0.038	0.123	0.145	0.164	0.181	0.248	0.348

Table 6. Risk-adjusted performance of the Lending Club loan portfolio: 2013-2017

This table shows the results of regressions in which the monthly index return for all Lending Club loans in excess of the risk-free rate, R_L-R_f , is regressed on various sets of risk factors. The construction of the loan portfolio index is described in Section III using a market-based intermediate valuation approach that incorporates changes in the yield for credit card ABS. The factors used in the regressions include the value-weighted CRSP stock market index return in excess of the risk free rate (*MKT*), the size (*SMB*), value (*HML*), profitability (*RMW*), and investment factors (*CMA*), the momentum factor (*MOM*), the bond market factor defined as the change in the yield on 10-year treasury bonds (*BM*), and the credit spread factor defined as the change in the yield spread between 10-year Treasury bonds and Moody's Baa bonds (*CS*). The risk-free rate, R_f, is the one-month Treasury bill rate. The five equity factors and the risk free rate are from Kenneth French's data library. The two bond factors are calculated using data available at the St. Louis FRED website. The *t*-statistics based on Newey-West standard errors with a lag length of 12 are shown in parentheses below the coefficients. The sample period is from January 2013 to March 2017. The asterisks *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Category	All	All	All	All	All	All	All	All
Alpha	0.0048***	0.0048***	0.0048***	0.0047***	0.0048***	0.0048***	0.0047***	0.0047***
	(6.63)	(6.85)	(7.02)	(6.87)	(6.94)	(6.75)	(6.37)	(6.34)
MKT		0.0038	0.0058	0.0064	0.0063	0.0069	0.0117	0.0108
		(0.58)	(0.87)	(0.89)	(0.97)	(0.99)	(1.42)	(1.37)
SMB			-0.0070	-0.0072	-0.0095	-0.0094		-0.0094
			(-1.26)	(-1.29)	(-1.36)	(-1.38)		(-1.34)
HML			-0.0187	-0.0173	-0.0267	-0.0254		-0.0164
			(-1.60)	(-1.54)	(-1.49)	(-1.57)		(-1.08)
MOM				0.0020		0.0021		-0.0015
				(0.23)		(0.25)		(-0.17)
RMW					-0.0099	-0.0094		-0.0122
					(-0.58)	(-0.59)		(-0.82)
CMA					0.0259	0.0261		0.0162
					(0.98)	(0.96)		(0.57)
BM							-0.214	-0.1491
							(-1.65)	(-1.13)
CS							0.1794	0.1305
							(0.68)	(0.58)
N	51	51	51	51	51	51	51	51
R^2		0.004	0.069	0.070	0.089	0.090	0.082	0.113

Table 7. Risk-adjusted performance of the loan portfolio using different liquidity factors

This table shows the results of regressions in which the monthly index return for all Lending Club loans in excess of the risk-free rate, R_L-R_f, is regressed on various sets of risk factors. The construction of the loan portfolio index is described in Section III using a market-based intermediate valuation approach that incorporates changes in the yield for credit card ABS. The factors used in the regressions include the value-weighted CRSP stock market index return in excess of the risk free rate (*MKT*), the size (*SMB*), value (*HML*), profitability (*RMW*), and investment factors (*CMA*), the momentum factor (*MOM*), the bond market factor defined as the change in the yield on 10-year Treasury bonds (*BM*), and the credit spread factor defined as the change in the yield spread between 10-year Treasury bonds and Moody's Baa bonds (*CS*). The used liquidity factors are the following: 1) the change in the spread between 3-month Libor based on US dollars and 3-month Treasury Bill rate (TED), from St. Louis FRED, 2) Pastor and Stambaugh (P&S) liquidity factor, from Lubos Pastor's website, and 3) Short-term reversal factor, from Kenneth French's data library. The risk-free rate, R_f, is the one-month Treasury bill rate. The five equity factors and the risk free rate are from Kenneth French's data library. The two bond factors are calculated using data available at the St. Louis FRED website. The *t*-statistics based on Newey-West standard errors with a lag length of 12 are shown in parentheses below the coefficients. The sample period is from January 2008 to March 2017. The asterisks *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Category	All	All	All	All	All	All	All	All
Alpha	0.0039***	0.0041***	0.0040***	0.0041***	0.0042***	0.0043***	0.0042***	0.0043***
	(5.06)	(6.03)	(5.26)	(6.28)	(6.38)	(6.79)	(6.63)	(6.72)
R_M-R_F	0.0249	0.0200	0.0185	0.0103	-0.0134*	-0.0111	-0.0193*	-0.0179
	(1.11)	(1.27)	(1.02)	(0.77)	(-1.76)	(-1.44)	(-1.71)	(-1.58)
SMB	-0.0105	-0.0206	-0.0102	-0.0236				
	(-0.97)	(-1.36)	(-0.91)	(-1.41)				
HML	-0.0508	-0.0440**	-0.0648*	-0.0386**				
	(-1.50)	(-2.57)	(-1.77)	(-2.20)				
Mom	-0.0130*	-0.0192**	-0.0164*	-0.0169				
	(-1.95)	(-2.46)	(-1.79)	(-1.63)				
BM					0.0247	-0.1158	-0.0424	-0.0448
					(0.08)	(-0.52)	(-0.15)	(-0.20)
CS					-0.9096***	-0.8908***	-0.9855***	-0.8107***
					(-2.81)	(-3.83)	(-3.08)	(-3.43)
TED	-0.3351			-0.3232	-0.3709**			-0.3511*
	(-1.33)			(-1.34)	(-2.08)			(-1.79)
P&S		0.0354		0.0326		0.0228		0.0192
		(1.21)		(1.08)		(1.08)		(0.94)
ST Rev			0.0303	0.0280			0.0207	0.0217
			(1.27)	(1.10)			(1.14)	(0.99)
N	111	111	111	111	111	111	111	111
R^2	0.170	0.207	0.180	0.259	0.281	0.275	0.265	0.320

Table 8. Risk-adjusted performance of the loan portfolio using different bond factors

This table shows the results of regressions in which the monthly index return for all Lending Club loans in excess of the risk-free rate, R_L-R_f, is regressed on various sets of risk factors. The construction of the loan portfolio index is described in Section III using a market-based intermediate valuation approach that incorporates changes in the yield for credit card ABS. The factors used in the regressions include the value-weighted CRSP stock market index return in excess of the risk free rate (*MKT*), the size (*SMB*), value (*HML*), profitability (*RMW*), and investment factors (*CMA*), the momentum factor (*MOM*). The five equity factors and the risk free rate are from Kenneth French's data library. The bond factors use returns calculated from various Bank of America Merrill Lynch US Corporate Bond indices available from the St. Louis FRED website. The credit return factor (CR) is the difference between AAA index return and the BBB index return, the term return factor (TR) is the difference between the 7 to 10 year index return and the 1 to 3 year index return, and the matched maturity factor (MM) is the 1 to 3 year index return minus the risk-free rate. The risk-free rate, R_f, is the one-month treasury bill rate. The *t*-statistics based on Newey-West standard errors with a lag length of 12 are shown in parentheses below the coefficients. The sample period is from January 2008 to March 2017. The asterisks *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Category	All	All	All	All	All	All
Alpha	0.0035***	0.0034***	0.0038***	0.0035***	0.0040***	0.0036***
	(4.55)	(4.53)	(4.55)	(3.97)	(5.89)	(5.39)
MKT		0.0006	-0.0110	-0.0165**	-0.0054	-0.0113
		(0.05)	(-0.95)	(-2.14)	(-0.42)	(-1.32)
SMB					-0.0173	-0.0198
					(-1.57)	(-1.31)
HML					-0.0382*	-0.0096
					(-1.94)	(-0.43)
MOM		0.0125**			0.0002	0.0179
		(2.46)			(0.03)	(1.48)
RMW					-0.0518	-0.0396
					(-1.38)	(-1.30)
CMA					-0.0176	-0.0394
					(-0.50)	(-0.84)
CR			0.1525***	0.1079**	0.1414***	0.1108***
			(3.47)	(2.32)	(4.47)	(2.82)
TR			0.0394	-0.0459	0.0234	-0.0654
			(1.19)	(-1.12)	(0.91)	(-1.44)
MM	0.2801***	0.3109***		0.2684**		0.2996**
	(3.60)	(4.69)		(2.05)		(2.18)
N	111	111	111	111	111	111
R^2	0.250	0.264	0.246	0.353	0.330	0.437

Table 9. Performance of Lending Club loan portfolios by credit risk category

This table shows the results of regressions in which the monthly index return for Lending Club loans in a credit risk category minus the risk-free rate, R_L-R_f, is regressed on an expansive set of risk factors. The credit risk categories are determined using a proprietary assessment of creditworthiness of each loan by Lending Club. This assessment uses variables including FICO score, employment status, home ownership, and geographic area (first 3 digits of the zip code). Loans in the credit risk categories E, F, and G are included in the All category reflecting all loans, but these loans are not reported in separate groups because the sample size is very small and the categories became obsolete. The construction of the loan portfolio index is described in Section III using a market-based intermediate valuation approach that incorporates changes in the yield for credit card ABS. The factors used in the regressions include the value-weighted CRSP stock market index return in excess of the risk free rate (*MKT*), the size (*SMB*), value (*HML*), profitability (*RMW*), and investment factors (*CMA*), the momentum factor (*MOM*), the bond market factor defined as the change in the yield on 10-year Treasury bonds (*BM*), and the credit spread factor defined as the change in the yield spread between 10-year Treasury bonds and Moody's Baa bonds (*CS*). The risk-free rate, R_f, is the one-month Treasury bill rate. The five equity factors and the risk-free rate are from Kenneth French's data library. The two bond factors are calculated using data available at the St. Louis FRED website. The *t*-statistics based on Newey-West standard errors with a lag length of 12 are shown in parentheses below the coefficients. The sample period is from January 2008 to March 2017. The asterisks *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Category	All	A	B	C	D
Alpha	0.0044***	0.0044***	0.0050***	0.0048***	0.0044***
	(7.74)	(10.65)	(10.94)	(7.01)	(4.47)
MKT	-0.0072	-0.0258*	-0.0206	-0.0062	0.0088
	(-0.82)	(-1.96)	(-1.61)	(-0.57)	(0.57)
SMB	-0.0249	0.0010	-0.0050	-0.0363**	-0.0371
	(-1.59)	(0.08)	(-0.59)	(-2.29)	(-1.33)
HML	-0.0429***	-0.0346**	-0.0441**	-0.0384**	-0.0705***
	(-2.71)	(-2.35)	(-2.29)	(-2.29)	(-2.75)
MOM	-0.0042	-0.0185***	-0.0057	-0.0072	-0.0022
	(-0.70)	(-2.71)	(-0.97)	(-0.83)	(-0.25)
RMW	-0.0468	-0.0159	-0.0381	-0.0475	-0.0832
	(-1.31)	(-0.61)	(-1.03)	(-1.63)	(-1.48)
CMA	-0.0176	-0.0274	-0.0163	-0.0174	0.0072
	(-0.46)	(-0.85)	(-0.43)	(-0.35)	(0.15)
BM	0.0216	-0.2039	-0.0457	-0.0141	0.0752
	(0.09)	(-1.52)	(-0.23)	(-0.06)	(0.23)
CS	-0.8986***	-1.2615***	-1.0975***	-0.8381**	-0.8946***
	(-3.44)	(-4.47)	(-3.76)	(-2.19)	(-3.89)
N	111	111	111	111	111
R^2	0.348	0.532	0.405	0.278	0.284

Table 10. Performance of Lending Club loan portfolios by credit risk category

Alternative valuation methodology using Lending Club interest rates

This table shows the results of regressions in which the monthly index return for Lending Club loans in a credit risk category minus the risk-free rate, R_L-R_f, is regressed on an expansive set of risk factors. The credit risk categories are determined using a proprietary assessment of creditworthiness of each loan by Lending Club. This assessment uses variables including FICO score, employment status, home ownership, and geographic area (first 3 digits of the zip code). Loans in the credit risk categories E, F, and G are included in the All category reflecting all loans, but these loans are not reported in separate groups because the sample size is very small and the categories became obsolete. The construction of the loan portfolio index is described in Section III and uses the present value for a loan in good standing based on to the interest rate of newly issued Lending Club loans in the same sub-credit risk category. The factors used in the regressions include the value-weighted CRSP stock market index return in excess of the risk free rate (*MKT*), the size (*SMB*), value (*HML*), profitability (*RMW*), and investment factors (*CMA*), the momentum factor (*MOM*), the bond market factor defined as the change in the yield on 10-year Treasury bonds (*BM*), and the credit spread factor defined as the change in the yield spread between 10-year Treasury bonds and Moody's Baa bonds (*CS*). The risk-free rate, R_f, is the one-month Treasury bill rate. The five equity factors and the risk-free rate are from Kenneth French's data library. The two bond factors are calculated using data available at the St. Louis FRED website. The *t*-statistics based on Newey-West standard errors with a lag length of 12 are shown in parentheses below the coefficients. The sample period is from January 2008 to March 2017. The asterisks *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Category	All	A	B	C	D
Alpha	0.0038***	0.0039***	0.0043***	0.0042***	0.0038***
	(4.90)	(14.88)	(6.69)	(4.53)	(3.28)
MKT	0.0275*	0.0037	0.0221**	0.0299**	0.0392
	(1.85)	(1.07)	(2.44)	(2.42)	(1.47)
SMB	-0.0235	0.0025	-0.0022	-0.0324	-0.0386
	(-1.09)	(0.26)	(-0.15)	(-1.64)	(-1.09)
HML	-0.0062	0.0128*	-0.0092	-0.0010	-0.0314
	(-0.47)	(1.69)	(-0.83)	(-0.06)	(-1.15)
MOM	0.0176***	0.0006	0.0129**	0.0176*	0.0210**
	(3.10)	(0.16)	(2.19)	(1.83)	(2.31)
RMW	-0.0255	0.0042	-0.0095	-0.0275	-0.0724
	(-0.87)	(0.24)	(-0.30)	(-0.81)	(-1.53)
CMA	0.0029	0.0032	0.0131	-0.0003	0.0164
	(0.12)	(0.29)	(0.61)	(-0.01)	(0.39)
BM	0.3487	0.0485	0.2413	0.3176	0.4664
	(1.53)	(0.84)	(1.45)	(1.54)	(1.31)
CS	0.2290	-0.1113	0.0766	0.2675	0.2173
	(1.41)	(-1.38)	(0.50)	(1.02)	(1.06)
N	111	111	111	111	111
R^2	0.180	0.101	0.112	0.145	0.178

Table 11. Local competition between banks and the performance of Lending Club loans

This table presents the results of regressions in which monthly internal rate of return (IRR) for the sub-portfolio of Lending Club loans in each issue month, credit risk category, and bank concentration status is regressed on an indicator variable equal to 1 for the loan portfolio in which borrowers live in a 3-digit zip code area with above median top-5 concentration ratio (High Bank Concentration), an indicator variable for high credit risk, i.e., loans within risk category C or risk category D (High Credit Risk), and the interaction between these two indicator variables. The IRR for each sub-portfolio is calculated using the monthly cash flows aggregated by issue month, credit risk category, and bank concentration status. There are 70 issue months with sufficient time after issuance to calculate the IRR for each loan sub-portfolio. FDIC Summary of Deposits data on the deposits of bank branches is used to measure bank concentration for the local area. Loans are matched to the characteristics of the local banking environment by truncated three digit zip code within a state due to the limitations imposed by the loan location data in Lending Club. Standard errors are clustered by the vintage month. The asterisks *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	IRR	IRR	IRR	IRR	IRR	IRR
High Bank Concentration	0.0006**	0.0006**	0.0006**	0.0000	0.0000	0.0000
	(2.11)	(2.11)	(1.97)	(0.14)	(0.14)	(0.13)
High Credit Risk	0.0003			-0.0003		
	(0.72)			(-0.50)		
Interaction of Bank Concentration and High Credit Risk				0.0010**	0.0010**	0.0010**
				(2.38)	(2.38)	(2.23)
Intercept	0.0038***	0.0037***		0.0041***	0.0040***	
	(15.54)	(17.88)		(15.48)	(18.27)	
Risk category fixed effects	NO	YES	YES	NO	YES	YES
Time fixed effects	NO	NO	YES	NO	NO	YES
N	560	560	560	560	560	560
R^2	0.007	0.008	0.298	0.012	0.013	0.303

Table 12. National bank presence and the performance of Lending Club loans

This table presents the results of regressions in which monthly internal rate of return (IRR) of Lending Club loans is regressed on indicator variable for loans in which the borrower is living on 3-digit zip code area with below median national bank presence measured by the top-5 national bank share of branches in the area (Low National Bank Presence), on the indicator variable for credit risk above risk category B (High Risk), and their interaction. The IRRs are calculated using the monthly cash flows aggregated by issue month (and by risk category, and by National Bank Presence). There are 70 issue months with sufficient time after issuance to calculate the IRR of the loan portfolio. FDIC Summary of Deposits data on the number of bank branches is used to measure national bank presence. The matching of loans and banking data is by truncated three digit zip code within a state. Standard errors are clustered by the vintage month. The asterisks *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	IRR	IRR	IRR	IRR	IRR	IRR
Low National Bank Presence	0.0006**	0.0006**	0.0006**	0.0004*	0.0004*	0.0004
	(2.40)	(2.39)	(2.22)	(1.82)	(1.82)	(1.64)
High Credit Risk	0.0003			0.0002		
	(1.05)			(0.37)		
Interaction of Low National Bank Presence and High Credit Risk				0.0003	0.0003	0.0003
				(0.62)	(0.62)	(0.60)
Intercept	0.0038***	0.0037***		0.0039***	0.0038***	
	(17.50)	(20.38)		(17.58)	(18.52)	
Risk category fixed effects	NO	YES	YES	NO	YES	YES
Time fixed effects	NO	NO	YES	NO	NO	YES
N	559	559	559	559	559	559
R^2	0.009	0.011	0.283	0.010	0.012	0.283

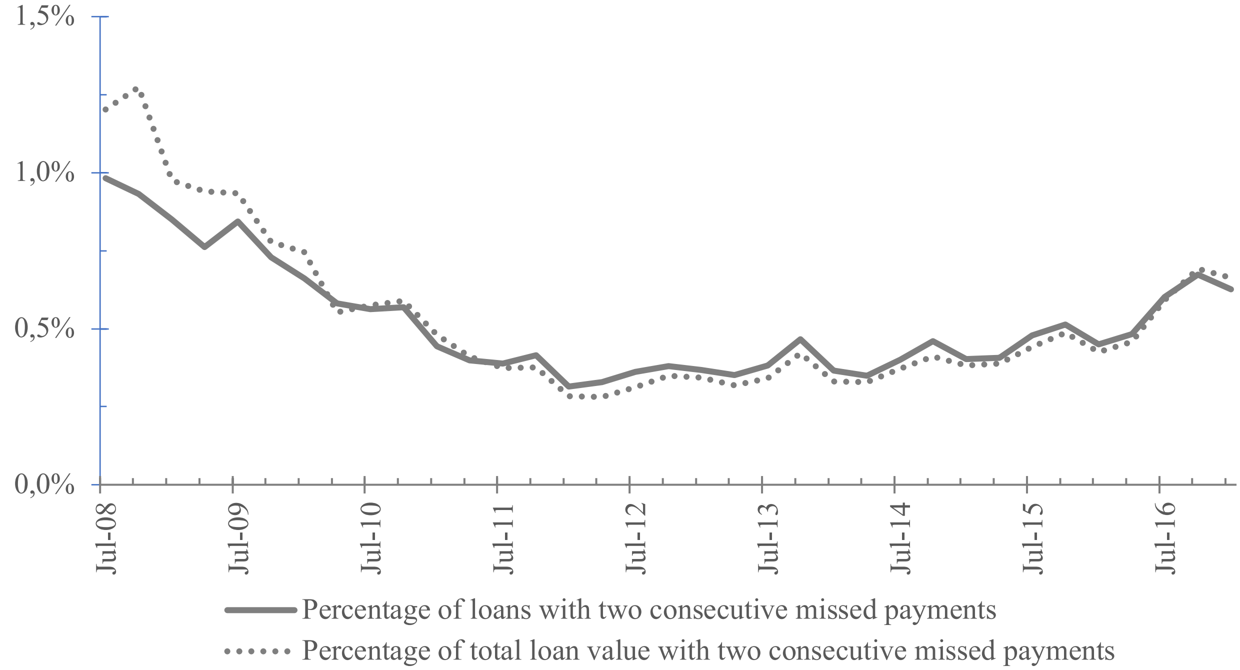
Table 13. Characteristics of local banks and the performance of Lending Club loans

This table presents the results of regressions in which monthly internal rate of return (IRR) of Lending Club loans is regressed on indicator variable for loans in which the borrower is living on 3-digit zip code area with above median top-5 concentration ratio measuring local banking competition (High Bank Concentration), on indicator variable for loans in which the borrower is living on 3-digit zip code area with above median national bank presence measured by the top-5 national bank share of branches in the area (Low National Bank Presence), on the indicator variable for credit risk above risk category B (High Risk), and their interactions. The IRRs are calculated using the monthly cash flows aggregated by issue month (and by risk category, by Bank Concentration, and by National Bank Presence). There are 70 issue months with sufficient time after issuance to calculate the IRR of the loan portfolio. FDIC Summary of Deposits data on the deposits and number of bank branches is used to measure local banking competition and national bank presence. The matching of loans and banking data is by truncated three digit zip code within a state. Standard errors are clustered by the vintage month. The asterisks *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	IRR	IRR	IRR	IRR	IRR	IRR
High Bank Concentration	0.0017**	0.0017**	0.0018**	0.0029**	0.0029**	0.0030**
	(2.25)	(2.24)	(2.36)	(2.17)	(2.16)	(2.34)
Low National Bank Presence	0.0013*	0.0014*	0.0013*	0.0025*	0.0026*	0.0025**
	(1.85)	(1.88)	(1.80)	(1.93)	(1.94)	(1.97)
Interaction of Bank Concentration				-0.0024*	-0.0024	-0.0024*
and Low National Bank Presence				(-1.65)	(-1.64)	(-1.69)
Intercept	0.0020*	0.0011		0.0014	0.0005	
	(1.91)	(0.81)		(1.04)	(0.29)	
Risk category fixed effects	NO	YES	YES	NO	YES	YES
Time fixed effects	NO	NO	YES	NO	NO	YES
N	1,115	1,115	1,115	1,115	1,115	1,115
R^2	0.008	0.011	0.098	0.010	0.014	0.100

Figure 1: Default rates for Lending Club loans

Panel A: Aggregate default rates for Lending Club loans



Panel B: Default rates by loan credit category for Lending Club loans

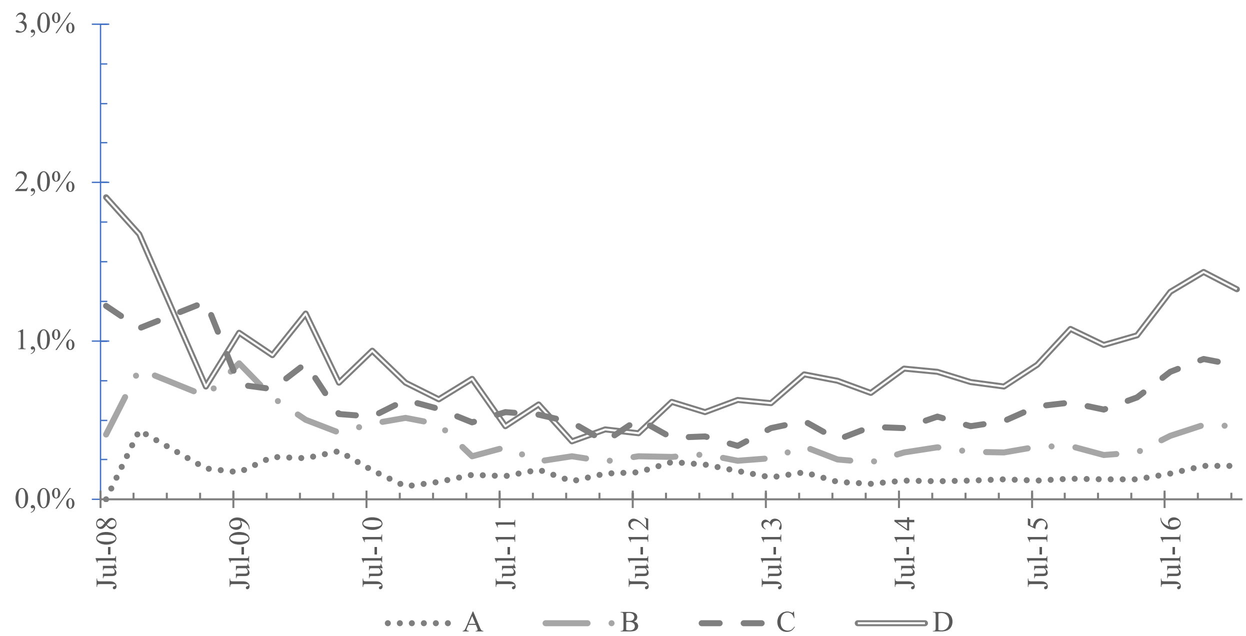
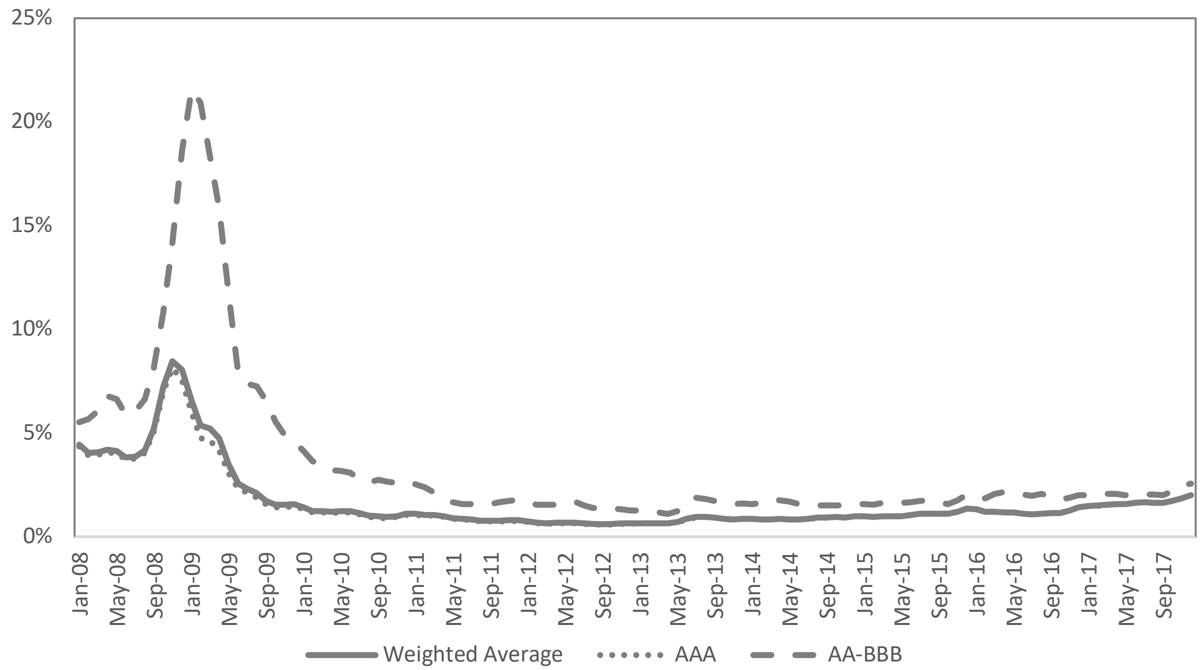


Figure 1. Panel A of the figure shows the equal-weighted and value-weighted default rates for Lending Club loans. Default is defined as two consecutive missed payments. The solid black line is the number of loans with two consecutive missed payments as a percentage of the total number of active loans. The dotted line is the balance of loans with two missed payments as a percentage of the total balance for active loans. Each series is calculated on a quarterly basis. Panel B of the figure shows the value-weighted default rates for Lending Club loans for each credit risk category.

Figure 2: Interest rates and yields for Lending Club loans and credit card ABS

Panel A: Average yields of credit card asset backed securities (ABS)



Panel B: Interest rates of newly issued Lending Club loans

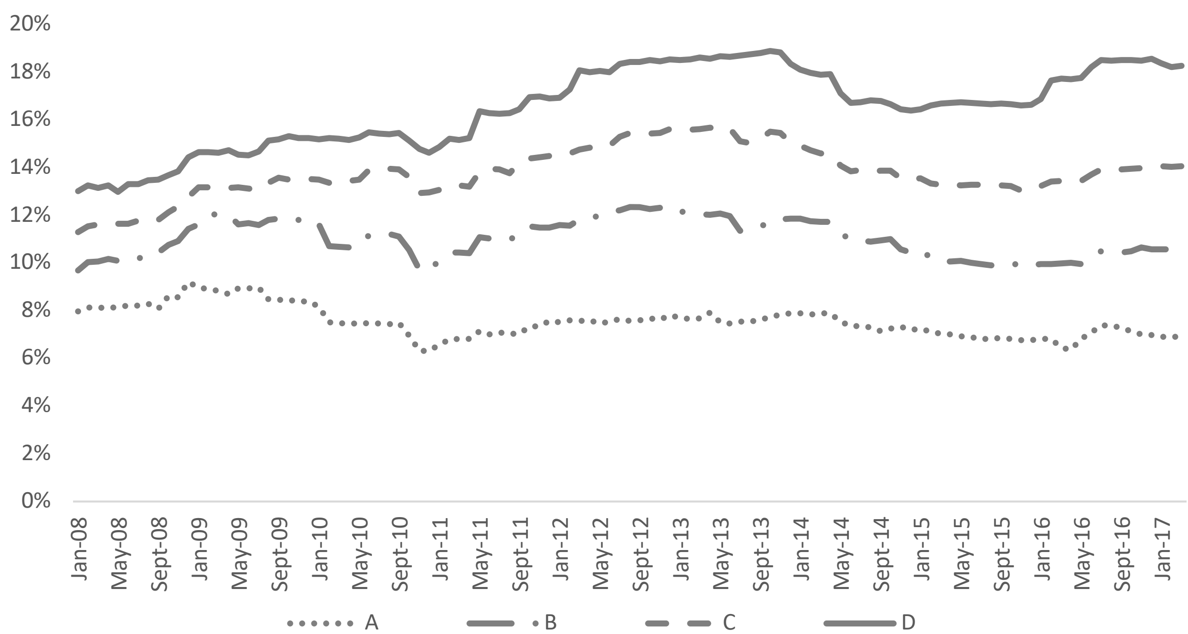


Figure 2. Panel A shows the yield for a value-weighted index of a portfolio of credit card ABS on a monthly basis. Panel B of this figure shows the average interest rate, equal-weighted, for newly issued Lending Club loans by rating category for each month of loan issuance.

Figure 3: Distribution of Lending Club loan portfolio returns

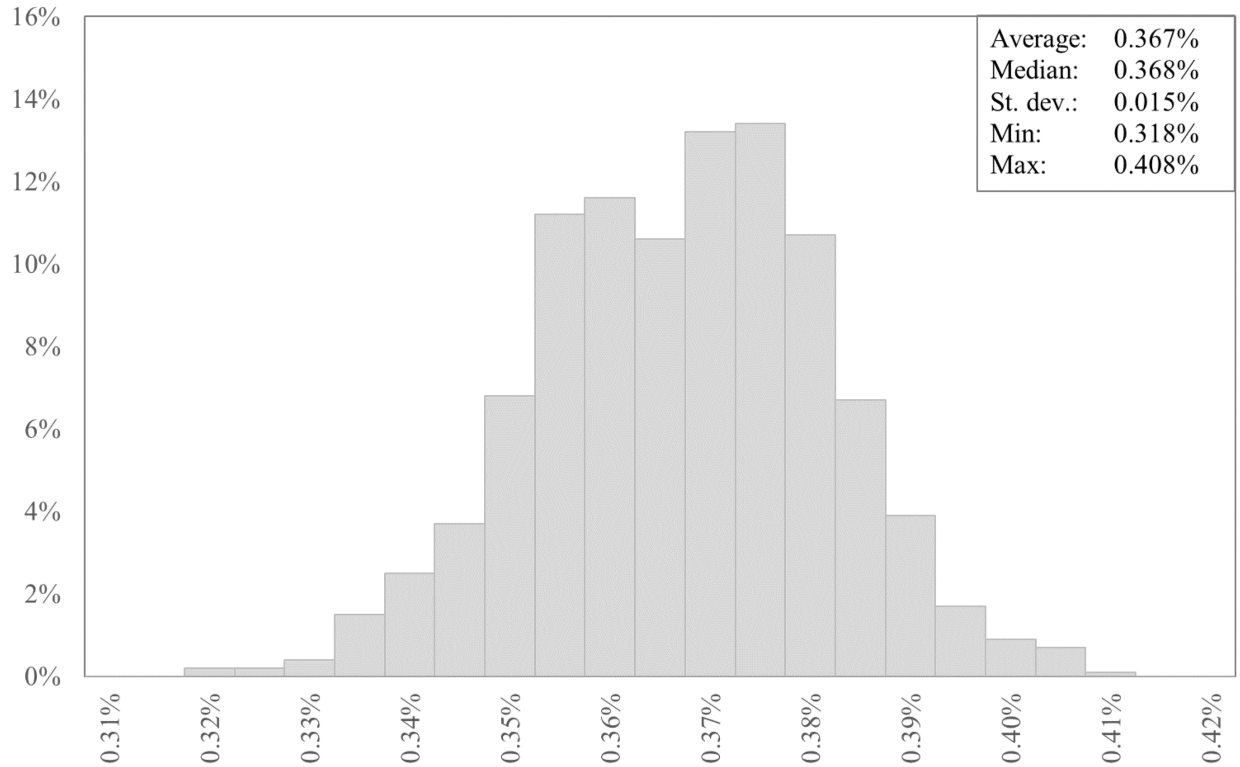


Figure 3. This figure presents a histogram for the average monthly index return from 1,000 simulations using randomly selected loan portfolios. For each simulation, $25 is invested in 100 different loans randomly selected from all loans originating in a month. The loans at origination are sampled without replacement within each simulation and this investment selection approach is repeated using the newly originated loans in each month during the sample period. For each simulation, the loans purchased are held from origination through maturity or default. The loan index for each simulation, and the associated index return, is constructed following the methodology outlined in Section 3 using the baseline intermediate valuation methodology.

Appendix Table 1. Validation of loan data with cash flow information

This table shows the number of loans and aggregate loan volume by issue year in our data set and compares these variables to the analogous information directly available from Lending Club's public website (See https://www.lendingclub.com/info/demand-and-credit-profile.action). The columns from the monthly payment data match the summary statistics available from Lending Club exactly (i.e., no typographical errors).

	Aggregated from monthly payment data		Lending Club Summary Statistics	
Issue year	Number of loans	Loan volume ($M)	Number of loans	Loan volume ($M)
2008	2,393	19.98	2,393	19.98
2009	5,281	51.81	5,281	51.81
2010	12,537	126.35	12,537	126.35
2011	21,721	257.36	21,721	257.36
2012	53,367	717.94	53,367	717.94
2013	134,814	1,982.76	134,814	1,982.76
2014	235,629	3,503.84	235,629	3,503.84
2015	421,095	6,417.61	421,095	6,417.61
2016	434,407	6,400.54	434,407	6,400.54

Appendix Table 2. Statistics by time period for the Lending Club monthly index return

This table provides the summary statistics for the monthly index return for Lending Club in sub-samples. The credit risk categories are determined using a proprietary assessment of creditworthiness of each loan by Lending Club. This assessment uses variables including FICO score, employment status, home ownership, and geographic area (first 3 digits of the zip code). Loans in the credit risk categories E, F, and G are included in the All category reflecting all loans, but these loans are not reported in separate groups because the sample size is very small and the categories became obsolete. The construction of the loan portfolio index is described in Section III and uses the present value for a loan in good standing based on the change in the yield on credit card ABS since loan origination and the original interest rate (yield) of the Lending Club loan. The risk-free rate, R_f, used to calculate the Sharpe ratio is the one-month Treasury bill rate. For comparison purposes, we also report the analogous performance statistics for the stock market using the value-weighted CRSP stock market index and for corporate bonds using the Bank of America Merrill Lynch US Corporate Bond 1 to 3 year index available from the St. Louis FRED website.

2008-2010	All loans	A	B	C	D	Stock Market	Corporate Bonds
Average Return	0.30%	0.55%	0.42%	0.32%	0.20%	0.08%	0.45%
Standard Deviation	0.79%	0.79%	0.80%	0.81%	1.03%	6.51%	1.42%
Minimum Return	-1.80%	-2.11%	-1.75%	-1.67%	-3.44%	-17.15%	-4.75%
Maximum Return	1.84%	2.17%	2.60%	1.85%	1.88%	10.20%	3.05%
Median Return	0.29%	0.52%	0.38%	0.34%	0.34%	1.70%	0.52%
Sharpe ratio	0.31	0.63	0.46	0.33	0.15	0.00	0.28
2011-2013	**All loans**	**A**	**B**	**C**	**D**	**Stock Market**	**Corporate Bonds**
Average Return	0.56%	0.39%	0.58%	0.64%	0.74%	1.34%	0.22%
Standard Deviation	0.12%	0.07%	0.15%	0.19%	0.20%	3.67%	0.35%
Minimum Return	0.15%	0.22%	-0.02%	0.12%	0.31%	-7.59%	-0.58%
Maximum Return	0.71%	0.55%	0.83%	0.89%	1.07%	11.35%	1.07%
Median Return	0.58%	0.38%	0.59%	0.68%	0.79%	1.78%	0.26%
Sharpe ratio	4.61	5.39	3.94	3.36	3.67	0.37	0.62
2014-2016	**All loans**	**A**	**B**	**C**	**D**	**Stock Market**	**Corporate Bonds**
Average Return	0.46%	0.41%	0.50%	0.51%	0.41%	0.71%	0.13%
Standard Deviation	0.18%	0.09%	0.14%	0.22%	0.30%	3.23%	0.25%
Minimum Return	0.02%	0.14%	0.15%	0.00%	-0.26%	-6.04%	-0.42%
Maximum Return	0.77%	0.53%	0.73%	0.94%	0.92%	7.75%	0.85%
Median Return	0.50%	0.43%	0.53%	0.55%	0.46%	0.54%	0.13%
Sharpe ratio	2.51	4.24	3.45	2.23	1.32	0.22	0.48

Appendix Table 3. Risk-adjusted performance using the loan balance for valuation

This table shows the results of regressions in which the monthly index return for all Lending Club loans in excess of the risk-free rate, R_L-R_f, is regressed on various sets of risk factors. The construction of the loan portfolio index is described in Section III. The specification in this table uses the present value for a loan in good standing based on to the outstanding loan balance. The factors used in the regressions include the value-weighted CRSP stock market index return in excess of the risk free rate (*MKT*), the size (*SMB*), value (*HML*), profitability (*RMW*), and investment factors (*CMA*), the momentum factor (*MOM*). The five equity factors and the risk free rate are from Kenneth French's data library. The bond factors use returns calculated from various Bank of America Merrill Lynch US Corporate Bond indices available from the St. Louis FRED website. The credit return factor (CR) is the difference between AAA index return and the BBB index return, the term return factor (TR) is the difference between the 7 to 10 year index return and the 1 to 3 year index return, and the matched maturity factor (MM) is the 1 to 3 year index return minus the risk-free rate, R_f, the one-month Treasury bill rate. The *t*-statistics based on Newey-West standard errors with a lag length of 12 are shown in parentheses below the coefficients. The sample period is from January 2008 to March 2017. The asterisks *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Category	All	All	All	All	All	All	All	All
Alpha	0.0040***	0.0039***	0.0039***	0.0039***	0.0040***	0.0040***	0.0039***	0.0040***
	(5.33)	(5.27)	(5.41)	(5.86)	(5.48)	(6.04)	(5.36)	(5.96)
MKT		0.0083	0.0140*	0.0186*	0.0116	0.0151*	0.0136*	0.0197
		(1.33)	(1.67)	(1.79)	(1.65)	(1.79)	(1.94)	(1.64)
SMB			-0.0202	-0.0211	-0.0242	-0.0240		-0.0268
			(-1.43)	(-1.62)	(-1.50)	(-1.57)		(-1.58)
HML			-0.0104	-0.0009	-0.0134	-0.0005		-0.0054
			(-1.26)	(-0.10)	(-1.34)	(-0.04)		(-0.43)
MOM				0.0149***		0.0147***		0.0124***
				(3.22)		(3.12)		(2.67)
RMW					-0.0269	-0.0265		-0.0237
					(-1.20)	(-1.14)		(-1.14)
CMA					0.0143	0.0024		0.0049
					(0.71)	(0.12)		(0.22)
BM							0.2092	0.2411
							(1.10)	(1.20)
CS							0.2677*	0.2299*
							(1.81)	(1.72)
N	111	111	111	111	111	111	111	111
R^2		0.017	0.050	0.101	0.069	0.117	0.065	0.161

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