The Performance of Marketplace Lenders: Evidence from Lending Club Payment Data[*]

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Direct financing of consumer credit by individual investors or non-bank institutions through an implementation of marketplace lending is a relatively new phenomenon in financial markets. The emergence of online platforms has made this type of financial intermediation widely available. This paper analyzes the performance of marketplace lending using proprietary cash flow data for each individual loan from the largest platform, Lending Club. While individual loan characteristics would be important for amateur investors holding a few loans, sophisticated lenders usually form broad portfolios to benefit from diversification. We find high risk-adjusted performance of 38 basis points per month for the entire loan portfolio. This performance indicates that Lending Club, and other marketplace lenders, are likely to attract capital to finance a growing share of the consumer credit market. Absent a competitive response from traditional credit providers, these loans may lower the total cost to individual borrowers and increase loan performance for the ultimate lenders by reducing financial intermediation expenses.

Keywords: Marketplace lending, household finance, peer-to-peer, financial innovation, finance and technology

JEL Codes: G12, G21

I. Introduction

The development of peer-to-peer technology platforms, and the even broader adoption of online marketplaces in different business domains provide innovative tools for financial intermediaries. 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. Marketplace lending can be interpreted as a particular type of crowdfunding as in Morse (2015). This innovation led to the emergence of new financial intermediaries offering competitive financial services along specific dimensions that play an increasingly significant role in household finance. Butler et al. (2016) show that consumers with better access to bank financing receive loans at lower interest rates. Extending this analogy to online platforms, consumers implement borrowing decisions while considering several, if not all, of the financing alternatives. De Roure et al. (2016) find that more risky borrowers exhibit greater sensitivity to the availability of competing sources of finance, thus, increasing the likelihood that marketplace lending will have a more pronounced impact among more risky borrowers.

Our findings indicate that the loan portfolios issued via the largest marketplace lending platform in the US has an average internal rate of return (IRR) of 40 basis points per month. Furthermore, the monthly index return for the entire loan portfolio has a Sharpe ratio of 1.02 and an average risk-adjusted return of 38 basis points per month. These loans are fixed income securities, and therefore, this loan portfolio performance is associated with low volatility compared to the volatility of typical equity portfolios. The average IRR of 0.40% per month is approximately 5% on an annualized basis. For comparison purposes, the average 1-year Treasury Constant Maturity Rate for the issue months in the IRR sample period is about 0.5% on an annualized basis. Similarly, the average 3-year Treasury Constant Maturity Rate for the same issue months is about 1% on an annualized basis. Thus, the average IRR for the typical portfolio of LC loans is much higher than these benchmark interest rates. While some portion of this difference in performance may reflect compensation for the risk properties of the loan portfolio compared to Treasury securities, a risk premium of at least 4% per year would be more consistent with the systematic risk premium associated with more risky fixed income portfolios. For instance, the average monthly total return calculated for the US Corporate 1-3 Year Index for investment grade bonds during the same time period is about 4% per year.

Since the underlying fixed income notes are not actively traded, the potential for abnormal performance should be less surprising compared to simple trading strategies for individual stocks. The risk-adjusted performance for these loans is more analogous to the potential for private equity funds to generate abnormal returns. However, if this level of performance is expected to persist, then this superior performance will attract more capital. Indeed, a similar pattern has already been established in private equity funds (Metrick and Yasuda, 2010). As capital continues to enter marketplace lending in search of abnormal performance, a new equilibrium is likely to develop. Marketplace lending is a rapidly growing business with loan volume for 2017 of $25.7 billion in the United States (US).[1] In comparison, the credit card debt of US households is $808 billion for the third quarter of 2017.[2] Marketplace lending has been attracting more institutional investors to secure the issued loans (Financial Times, 2014 and 2015).

If marketplace lending platforms have substantial market power, then there is the chance that these platforms will extract some of this risk-adjusted performance from investors by raising origination or payment fees. If marketplace lending becomes a very competitive environment, then we might anticipate lower interest rates to attract borrowers and/or a decrease in average loan quality to maintain market share. In each of these cases, we would expect high risk-adjusted returns for portfolios of marketplace loans to eventually disappear as loans in this market reach an equilibrium with other fixed income securities, such as bonds issued by financial institutions and asset backed securities for consumer loan portfolios.

As a consequence, we are particularly interested in investigating the historical risk and return characteristics of consumer loans issued by marketplace lending platforms. While the volatility of individual loan performance will be more important to naive lenders financing a few loans, more sophisticated lenders, including institutional investors, are likely to form substantial portfolios of loans to benefit of diversification. In this context, a performance analysis of loan portfolios available on marketplace platforms is of critical relevance as this new approach to financial intermediation emerges. Our results show that investing in personal loans provides relatively stable internal rate of return that is significantly above the average return to US Treasuries bills during the same time period.

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[1] See https://www.statista.com/outlook/338/109/marketplace-lending--personal-/united-states#

[2] See the detailed FED New York report on Household Debt and Credit under https://www.newyorkfed.org/medialibrary/interactives/householdcredit/data/pdf/HHDC_2017Q4.pdf

Of course, this performance depends on the default probability for an individual loan as well as on the potential for default correlation across different loans in the portfolio. The relatively high default rate for consumer loans during the financial crisis suggests that marketplace loans may be exposed to systematic risk because correlated default is much more likely to occur when macroeconomic conditions deteriorate. This possibility emphasizes the need to risk-adjust performance rather than focus only on IRR of the loan portfolios. However, the typical risk factors used to explain the cross-section of stock and bond returns has fairly limited explanatory power in this context.

Our findings are based on loans issued through Lending Club (LC), the largest marketplace lending platform in the US (based on volume issued per year). The main innovative feature of LC appears to be the partial reallocation of revenue historically captured by traditional financial institutions, such as banks, to individual borrowers in the form of lower interest rates and to the ultimate lenders as higher risk-adjusted returns. LC started operating as one of the first Facebook applications during 2007 (VentureBeat, 2007) by utilizing the existing trust among interlinked individuals of the social network. The lending service became sufficiently successful that LC grew into an independent, marketplace lending platform. From December 2007, the beginning of our sample, to March 2017, the end of our sample, LC have facilitated more than $20 billion in loans while paying more than $3 billion in interest to the independent lenders. Essentially, LC appears to provide financial intermediation services at a much lower cost than traditional banks to this segment of borrowers (Milne and Parboteeah, 2016).[3]

We use a unique dataset of monthly loan payments for all LC loans from December 2007 until March 2017. This monthly cash-flow information for each individual loan is provided by RiverNorth; a closed-end fund specialized in marketplace lending.[4] 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. Personal identifiers are not included. This data set includes the entire spectrum of consumer loans issued by LC, without any selection bias. We verify that the publicly available aggregates on annual loan volumes and on the number of issued loans match the number and volume of loans in our proprietary cash flow data.

[3] LC may be able to provide services at a lower cost because a bank is required to hold reserves to offset potential defaults while LC distributes loan losses that are directly to investors, and therefore, does not require reserves.
[4] See https://www.rivernorth.com.

Each loan is carefully screened to ensure heterogeneous borrower characteristics along several dimensions (Jagtiani and Lemieux, 2017) including FICO ratings, employment status, home ownership, stated purpose of loan, and geographic area (first 3 digits of the zip code). Given the level of access to detailed information, investors can carefully screen potential borrowers and browse these loans on the LC platform to build customized portfolios. Investors may also set mechanical rules to allocate capital to many loans within the different risk categories. As of 2017, more than 40 banks provide capital to finance the loans originated by LC. In fact, banks were responsible for at least 40% of the total LC loan origination during the first, second and third quarter of 2017.[5] This substantial level of participation suggests that many banks may find it at least as profitable to finance LC loans rather than investing resources to develop a competing online platform.[6]

The initial balance of a personal loan from LC ranges from $1,000 to $40,000. An individual can have as a maximum two independently managed loans at the same time. Investors only decide what fraction of the specific loan to finance, given the loan terms set by LC. 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. For large loan portfolios, the lack of segmentation below this $25 threshold should be completely irrelevant to investors. If no investor agrees to finance a posted loan request, then the loan does not get issued.[7] A personal loan request remains active until it is fully funded or a maximum of 14 days. Origination fees for personal loans range between 1% and 6% of the loan amount, due to the credit rating and other items used for the risk assessment. The monthly payment obligations begin within 30 days of origination and include the standard components: the principal of the loan, plus the interest based on the borrower's risk profile.

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

[5] See the presentation on LendingClub's First Investor Day, https://www.crowdfundinsider.com/2017/12/125767-lendingclub-presentation-shared-investor-day-event/

[6] Recently, Goldman Sachs created its own marketplace lending platform, called Marcus. It is not yet feasible to evaluate the long-term profitability of this business decision.

[7] 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.

business of the traditional credit institutions for households (Berger and Gleisner, 2009; Michels, 2012; Miller, 2015; and Wei and Lin, 2016). The second area of interest is the behavior of agents participating in marketplace lending. This research analyzes the selection process of individual lenders and the individual loan characteristics associated with eventual default (Herzenstein et. al., 2011a, b; Zhan and Liu, 2012; Lin et al., 2013; Lin and Viswanathan, 2015; Iyer et al., 2015; Dorfleitner et al., 2016; and Hertzberg et al, 2018). Online financial intermediation for household credit allows many independent lenders to to assess the detailed characteristics of individual borrowers along several dimensions. One of the main information channels is voluntary disclosure directly by the borrower. It is not obvious whether traditional lenders attempt to collect this information with the same level of detail during the loan application process. In addition, it is also possible that disseminating the same information to many independent lenders leads to improved accuracy in the decision to finance the loan.

It is clear from subsequent loan performance that LC is able to assess the probability of loan default with considerable precision. For instance, Serrano-Cinca et al. (2015) shows that there is a clear relationship between the credit risk category assigned to loans and the probability of default using publicly available data from LC. Franks et al. (2018) indicates that if a platform uses an auction to determine interest rates rather than setting interest rates directly based on assessment of default probabilities, then interest rates are likely to be too high relative to default probabilities, especially when there are many loans auctioned at the same time. 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. For example, monthly risk-adusted performance for credit risk categories A through D ranges from 0.38% to 0.43% and these estimates are virtually indistinguishable from a statistical perspective. Furthermore, the monthly risk-adjusted performance for the worst credit risk category EGF is 0.28%, but even this lower point estimate is not statistically different from the performance of the other categories. This relation across credit risk categories indicates that the higher interest rates set by LC for loans deemed more risky is largely offset by higher default rates in general.

The approximate equivalence of risk-adjusted performance across most credit categories implies that diversified investors are not highly motivated to allocate capital only to the loans in specific credit categories. Indeed, generating investor indifference across lending categories may be a key determinant of the interest rate set by LC for each credit category. Since origination fees collected by LC are proportional to loan volume and the losses associated with loan default are largely borne by the independent lenders, LC has a strong incentive to ensure more loans receive financing from these lenders. This incentive structure may be different from that of traditional banks. While bank profitability is also strongly related to loan volume, the extent to which traditional banks retain some portion of the underlying loans may force banks to allocate limited capital to the most profitable lending opportunities and to forgo other opportunities. Essentially, traditional banks must rank potential lending opportunities by profitability to allocate limited resources while LC and other market platforms are capable of originating all lending opportunities that independent investors view as profitable. This may be the key innovation that allows marketplace lending to compete effectively with traditional banks. However, this innovation is associated with the additional cost that loan performance after all fees must also implicitly compensate the independent lenders for exposure to the default risk of the marketplace platform itself.

To the best of our knowledge, this paper is the first attempt to carefully analyze the performance of marketplace lending using payment data for individual loans. The goal is to provide a more accurate assessment of risk-adjusted performance from the perspective of a sophisticated investor. The remainder of this paper is organized as follows. The next section discusses our data in detail, and the initial phases of our analysis. Section 3 discusses the specifics and the development of the monthly portfolio index return. Section 4 presents the results and Section 5 concludes.

II. Data and initial analysis

Our proprietary data includes monthly payment information of all LC loans that were financed between December 2007 and March 2017 matched to borrower characteristics measured at the time the loan is financed. This unique feature provides cash flows on a monthly basis for each loan so that it is not necessary to infer the timing of payments from the fixed public status. We can calculate more accurate internal rate of returns (IRRs) as well as monthly portfolio returns, compared to previous research (Serrano-Cinca et al., 2015; Herzberg et. al, 2016). To verify the completeness of the loan histories in our database, we compare the number of issued loans and aggregate loan volume calculated from proprietary payment data provided by RiverNorth with the publicly available information of LC's own statistics.[8] These statistics match perfectly, and therefore, Table 1 confirms that we have the full population of loans issued by LC.

Our dataset 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. The data set includes socio-economic 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. LC 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 through A5 and all of the loans within each of these subcategories receives the same interest rate. There are 35 different credit risk subcategories in total.

Table 2 provides the summary statistics of the 36-month maturity loans by LC-assigned broad credit category and issue year.[9] In order to have a sufficient number of loans observations in each credit risk category to form a diversified portfolio, we merge the three lowest credit risk categories E, F and G into one single category, EFG. 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.

[8] See https://www.lendingclub.com/info/demand-and-credit-profile.action

[9] 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.

A thorough performance analysis of a loan portfolio begins with a monthly payment history for each issued loan after subtracting LC fees. 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 issued in a particular month. For each of the next 42 months, we sum all of the payments, net of LC fees, from the loans in the initial portfolio. To ensure that we capture the vast majority of payments after the stated maturity of 36 months, we include an additional 6 months of payments. Given the 42 months of payment data for the loan portfolio and the combined balance at time of issue, we calculate the monthly internal rate of return of the loan portfolio for that issue 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. We present the statistics for the resulting time series of monthly IRRs for the LC loan portfolios in Panel A of Table 3. We follow the same approach to evaluate the performance of portfolios for each issue month separately for each of the broad credit categories.

Based on the first column in Panel A of Table 3, the average monthly IRR across portfolios formed by issue month is 0.40%, that is, approximately 5% on an annual basis. For comparison purposes, the average 1-year Treasury Constant Maturity Rate for the issue months in the IRR sample period is about 0.5%. Similarly, the average 3-year Treasury Constant Maturity Rate for the same issue months is about 1% on an annual basis. The average IRR for the typical portfolio of LC loans is much higher than these benchmark interest rates. Some portion of this difference in performance may reflect compensation for the risk properties of the loan portfolio compared to Treasury securities, a risk premium of 4% per year could be more consistent with the premium associated with risky fixed income portfolios. For instance, the average monthly total return calculated for the US Corporate 1-3 Year Index for investment grade bonds during the same time period is 4% per year.[10]

Nevertheless, if compensation for systematic risk explains the high average IRR of these loan portfolios, then systematically risky loans in the portfolios should have a higher average IRR compared to the relatively safe loans in portfolios. Subdividing the issue month loan

[10] 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).

portfolio by credit category, we observe a threefold increase in the volatility of loan portfolio IRR between Category A and Category D.[11] Since Panel B of Table 3 shows that the interest rates are about twice as large for the risky credit categories compared to the relatively safe credit categories, the more risky credit categories must also have much higher loan default rates to offset the strong monotonic pattern for interest rates so that the average IRR is approximately unchanged across categories. However, the differences in volatility and loan default rates between categories are only associated with a very modest increase 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. While it could be the case that the difference in volatility or default rates across credit categories is due entirely to idiosyncratic characteristics that should not receive a risk premium, it is much more likely that the relatively risky loan portfolios have greater exposure to systematic risk.

Unfortunately, it is difficult to quantify systematic risk exposure directly from the IRR measure. In this context, the rate of loan defaults, especially during the financial crisis, should be correlated with systematic risk exposure. We use two consecutive missed loan payments as a proxy for loan default.[12] Panel A of Figure 1 shows the percentage of all borrowers that miss two consecutive payments during each quarter. 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. For example, Panel B of Figure 1 shows that Category D has a much greater rate of loan defaults especially during the financial crisis compared to Category A. Nevertheless, the average IRR for Category D is only a few basis points higher than the IRR for Category A and this difference is not statistically significant. The average IRR for the loan portfolios is not tightly linked in the cross-section to the variation in the exposure to systematic default risk for the credit categories. Thus, the most obvious measure of systematic risk, exposure to systematic

[11] The IRR for each issue month exhibits considerable volatility within a credit category. Indeed, we find negative IRRs for some issue months during the financial crisis of 2008/09. Since the financial crisis occurs during the sample period, the average IRRs in Table 3 may actually be substantially lower than than the expected IRRs for these loan portfolios in the future because the financial crisis is likely to be a rare event.

[12] In Table 4 we confirm that this definition is highly correlated with the eventual failure of the borrower to make any subsequent payments, that is, loan default.

loan default, appears to be virtually unrelated to the average IRR of the loan portfolios across credit categories.

While we conduct a formal analysis of risk-adjusted performance for LC loan portfolios in a subsequent section, the apparent absence of a relation between IRR performance and systematic risk proxies across credit categories brings attention to an important topic. In this particular implementation of marketplace lending, LC sets the price, that is, the interest rate. Borrowers and lenders only accept or reject the particular opportunity. To the extent that LC has market power, there may be a range of interest rates that both borrowers and lenders would be willing to accept. Unlike the stock market, or to a lesser extent the corporate bond market, the resulting securities are not frequently traded following origination.[13] Hence, the typical forces that lead to market efficiency in terms of the price observed in public markets may not be relevant for LC loan portfolios. Consequently, the potential absence of a strong trade-off between risk characteristics and expected return may be less surprising in this context.

III. Monthly loan portfolio index return

To construct a monthly loan portfolio index return, we need to infer the intermediate valuation of existing loans every month using the data set containing the complete payment history for each issued loan. 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 loan value every month.

Table 4 shows the relevant statistics. Panel A focuses on the probability of borrowers making any subsequent payments, that is loan default, after a given pattern missed payments or partial payments. For each rating class, 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 virtually identical across credit categories. Rather than using LC'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. This assumption will slightly understate loan portfolio performance in our tests because about 13% of

[13] The secondary market of LC loans, *Folio Investing*, is far from liquid. In addition, the explicit transaction costs of secondary trades amount to 1%. LC recently announced the introduction of Exchange Traded Partnership (ETP) during 2018, which allows investors to trade LC loans similarly as Exchange Traded Funds (ETFs).

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.[14] 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 shows the probability of each loan status within each credit category. Unsurprisingly, the probability of missing a payment or missing two consecutive payments increases monotonically from Category A to Category EFG. 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. Of 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 for the loan using the highest interest rate for all newly issued LC loans. These loans will use this 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. More specifically, 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. This benchmark should reflect the changes in market conditions and also changes in credit category-specific credit spread forecast by LC. Panel A of Figure 2 shows 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 LC may reflect other strategic considerations beyond the fundamental risk properties of the loans in the category.

[14] Unreported results show that this change would increase risk-adjusted performance by about 5 basis points per month compared to the baseline specification.

To ensure that the results do not depend on LC assigned interest rates we also consider an alternative calculation the present value of the remaining scheduled payments using a different discount rate series, based on credit card asset backed securities (ABS) yields. Panel B of Figure 2 depicts the value-weighted yield for a portfolio of credit card ABS available from Datastream. This yield series may better reflect credit market conditions and default expectations for consumer loans because these fixed income instruments are traded to some extent. In this alternative formulation, we use changes in the yield for credit card ABS along with the original LC interest rate to calculate the appropriate discount rate for subsequent scheduled payments.

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

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

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 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. First, we assume that the interest rate, that is 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 credit category. This interest rate for newly originated loains is determined by market conditions to some extent because many borrowers and lenders agree to these terms each month. The value of loan i at time t is then calculated accordingly,

$$V_{i,t} = \sum_{j=1}^{T} \frac{C_{t+j}}{\left(1+y_{i,t}\right)^{j}}, \tag{2}$$

where C_{t+j} is the scheduled payment at $t+j$, and $y_{i,t}$ is the discount rate for scheduled payment and is set to $y_{z,t}$, the interest rate on all newly issued loans in the same narrow credit category at time t. Therefore, if a particular loan was originally in Category A3 and the loan status remains current, then the interest rate used to calculate the present value of the remaining loan payments is the interest newly issued loans in Category A3. 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 all newly issued loans in the lowest narrow credit category. 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. This loan is then removed from the loan portfolio index in subsequent months.

Second, it may be the case that the interest rates set by LC do not reflect changing market conditions and default probabilities in the consumer loan market. To address this possibility, we use an alternative assumption to specify the discount rate for scheduled payments. We set the discount rate in the present value calculation for loan i as follows

$$y_{i,t} = y_{i,0} + (y_{ABS,t} - y_{ABS,0}) \ , \tag{3}$$

where $y_{i,0}$ is the interest rate set at origination, and $y_{ABS,t} - y_{ABS,0}$ is the change in the yield on credit card ABS since loan origination. This alternative approach embeds the time series variation in the default spread for credit card lending to discount the cash flows of LC loans. This variation could be critical during the financial crisis when credit card ABS yields spiked even though LC 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.

Lastly, we confirm that the use of the time variation in LC interest rates or credit card ABS yields 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.

IV. Results

Our results indicate that the risk-adjusted performance of our monthly return index for LC loans is large and statistically significant. Before investigating risk-adjusted performance, Table 5 presents the basic performance statistics for the montly 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 0.40%. The average monthly return for each credit category varies between 0.39% and 0.42% , except for Category EFG with an average return of 0.28%. The monthly volatility for the entire loan portfolio is 0.36%. Monthly volatility increases monotonically from 0.21% for risk category A to 0.77% for category EFG. The Sharpe ratio for all LC loans based on the monthly return index is 1.02. This Sharpe ratio is more than 5 times larger than the Sharpe ratio of 0.16 for the US stock market during the same time period. It is also much higher than the Sharpe ratio for the US stock market of 0.12 from 1926 until 2017. While the average return across credit categories does not exhibit a particular pattern, the Sharpe ratio associated with the performance of each credit category decreases monotonically with credit risk. For instance, the Sharpe ratio for category A is 1.85, the Sharpe ratio for category C is 0.99, and the Sharp ratio for category EGF is 0.34. The summary statistics for the monthly portfolio index return provided in Table 5 are not directly comparable to the average IRR statistics reported in Table 3 because the sample period is 42 months shorter for Table 3 due to the data requirements for calculating the IRR for all loans originated in a particular month. Consequently, the financial crisis has a larger impact on the IRR statistics compared to the monthly loan portfolio index return statistics.

In Table 6, 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. Investors investing in marketplace lending loans are exposed to two primary risks: interest rate risk and default risk. These two risks are 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, Rf, 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 St. Louis FRED 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 6 use the 1-factor, 3-factor model, and 5-factor model. Two of these six specifications are augmented with the momentum factor. The last two specifications also include bond factors. Our results show that the risk-adjusted performance of LC loans is not driven by any particular specification of the risk factor model. Indeed, the relatively low R^2 for these regressions indicates that the traditional risk factors only explain a small fraction of the performance of marketplace loans. The estimates of risk-adjusted performance range from 0.36% per month to 0.38% per month, depending on the specification. Each of the performance estimates is significantly different from zero with a *t*-statistic greater than 4.[15] The only significant factors coefficients are for the market factor and momentum. Both are significantly positive in almost every specification. Even though market beta is significant, its value is close to zero. The significance of momentum seems to be partly driven by its exceptionally low performance in 2009 when LC loans also experienced higher default rates. Unreported results indicate that the estimate for momentum falls by about 50% and the estimate is not statistically significant if observations before 2010 are excluded. All other coeffiecients, including those for the bond factors, are insignificant at conventional levels. Since it is plausible that the bond factors are more closely related to the performance of fixed income instruments, the lack of statistical relevance is somewhat surprising. In general, the explanatory power of all factor models is low, with the highest R^2 being 0.18. In unreported results, we also analyzed a few specifications including various liquidity risk factors and the estimates of risk-adjusted performance in these augmented specifications increase relative to the reported results.

In Table 7 we revisit select specifications while using alternative bond factors constructed from various Bank of America Merril Lynch US Corporate Bond indices available from St.

[15] 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 statistical findings.

Louis FRED. The credit return factor (CR) is the difference between 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 risk free 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 estimated coefficients for these alternative bond factors are not statistically significant in any specifications. Again, even though LC loan portfolios have fixed income properties, the proxies for various components of corporate bond performance appear to be unrelated to LC loan portfolio performance. Given this result regarding the alternative bond factors, it should not be surprising that the estimates of risk-adjusted performance are virtually identical to those found in Table 6. The patterns of statistical significance for the equity factors are largely unchanged as well. Only the coefficients for the market factor and the momentum factor are ever statistically significant in any of these specifications.

Table 8 analyzes risk-adjusted performance separately for each credit rating category. The results show that risk-adjusted performance is about 0.40% per month for most credit rating categories, with the exception that risk-adjusted performance is only 0.28% per month for the loan portfolio with the highest credit risk. However, the apparent differences in risk-adjusted performance across loan categories are not statistically significant. The statistical significance of the risk-adjusted performance is substantial for most credit categories and decreases monotonically credit risk. Indeed, the estimate of risk-adjusted performance for category EFG is not statistically significant. This pattern is consistent with the impact of higher idiosyncratic risk for the more risky loan portfolios. The significance of risk factors varies to some extent depending on the credit category. For example, the coefficient for the market factor are positive and significant in credit categories with medium risk, and the coefficient for momentum is positive and significant in high credit risk categories.

The close similarity of risk-adjusted performance across almost all of the credit categories implies that diversified investors are not highly motivated to allocate capital only to the loans in one or two of the particular credit categories. Setting interest rates so that investors are approximately indifferent to loans in the different lending risk categories is likely an important consideration for LC. Since LC profitability is partially generated from origination fees that are proportional to loan volume and the costs of loan default are largely absorbed by the independent lenders, LC has a strong incentive to ensure that as many loans as possible receive financing from the lenders. This incentive structure may be quite different from that of traditional banks. While bank profitability is also strongly related to loan volume, the extent to which banks retain some portion of the underlying loans and also maintain capital reserves may force them 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 LC with a competitive advantage that offers borrowers lower interest rates for a given level of credit risk and generates more loan origination.

Table 9 depicts the regression results based on return series in which the values of loans are estimated based on the change in the yield for credit card ABS since LC loan issuance instead of the yield-to-maturity of newly originated LC loans in the same credit category. Please see the methodology discussion in Section 3. Our results show similar risk-adjusted performance compared to the baseline specification in Table 6. These findings confirm that the estimates of this performance are not a consequence of the specific assumption utilized to value LC loans each period. The risk-adjusted estimates range from 0.40% to 0.44% and these coefficients are highly statistically significant. Most of the risk factors are not statistically significant in most specifications at conventional levels. The coefficients for the value factor and the momentum factor are always negative and the estimates are significant in some specifications. Since the sign of these risk factor coefficients is negative, the high risk-adjusted performance of the LC portfolio is not generated by these risk factors. The credit spread factor is negative and significant, but this is not at all surprising since the ABS yield is part of this alternative valuation approach. An increase in the ABS yield lowers the value of the loan portfolio leading to a lower portfolio return and the ABS yield is correlated with the credit spread.

Table 10 shows that the risk-adjusted performance estimates for each credit category are also not sensitive to the particular valuation methodology. Monthly risk-adjusted performance ranges from 0.44% to 0.51% using intermediate valuation based on the change in the credit card ABS yield, except the performance for the credit category with the most risk is only 0.27% per month. All estimates except EFG are statistically significant at conventional levels. This pattern of risk-adjusted performance is virtually identical to the analogous credit category estimates in Table 8 using the yield on newly issued LC loans for valuation rather than the change in the yield for credit card ABS. The coefficients for the value factor and the momentum factor are usually negative and significant. Since the sign of these risk factor coefficients is negative, the high average performance of the LC portfolio is not generated by these risk factors. Again, the credit spread factor is negative and significant, but this reflects the use of the yield change on credit card ABS in the valuation approach and the correlation between the yield change on credit card ABS and the credit spread factor.

Lastly, we confirm that the use of the time variation in LC interest rates or yields on credit card ABS are not the source of our findings. We remove 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 approapriate interest rate may have changed. In Table 11 we find similar risk-adjusted performance results of approximately 0.40% per month. Most of the risk factors are unrelated to the performance of the LC loan portfolio. The only exception is the positive and significant estimate for the momentum factor using this particular valuation approach.

In general, the analysis in this section indicates that the risk-adjusted performance of the LC loan portfolio is positive and significant. This finding is not due to a particular intermediate valuation methodology or based on a specific construction of the bond factors. Only a small proportion of the variation in LC portfolio performance can be explained by the typical equity and bond factors. The findings indicate that marketplace lending appears to be attractive investment strategy for sophisticated investors.

V. **Conclusion**

This paper analyzes the risk and return characteristics of marketplace lending by evaluating the performance of personal loan portfolios using a unique data set of monthly loan payments from LC. Our findings indicate that the risk-adjusted performance of LC loan portfolios generated via marketplace lending is substantial and the monthly Sharpe ratio of the aggregate LC loan portfolio is greater than 1. A more sophisticated approach selecting LC loans with low credit risk generates similarly large abnormal performance and an even higher Sharpe ratio. While the core analysis is based on the monthly loan portfolio index return, the IRR calculations are broadly consistent with this assessment of performance for LC loan portfolios.

Financing of consumer credit by individual investors or non-bank institutions using marketplace lending platforms has made this type of financial intermediation more widespread. The risk-adjusted returns of these personal loan portfolios are more analogous to the potential for private equity funds to generate abnormal performance. If substantial risk-adjusted performance is expected to persist, then this superior performance will attract more capital, similar to the pattern of investment behavior in private equity funds (Metrick and Yasuda, 2010). Consequently, we expect the development of a new market equilibrium; either as a result of increasing competition, or as a result of decreasing loan quality on average. Following the parallel analogy, both cases would potentially result in the radical decrease of the average risk-adjusted return, since personal loans in marketplace lending would reach an equilibrium with traditional banks as well as other fixed income securities.

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Table 1. Validation of proprietary 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 (LC) public website. The columns from the proprietary data match the publicly available information exactly (i.e., no typographical errors).

	Proprietary loan data		Lending Club website	
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

Table 2. Summary statistics for Lending Club loans

This table shows the summary statistics for Lending Club (LC) loans with 36 months until maturity. The reported statistics are number of loans, average loan size, and average interest rate by broad credit category and issue year. The broad credit categories, such as A, B, C, and D are determined using a proprietary assessment of credit worthiness of each loan by LC. This assessment uses variables including FICO score, employment status, home ownership, and geographic area (first 3 digits of the zip code). The interest rate for each loan is assigned by LC and is directly linked to the more narrow credit grades within each broad credit category, such as A1 through A6 in broad category A. We combine broad credit categories E, F, and G within each year.

Category	A			B			C			D			EFG		
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	318	5,974	8.4%	594	8,440	10.4%	580	8,315	11.8%	419	8,588	13.4%	482	9,627	15.7%
2009	1,203	7,232	8.6%	1,445	10,851	11.8%	1,348	9,750	13.3%	817	10,642	14.9%	468	11,958	17.3%
2010	2,567	8,044	7.2%	2,805	10,112	10.7%	2,070	9,126	13.5%	1,253	10,816	15.2%	461	13,165	17.5%
2011	5,579	8,923	7.1%	4,722	9,545	11.0%	2,203	9,010	13.9%	1,261	10,567	16.2%	336	13,398	18.6%
2012	10,753	11,117	7.6%	16,805	11,006	12.1%	9,902	11,516	15.2%	5,088	13,849	18.2%	922	20,253	21.2%
2013	17,057	15,172	7.7%	40,313	12,878	11.8%	24,693	12,265	15.4%	14,505	10,549	18.7%	3,854	9,926	22.0%
2014	35,333	14,397	7.5%	53,460	12,653	11.2%	44,042	11,994	14.1%	20,510	11,532	17.0%	9,225	10,424	21.3%
2015	70,132	14,473	6.9%	91,783	12,520	10.0%	77,457	11,895	13.2%	32,740	12,304	16.6%	11,061	12,489	19.8%
2016	66,862	13,953	6.9%	114,783	12,091	10.3%	92,317	12,463	13.7%	36,707	13,450	18.1%	12,826	12,884	23.2%

Table 3. Basic performance statistics for Lending Club loans

Panel A of this table presents the monthly internal rate of return (IRR) statistics of Lending Club (LC) loans. The IRRs are calculated using the monthly cash flows aggregated by issue month (and by risk category). There are 70 issue months with sufficient time after issuance to calculate the IRR of the loan portfolio. Panel B shows (monthly) interest rate statistics of LC loans for the same sample of months.

Panel A: Monthly internal rate of return statistics

	All loans	A	B	C	D	EFG
Average	0.40%	0.40%	0.42%	0.44%	0.44%	0.43%
Median	0.46%	0.40%	0.49%	0.51%	0.53%	0.50%
Min	-0.44%	-0.42%	-1.15%	-0.51%	-1.11%	-1.37%
Max	0.62%	0.67%	0.83%	0.77%	1.04%	1.34%
Std. Dev.	0.22%	0.14%	0.27%	0.29%	0.39%	0.52%

Panel B: Monthly interest rates

	All loans	A	B	C	D	EFG
Average	1.00%	0.65%	0.94%	1.14%	1.32%	1.54%
Median	1.00%	0.63%	0.95%	1.13%	1.27%	1.47%
Min	0.79%	0.53%	0.78%	0.90%	1.04%	1.23%
Max	1.16%	0.77%	1.03%	1.31%	1.57%	1.83%
Std. Dev.	0.09%	0.05%	0.07%	0.11%	0.16%	0.18%

Table 4. 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 category and specific loan status, such as number of consecutive missed payments or consecutive partial payments. Panel B shows the frequencies of each loan status, such as number of consecutive missed payments and partial payments.

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
EFG	0.0479	0.0101	0.7024	0.8637	0.9363	0.5794	0.1275

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
EFG	0.9464	0.0180	0.0136	0.0110	0.0045	0.0010

Table 5. 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 (LC). The credit categories are determined using a proprietary assessment of credit worthiness of each loan by LC. This assessment uses variables including FICO score, employment status, home ownership, and geographic area (first 3 digits of the zip code). We combine credit categories E, F, and G into one category EFG. The construction of the loan portfolio index is described in Section 3. The specification in this table uses the present value for a loan in good standing based on to the interest rate of newly issued LC loans in the same sub-credit risk category. 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 Merril Lynch US Corporate Bond 1 to 3 year index available from St. Louis FRED. The sample period is from January 2008 to March 2017.

	All loans	A	B	C	D	EFG	Stock Market	Corporate Bonds
Average Return	0.40%	0.42%	0.45%	0.44%	0.39%	0.28%	0.75%	0.26%
Standard Deviation	0.36%	0.21%	0.35%	0.41%	0.59%	0.77%	4.63%	0.85%
Minimum Return	-1.40%	-0.26%	-0.69%	-0.90%	-2.23%	-2.49%	-17.15%	-4.75%
Maximum Return	1.10%	1.12%	1.36%	1.46%	1.52%	1.83%	11.35%	3.05%
Median Return	0.44%	0.41%	0.50%	0.49%	0.47%	0.41%	1.29%	0.22%
Sharpe ratio	1.02	1.85	1.19	0.99	0.61	0.34	0.16	0.28

Table 6. 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 (LC) 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 3. The specification in this table uses the present value for a loan in good standing based on to the interest rate of newly issued LC 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 St. Louis FRED. 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. All coefficients that are statistically significant at the 5% level are reported in bold.

Category	All	All	All	All	All	All	All	All
Alpha	**0.0038**	**0.0037**	**0.0036**	**0.0036**	**0.0037**	**0.0038**	**0.0037**	**0.0038**
	(4.36)	(4.35)	(4.42)	(4.83)	(4.50)	(5.01)	(4.42)	(4.90)
MKT		**0.0167**	**0.0222**	**0.0282**	**0.0190**	**0.0238**	**0.0205**	0.0275
		(2.16)	(2.09)	(2.17)	(2.25)	(2.31)	(2.25)	(1.85)
SMB			-0.0150	-0.0162	-0.0189	-0.0187		-0.0235
			(-0.78)	(-0.93)	(-0.89)	(-0.93)		(-1.09)
HML			-0.0137	-0.0012	-0.0180	-0.0006		-0.0062
			(-1.37)	(-0.12)	(-1.52)	(-0.05)		(-0.47)
MOM				**0.0197**		**0.0198**		**0.0176**
				(4.07)		(3.70)		(3.10)
RMW					-0.0313	-0.0308		-0.0255
					(-1.05)	(-1.01)		(-0.87)
CMA					0.0152	-0.0008		0.0029
					(0.70)	(-0.04)		(0.12)
BM							0.3231	0.3487
							(1.56)	(1.53)
CS							0.2848	0.2290
							(1.65)	(1.41)
N	111	111	111	111	111	111	111	111
R^2		0.044	0.063	0.119	0.078	0.132	0.094	0.180

Table 7. 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 (LC) 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 3 and uses the present value for a loan in good standing based on to the interest rate of newly issued LC 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 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 Merril Lynch US Corporate Bond indices available from St. Louis FRED. 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. All coefficients that are statistically significant at the 5% level are reported in bold.

Category	All	All	All	All	All	All
Alpha	**0.0038**	**0.0037**	**0.0037**	**0.0038**	**0.0038**	**0.0039**
	(4.21)	(4.67)	(4.60)	(4.45)	(5.16)	(4.89)
MKT		**0.0280**	**0.0241**	**0.0253**	0.0314	**0.0319**
		(2.45)	(2.50)	(2.72)	(1.87)	(1.96)
SMB					-0.0239	-0.0237
					(-1.03)	(-1.02)
HML					-0.0068	-0.0095
					(-0.55)	(-0.91)
MOM		**0.0173**			**0.0174**	**0.0158**
		(2.80)			(3.03)	(2.03)
RMW					-0.0278	-0.0290
					(-0.92)	(-0.98)
CMA					0.0016	0.0037
					(0.07)	(0.17)
CR			-0.0233	-0.0134	-0.0090	-0.0061
			(-1.23)	(-0.65)	(-0.48)	(-0.32)
TR			-0.0344	-0.0155	-0.0430	-0.0347
			(-0.98)	(-0.40)	(-1.05)	(-0.68)
MM	-0.0289	-0.0498		-0.0596		-0.0281
	(-0.47)	(-0.86)		(-0.76)		(-0.37)
N	111	111	111	111	111	111
R^2	0.005	0.120	0.069	0.078	0.156	0.157

Table 8. 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 (LC) 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 categories are determined using a proprietary assessment of credit worthiness of each loan by LC. This assessment uses variables including FICO score, employment status, home ownership, and geographic area (first 3 digits of the zip code). We combine credit categories E, F, and G into one category EFG. The construction of the loan portfolio index is described in Section 3 and uses the present value for a loan in good standing based on to the interest rate of newly issued LC 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 St. Louis FRED. 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. All coefficients that are statistically significant at the 5% level are reported in bold.

Category	All	A	B	C	D	EFG
Alpha	**0.0038**	**0.0039**	**0.0043**	**0.0042**	**0.0038**	0.0028
	(4.90)	(14.88)	(6.69)	(4.53)	(3.28)	(1.63)
MKT	0.0275	0.0037	**0.0221**	**0.0299**	0.0392	0.0212
	(1.85)	(1.07)	(2.44)	(2.42)	(1.47)	(0.79)
SMB	-0.0235	0.0025	-0.0022	-0.0324	-0.0386	-0.0313
	(-1.09)	(0.26)	(-0.15)	(-1.64)	(-1.09)	(-0.77)
HML	-0.0062	0.0128	-0.0092	-0.0010	-0.0314	-0.0181
	(-0.47)	(1.69)	(-0.83)	(-0.06)	(-1.15)	(-0.50)
MOM	**0.0176**	0.0006	**0.0129**	0.0176	**0.0210**	**0.0257**
	(3.10)	(0.16)	(2.19)	(1.83)	(2.31)	(2.04)
RMW	-0.0255	0.0042	-0.0095	-0.0275	-0.0724	-0.0665
	(-0.87)	(0.24)	(-0.30)	(-0.81)	(-1.53)	(-1.29)
CMA	0.0029	0.0032	0.0131	-0.0003	0.0164	-0.0206
	(0.12)	(0.29)	(0.61)	(-0.01)	(0.39)	(-0.31)
BM	0.3487	0.0485	0.2413	0.3176	0.4664	0.1953
	(1.53)	(0.84)	(1.45)	(1.54)	(1.31)	(0.44)
CS	0.2290	-0.1113	0.0766	0.2675	0.2173	0.5298
	(1.41)	(-1.38)	(0.50)	(1.02)	(1.06)	(1.85)
N	111	111	111	111	111	111
R^2	0.180	0.101	0.112	0.145	0.178	0.087

Table 9. Risk-adjusted performance using credit card ABS yield for valuation

This table shows the results of regressions in which the monthly index return for all Lending Club (LC) loans in excess of the risk-free rate, RL-Rf, is regressed on various sets of risk factors. The construction of the loan portfolio index is described in Section 3. The specification in this table uses the present value for a loan in good standing based on to the change in the yield on credit card ABS since loan origination and the original interest rate (yield) of the LC loan at origination. 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, Rf, 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 St. Louis FRED. 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. All coefficients that are statistically significant at the 5% level are reported in bold.

Category	All	All	All	All	All	All	All	All
Alpha	**0.0042**	**0.0041**	**0.0040**	**0.0040**	**0.0043**	**0.0043**	**0.0043**	**0.0044**
	(6.34)	(5.83)	(5.51)	(5.16)	(7.67)	(7.11)	(6.74)	(7.87)
MKT		0.0199	0.0319	0.0270	0.0224	0.0189	-0.0132	-0.0068
		(1.07)	(1.29)	(1.19)	(1.31)	(1.14)	(-1.62)	(-0.77)
SMB			-0.0089	-0.0079	-0.0179	-0.0181		-0.0247
			(-0.84)	(-0.77)	(-1.40)	(-1.40)		(-1.57)
HML			-0.0517	-0.0619	-0.0449	-0.0577		**-0.0444**
			(-1.63)	(-1.79)	(-1.48)	(-1.73)		(-2.72)
MOM				**-0.0159**		**-0.0146**		-0.0046
				(-2.47)		(-2.14)		(-0.78)
RMW					-0.0572	-0.0576		-0.0454
					(-1.27)	(-1.27)		(-1.28)
CMA					-0.0283	-0.0165		-0.0159
					(-0.73)	(-0.45)		(-0.42)
BM							-0.0324	0.0323
							(-0.11)	(0.13)
CS							**-0.9860**	**-0.8839**
							(-3.04)	(-3.48)
N	111	111	111	111	111	111	111	111
R^2		0.037	0.124	0.146	0.163	0.181	0.243	0.344

Table 10. Performance for each credit category using credit card ABS yield for valuation

This table shows the results of regressions in which the monthly index return for Lending Club (LC) 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 categories are determined using a proprietary assessment of credit worthiness of each loan by LC. This assessment uses variables including FICO score, employment status, home ownership, and geographic area (first 3 digits of the zip code). We combine credit categories E, F, and G into one category EFG. The construction of the loan portfolio index is described in Section 3 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 LC loan. 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 St. Louis FRED. 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. All coefficients that are statistically significant at the 5% level are reported in bold.

Category	All	A	B	C	D	EFG
Alpha	**0.0044**	**0.0044**	**0.0051**	**0.0049**	**0.0045**	0.0027
	(7.87)	(10.51)	(10.95)	(7.12)	(4.57)	(1.92)
MKT	-0.0068	-0.0267	-0.0199	-0.0054	0.0085	-0.0006
	(-0.77)	(-1.97)	(-1.53)	(-0.49)	(0.53)	(-0.03)
SMB	-0.0247	0.0022	-0.0040	-0.0372	-0.0364	-0.0330
	(-1.57)	(0.18)	(-0.47)	(-2.30)	(-1.29)	(-1.00)
HML	**-0.0444**	**-0.0331**	**-0.0465**	**-0.0389**	**-0.0740**	-0.0414
	(-2.72)	(-2.18)	(-2.27)	(-2.33)	(-2.76)	(-1.29)
MOM	-0.0046	**-0.0184**	-0.0068	-0.0389	-0.0028	0.0098
	(-0.78)	(-2.68)	(-1.08)	(-0.82)	(-0.32)	(0.99)
RMW	-0.0454	-0.0160	-0.0359	-0.0448	-0.0836	-0.0662
	(-1.28)	(-0.62)	(-0.97)	(-1.61)	(-1.45)	(-1.31)
CMA	-0.0159	-0.0288	-0.0120	-0.0182	0.0099	-0.0271
	(-0.42)	(-0.88)	(-0.33)	(-0.36)	(0.20)	(-0.37)
BM	0.0323	-0.2385	-0.0280	-0.0131	0.1063	0.0137
	(0.13)	(-1.82)	(-0.13)	(-0.05)	(0.31)	(0.04)
CS	**-0.8839**	**-1.2834**	**-1.0809**	**-0.8269**	**-0.8805**	**-0.5319**
	(-3.48)	(-4.39)	(-3.78)	(-2.14)	(-3.98)	(-2.27)
N	111	111	111	111	111	111
R^2	0.344	0.532	0.395	0.272	0.279	0.117

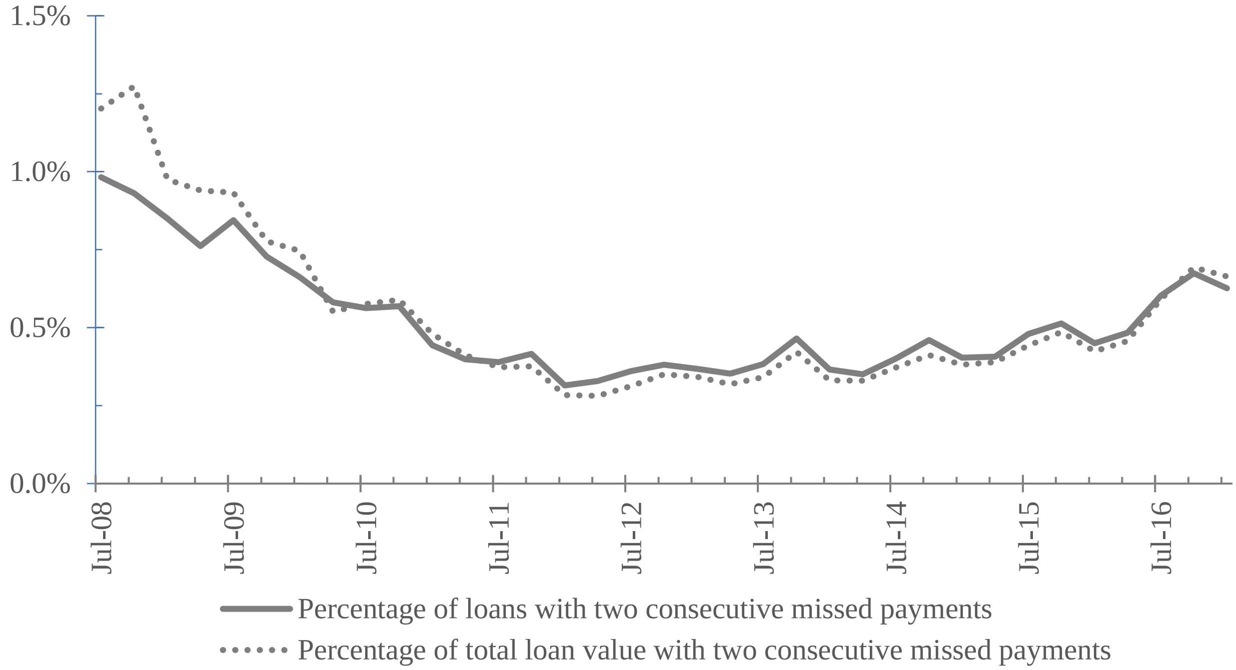
Table 11. Risk-adjusted performance using the loan balance for valuation

This table shows the results of regressions in which the monthly index return for all Lending Club (LC) 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 3. 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 Merril Lynch US Corporate Bond indices available from St. Louis FRED. 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. All coefficients that are statistically significant at the 5% level are reported in bold.

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

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

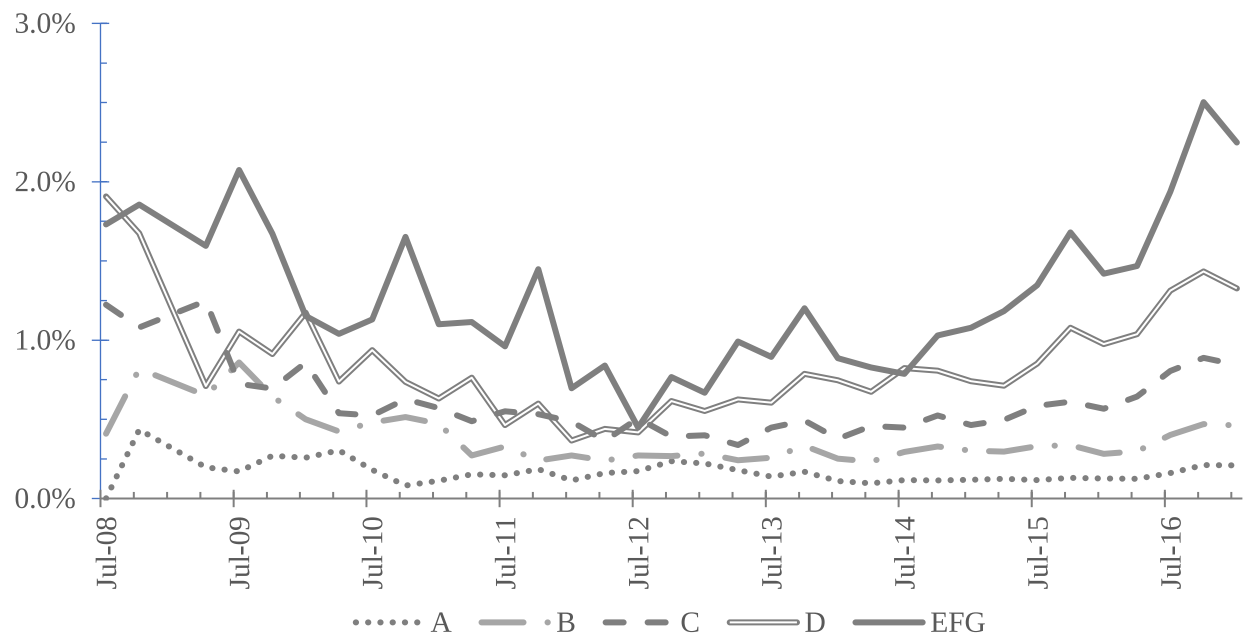
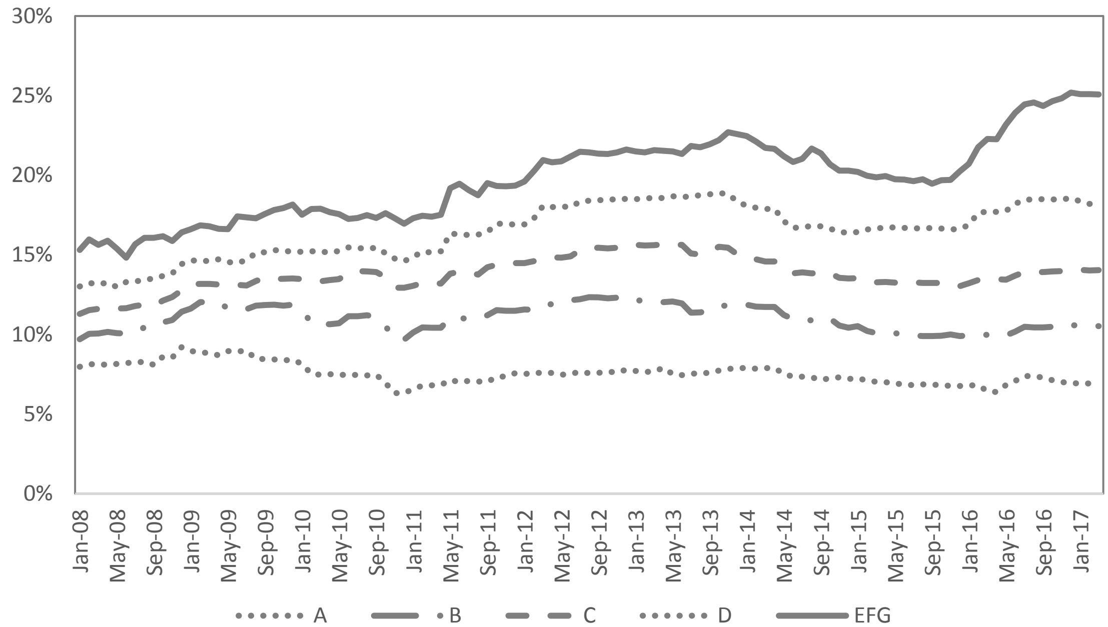


Figure 1. Panel A of the figure shows equal-weighted and value-weighted default rates for Lending Club (LC) loans. Default is defined as two consecutive missed payments. The solid black line is the number of loans with two consecutive missed payments as a percentage of the total number of active loans. 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 value-weighted default rates for LC loans for each credit category.

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

Panel A: Interest rates of newly issued Lending Club loans



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

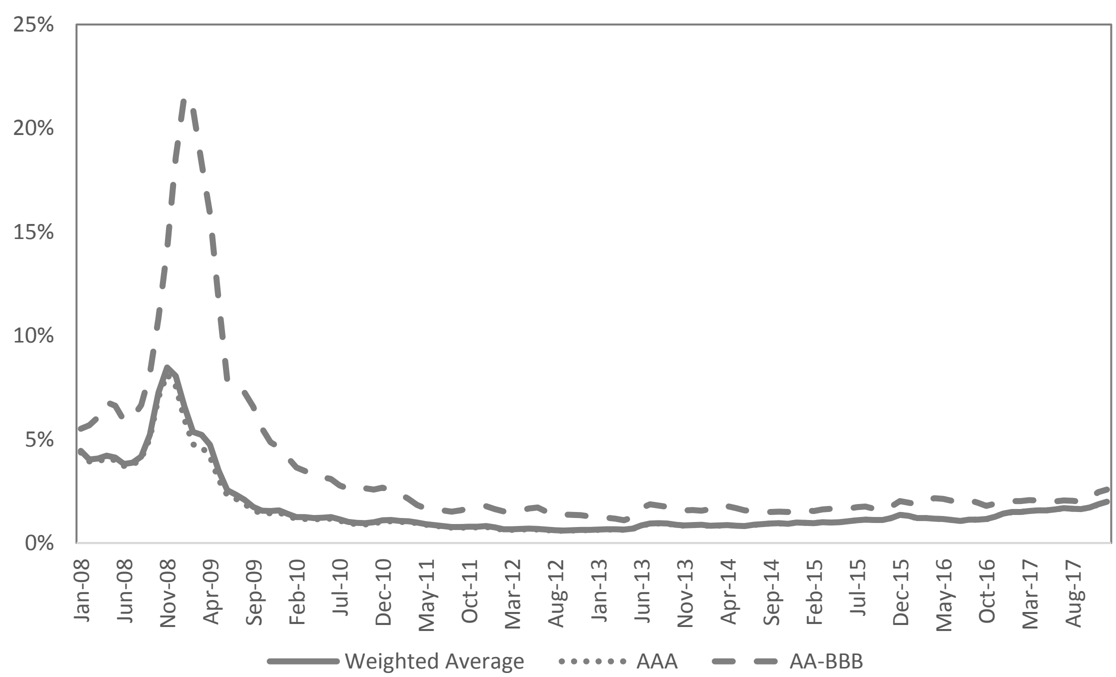


Figure 2. Panel A of this figure shows the average interest rate, equal-weighted, for newly issued Lending Club (LC) loans by rating category for each month of loan issuance. Panel B shows the value-weighted yields of credit card asset backed securities on a monthly basis.