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Roman Kräussl, Zsofia Kräussl, Joshua Pollet, and Kalle Rinne

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Center for Financial Studies | Goethe University | Theodor-W.-Adorno-Platz 3 | 60323 Frankfurt am Main | Germany
Phone +49 69 798 30050 | Fax +49 69 798 30077 | info@ifk-cfs.de | www.ifk-cfs.de

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

Roman Kräussl
Luxembourg School of Finance, University of Luxembourg
Hoover Institution, Stanford University

Zsofia Kräussl
Luxembourg School of Finance, University of Luxembourg

Joshua Pollet
Gies College of Business, University of Illinois at Urbana-Champaign

Kalle Rinne
Luxembourg Institute of Science and Technology

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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, including institutional investors, usually form broad portfolios to benefit from diversification. We find high risk-adjusted performance of approximately 40 basis points per month for these basic loan portfolios. This abnormal performance indicates that Lending Club, and similar marketplace lenders, are likely to attract capital to finance a growing share of the consumer credit market. In the absence of a competitive response from traditional credit providers, these loans lower costs to the ultimate borrowers and increase returns for the ultimate lenders.

Keywords: marketplace lending, peer-to-peer, portfolio performance, household finance, financial innovation, finance and technology

JEL Codes: G12, G21

*Contact information of authors: Roman Kräussl, roman.kraussl@uni.lu; Zsofia Kräussl, zsofia.kraussl@uni.lu; Joshua Pollet, pollet@illinois.edu; and Kalle Rinne, kalle.rinne@list.lu.

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 make borrowing decisions while considering most, 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 loans issued via the largest marketplace lending platform in the US earn substantial risk-adjusted returns of 40 basis points per month. These loans are fixed income securities, and therefore, this abnormal performance is associated with extremely low volatility compared to the volatility of typical equity portfolios. 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 abnormal performance for these loans is more analogous to the potential for private equity funds to generate abnormal returns. However, if this abnormal performance is expected to persist, then this superior performance will attract more capital. Indeed, this pattern has already been established in private equity funds (Metrick and Yasuda, 2010). As capital continues to enter marketplace lending in search of abnormal returns, a new equilibrium is likely to develop.

Marketplace lending is a rapidly growing business. In terms of its loan volume, marketplace lending in the United States amounted to $25.7 billion in 2017.[1] In comparison, credit

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

card debt of US households was $808 billion in 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 abnormal 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 the abnormal 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 risk and return characteristics of consumer loans issued by marketplace lending platforms. While the volatility of individual loan performance will be extremely important for holders of smaller loan pools, more sophisticated lenders, such as institutional investors, are likely to form substantial portfolios of loans to benefit of diversification. In this context, a performance analysis of a loan portfolios available on marketplace platforms is of critical relevance as this new approach to financial intermediation emerges. We find that the performance of these pools of marketplace loans depends on the expected default probability for an individual loan as well as on the default correlation across different loans in the portfolio. Our results show that investing in personal loans provides relatively stable returns that are significantly above the returns to US Treasuries during the same time period.

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 redistribution of profits 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 high abnormal 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,

[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

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 provides financial intermediation services at a much lower cost than traditional banks to this segment of borrowers (Milne and Parboteeah, 2016).[3]

We are the first to use a unique dataset of LC loan payments with a monthly frequency, ranging from December 2007 until March 2017. Our data set is from monthly cash-flow information for each individual loan, 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. This data set covers the whole spectrum of consumer loans issued by LC, without any selection bias. We verified 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 data.[5]

Each loan is carefully screened to ensure heterogeneous borrower characteristics along several dimensions (Jagtiani and Lemieux, 2017) including FICO ratings, employment status, home ownership, 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 and more than 70 institutional investors 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.[6] This level of participation suggests that many banks may find it at least as profitable to finance LC loans compared to developing a competing online platform.[7]

The initial balance of a personal loan ranges from $1,000 to $40,000. An individual can have as a maximum two active, independently managed loans at the same time.[8] Investors only

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[3] This could be due to more efficient assessments of credit worthiness for potential loans or due to a lower cost of capital created by this more direct funding mechanism for loans. Also, a deposit taking bank is required to hold reserves to offset potential losses from risky loans while LC does not need reserves against loans in default because the losses are distributed directly to investors.

[4] See https://www.rivernorth.com

[5] A more detailed introduction on our data can be found in Section 2. For the publicly available signals on basic LC loan statistics see https://www.lendingclub.com/info/demand-and-credit-profile.action

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

[7] 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.

[8] It is possible to apply for a joint loan, too, assuming that both of the peers are eligible for a loan.

decide what fraction of the specific loan to finance. 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. If no investor agrees to finance a loan request that is being listed, then the loan does not get issued.[9] A personal loan request remains active for up to 14 days. Once the funding is complete, and the borrower complies with the credit risk assessment of the platform, the borrower receives the requested loan, and is obliged to start making payments within 30 days. Origination fees for personal loans range between 1% and 6% of the loan amount, due to the credit rating and other, unconventional items used for the risk assessment. The monthly payments include the standard components: the principal of the loan, plus the interest based on the borrower's risk profile.[10]

Previous work on 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 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, 2016).

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 from the borrower. As Lin et al. (2013) show, soft information provided by marketplace lenders contains valuable signals for risk assessment that might increase the performance of lending decisions.

It is clear that LC is able to assess the probability of loan default with considerable accuracy. For instance, Serrano-Cinca et al. (2015) show that there is a clear relationship between the credit category assigned to loans and the probability of default using publicly available data

[9] 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.
[10] See for reference http://lendacademy.com and http://lendingclub.com

from LC. 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 different credit categories. This pattern indicates that the higher interest rate set by LC for loans deemed more risky is almost perfectly offset by higher default rates in general.

To the best of our knowledge, our paper is a pioneering research work to address the performance of marketplace lending using transaction data of individual loans, thus providing a more feasible assessment on performance from the investor's point of view. Furthermore, our research is the first to address whether and to what extend marketplace lending as a new innovative approach to financial intermediation opens up investors an attractive asset class to invest. Finally, we provide as well a novel analytical design for performance evaluation.

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.[11] 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

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

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.[12] In order to have a sufficient number of loans observations in each credit 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 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 LC fees. Before considering risk-adjusted performance using a monthly return index generated 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

[12] 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 we find that 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.

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 all 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. 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 associated with a stock portfolio rather than a fixed income portfolio. 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 only 4% per year.[13]

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 portfolio by credit category, we observe a threefold increase in the volatility of loan portfolio IRR between Category A and Category D.[14] 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

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

[14] 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.

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 0.46%, 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 portfolio has 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.[15] 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 loan default, appears to be virtually unrelated to the average IRR of the loan portfolios.

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 raises an important question. In this particular implementation of marketplace lending, LC sets the price, that is, the interest rate while the borrowers and lenders only accept/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

[15] 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.

frequently traded following origination.[16] Hence, the typical forces that lead to market efficiency in terms of the price observed in public markets may not be relevant for LC loans. Consequently, the potential absence of a strong trade-off between risk characteristics and expected return is less surprising in this context.

III. Monthly loan portfolio return index

To construct a monthly loan portfolio return index, we need to infer the value 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 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 abnormal performance estimates substantially.[17] 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

[16] 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).

[17] Unreported results show that the abnormal performance increases but only approximately ten percent compared to our standard definition.

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 on the loan using the highest interest rate for all LC loans. These loans will use this elevated interest rate until the borrower returns to the original payment schedule.

Next, we explain our methodology to calculate 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 raises the possibility that the interest rates for each credit category that are assigned by LC may reflect other strategic considerations beyond the fundamental risk properties of the loans in the category.

To ensure that the results do not depend on LC assigned interest rates we also calculate the present value of the remaining scheduled payments using an alternative interest rate series, based on credit card asset backed securities (ABS) yields. Panel B depicts the value-weighted yield for a portfolio of credit card ABS available from Datastream. Those yields may better reflect market conditions and default expectations for consumer loans because these fixed income instruments are traded to some extent. In an alternative specification, 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:

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

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 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. The value of loan i at time t is then calculated accordingly,

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

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 $y_{ABS,0}$ - $y_{ABS,0}$ 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.

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. In the third specification, we shut down the influence of variation in default rates and monetary policy 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.

IV. Results

Our results indicate that the risk-adjusted performance of our monthly return index for LC loans is large and statistically significant. In addition to high returns, we also observe a low volatility of returns. The average monthly return is 0.40%. In general, monthly returns in different credit categories vary between 45 basis points (bps) to 39 bps, except for Category EFG with an average return of 28 bps. The average monthly volatility is 0.36%, increasing monotonically by credit category, ranging from 0.21% to 0.77%. Combining these two observations, the Sharpe ratios available from LC loans are as high as 1.02. This average Sharpe ratio is 6.54 times larger than the Sharpe ratio of 0.16 for the US stock market during the same time period, whereas this ratio reached only 0.12 from 1926 until 2017. The Sharpe ratios of credit category specific returns decrease monotonically when credit risk increases, ranging from 1.85 to 0.34.

We revisit the calculated portfolio level returns series to estimate how much commonly used factor models explain the performance of marketplace loans. Investors investing in marketplace lending loans are exposed to three primary risks: Interest rate risk, prepayment risk, and credit risk. In the following, we apply various commonly used factor models both from the equity and fixed income markets. Our results show that the abnormal performance of LC loans is not driven by the chosen risk factor model. Thus, traditional risk factors only explain the performance of marketplace loans at small extent.

To show the robustness of our results, we apply different factor models on our LC loan return series. Then, we show that our assumptions related to discount rate, i.e., using the interest rates of newly issued loans to discount scheduled payments, are robust by showing that the performance is unaffected if we replace these discount rates with discount rates calculated using credit card ABS yields. Second, we show that the results are also unaffected if we use nominal loan balances as our proxies for prices. Finally, in unreported test, we revisit our conservative evaluation approach on the default spread of LC loans, and assume direct defaulting after three missed payments. The results of these regressions, especially the highly statistically significant alphas, allow us to consider marketplace lending as an attractive asset class.

Table 5 depicts our analytical results using the Fama-French 3-factor (1993, 1996) and 5-factor models (2016) with and without the Carhart (1997) momentum factor. This analysis allows us to show how big proportion of LC performance can be explained by standard equity factors. We also consider standard fixed income factors such as the default spread (the return on Baclays Corporate bond index minus the return on Barclays Treasury bond index), and the term spread (the return on 5Y Treasury bonds minus the return on 1M Treasury note).[18] [19]

The results show that standard factors can only explain small proportion of the performance of LC loans. The alphas are in the range of 36 to 40 bps per month depending on the specification, and always highly statistically significant. The most significant factors are the market factor and momentum. Both are significantly positive in every specification. Even though market beta is significant, its value is very close to zero. The significance of momentum seems to be partly driven by its exceptionally low performance in 2009, as unreported test results show that the estimated coefficient is only half of the full sample coefficient and insignificant if we exclude observations before 2010. All other factors are insignificant. In general, the explanatory power of all factor models is low, with the highest R^2 being 0.18.

Table 6 depicts the similar results by different credit categories. The results show that alphas are in the range of 40 to 44 bps, but that the alpha of the credit category with the highest

[18] We also tested whether our results are affected if we also control the return of short-term bonds (1-3 years to maturity) and unreported results confirm the robustness of our results.
[19] We use Newey West standard errors with 12 lags. Unreported tests show that the results are robust to different lag lengths, i.e., from 0 to 36.

risk is only 31 bps. However, the differences in abnormal performance are not statistically significant. All alphas except the EFG alpha are highly statistically significant. The significance of alphas decreases monotonically consistent with the increasing risk. The significance of risk factors varies a lot depending on the credit category. For example, market betas are positive and significant in credit categories with medium risk, and momentum is positive and significant in high credit risk categories. The term spread is also significantly negative in Category A.

Table 7 depicts the regression results based on return series in which the values of loans are estimated using credit card ABS yield based discount rates. Our results show similar abnormal performance as above confirming the robustness of our main specification. Alphas are approximately 40 bps to 44 bps and highly statistically significant. The default spread is significantly positive. The significance of other factors varies a lot depending on the model specification. The market beta is usually positive but changes its sign to negative when fixed income factors are controlled for. Momentum is usually significantly negative. All other factors are insignificant. The explanatory power of all factor models is higher than in Table 5.

Table 8 shows that our earlier credit category-specific results are robust. Monthly alphas are in the range of 43 bps to 49 bps, except that the alpha of the credit category with the highest risk is only 28 bps. All alphas are statistically significant, though the alpha of EFG is only borderline significant. The statistical significance of alphas is almost monotonically decreasing in credit category, i.e., Category A has a little bit lower *t*-statistic than Category B. Note than none of the differences in alphas between categories are statistically significant. The market betas are positive but significant only for the credit category with the lowest risk. The default spread is positive and significant in most of the credit categories.

Finally in Table 9, we also consider the performance of LC loans based on return series where we assume that the value of the loan is equal to the remaining nominal loan balance. Similar results as above confirm the robustness of our results. Alphas are ranging from 39 bps to 41 bps depending on the specification and are always statistically highly significant. The momentum factor has a significantly positive beta. All other factors are insignificant.

In sum, the performed factor analysis shows that the abnormal performance of the LC return series cannot be eliminated with any considered factor model. In overall, the considered factor models only explain small proportion of the variation in LC returns. Interestingly, the alpha is always highly statistically significantly positive.

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 transactions. We argue that the innovative feature of marketplace lending is that it provides a different distribution channel for profit: The generated abnormal returns are redistributed among *both* the borrowers and the lenders engaging in marketplace lending, as opposed to being captured *only* by traditional financial institutions, such as banks. We selected Lending Club to perform our analysis, as this platform is the biggest marketplace lending platform in the US in terms of annual transaction volume.

Our findings proves the existence of substantial abnormal returns of personal loan portfolios, generated via marketplace lending. The average monthly return is 0.40% and average monthly volatility is 0.36%. The Sharpe ratios available from LC loans are as high as 1.02, and those are decreasing monotonically by credit category, ranging from 1.85 to 0.34.

The abnormal returns of these personal loan portfolios are more analogous to the potential for private equity funds to generate abnormal performance. If our findings on substantial abnormal returns 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). We expect therefore 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 these abnormal returns, since personal loans in marketplace lending would reach an equilibrium with other fixed income securities.

Recent signals of the market, however, indicate turbulences and the growing shadow of distrust in these investments (Financial Times, 2017). High performance might be needed to compensate investors to take default risk of LC as a company. Ever since its IPO, the market value of LC stocks, as well as the likelihood of investing into LC's issued loans was put on a rollercoaster, indicating a rather skeptical resonance of the market on LC's operations (TMR, 2016). In addition, the news of an internal fraud, leading to the resignation of the CEO and founder Renaud Laplanche in May 2016, have overshadowed its prosperous growth.

Our analysis is based on the whole spectrum of personal loans. Therefore, we might consider performing a more detailed analysis in the future, segmenting the performance analysis along different credit categories. Furthermore, by random sampling we could define different portfolio strategies and show the effect of diversification on loan performance. Our current results on the whole data set prove lower performance attached to riskier categories, so an optimal strategy to reach good performance might be against broad diversification. This hypothesis needs, however, further investigation. Based on the redistribution of abnormal returns, an interesting question is to explore the optimal win-win strategy for all stakeholders involved.

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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. Risk-adjusted performance of 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 factors used in the regressions include the value-weighted CRSP stock market index return in excess of the risk free rate, R_m-R_f, the Fama-French size (*SMB*), value (*HML*), profitability (*RMW*), and investment factors (*CMA*), the Carhart momentum factor (*MOM*), *Default Spread* (return on Baclays Corporate bond index – return on Barclays Treasury bond index), and *Term Spread* (return on 5Y Treasury bonds – return on 1M Treasury note). 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	**0.0038**	**0.0037**	**0.0036**	**0.0036**	**0.0037**	**0.0038**	**0.0039**	**0.0040**
	(4.36)	(4.35)	(4.42)	(4.83)	(4.50)	(5.01)	(5.16)	(5.74)
R_M-R_F		**0.0167**	**0.0222**	**0.0282**	**0.0190**	**0.0238**	**0.0184**	**0.0265**
		(2.16)	(2.09)	(2.17)	(2.25)	(2.31)	(2.44)	(2.03)
SMB			-0.0150	-0.0162	-0.0189	-0.0187		-0.0243
			(-0.78)	(-0.93)	(-0.89)	(-0.93)		(-1.14)
HML			-0.0137	-0.0012	-0.0180	-0.0006		-0.0102
			(-1.37)	(-0.12)	(-1.52)	(-0.05)		(-0.90)
Mom				**0.0197**		**0.0198**		**0.0160**
				(4.07)		(3.70)		(3.02)
RMW					-0.0313	-0.0308		-0.0249
					(-1.05)	(-1.01)		(-0.81)
CMA					0.0152	-0.0008		0.0072
					(0.70)	(-0.04)		(0.30)
Default Spread							-0.0328	-0.0276
							(-1.01)	(-0.99)
Term Spread							-0.0689	-0.0744
							(-1.67)	(-1.71)
N	111	111	111	111	111	111	111	111
R^2		0.044	0.063	0.119	0.078	0.132	0.097	0.182

Table 6. Regressions of Lending Club returns by credit category

This table shows the results of regressions by Lending Club (LC) assigned credit categories. 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. In the regressions, the credit category-specific monthly index return for LC loans in excess of the risk-free rate, R_L-R_f, is regressed on various sets of risk factors. The factors used in the regressions include the value-weighted US stock market index return in excess of the risk free rate, R_m-R_f, the Fama-French size (*SMB*), value (*HML*), profitability (*RMW*), and investment factors (*CMA*), the Carhart momentum factor (*MOM*), *Default Spread* (return on Baclays Corporate bond index – return on Barclays Treasury bond index), and *Term Spread* (return on 5Y Treasury bonds – return on 1M Treasury note). 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	A	B	C	D	EFG
Alpha	**0.0040**	**0.0040**	**0.0044**	**0.0044**	**0.0040**	0.0031
	(5.74)	(15.26)	(7.29)	(5.06)	(3.81)	(1.77)
R_M-R_F	**0.0265**	0.0067	**0.0225**	**0.0333**	0.0295	0.0180
	(2.03)	(1.24)	(2.87)	(2.81)	(1.40)	(0.64)
SMB	-0.0243	0.0022	-0.0022	-0.0344	-0.0386	-0.0352
	(-1.14)	(0.24)	(-0.15)	(-1.73)	(-1.11)	(-0.88)
HML	-0.0102	0.0096	-0.0119	-0.0107	-0.0266	-0.0239
	(-0.90)	(1.26)	(-1.04)	(-0.72)	(-1.13)	(-0.68)
Mom	**0.0160**	-0.0013	0.0115	0.0134	**0.0235**	**0.0246**
	(3.02)	(-0.29)	(1.85)	(1.39)	(2.76)	(2.27)
RMW	-0.0249	0.0042	-0.0098	-0.0277	-0.0691	-0.0636
	(-0.81)	(0.24)	(-0.30)	(-0.80)	(-1.42)	(-1.21)
CMA	0.0072	0.0049	0.0155	0.0064	0.0179	-0.0143
	(0.30)	(0.40)	(0.72)	(0.23)	(0.41)	(-0.21)
Default Spread	-0.0276	-0.0027	-0.0134	-0.0541	0.0137	-0.0572
	(-0.99)	(-0.29)	(-0.78)	(-1.55)	(0.35)	(-1.03)
Term Spread	-0.0744	**-0.0258**	-0.0505	-0.0751	-0.0968	-0.0473
	(-1.71)	(-2.03)	(-1.72)	(-1.81)	(-1.46)	(-0.58)
N	111	111	111	111	111	111
R^2	0.182	0.097	0.112	0.165	0.180	0.079

Table 7. The robustness of risk-adjusted performance: discount rate assumption

This table shows that the risk-adjusted performance of Lending Club loans is robust to different discount rate assumption. That is we estimate the value of the loan using credit card ABS yield based discount rates instead of discount rates determined by LC assigned interest rate on all newly issued loans in the same narrow credit category. The risk-adjusted performance is determined using 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 factors used in the regressions include the value-weighted US stock market index return in excess of the risk free rate, R_m-R_f, the Fama-French size (*SMB*), value (*HML*), profitability (*RMW*), and investment factors (*CMA*), the Carhart momentum factor (*MOM*), *Default Spread* (return on Baclays Corporate bond index – return on Barclays Treasury bond index), and *Term Spread* (return on 5Y Treasury bonds – return on 1M Treasury note). 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. 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**	**0.0042**	**0.0044**
	(6.34)	(5.83)	(5.51)	(5.16)	(7.67)	(7.11)	(6.70)	(8.17)
R_M-R_F		0.0199	0.0319	0.0270	0.0224	0.0189	**-0.0175**	-0.0102
		(1.07)	(1.29)	(1.19)	(1.31)	(1.14)	(-2.38)	(-1.09)
SMB			-0.0089	-0.0079	-0.0179	-0.0181		-0.0208
			(-0.84)	(-0.77)	(-1.40)	(-1.40)		(-1.51)
HML			-0.0517	-0.0619	-0.0449	-0.0577		-0.0323
			(-1.63)	(-1.79)	(-1.48)	(-1.73)		(-1.64)
Mom				**-0.0159**		**-0.0146**		-0.0014
				(-2.47)		(-2.14)		(-0.23)
RMW					-0.0572	-0.0576		-0.0427
					(-1.27)	(-1.27)		(-1.21)
CMA					-0.0283	-0.0165		-0.0223
					(-0.73)	(-0.45)		(-0.53)
Default Spread							**0.1447**	**0.1220**
							(3.25)	(3.16)
Term Spread							-0.0427	-0.0491
							(-0.56)	(-0.67)
N	111	111	111	111	111	111	111	111
R^2		0.037	0.124	0.146	0.163	0.181	0.244	0.314

Table 8. The robustness of performance regressions by credit category

This table shows that the performance of Lending Club loans by credit category is robust to different discount rate assumption. That is we estimate the value of the loan using credit card ABS yield based discount rates instead of discount rates determined by LC assigned interest rate on all newly issued loans in the same narrow credit category. The Lending Club assigned 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 single category EFG. The risk-adjusted performance is determined using regressions in which the credit category-specific monthly index return for LC loans in excess of the risk-free rate, R_L-R_f, is regressed on various sets of risk factors. The factors used in the regressions include the value-weighted US stock market index return in excess of the risk free rate, R_m-R_f, the Fama-French size (*SMB*), value (*HML*), profitability (*RMW*), and investment factors (*CMA*), the Carhart momentum factor (*MOM*), *Default Spread* (return on Baclays Corporate bond index – return on Barclays Treasury bond index), and *Term Spread* (return on 5Y Treasury bonds – return on 1M Treasury note). 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	A	B	C	D	EFG
Alpha	**0.0044**	**0.0043**	**0.0049**	**0.0049**	**0.0044**	0.0028
	(8.17)	(9.43)	(10.26)	(7.20)	(4.67)	(1.92)
R_M-R_F	-0.0102	**-0.0250**	-0.0218	-0.0051	-0.0047	-0.0042
	(-1.09)	(-2.42)	(-1.77)	(-0.45)	(-0.34)	(-0.22)
SMB	-0.0208	0.0061	0.0013	**-0.0343**	-0.0314	-0.0316
	(-1.51)	(0.45)	(0.12)	(-2.41)	(-1.22)	(-1.00)
HML	-0.0323	-0.0220	-0.0327	-0.0315	**-0.0515**	-0.0336
	(-1.64)	(-1.02)	(-1.25)	(-1.38)	(-2.52)	(-0.95)
Mom	-0.0014	**-0.0164**	-0.0034	-0.0063	0.0053	0.0122
	(-0.23)	(-2.38)	(-0.53)	(-0.61)	(0.63)	(1.20)
RMW	-0.0427	-0.0132	-0.0344	-0.0428	-0.0784	-0.0629
	(-1.21)	(-0.49)	(-0.92)	(-1.55)	(-1.41)	(-1.23)
CMA	-0.0223	-0.0365	-0.0204	-0.0226	-0.0003	-0.0304
	(-0.53)	(-0.86)	(-0.48)	(-0.40)	(-0.01)	(-0.41)
Default Spread	**0.1220**	**0.1462**	**0.1414**	0.0973	**0.1673**	0.0782
	(3.16)	(5.37)	(4.15)	(1.89)	(3.32)	(1.73)
Term Spread	-0.0491	-0.0218	-0.0353	-0.0442	-0.0560	-0.0414
	(-0.67)	(-0.45)	(-0.55)	(-0.62)	(-0.62)	(-0.45)
N	111	111	111	111	111	111
R^2	0.314	0.387	0.326	0.229	0.312	0.118

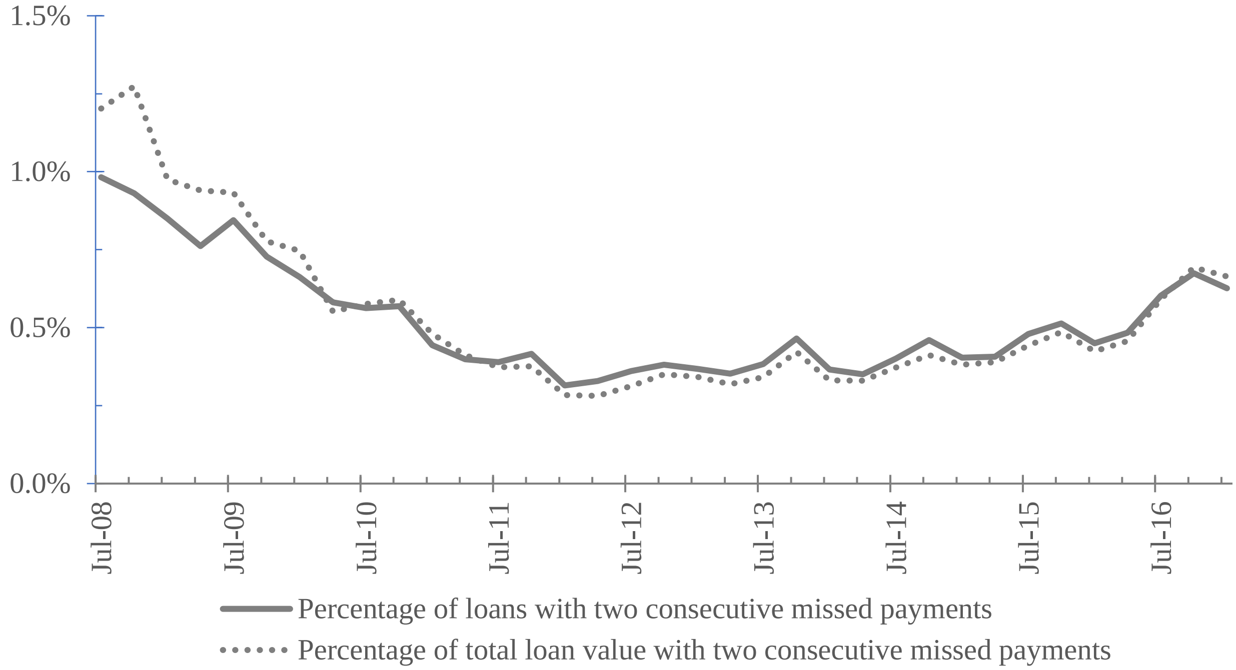
Table 9. The robustness of risk-adjusted performance: the estimated value of the loan

This table shows that the risk-adjusted performance of Lending Club loans is robust to different assumptions related to the value of the loan. Here, we assume that the value of the loan is equal to the outstanding loan balance instead of estimating it as a discounted sum of remaining scheduled payments where discount rates are determined by LC assigned interest rate on all newly issued loans in the same narrow credit category. The risk-adjusted performance is determined using 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 factors used in the regressions include the value-weighted US stock market index return in excess of the risk free rate, R_m-R_f, the Fama-French size (*SMB*), value (*HML*), profitability (*RMW*), and investment factors (*CMA*), the Carhart momentum factor (*MOM*), *Default Spread* (return on Baclays Corporate bond index – return on Barclays Treasury bond index), and *Term Spread* (return on 5Y Treasury bonds – return on 1M Treasury note). 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 bolded.

Category	All	All	All	All	All	All	All	All
Alpha	**0.0040**	**0.0039**	**0.0039**	**0.0039**	**0.0040**	**0.0040**	**0.0040**	**0.0041**
	(5.33)	(5.27)	(5.41)	(5.86)	(5.48)	(6.04)	(5.94)	(6.70)
R_M-R_F		0.0083	0.0140	0.0186	0.0116	0.0151	0.0098	0.0163
		(1.33)	(1.67)	(1.79)	(1.65)	(1.79)	(1.74)	(1.70)
SMB			-0.0202	-0.0211	-0.0242	-0.0240		-0.0268
			(-1.43)	(-1.62)	(-1.50)	(-1.57)		(-1.59)
HML			-0.0104	-0.0009	-0.0134	-0.0005		-0.0051
			(-1.26)	(-0.10)	(-1.34)	(-0.04)		(-0.48)
Mom				**0.0149**		**0.0147**		**0.0129**
				(3.22)		(3.12)		(2.97)
RMW					-0.0269	-0.0265		-0.0235
					(-1.20)	(-1.14)		(-1.09)
CMA					0.0143	0.0024		0.0063
					(0.71)	(0.12)		(0.28)
Default Spread							-0.0181	-0.0131
							(-0.59)	(-0.52)
Term Spread							-0.0317	-0.0372
							(-0.86)	(-0.95)
N	111	111	111	111	111	111	111	111
R^2		0.017	0.050	0.101	0.069	0.117	0.037	0.136

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

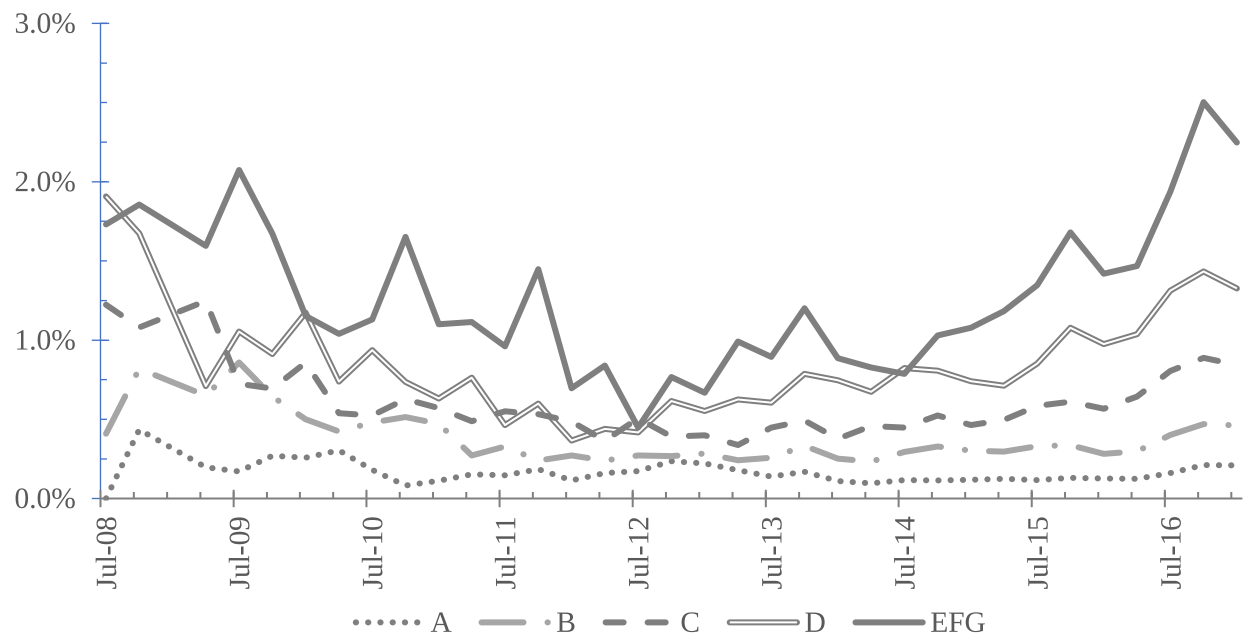
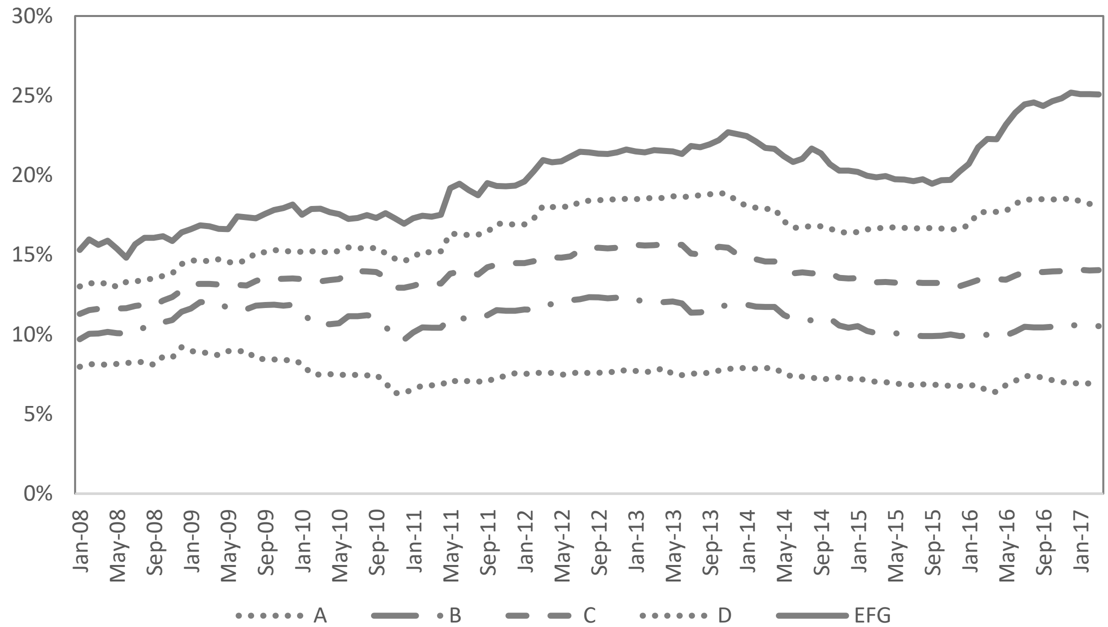


Figure 1. Panel A of the figure shows equal-weighted and value-weighted default rates for Lending Club (LC) loans. Default is defined as two consecutive missed payments. The solid black line is the number of loans with two consecutive missed payments as a percentage of the total number of active loans.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

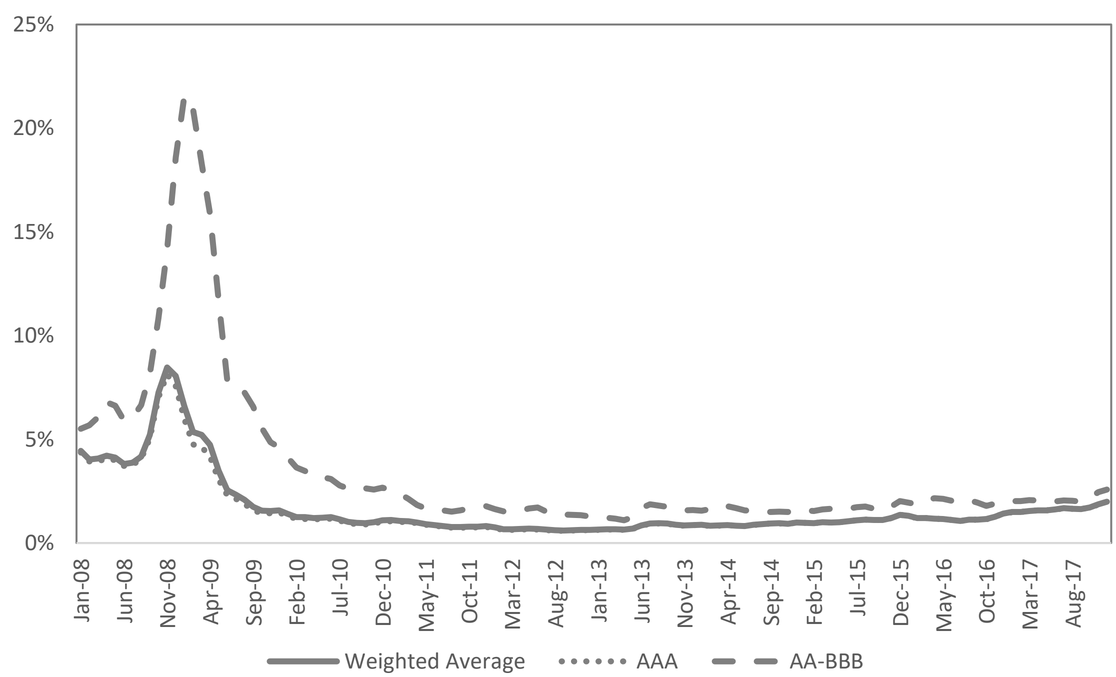


Figure 2. Panel A of this figure shows the average interest rate, equal-weighted, for newly issued Lending Club (LC) loans by rating category for each month of loan issuance. Panel B shows the value-weighted yields of credit card asset backed securities on a monthly basis.

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