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This paper uses a unique dataset from Lending Club (LC), the largest online lender in the U.S, to analyze the consequences of income rounding in terms of loans performance. We find that rounding of income by a borrower may indicate a bad outcome for a loan. Borrowers with a rounding tendency are more likely to default and less likely to prepay than borrowers with more accurate income reporting. Furthermore, investors are not compensated for the extra risk associated with rounding. Borrowers who misreport income by means of rounding obtain lower interest rates and larger loans with longer maturity than those who do not round. These results are consistent across various specifications and sub-samples.

Keywords: Peer-to-Peer (P2P) lending, Rounding, Misreporting, Performance

JEL Code: D12, G02, G20

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1. Introduction

Peer-to-peer lending (P2P) is an online process where borrowers and lenders meet directly. Online platforms provide individuals with alternative source of finance where they can shop freely for borrowing and investment opportunities with increased convenience and lower cost. However, this cost efficiency may result in a questionable credit check process and increased risk of fraud.[1] The peer-to-peer lending industry started in 2005 and ever since online platforms are steadily becoming an important part of the credit market. Although online platforms are growing at an increased pace, there has not been a proper unified regulatory framework for the industry. Furthermore, the absence of a proper background check inherently increases the risk of information falsification. Marketplace users are more likely to misreport personal information either by mistake or intentionally.

In this paper, we study the prevalence of income misreporting by means of rounding in the online market. We offer an insight into the effect of behavioral biases on the performance of online borrowers using a unique dataset from Lending Club (LC), one of the largest US-based peer-to-peer platforms. Our data contain information on almost 10 million loan-month observations pertaining to about 673,000 loans. It allows us to observe the monthly performance of loans originated between 2008 and 2015. Furthermore, it gives detailed information on borrowers' credit and loan characteristics.

This paper relates to several strands of literature. First, the existence of rounding has been established in self-reported data with extra spikes in the data observed at numbers ending in zero (Pudney 2008, A'Hearn et al. 2009, Manski and Molinari 2010). Furthermore, the predilection for round numbers is evident in the stock market and analysts' forecasts (Herrmann and Thomas 2005, Bollen and Pool 2009, Dechow and You 2012). Behavioral literature attributes rounding behavior to an availability heuristic, number preference, recall error, and lack of information (Tversky and Kahneman 1973, Tarrant et al. 1993, Ormerod and Ritchie 2007).

[1] Although marketplace lenders usually pull applicants' credit files from credit agencies, this could differ for self-reported data as they may not verify all personal data (e.g., income, employment status) reported by applicants.

In an unregulated market, it is expected that rounding is a predominant phenomenon, particularly when it is associated with increased benefit for the individual. The level of income can be a determining factor in lending decisions; therefore, it is the variable most susceptible to misreporting. Rounding behavior may be associated with unobserved borrowers' risk; Gerardi et al. (2010) suggest that cognitively constrained borrowers and those with low numerical ability may experience worse loan outcomes. In this paper, we specifically focus on the impact of income rounding on loans' performance in the online market. Self-reported data do not usually give exact information about the extent of rounding (Manski and Molinari 2010). However, a significant number of applicants who round their income, may distort the distribution of income (Czajka and Denmead 2008). This may create several spikes in the reported income at rounded values. We observe extra spikes around income multiples of $5,000 in our sample, therefore, we consider $5,000 as our main rounding heuristic. Financially ill-informed borrowers are more likely to round, as they may be less precise than those who are more financially experienced. Therefore, the propensity to round may be a function of borrowers' financial expertise. We find that borrowers with a long credit history are less likely to round their income. This pattern is apparent across different modes of rounding.

Our analysis also relates to the literature on the performance of loans. Most studies of performance focus on the impact of various loan and borrowers' characteristics in the mortgage market (Clapp et al. 2006, Danis and Pennington-Cross 2008, Keys et al. 2010, Demyanyk and Hemert 2011). We define loans as delinquent if in a given month they are 31-120 days late in payment, default or are charged off. Our results for the binary outcome model suggest that rounding may result in worse loan performance. The occurrence of rounding significantly increases the probability that a current loan become delinquent in a given month. Furthermore, we categorize borrowers in two groups: those who are more likely to round into those who make errors in their recall of earnings, whom we term "recallers" and those who strategically round, here termed "opportunists". This grouping is based on borrowers' homeownership and credit risk. The results indicate that rounding by more financially stable borrowers is not associated with worse performance, while rounding by individuals with less stable income as well as higher risk borrowers have a positive impact on loans' delinquency.

Additionally, the volatility of changes in monthly credit score can be a measure of borrowers' uncertainty. Our findings suggest that borrowers who are likely to round their income figures experience higher monthly fluctuations in their credit score than those who may have reported precise figures. We employ a competing risk model to complement our findings for the binary outcome model and to account for different loan outcomes. We find that rounding is significantly associated with worse outcomes. Borrowers who round their income are more likely to end up in delinquency than to stay up-to-date with their payments. One way to mitigate the consequences of rounding is to compensate investors for the extra risk. We find that loans are not priced in a way that reflects the risk associated with rounding. Borrowers who round their income have a lower interest rate than those who do not round. This is also observed for the non-price term of loans; misreported borrowers have larger loans and longer maturity.

The study currently closest to our paper is Garmaise (2015). While Garmaise (2015) studies the performance of mortgage borrowers who over-report their asset level, we focus on the outcome of income rounding. In the lending process, income may be a signal of borrowers' ability to make payments and thus, have an effect on loan terms. Furthermore, we focus on online loans where misreporting is highly likely. To the best of our knowledge, this paper is the first to investigate misreporting in peer-to-peer lending using a complete loan dataset.

The rest of the paper proceeds as follows. In the next section, we provide an overview of the peer-to-peer market. In section 3, we discuss the related literature on loan performance and the psychology of rounding. Section 4 gives an overview of the data used with descriptive statistics. Section 5 illustrates the specification used in the course of our analysis. We discuss results in section 6. Finally, section 7 concludes.

2. Peer-to-Peer industry

The peer-to-peer industry started in 2005 with the launch of Zopa, the first online marketplace, in the UK.[2] A year later, the US joined the industry with the launch of Prosper followed by Lending Club (LC). By the end of 2015, LC has facilitated around $16 billion in loan originations of which $3.3 billion were through issuance of loans' notes, $5.5 billion certificates issued by trusts, and $7.2 billion invested by institutional investors through whole loan sales.[3] In 2015, LC issued around $8.5 billion loans, which are nearly double the loans originated in 2014. PwC (2015) estimates that the online market may reach $150 billion or more by 2025.

Marketplace lenders distinguish themselves from conventional banks in a number of ways. Internet-based platforms may reach under-served segments that are usually difficult for banks to finance. In addition, the decision-making process in online platforms is expeditious, owing to the implemented data and technology driven assessment models. Due to the online nature of these platforms, they are cost efficient because of lower overhead and transaction costs. This cost saving is then passed to the end-user. Furthermore, online lenders are highly transparent, as most loan data are publicly available for marketplace users to analyze and take their investment decisions. More importantly, online platforms provide investors an opportunity to diversify their risk across different types of loans and various platforms. Similarly, borrowers usually do not rely on a single investor and thus have greater chances of being funded. Finally, the ease and convenience of the credit process make online marketplaces appealing to most users (PwC 2015).

However, this ease of lending is accompanied by inherent risk. Since most marketplaces do not put their own capital at risk, investors are the ones who bear the whole loss in case of default (Li 2015).[4] As with any online activity, there is an increased risk of fraud, cyber-security, and identity theft. Online platforms may have the incentive to understate the risk associated with online lending, which may mislead marketplace users (Verstein 2011). Moreover, the credit check process in online lending could be

[2] https://www.zopa.com/about [Accessed 07 June 2016].
[3] http://ir.lendingclub.com/Cache/c33047201.html [Accessed 07 June 2016].
[4] However, online lenders report all default and late payment cases to the credit bureaus.

doubtful, as most platforms do not verify all information provided by the applicants, which may explain the low underwriting costs in online markets (Carney 2016). Marketplace users are exposed to illiquidity risk as only some platforms provide access to secondary market.[5] Therefore, users face higher default risk as notes can only be transferred to lenders on the same platform and if lenders could not reach an appropriate price, they are obliged to hold those notes until maturity (Verstein 2011, Moenninghoff and Wieandt 2013). Lastly, the virtual aspect of the relation between marketplace users can be a cause of mistrust in the online process.

In the US, the regulation of marketplaces has been controversial. Each loan issued through marketplace lenders has to register as a security with the U.S Securities and Exchange Commission (SEC). The SEC regulation has been criticized as highly rigorous and thus unable to cope with the rapidly innovating industry. Furthermore, it is claimed that this imposes an extra burden on marketplace lenders rather than providing them with a properly regulated environment.[6] In a proactive move, the US Department of Treasury has requested marketplace lenders and analysts to provide information about their business model to allow better understanding of the growing industry.[7] Most of the responses received called for initiating an independent regulating body that fully grasps the fundamentals of the online industry.

3. Literature Review

3.1. Performance of Loans in Peer-to-Peer Lending

The peer-to-peer industry is evolving and the research in this area is still scarce. We contribute to the growing peer-to-peer literature by providing empirical evidence on how the behavioral aspect of marketplace users may affect loan's performance. The first stream of literature investigates the performance of online loans relative to the borrower's credit characteristics. The most critical aspect that concerns investors in the lending process is whether a loan will end up in default or not. Emekter et al. (2015) find

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[5] Investors in LC and Prosper have only access to *FOLIOfn*, an online secondary market.
[6] Describing the SEC regulations as an "ill-fitting framework", Verstein (2011) discusses how the SEC regulation might be considered as a risk to the new industry and its possible consequences.
[7] https://www.treasury.gov/press-center/press-releases/Pages/jl0116.aspx [Accessed 07 June 2016].

significant disparity in credit characteristics between defaulted and current loans. Further, revolving line utilization, debt-to-income ratio and credit score significantly predict default. Comparing the calculated theoretical and assigned interest rate by LC, Emekter et al. (2015) find that the price of high-risk loans is not enough to reimburse investors in case of default. Moreover, Serrano-Cinca et al. (2015) demonstrate that the credit score given by LC is the most significant predictor of default. Theoretically, the credit score should be the best predictor of a borrower's default. However, using data from Prosper, Iyer et al. (2015) provide evidence that the predictability power of the interest rate outperforms the credit score by 45 percent.

Beside the credit characteristics of debtors, the mechanism of the online platform may have an effect on the default rate. For instance, Prosper allows users to form online borrowing groups where members can endorse and invest in each other's loans. On the one hand, Freedman and Jin (2014) find that loans to a group are more likely to default and less likely to prepay than those to individuals. Moreover, they find that being a group member and getting endorsement from a friend are associated with a lower interest rate and higher probability of funding. On the other hand, Everett (2015) finds that loans listed with a group affiliation tend to have a lower default rate than those without group links.

The second strand of literature focuses on analyzing the role of soft information in the peer-to-peer market and its impact on the success of loan funding. Soft information can be an important factor in investors' decision to fund a loan or not (Dorfleitner et al. 2016).[8] Several findings support the existence of discrimination in online platforms. Pope and Sydnor (2011) use applicants' photographs from Prosper to determine applicants' demographic characteristics. They argue that black borrowers are less likely to receive funding and that they were charged interest 60-80 points higher than did white applicants. Interestingly, lenders discriminate against the elderly and give preference to female applicants. Lin et al. (2013) provide further evidence of discrimination against men applicants.[9] On the contrary, employing several proxies of funding success from a German platform, Barasinska and Schäfer (2014) failed to find such discrimination

[8] Dorfleitner et al. (2016) analyze the effect of misspelled words, text length and positive words in loan applications on funding probability.

[9] Ravina (2012) obtains similar results in support of taste-based discrimination, she conclude that there is presence of the beauty effect using data from Prosper.

between female and male applicants. They argue that discrimination may be platform rather than market specific.

Information asymmetry may be a prevalent problem in the online market due to the anonymity of borrowers, which may put lenders' investment at risk (Yum et al. 2012, Emekter et al. 2015). However, the requirement for borrowers to share more financial and personal information can mitigate this risk (Feng et al. 2015). Accordingly, Freedman and Jin (2008) find that the average funding rate by Prosper has increased since it started asking borrowers to disclose more information. Social networking such as group borrowing can be another way of reducing information asymmetry in the online market; due to their shared liability, group leaders may act as an effective monitoring mechanism (Yum et al. 2012, Freedman and Jin 2014). Moreover, having online friendship ties can act as a signal of the borrower's quality and thus, may mitigate adverse selection and improve loan performance (Lin et al. 2013). However, Freedman and Jin (2014) find that this tool has drawbacks as investors may misinterpret the borrower's quality due to being in a social network. Moreover, the virtual leadership of geographically dispersed teams may pose challenges to the monitoring process (Bell and Kozlowski 2002, Hill and Bartol 2015). We add to this part of the literature by arguing that having a proper verification process may protect marketplace users and thus help mitigating the problem of information asymmetry.

3.2. The Psychology of Rounding and Misreporting

It is recognized that numbers ending in zero and five are more attractive to individuals than those with other rightmost digits (see, e.g., Tarrant et al. 1993, Schindler and Kirby 1997), and that people tend to provide rounded responses to quantifiable questions even if an exact response is desired (Myers 1954). Behavioral theories suggest that the round number tendency arises due to the "availability heuristic" (Tversky and Kahneman 1973). Round numbers are cognitively accessible without the need to perform complex algorithms (Schindler and Kirby 1997), particularly in the case of large numbers (Kaufman et al. 1949). Moreover, rounding behavior may be caused by recall error (Wang and Heitjan 2008) or due to lack of information about the subject matter (Ormerod and Ritchie

2007). This implies that rounding behavior may indicate imprecision or uncertainty (Jansen and Pollmann 2001, Krifka 2002, Binder 2015).

Rounding occurs predominantly in surveys or self-reported data (Pudney 2008, Manski and Molinari 2010). This natural behavior may lead to unusual patterns in the observed data and consequently, result in erroneous inference about the subject matter. Development economists and demographers observe extra spikes around certain numbers when people report age (Myers 1954, Zelnik 1961, Gráda 2006, A'Hearn et al. 2009). They observe that rounding does not happen randomly, nevertheless, individuals exhibit preference for numbers ending in five or zero, which is explained by the "age heaping" phenomenon (A'Hearn et al. 2009). Binder (2015) finds that nearly half of the responses about expected inflation rate exhibit heaping behavior around multiples of five. Pudney (2008) demonstrates that the distribution of households' expenditure significantly shows extra spikes at round responses. Furthermore, most of reported income data is rounded on one level or another (Schweitzer and Severance-Lossin 1996, Hanisch 2005). Zinn and Würbach (2015) show that heaping around multiples of 1,000 increases with higher income. Similarly, Schweitzer and Severance-Lossin (1996) find that there is variation in rounding within different income levels.

The financial market has also been subject to rounding (Niederhoffer 1966, Harris 1991, Grossman et al. 1997). Bollen and Pool (2009) find that the distribution of hedge funds returns contains a clear discontinuity around zero; they suggest it is an indication of manipulation.[10] Herrmann and Thomas (2005) find analysts' forecasts for earnings per share persistently use 5-cent intervals. Additionally, they find that analysts who show evidence of heaping behavior tend to provide less accurate predictions. Dechow and You (2012) argue that rounding occurs when analysts do not have enough motive to exert more effort to obtain accurate information. Aitken et al. (1996) demonstrate that traders in the Australian stock exchange have a strong preference for prices ending in zero. Our paper contributes to the behavioral finance literature by providing evidence of the prevalence and consequences of rounding in the online market.

[10] Carhart et al. (2002) and Agarwal et al. (2011) present further evidence supporting manipulation in hedge and mutual funds.

One would expect misreporting or manipulation to be prevalent when it is associated with better outcomes for the individual. For instance, hedge fund managers may have a greater incentive to manipulate performance reports as investors evaluate funds based on their progress and managers' appraisal is usually based on the fund's performance (Asness et al. 2001, Ben-David et al. 2013). Ben-David et al. (2013) support this claim by finding significant occurrence of manipulation in hedge funds that have more incentives to enhance their position compared to competitors. Moreover, managers may be motivated to manage corporate earnings upwards in order to maintain past performance, meet analysts' forecasts and avoid losses (Degeorge et al. 1999). In the same way, individuals may manipulate information within loan applications such as rounding income in order to increase the odds of receiving funding (Dorfleitner and Jahnes 2014). Importantly, misreporting has been associated with adverse outcomes. Garmaise (2015) shows that borrowers who systematically misreport personal assets above round number thresholds are more likely to become delinquent[11], and he concludes that the effect of misreporting is not reflected in the pricing of loans. We add to this part of the literature by offering evidence that borrowers who misreport by rounding their income tend to have better loan terms and that investors are not compensated for the extra risk.

This paper offers insights into the behavioral aspect of online borrowers by considering studies that suggest there is a strong human tendency toward rounding. In order to understand the impact of rounding, we examine the link between reported income figures and associated loan outcomes. Borrowers may report rounded figures due to lack of information about their current financial position. What kind of signals do borrowers with inaccurate financial information provide? Gerardi et al. (2010) and Garmaise (2015) suggest that borrowers who are considered less financially informed and more cognitively constrained are associated with worse loan outcomes. Taken together, this suggests that borrowers who report rounded income figures may have worse loan performance than those who do not round.[12]

[11] Piskorski et al. (2015), Griffin and Maturana (2016) find similar unfavorable performance for misreported borrowers in mortgage applications.

[12] This is considered in line with Garmaise's (2015) interpretation of the above round-number threshold assets reporting by mortgage applicants.

4. Data Description

4.1. LC Overview

In this paper, we use a unique dataset from LC, the largest marketplace lender in the US. The data enable us to observe around 673,000 online loans throughout their monthly credit cycle, giving us information on almost 10 million observations. In order for an individual to qualify for a loan with LC, they need to comply with certain requirements. LC borrowers must be above 18 years old and meet the platform's credit criteria. Normally, LC requires that applicants have a minimum FICO score of 660, a debt-to-income ratio of not more than 40% and a credit history for a minimum of 36 months.[13] Moreover, applicants must have been the subject of no more than five inquiries in the last six months and have in their credit profile at least two revolving accounts.[14]

If borrowers meet the eligibility criteria, LC offers them a fixed interest rate based on the assigned credit grade. The loan grades on LC range from A1 to G5 with a base interest rate between 5.32% and 30.99%.[15] Additionally, the maximum amount of loan that a borrower can apply for is $35,000 with a maturity of either three or five years.[16] Potential investors may decide to fund parts of the loan, usually in increments of $25, based on their assessment of the loan's characteristics and borrower's credit history. LC investors are usually able to view each borrower's credit history online. If there are enough investors willing to fund the loan, an intermediate bank originates the loan in agreement with the platform. In the final step of the lending process, the borrower's monthly payment less servicing and other associated fees is distributed across investors.[17] If the borrower fails to make payment on time, LC will attempt to recover the payments due. In case of successful collection, LC charges investors either 18% of the amount recovered if no legal action were taken or 30% of hourly lawyer fees. On the

[13] FICO scores are claimed to be "the most-used credit bureau scores in the world… the standard measure of US consumer credit risk. They are used by lenders, rating agencies and the secondary market" (FICO 2015).
[14] https://www.lendingclub.com/fileDownload.action?file=Clean_As_Filed_20140822.pdf&type=docs [Accessed 07 June 2016].
[15] https://www.lendingclub.com/public/rates-and-fees.action [Accessed 07 June 2016].
[16] LC charges borrowers origination fees of from 1.11% to 5.00%, which is paid when the loan is issued.
[17] LC charges investors 1% service fee of any borrower's payment.

other hand, LC does not charge borrowers if they decide to repay the loan before its due date.

As part of the online application, applicants report their annual income beside other personal information. LC does not state a preference for whether the figure provided is actual or approximate. Thus, there is a high chance that borrowers misreport their income figures by providing rounded numbers. Furthermore, LC does not necessarily verify income and employment information for all applicants. If LC has targeted loan applicants for verification, it may verify either that their stated income is within 10% of actual income or their employment status. In both cases, LC grants applicants the loan. However, the first case falls in the "income verified" category and the latter falls in "income source verified" category. If LC chooses not to carry any verification on the borrower's stated income, the loan is regarded as "not verified" and is granted.[18] In the investor agreement, LC does not guarantee the accuracy of information provided by borrowers: rather they say that they carried out reasonable efforts to verify borrowers' identity (Shubber 2016). Moreover, in their prospectus LC states clearly that there is high risk in investing in their notes as they may contain "unverified" or "inaccurate" information.[19]

LC argues that they do not carry out income verification for all borrowers as it would result in a more cumbersome process and inconvenience to customers. Furthermore, they claim that the performance of both verified and unverified loans is substantially the same. However, what happens if reporting income rounded only to the nearest dollar results in a worse loan performance? According to LC's policy, in this case the borrower is not penalized and is granted the loan since the reported income is still within 10%.

[18] https://www.lendingclub.com/public/income-verification.action [Accessed 07 June 2016].

[19] https://www.lendingclub.com/fileDownload.action?file=Clean_As_Filed_20140822.pdf&type=docs [Accessed 07 June 2016].

4.2. Descriptive Statistics

The LC dataset gives information about each borrower's credit history and loan characteristics obtained at the time of issuance of loans. Further, the data enable us to examine monthly performance of online loans that originated in the period between 2008 and 2015. The monthly repayment status of each loan is disclosed, i.e. whether loans went into delinquency or default or were charged off. Additionally, we are able to consider borrowers' uncertainty by examining monthly changes in credit score. Over the observed period, LC has provided loans in 51 US states. Around 15% of the loans were originated to borrowers located in California. About 35% of the borrowers are non-prime, 56% prime and 9% fall in the super-prime category.[20] LC is noticeably growing over the sample period in regards of the number and amount of loans issued. It starts activities in 2008 with loans amounting to around $5,818,000. Around 41% of the loans in our sample amounting to $4,213,309,000, were issued in 2015.

Table 1 reports a detailed summary of statistics of most of the variables used in the statistical analysis. In the first part, we report loan specific characteristics. During the observed period, LC has originated loans with a total value of around $9,892,168,000 with a mean interest rate of about 13.4%. The average loan value is $14,695 and the loans' cycle is on average around 14 months. LC has recovered on average around $1,850 of defaulted loans' principal and investors paid on average $203 collection fees. Around 22 percent of borrowers prepaid on average 63% of total loan amount. On the other hand, 5 percent of borrowers failed to pay back on average 76% of their loan with a mean value of $11,814 and around 2% are late in payment.[21]

[20] We classify borrowers according to Elul and Tilson (2015) as follows: non-prime borrowers with FICO score between 620 and 679, prime borrowers with FICO score ranging between 680 and 739, and super-prime borrowers with FICO score between 740 and 850.

[21] This makes the average delinquency rate for the whole sample around 7%. We define delinquency rate as the fraction of loans that falls in first-time delinquency.

Table 1 Summary Statistics.

Variables	Mean	SD	25%	Median	75%	N
			Panel A: Loan Characteristics			
Loan Amount ($)	14,695	8,228	8,000	13,000	20,000	672,253
Interest Rate (%)	13.350	4.341	9.990	13.06	16.29	672,253
Loan Age (Months)	14.139	9.274	7	12	19	672,253
Delinquency rate (%)	7.388	26.158	0	0	0	672,253
Charged off Rate (%)	76.106	19.308	66.714	81.614	90.726	30,508
Charged off Amount ($)	11,814	7,661	5,670	10,267	16,533	30,508
Prepayment Rate (%)	63.104	28.057	44.757	70.668	85.899	146,545
Recovery Rate (%)	15.488	11.788	13.883	14.339	17.990	16,332
Principal Recovered ($)	1,849	1,889	603.29	1,354	2,586	16,332
Collection Fees ($)	203.473	347.305	8.550	30.295	297.315	16,332
			Panel B: Borrower Characteristics			
Annual income ($)	73,394	40,435	45,000	64,500	90,000	672,253
Credit Age (Months)	195	86.541	135	178	240	672,253
Average FICO Applied	696.510	29.639	672	692	712	672,253
Employment length (Years)	5.896	3.600	2	6	10	667,704
Debt-to-income (%)	18.083	8.137	11.95	17.64	23.87	672,253
Open credit lines	11.511	5.041	8	11	14	672,253
Total credit lines	25.375	11.491	17	24	32	672,253
No of Inquiries in last 6 Months	0.899	1.158	0	1	1	672,253
No of Delinquencies in last 2 years	0.297	0.724	0	0	0	672,253
Months since Last Delinquency	34.032	21.723	15	31	50	328,308
Months since Last Record	71.491	27.829	52	71	95	102,201
Last FICO SD	19.439	13.807	9.618	16.047	25.279	672,253
Mean of Last FICO	702.761	40.053	676.445	699.5	726.861	672,253

Notes. All observations are at loan level. Panel A includes variables that are related to loan characteristics. Loan amount is the funded amount by investors. Loan age is last observed month on the books for each loan. Delinquency rate is the fraction of loans that went into first-time delinquency. Charged off rate is the amount of loan that has been charged off in percentage. Charged off Amount is in dollar value. Prepayment Rate is the percentage of loan that has been prepaid by borrower before loan's maturity. Recovery Rate is the principal that has been recovered successfully by LC. Principal Recovered is in dollar amount. Collection Fees are paid by investors to LC for recovering part/all of the charged off amount. Panel B lists borrower's credit history and personal information at the time of loan's origination. Credit age is the length of credit history in months; it is the time difference between borrower's earliest credit line and loan's issue date at LC. Average FICO applied is the credit score at the time of application. Last FICO SD is the volatility of changes in borrower's monthly credit score. Other variables are related to the credit information pulled by LC at the time of origination.

Panel B of Table 1 reports borrowers' characteristics. A typical borrower at LC has at the time of the loan's origination an average debt-to-income ratio of 18%, a FICO score of 697 and credit history length of 195 months. In the six months preceding the application, an average borrower has in total 25 credit lines with 11 lines currently open and around one credit inquiry. An average of 34 months has passed since her/his last delinquency and 71 months since the last public record. S/he has annual income of $73,400 and an employment length of around 6 years. The 36-month loans constitute around 70% of the sample and 30% are 60-month loans, which were introduced and enter the sample in 2010.

5. Econometric Specification and Estimation

The dataset used in this paper is an unbalanced panel data as the exit time for each loan is different; a loan can be prepaid, delinquent or charged off before its due date. However, for the implementation we only use one observation for each loan, as the main variable of interest is constant for each month. In this section, we start by defining the two measures of loan performance. In the second part, we define the estimation of income rounding. Lastly, we describe other models used to measure the performance of loans.

5.1. Loan Performance

In the first part of the analysis, we follow Jiang et al. (2014), Arentsen et al. (2015), Schmeiser and Gross (2016), and use a probit model to test the prediction that rounding has adverse effects on loan performance:

$$Performance_i = \alpha + \beta\, \tilde{\mathrm{I}}_i + Borrower_i\gamma + Controls_i x + \varepsilon_i \tag{1}$$

Where $Performance_i$ is a binary variable of whether loan i becomes delinquent for the first time compared to loans that did not experience delinquency at any point. This is measured by loan delinquency. The available data do not state exactly how many days the loan has been delinquent; rather we have a loan status of 31 to 120 days.[22] Therefore, we define loans as delinquent if they are 31-120 days late in payment, default or are charged off. We also measure $Performance_i$ by the volatility of monthly changes in the credit score, which can serve as an indicator of borrower's credit deterioration (Agarwal et al. 2006). $\tilde{\mathrm{I}}_i$ is an indicator variable for whether the reported annual income is rounded to the nearest multiples of 5,000. According to Binder (2015), a dummy variable of rounding can be a simple measure of uncertainty. In the above model, we consider all loans, active and terminated. We further narrow our sample and run the model for only

[22] Most of the literature concerned with mortgage loan performance tends to define a loan as delinquent if it is 60 days late in payment or more (Keys et al. 2010, Demyanyk and Hemert 2011). However, we are not able to differentiate these loans, as the data only enable us to observe delinquency as a status of 31-120 days late in payment.

loans that are terminated through either paying back or charging off. This allows us to check whether results are driven by active loans. In our sample, around 30% of the loans has been terminated with 16% charged off and 84% ended their cycle by paying back.

Lenders usually assign a credit grade for each loan based on a credit risk model that distinguishes borrowers who are more likely to make payments on time and fully repay loans (Crook et al. 2007). This model is partially based on the borrower's credit report. Good credit borrowers are expected to have low debt-to-income ratio, long credit history, long employment duration and other previous successful credit lines. These borrowers are expected to be more prompt on their payments, therefore, $Borrower_i$ is a set of borrowers' credit characteristics. While examining the impact of rounding on loan performance, we control for a number of variables. $Controls_i$ is a vector of control variables that include origination year to account for any variation in the performance of specific loan cohorts. Additionally, we control for different types of borrowers by credit score groups in order to solely capture the risk of rounding and ε_i is an error term.

5.2. Rounding Estimation

If borrowers are cognitively constrained, one will find an overrepresentation of zero as number ending in numerical responses (Schindler and Kirby 1997, Kuo et al. 2015). Dehaene and Mehler (1992) attribute the overrepresentation of numbers ending in zeros to the saliency of round numbers. This overrepresentation may distort the income distribution by creating extra spikes at rounded values (Czajka and Denmead 2008). Figure 1 shows that there is apparent heaping in the distribution of income around the multiples of $5,000.[23] Therefore, we use $5,000 as our rounding heuristic.

[23] This interpretation is common in studies concerned about heaping in the observed data (Pudney 2008, Binder 2015). Further, Pope et al. (2015) carry out a graphical analysis to determine round numbers as focal points.

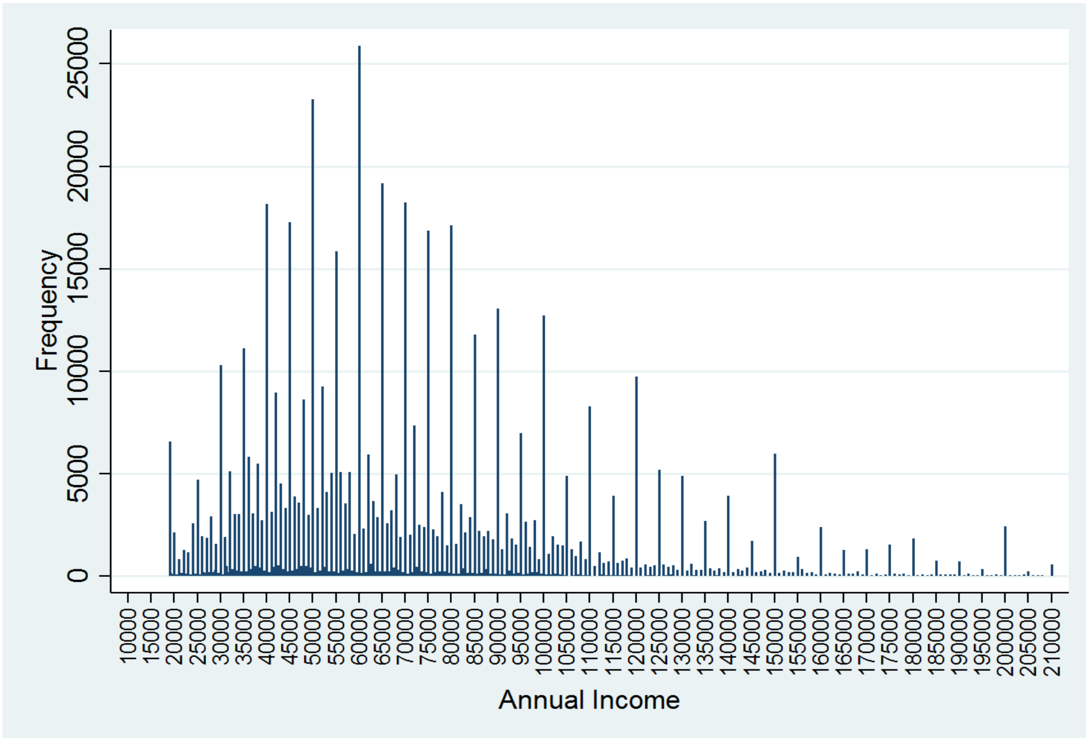

Fig. 1. Frequency of Annual income.

Based on the graphical interpretation, we adopt a modified specification of Garmaise (2015) model in order to identify borrowers with rounded income figures. Annual income is normalized to the nearest multiples of 5,000, as follows:

$$\mathrm{I} \ = Annual\ Income - \ round(Annual\ Income, 5{,}000) \tag{2}$$

$$\tilde{\mathrm{I}}_{(1,0)} \begin{cases} 1 & \text{If } \ \tilde{\mathrm{I}} = 0 \\ 0 & \text{If } \ \tilde{\mathrm{I}} \neq 0 \end{cases} \tag{3}$$

Where $\tilde{\mathrm{I}}$ is an indicator of whether the reported income is likely to be rounded to the nearest multiples of 5,000 or not. A normalized income of zero implies that the reported income is a rounded figure (Garmaise 2015). In our sample, around half of borrowers stated income amounts that is rounded to the nearest multiple of $5,000. The tendency toward rounding can be a function of borrowers' financial expertise. Borrowers with longer credit history are expected to be more financially informative and thus, are more likely to provide a more accurate figure. Further, rounding over different threshold can vary with income level.

$$\mathrm{P}(\tilde{\mathrm{I}} = 1) = F(\text{ Credit Age, Income }, x) \tag{4}$$

Equation (4) is estimated via a probit model, we consider multiples of \$500, \$1,000, \$5,000 and \$10,000 as different threshold of rounding. Credit Age is the length of borrowers' credit history and Income is in quartile groups. x is vector of control variables.

5.3. Competing Risk Model

The second set of analysis in this paper takes into consideration that a loan does not necessarily fall in only two categories but can have various outcomes. Borrowers may show inconsistency in their transition from one status to another. They may fail to make payments on time at any given point in their life but may recover and get back on track with their payments. Therefore, we distinguish between loans that were in delinquency but recovered later in their cycle and either went into continuous payment status or paid off from those who failed to recover and went into a worse status. Danis and Pennington-Cross (2008) argue that it is critical for any predictive model to account for the different levels of delinquency and to identify their competing risk natures. Therefore, we employ a multinomial logit model to account for these different outcomes.[24] The multinomial specification does not only account for the probability of several events occurrence but also consider the competing risk feature of these outcomes (D'Addio et al. 2005). Loans can be terminated through either paying off or default. These events are considered mutually exclusive events, since the occurrence of one naturally prevents observing the other event (Calhoun and Deng 2002).

Therefore, Equation (1) is re-estimated using multinomial logit model, where the probability of observing outcome j for loan i is

$$P(Y_i = j|x_i) = \frac{e^{\beta'_j x_i}}{1 + \sum_{k=1}^{J} e^{\beta'_j x_i}} \qquad for \quad j \in \ [State_1, State_2, State_3] \tag{5}$$

[24] Calhoun and Deng (2002) give a comparative analysis between different statistical models that are usually used in analyzing mortgage loan terminations and explain why a discrete choice model like multinomial logit model is the most appropriate for loan termination analysis.

Where x_i is a vector of independent variables for loan i and β_j' is a vector of coefficients for each state of j. The possible states are current, delinquency, and paying off, respectively. Furthermore, in order to test the robustness of our model, we estimate a number of alternatives for model (5) by observing other possible states. We consider that a borrower may settle the loan and prepay it before the due date.

In the last part of our analysis, we conduct several models to see if loans to borrowers who were associated with worse performance are adequately priced and their behavior is taken into account in loan terms. The price and non-price terms are normally used to manage and monitor borrower's risk (Strahan 1999). Furthermore, information asymmetry problems in risky lending practices may be mitigated by having restrictive covenants (Ortiz-Molina and Penas 2008). For the pricing term, it is expected that risky borrowers be charged higher interest rate to compensate lenders for the extra risk of default. Additionally, risky borrowers may face tighter non-price terms by having shorter maturity and small loan to limit investors' risk exposure.

6. Discussion

6.1. Income Rounding and Loan Performance

In this section, we estimate the consequences of rounding in terms of loans that went into delinquency for the first time in their cycle compared with those who did not experience delinquency throughout their credit cycle. These tests take into consideration the previous argument that borrowers who misreport their income by means of rounding may have imprecise financial information and hence, may experience worse performance than those who report a more accurate figure. As expected, Table 2 shows that the propensity toward rounding decreases significantly for more experienced borrowers across different rounding thresholds. Furthermore, rounding varies significantly for different income levels, controlling for loans' origination year.

Table 2 Rounding probabilities.

	Round 500	Round 1000	Round 5000	Round 10000
Credit Age	-0.036***	-0.037***	-0.046***	-0.031***
	(0.001)	(0.001)	(0.001)	(0.001)
Income Quartiles				
2nd Quartile	0.020***	0.018***	0.015***	0.114***
	(0.001)	(0.001)	(0.002)	(0.001)
3rd Quartile	0.063***	0.066***	0.177***	0.098***
	(0.001)	(0.001)	(0.002)	(0.001)
4th Quartile	0.039***	0.051***	0.186***	0.179***
	(0.001)	(0.001)	(0.002)	(0.002)
Control Variables				
Origination year	Yes	Yes	Yes	Yes
N	672,253	672,253	672,253	672,253

Notes. This table presents the average marginal results of probit estimations. Where the dependent variable is one if the observed normalized income is rounded to the nearest thresholds. We consider multiples of 500, 1,000, 5,000 and 10,000. The covariates used are the length of credit history in months and a dummy variable of income quartiles, where the 1st income quartile is the base group. We control for loans' origination year. Robust standard errors are reported in parentheses.
$***$, $**$ and $*$ denote statistical significance at the 1%, 5% and 10% levels, respectively.

The first specification in Table 3 shows the results for probit estimation that a loan will subsequently experience delinquency for the first time. We report the average marginal effects calculated around mean points using all loans in our dataset. As expected, the results indicate that the occurrence of rounding is associated with adverse outcomes. Borrowers who report a rounded income are almost 0.4 percent more likely to experience first-time delinquency than those who reported a more accurate figure, controlling for the credit score groups and origination year. Given that the average delinquency rate for the whole sample is 7 percent, detecting borrowers with misreported income may decrease the average delinquency rate by 0.4 percentage points. For borrowers' characteristics, we find that a 1 percent increase in the debt-to-income ratio is associated with 0.2 percent increase in the probability that a current loan will experience delinquency. Further, having a long history of credit decreases the probability of delinquency and an increase in the number of delinquencies in the last 2 years increases the possibility of delinquency.

Table 3 Rounding and loan performance.

	Model (1)		Model (2)	
	Delinquency		Log (SD of FICO)	
	(1)	(2)	(3)	(4)
Round Income	0.004***	0.012***	0.012***	0.028***
	(0.001)	(0.002)	(0.002)	(0.005)
Borrower Characteristics				
Debt-to-income ratio	0.002***	0.006***	0.002***	0.008***
	(0.000)	(0.000)	(0.000)	(0.000)
Credit Age	-0.017***	-0.012***	-0.170***	-0.113***
	(0.001)	(0.003)	(0.003)	(0.006)
Months since Last Delinquency	-0.003***	-0.007***	-0.039***	-0.023***
	(0.001)	(0.002)	(0.001)	(0.004)
No of Delinquencies in last 2 years	0.003***	0.006**	0.029***	0.025***
	(0.001)	(0.002)	(0.001)	(0.004)
No of Inquiries in 6 Months	0.009***	0.013***	-0.004***	0.002
	(0.000)	(0.001)	(0.001)	(0.002)
Open Credit Lines	-0.003**	-0.007*	0.006	0.006
	(0.001)	(0.003)	(0.003)	(0.006)
Employment Length	-0.004***	-0.010***	-0.006***	-0.016***
	(0.000)	(0.001)	(0.000)	(0.003)
Control Variables				
FICO Groups	Yes	Yes	Yes	Yes
Origination year	Yes	Yes	Yes	Yes
Sample	Full sample	Terminated loans	Full sample	Terminated loans
N	326,478	85,861	324,122	86,716

Notes. The first model in this table reports the results of the average marginal effects from probit regression. In the first column, the dependent variable is one if the loan experience delinquency for the first time at any point of their cycle and the base category is loans that did not encounter delinquency throughout their credit cycle. In the second column, the dependent variable is one if the loan is terminated through charging off rather than paying back. The covariates include variables discussed in equation (1). Credits age, months since last delinquency, open credit lines and employment length are in natural logarithms. The second model contains estimates for the OLS model where the dependent variable is the natural logarithm of the standard deviation of monthly changes in the credit score. The covariates are the same as the first model. Both models are estimated for the full sample (column 1 & 3) and the sample of terminated loans column (2 & 4) with control variables including Credit score groups and loans' origination year. Robust standard errors are reported in parentheses.
$***$, $**$ and $*$ denote statistical significance at the 1%, 5% and 10% levels, respectively.

In the second specification, equation (1) is re-estimated for terminated loans. The same pattern is observed for the rounding indicator. As described in the second column of Table 3, borrowers with misreported income are more likely to end up in default than to repay in full. The probability of a loan terminating through default for borrowers with rounded income is 1.2 percent higher than through normal payment. Similar to the whole sample findings, distinguishing borrowers who are more likely to give rounded income during the application process may decrease the average delinquency rate by 1.2 percentage points.

The volatility of changes in monthly FICO can be a measure of borrowers' uncertainty. In the second model in Table 3, our dependent variable is volatility measured as standard deviation. The covariates are the same as in the first model. Borrowers with rounding tendency experience higher fluctuations in their monthly credit score. The results show that the occurrence of rounding is associated with a 1.2 percent increase in credit score volatility. For terminated loans, the volatility of changes is doubled, reaching around 3 percent for borrowers who have reported rounded income. FICO score can serve as a monthly indicator of the borrower's willingness to repay back; thus, our results imply that borrowers who have a tendency to round face higher uncertainty in their ability to make payments promptly. Furthermore, borrowers with long credit history and employment duration are less likely to encounter changes in their credit score. In summary, when considering different measures of borrowers' performance and uncertainty, we find that delinquency risk significantly increases when borrowers misreport by rounding their income.

Next, we advance our analysis by taking into consideration the reasons for rounding and identifying whether the effects of rounding are the same among different categories of rounders. We decompose rounding behavior into that of "opportunists" and that of "recallers" by differentiating between groups that may have the incentive to strategically round and those that do not. "Opportunists" are likely to be less stable and more risky, and therefore, rounding by these borrowers could be strategic in order to look more appealing to lenders, while "recallers" are likely to be more financially stable and have a good credit history. Rounding by recallers is likely to be due to recall error.

The "rounders" are grouped based on homeownership status. Unlike renters, homeowners are more geographically stable which in turn may affect many individuals' behaviors and thus there are major differences between owners and renters (DiPasquale and Glaeser 1999, Dietz and Haurin 2003). Furthermore, homeowners have higher life satisfaction, higher level of well-being and are happier than renters (Rohe and Stegman 1994, Rossi and Weber 1996, Rohe et al. 2002). Lastly, owners are considered better citizens; they are more politically and socially involved in local communities as they are less inclined to move and have more financial responsibilities (Rossi and Weber 1996, DiPasquale and Glaeser 1999, Dietz and Haurin 2003).

Table 4 reports the effect of rounding by different groups of "rounders" on loan's performance. In the first and third specification, we distinguish rounding by homeowners ("recallers") and renters ("opportunists"). We find that rounding by renters has a significant impact on loans' performance, but we do not find significant effects from rounding by homeowners. Borrowers who do round their income and are renters are about 1 percent more likely to experience first-time delinquency than renters who do not round. Furthermore, by limiting our sample only to loans that are terminated, we find that the probability of delinquency reaches about 2.5 percent. In the second and fourth specification, we further distinguish borrowers according to their credit score. Our results show that rounding by near-prime borrowers has a positive effect on loans' delinquency. The probability of delinquency for borrowers who round and are near-prime reaches 1.3 percent for the full sample and 3.3 percent for the sample of terminated loans. On the other hand, rounding by prime and super-prime borrowers does not have a negative effect on loans' performance. Super-prime borrowers who report a rounded income figure are almost 4 percent less likely to go into delinquency for the whole sample and about 8 percent for terminated loans.

Our results suggest that rounding may result in worse loan performance. This is consistent with Garmaise's (2015) findings for the default predictability of misreporting in the mortgage market and with Jiang et al. (2014) for the consequences of income falsification. But our results indicate that not all rounding will have a negative effect on loans' performance. Rounding by less risky and more stable borrowers is associated with lower chances of delinquency. On the other hand, rounding by borrowers who are considered more risky and may have higher incentives to strategically round is significantly associated with higher chances of experiencing delinquency. While traditional lenders may use some behavioral indicators to assess borrowers (Moulton 2007), the inconsistency in verifying self-reported data and the virtual aspect of the online market can make the situation more difficult. Therefore, distinguishing misreported borrowers and having a proper verification process of what the applicants self-report may help mitigate the risk of inaccurate disclosures in online lending.[25]

[25] Garmaise (2015) suggest that targeting some behavioral bias like rounding may help reduce the asymmetry information problem.

Table 4 Rounding and loan performance (subgroups).

	Delinquency (1)	Delinquency (2)	Delinquency (3)	Delinquency (4)
Home Ownership				
Round owner	-0.000		0.003	
	(0.001)		(0.003)	
Round rent	0.010***		0.026***	
	(0.001)		(0.003)	
Credit Score				
Round near-prime		0.013***		0.033***
		(0.001)		(0.003)
Round prime		-0.003***		-0.003
		(0.001)		(0.003)
Round super-prime		-0.037***		-0.079***
		(0.004)		(0.012)
Borrower Characteristics				
Debt-to-income ratio	0.002***	0.002***	0.006***	0.006***
	(0.000)	(0.000)	(0.000)	(0.000)
Credit Age	-0.018***	-0.018***	-0.016*	-0.015***
	(0.001)	(0.001)	(0.003)	(0.003)
Months since Last Delinquency	-0.004***	-0.004***	-0.009***	-0.008***
	(0.001)	(0.001)	(0.002)	(0.002)
No of Delinquencies in last 2 years	0.004***	0.003***	0.007***	0.007***
	(0.001)	(0.001)	(0.002)	(0.002)
No of Inquiries in 6 Months	0.009***	0.009***	0.015***	0.014***
	(0.000)	(0.000)	(0.001)	(0.001)
Open Credit Lines	-0.005***	-0.004***	-0.012***	-0.010**
	(0.001)	(0.001)	(0.003)	(0.003)
Employment Length	-0.004***	-0.004***	-0.009***	-0.010***
	(0.000)	(0.000)	(0.001)	(0.001)
Control Variables				
Origination Year	Yes	Yes	Yes	Yes
Sample	Full sample	Full sample	Terminated loans	Terminated loans
N	326,478	326,478	86,716	86,716

Notes. This table provides loan performance results for the decomposition of rounding by different groups for the full sample and for the sample of terminated loans. In the first and third model, borrowers who do round are differentiated according to their homeownership status (owners and renters). In the second and fourth model, rounded borrowers are decomposed according to their credit score. Borrowers are classified into credit groups according to Elul and Tilson (2015). Where the base category for each group is non-rounder and the list of covariates are the same as discussed in equation (1).
$***$, $**$ and $*$ denote statistical significance at the 1%, 5% and 10% levels, respectively.

6.3. Rounding and Loan Pricing

Borrowers may round their income to seem more desirable to lenders. Jiang et al. (2014) show that borrowers' income, with a major effect on loan terms and qualification, is the figure most subject to falsification. Thus, borrowers may alter their income figures in the hope of having higher loan amounts or lower interest rate. They may not have planned beforehand to misreport and may actually be willing to pay back the loan but will take the opportunity to receive better loan terms or increase their funding likelihood by rounding their annual income (Dorfleitner and Jahnes 2014).

Our results suggest that rounding is associated with severe adverse outcomes. It is therefore, critical to scrutinize whether lenders are aware of such misreporting ex ante and if the pricing terms adequately reflect the increased risk. Table 5 addresses this by analyzing the pricing terms reflected in interest rate and the non-pricing terms reflected in loan's size and maturity. The first two models are estimated via OLS regression and the last one via probit regression using the full sample and loans that completed their cycle, respectively. We control for the origination year and FICO groups as in previous models, except for the maturity model where we control only for FICO groups.

We find a number of differences when we compare the results for borrowers who do and those who do not round their income. The first specification shows that borrowers who tend to round their income are charged a significantly lower interest rate than non-rounder by twenty basis points and are associated with around an 8 percent increase in the loan's size. A similar pattern is observed for the terminated loans sample. Furthermore, borrowers who round their income are more likely to have a 60-month loan term; however, this is not significant if only completed loans are observed. In summary, borrowers who round have a lower interest rate, larger loans, and longer maturity than those who did not round. These results imply that LC does not account for the prevalence of rounding in either the pricing or the non-pricing loan terms. Furthermore, loans with income rounding tendency are not priced in a way that compensate investors for the extra delinquency risk.

Table 5 Rounding and Loan Terms.

	Interest		log (size)		Maturity	
	(1)	(2)	(3)	(4)	(5)	(6)
Round Income	-0.002***	-0.001***	0.078***	0.078***	0.008***	0.004
	(0.000)	(0.000)	(0.002)	(0.004)	(0.002)	(0.003)
Borrower Characteristics						
Debt-to-Income ratio	0.001***	0.001***	-0.002***	-0.002***	0.004***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Credit Age	-0.008***	-0.004***	0.195***	0.181***	0.049***	0.045***
	(0.000)	(0.000)	(0.003)	(0.006)	(0.002)	(0.004)
Months since Last Delinquency	-0.001***	-0.002***	-0.035***	-0.033***	-0.012***	-0.020***
	(0.000)	(0.000)	(0.002)	(0.004)	(0.001)	(0.002)
No of Delinquencies in last 2 year	0.000***	0.000	-0.020***	-0.018***	-0.008***	-0.012***
	(0.000)	(0.000)	(0.002)	(0.004)	(0.001)	(0.002)
No of Inquiries in 6 Months	0.008***	0.008***	-0.012***	-0.007***	0.006***	0.014***
	(0.000)	(0.000)	(0.001)	(0.002)	(0.001)	(0.001)
Open Credit Lines	-0.005***	-0.004***	0.242***	0.261***	0.045***	0.038***
	(0.000)	(0.000)	(0.003)	(0.006)	(0.002)	(0.004)
Employment Length	0.001***	0.001***	0.052***	0.051***	0.030***	0.025***
	(0.000)	(0.000)	(0.001)	(0.003)	(0.001)	(0.002)
Control Variables						
FICO Groups	Yes	Yes	Yes	Yes	Yes	Yes
Origination year	Yes	Yes	Yes	Yes	No	No
Sample	Full sample	Terminated loans	Full sample	Terminated loans	Full sample	Terminated loans
N	326,478	86,716	326,478	86,716	324,856	86,716

Notes. This table reports results from several regression of an indicator of rounding and other borrower characteristics on different loan terms. The results of the OLS model with interest rate as a dependent variable is presented in the first two columns for the full sample and terminated loans sample, respectively. Similarly, OLS results of the natural logarithms of loan amount are reported in the third and fourth columns. The average marginal results of a probit model where the dependent variable is 1 if loan's maturity is 60 month and 0 for 36 month is estimated in the last two columns. The regressions include origination and FICO groups as control variables for the first two models and only FICO groups for the last one. Robust standard errors are reported in parentheses.

$***$, $**$ and $*$ denote statistical significance at the 1%, 5% and 10% levels, respectively

6.2. Competing Risk Model

The competing risk model may provide additional insights as delinquent loans could either default or recover. Delinquency can be a turning point in loan's performance; a loan that is late in payment may eventually survive or enter a worse status like default. In this model, we amend our earlier definition of delinquency by adding a restrictive condition: loans that fall in the delinquency category are those that have experienced delinquency for the first time and failed to recover later. In contrast to the previous model, current and paid off loans include both borrowers who did not fail to pay at any point and those who experienced discrepancy in their payment status at time t but recovered at $t + n$ where n is the last observed month for each loan. Given that we have three discrete possible outcomes for each loan, the competing risk model is estimated via a multinomial logit specification with the same covariates as were used in equation (1).

The results for the competing risk model are consistent with the prediction that rounding behavior is associated more with inferior than with enhanced outcomes. The first model in Table 6 presents estimates for the full sample. Even after taking into consideration the volatility of transitions, borrowers with rounding behavior are significantly less likely to pay off loans. Furthermore, they are more likely to stay late in payment or enter a worse status. In the second model of Table 6, the option of prepayment is evaluated and the sample is limited only to terminated loans. The three possible outcomes are repayment, default, and prepayment, where the last is the base category.

The cost of prepayment is considered lower than default as investors only lose future interest payments, however, prepayment can imply that borrowers have enough liquidity to settle the loan. The likelihood that a loan will end up in default is significantly higher for borrowers who exhibit rounding behavior than it is for borrowers who are more accurate while reporting their income. They are significantly more likely to end their cycle through charging off than prepaying the loan. Furthermore, they are more likely to repay the loan at its due date, though the significance and magnitude of the repay coefficient is very small. The competing risk model confirms our results for the binary outcome model. Further, it proves that the occurrence of rounding is not only associated with an unfavorable loan outcome but also significantly lowers the likelihood that borrowers will pay back loans promptly.

Table 6 Competing Risk Model

	Model (1)		Model (2)	
	Delinquency	Paid off	Charged off	Paid off
	(1)	(2)	(3)	(4)
Round Income	0.033*	-0.062***	0.098***	0.043
	(0.015)	(0.010)	(0.019)	(0.030)
<u>Borrower Characteristics</u>				
Debt-to-Income ratio	0.022***	-0.021***	0.045***	0.015***
	(0.001)	(0.001)	(0.001)	(0.002)
Credit Age	-0.391***	-0.278***	-0.071**	0.219***
	(0.020)	(0.013)	(0.025)	(0.040)
Months since Last Delinquency	-0.034**	0.030***	-0.058***	-0.033
	(0.012)	(0.009)	(0.016)	(0.027)
No of Delinquencies in last 2 years	0.014	-0.038***	0.041**	0.001
	(0.011)	(0.008)	(0.015)	(0.027)
No of Inquiries in 6 Months	0.190***	0.104***	0.090***	-0.132***
	(0.006)	(0.004)	(0.008)	(0.014)
Open Credit Lines	0.015	0.070***	-0.053*	-0.114**
	(0.019)	(0.013)	(0.024)	(0.036)
Employment Length	-0.056***	0.018**	-0.074***	-0.005
	(0.009)	(0.006)	(0.011)	(0.019)
<u>Control Variables</u>				
FICO Groups	Yes	Yes	Yes	Yes
origination year	Yes	Yes	Yes	Yes
Sample	Full sample	Full sample	Terminated loans	Terminated loans
N	326,478	326,478	86,716	86,716

Notes. The estimates for the multinomial logit model are presented in this table. Observations are at loan level. The first model is estimated for the whole sample. The possible status for the first model are delinquency, paid off and continuous payment, where the latter is the reference category. The second model is evaluated only for loans that had a full cycle. The possible status are charged off, paid off and prepayment, where the latter is the reference category. The coefficients reported for dependent variables are a dummy variable for whether borrowers' normalized income is equal zero and other borrowers' characteristics at the time of loans' origination with control variables including Credit score groups and origination year. Robust standard errors are reported in parentheses.
$***$, $**$ and $*$ denote statistical significance at the 1%, 5% and 10% levels, respectively.

7. Conclusion

It is apparent that borrowing and lending habits are changing at an unprecedented rate. Marketplace lenders are becoming an important part of the credit market. However, the rules of the game as well as the terms of loans have to be stipulated. Online platforms have special characteristics that distinguish them from traditional lenders. However, there is an increased risk and higher chances of misreporting in marketplace lending due to the online nature of the process and the inconsistency in verifying the supplied personal information of users. Using loan data from LC, we have examined the consequences for loan outcomes of the tendency to round self-reported responses.

Our findings suggest that rounding behavior is prevalent in the online market and has severe adverse outcomes. Around half of borrowers in our sample have reported income that is rounded to the nearest multiple of $5,000. Furthermore, borrowers who are likely to report rounded income have higher chances of default compared to precise borrowers. The probability of first-time delinquency for borrowers with rounding tendency is 0.4 percent higher than those without. This percentage considerably increases for terminated loans; misreported borrowers are 1.3 percent more likely to end their loan cycle in default than paying back. Considering the volatility of changes in credit scores, we find that rounding is extensively associated with higher fluctuations, and rounding by more risky and less stable groups of borrowers is associated with worse loan performance.

We provide additional evidence of the adverse consequences of rounding by considering that a loan may experience first-time delinquency but borrowers may recover and stay up-to-date with their payment. Loans with rounded income are significantly less likely to pay off and more likely to experience first-time delinquency than to stay current. Limiting our sample to only completed loans we show that our results are consistent: borrowers who have rounded are less likely to prepay and more likely to end their loan cycle by being charged off. Lastly, by examining pricing and non-pricing terms of loan contracts, we show that investors are not compensated for the increased delinquency risk. The risk of misreporting income during the online application is not reflected in loans' pricing. Borrowers who may have misreported their income by rounding are charged lower interest rate by around twenty basis points. Furthermore, they tend to have larger loan amounts and longer maturity loans.

Our results suggest that misreporting income by means of rounding may play a role in loans' delinquency and that this could expose investors to extra risk, for which they are not compensated. This implies that there should be a more thorough check of the borrower's application, specifically for self-reported data. Ignoring the occurrence of rounding in the reported data may result in an invalid judgment about borrowers' creditworthiness. Finally, having a unified verification process that tries to provide investors with as much accurate information as possible may help securing the online lending process. This could be done by outsourcing the verification process to a third party similar to the credit scoring process. Lastly, using technology for process implementation can heavily reduce the burdens for users.

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Appendix (Not for publishing)

Table A1 Rounding and loan performance (Subsamples).

	Delinquency (1)	Delinquency (2)	Delinquency (3)	Delinquency (4)
Round Income	0.004***	0.005**	0.010***	0.018**
	(0.001)	(0.002)	(0.003)	(0.006)
Borrower Characteristics				
Debt-to-income ratio	0.002***	0.001***	0.005***	0.009***
	(0.000)	(0.000)	(0.000)	(0.000)
Credit Age	-0.015***	-0.027***	-0.013***	-0.030***
	(0.001)	(0.002)	(0.003)	(0.009)
Months since Last Delinquency	-0.003***	-0.003**	-0.007**	-0.000
	(0.001)	(0.001)	(0.002)	(0.005)
No of Delinquencies in last 2 years	0.003***	0.002	0.005*	0.014**
	(0.001)	(0.001)	(0.002)	(0.005)
No of Inquires in 6 Months	0.008***	0.010***	0.012***	0.010***
	(0.000)	(0.001)	(0.001)	(0.003)
Open Credit Lines	-0.004**	-0.005*	-0.007*	-0.033***
	(0.001)	(0.002)	(0.003)	(0.009)
Employment Length	-0.005***	-0.005***	-0.011***	-0.019***
	(0.001)	(0.001)	(0.002)	(0.004)
Control Variables				
FICO Groups	Yes	Yes	Yes	Yes
Origination year	Yes	Yes	Yes	Yes
Sample	Full sample 36 month loans	Full sample 60 month loans	Terminated loans 36 month	Terminated loans 60 month
N	228,462	98,016	67,114	19,602

This table presents the results of the average marginal effects from probit regressions for full sample and terminated loans sample the first two columns represent the results for the subsample of 36-month loans and the last two for 60-month loans. The list of covariates as described in equation (1). Robust standard errors are reported in parentheses. $***$, $**$ and $*$ denote statistical significance at the 1%, 5% and 10% levels, respectively.

Table A2 Rounding and loan performance (Subsamples).

	Log (SD of FICO) (1)	Log (SD of FICO) (2)	Log (SD of FICO) (3)	Log (SD of FICO) (4)
Round Income	0.013***	0.007	0.027***	0.028**
	(0.003)	(0.004)	(0.005)	(0.011)
Borrower Characteristics				
Debt-to-income ratio	0.002***	0.002***	0.007***	0.011***
	(0.000)	(0.000)	(0.000)	(0.001)
Credit Age	-0.171***	-0.185***	-0.122***	-0.110***
	(0.003)	(0.006)	(0.007)	(0.015)
Months since Last Delinquency	-0.040***	-0.034***	-0.023***	-0.011
	(0.002)	(0.003)	(0.005)	(0.009)
No of Delinquencies in last 2 years	0.029***	0.029***	0.026***	0.032***
	(0.002)	(0.003)	(0.004)	(0.009)
No of Inquires in 6 Months	-0.003**	-0.008***	0.000	-0.001
	(0.001)	(0.002)	(0.002)	(0.004)
Open Credit Lines	-0.000	0.006	0.004	-0.024
	(0.003)	(0.005)	(0.007)	(0.014)
Employment Length	-0.009***	-0.010***	-0.020***	-0.026***
	(0.002)	(0.003)	(0.003)	(0.007)
Control Variables				
FICO Groups	Yes	Yes	Yes	Yes
Origination year	Yes	Yes	Yes	Yes
Sample	Full sample 36 month loans	Full sample 60 month loans	Terminated loans 36 month	Terminated loans 60 month
N	226,773	97,349	66,470	19,391

This table presents the results of the average marginal effects from probit regressions for full sample and terminated loans sample the first two columns represent the results for the subsample of 36-month loans and the last two for 60-month loans. The list of covariates as described in equation (1). Robust standard errors are reported in parentheses. ∗∗∗, ∗∗ and ∗ denote statistical significance at the 1%, 5% and 10% levels, respectively.