Financial Decisions of Households

by

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Abstract

Left-digit bias refers to the tendency of individuals to focus attention on the left-most digit of numerical information when making decisions. This paper tests for the existence of left-digit bias in the consumer credit card market. Using a regression-discontinuity design, I find sharp increases in credit card repayments around $1,000 monthly balance thresholds. The estimated effect, an approximately $20 increase in repayment, translates to about 4.35 percent of the average payment. However, I find smaller effects on future repayment behavior and the amount of future purchases. Finally, I find the effect to be stronger in higher self-reported income groups.

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*As a disclaimer, this work reflects the author's independent research and does not necessarily reflect the views of the Consumer Financial Protection Bureau (CFPB) or the United States. All errors are my own.

1 Introduction

Credit cards are a significant source of household credit and liabilities in the United States, with over 70% of US consumers having at least one credit card (Federal Reserve Bank of Boston, 2013) and household debt totaling approximately $750 million in 2016 (Federal Reserve Bank of New York, 2016). Despite the magnitude of the credit card market, limited work exists to understand how consumers make credit card payment decisions.

In this paper, I explore discontinuities in consumers' payment behavior consistent with "left-digit bias," a term referring to people's tendency to place additional weight on the left-most digit of a number while partially ignoring digits to the right (Olsen, 2013). Relative inattention to subsequent digits can be demonstrated through decreased sensitivity to changes in magnitude that do not lead to a new left-most digit. For example, a consumer who exhibits left-digit bias will perceive an increase from $1,300 to $1,500 as smaller than one from $1,900 to $2,100. Using a large data set on monthly credit balances and payments that covers the majority of the credit card market, I find evidence consistent with this bias in credit card repayments. Specifically, there are sharp increases in credit card repayments around $1,000 monthly balance thresholds of approximately $20, or about 4.35% of the average monthly payment amount. I find little evidence of the effect on repayment and amount of additional purchases in the subsequent month. Finally, I find the effect to be stronger in the higher self-reported income groups.

This paper fits within a growing literature studying the influence of cognitive and attentional constraints on consumer behavior in the credit card market. One area of interest is the potential role of "anchoring effects," where consumer judgments are pulled toward salient numeric values (Kahneman and Tversky, 1974). Literature on credit cards has explored how consumers' credit card repayment decisions exhibit anchoring toward the minimum payment due. Specifically, anchoring effects are demonstrated in laboratory experiments in which participants report how much they would pay when seeing minimum payment information (Stewart, 2009; Navarro-Martinez et al., 2011). Anchoring is also found when studying actual repayment data. In a large analysis of general purpose credit cards, Keys and Wang (2016) find that 29% of accounts make payments near the minimum payment, of which at least 9-20% are estimated to be driven by anchoring. Other salient numeric values have been studied with more limited effects. In 2009, new regulations required credit card issuers to display, under certain circumstances, the payment amount required to fully pay off a debt in 36 months. Agarwal et al. (2014) find that these requirements increased the number of account holders making this payment amount by 0.5 percentage points, and Keys and Wang (2016) find that fewer than 1% of accounts adopted this suggested payment amount. Mounting evidence suggests an important role of psychological biases in credit card decision making amongst subsets of consumers. This paper provides some evidence of another potential source of behavioral bias, left-digit bias, in the consumer credit market.

Outside of the credit card market, the most closely related empirical paper to the current work is Lacetera et al. (2012), which shows evidence of left-digit bias in the wholesale used car market. These authors explore how prices for used cars change around 10,000-mile thresholds in odometer readings. They find that prices fall in a discontinuous manner around these thresholds; for instance, there is a larger price difference between cars with 59,500 and 60,000 miles than between cars with 60,000 and 60,500 miles. In a retail shopping setting, Ashton (2014) uses an experiment from Chetty et al. (2009) in which products are randomly assigned to have the tax-inclusive prices posted in a supermarket. Ashton (2014) finds that products for which the tax-inclusive price increased the left-digit experienced a larger decrease in demand than those that did not. Previous work observes left-digit bias in consumer shopping decisions while this paper explores the phenomena in a new setting.

Finally, left-digit bias is a specific example of a growing literature on limited attention in which consumers fail to fully incorporate all available information. Chetty et al. (2009) finds consumers respond differently to tax-inclusive versus tax-exclusive prices and Finkelstein (2009) shows electronic tolls make consumers less responsive to changes in toll costs. Bounded rationality models in macroeconomics posit "inattentive" consumers to explain empirical macroeconomic anomalies such as the insensitivity of aggregate consumption to income shocks (Reis, 2006) and interest rates (Gabaix, 2016). In these models, consumers make decisions sporadically as opposed to continuously or only when shocks to state variables become large. This paper briefly explores the possibility that left-digit bias may be a specific mechanism that triggers consumers to re-optimize decisions.

This paper proceeds with Section 2, which describes the monthly data set on credit card balances and payments used in this paper. Section 3 provides graphical evidence of the discontinuity around $1,000 thresholds and estimates the effect in a regression discontinuity design. Section 4 concludes with a discussion of the results and possible implications.

2 Data

This paper relies upon the Consumer Financial Protection Bureau (CFPB) Credit Card Database (CCDB).[1] The database contains de-identified account-level data on

[1]The CCDB is confidential supervisory information. The statistics in this paper are aggregated to maintain the confidentiality of the underlying data, consistent with the Bureaus confidentiality rules. The database does not contain any information on individual transactions nor can the same

monthly credit card balances, payments and fees from several of the largest credit card issuers from 2008 to the present, comprising 85 to 90 percent of credit card balances in the United States in a given year.[2] In this paper, I use a randomly selected 10 percent subset of the data.

Table B1 provides some aggregate summary statistics based upon the database. Most notably, the large differences between the means and median of monthly balances and payments suggest a high degree of skewness in the distribution. Keys and Wang (2016) provides additional descriptive analysis, noting that repayment patterns consist of three main types: those who pay the full amount each month, those who pay the near the minimum each month, and others whose behavior changes month-to-month. In approximately 33 percent of account-months, the account holder pays off the balance in its entirety. About 35 percent of the time, account holders pay near the minimum; the remaining 32 percent of periods fall somewhere in between. In this paper, I focus primarily on periods in which balances are not repaid in full.

In order to explore the effect of left-digit bias on repayment behavior, I restrict the sample to account holders with a balance remaining at the end of the month, referred to as "revolvers." In contrast to revolving accounts, some account holders have the balance completely paid off each month, referred to as "transactors." For transactors, the $\$1,000$ thresholds should not be salient since these account holders pay off the balance each month regardless of the amount. In addition to focusing on revolving accounts, I exclude accounts with balances greater than $\$11,500$. Balances above $\$10,000$ become exceedingly rare in the data, but I include a threshold above $\$10,000$ in order to evaluate whether the $\$10,000$ had an additional effect since "left-digit bias" might be even more salient at this threshold. Finally, I also exclude accounts

household or consumer be linked across accounts in the database.

[2]Based on estimates from Consumer Financial Protection Bureau (2015).

for which credit limits might confound the effect of left-digit bias. In particular, banks typically set credit limits, the maximum balance an account holder may accumulate, in $1,000 increments. This practice potentially complicates the analysis of left-digit bias since some accounts just below the $1,000 threshold will have lower credit limits than those just above the threshold. In order to account for credit limits, I restrict the sample to accounts with a credit limit at least $1,000 greater than the closest $1,000 balance threshold. For example, accounts balances between $500 and $1,499 must have a credit limit of at least $2,000 and accounts with balances between $1,500 and $2,499 must have a credit limit of at least $3,000. This sample restriction ensures that all accounts within a $500 bandwidth around the $1,000 cutoff will all have a credit limit at least greater than the same amount. Section 3.1 provides graphical results illustrating the smoothness of credit limits through the cut-off. After these restrictions, the resulting subsample of this data includes over 66 million account-month observations.

3 Results

3.1 Graphical Analysis

I begin with a graphical analysis of the discontinuity in credit card payments. For simplicity in exposition, I begin by examining the effect of left-digit bias solely around $1,000 and will then use the same process to aggregate the results in order to include the other thresholds ($2,000, ..., $11,000). In Section 3.2, I report results aggregated and by each threshold separately. As described in Section 2, for months in which an account has a balance within $500 of $1,000 (i.e., $500 to $1,500), I restrict the sample to revolvers who have a credit limit of $2,000 or more. Fig-

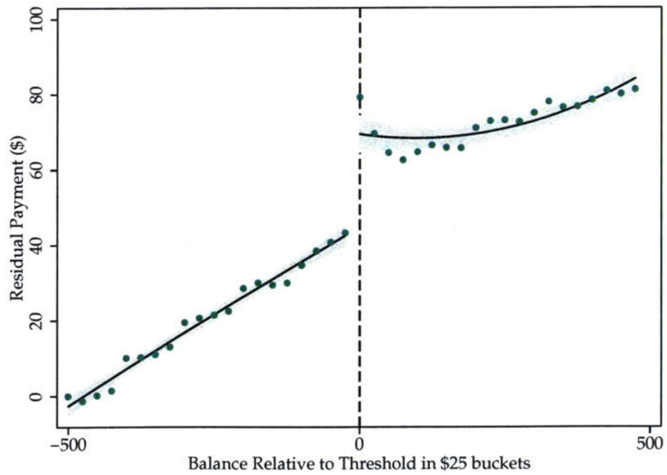

Figure 1: Credit Card Payment Amount in Dollars ($1,000 Threshold)

Notes: This figure plots the mean of total credit payments for the month within $25 bins of credit card balances away from the $1,000 threshold. Based on a random 10 percent sample of the Consumer Financial Protection Bureau (CFPB) Credit Card Database (CCDB). The sample is restricted to observations where accounts within a $500 window around a $1,000 threshold all have at least the same credit limit ($1,000 more than the threshold). Additionally, sample is restricted to accounts with a finance charge.

ure 1 shows the discontinuity in residualized credit card payments around $1,000. These are residualized payments because I have controlled for bank, month and other account observables to avoid confounding variables. Each point on the plot represents the average residualized payment amount of accounts in months where the credit card balance fell within half-open $25 intervals, i.e., [$500, $525), [$525, $550), ..., [$1,475, $1,500). Note that balances have been re-centered around the $1,000 threshold such that $500 becomes −$500 and $1,500 becomes $500. The vertical line indicates the $1,000 threshold, which when rescaled has been drawn at $0. Accounts immediately above the thresholds appear to pay approximately $20 to $40 more than those immediately below the threshold. The average payment for this sample was $367, so the effect translates to about 5% of the average payment.

Figure 2 generalizes this analysis across multiple thresholds, showing the discontinuity in residualized credit card payments aggregated across $1,000 thresholds from $1,000 to $11,000. As in the previous analysis, I restrict the sample to revolvers with

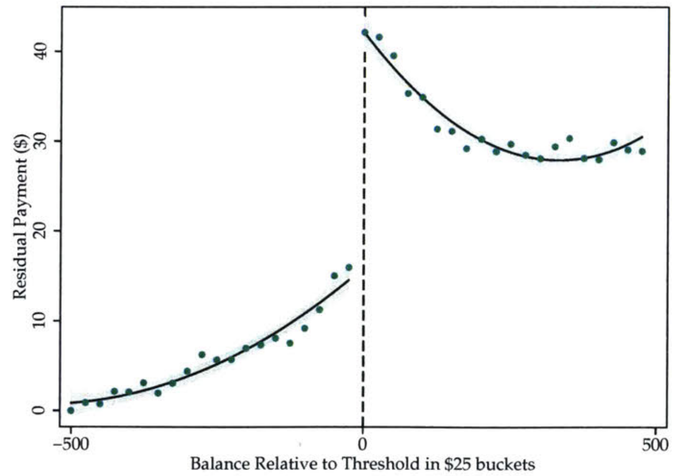

Figure 2: Credit Card Payment Amount in Dollars (Multiple $1,000 Thresholds)
Notes: This figure plots the mean of total credit payments for the month within $25 bins of credit card balances away from the a $1,000 threshold. Based on a random 10 percent sample of the Consumer Financial Protection Bureau (CFPB) Credit Card Database (CCDB). The sample is restricted to observations where accounts within a $500 window around a $1,000 threshold all have at least the same credit limit ($1,000 more than the threshold). Additionally, the sample is restricted to accounts with a finance charge and balances greater than $500.

a credit limit $1,000 more than the closest $1,000 threshold. Similar to Figure 1, I have re-centered balances around the nearest $1,000 threshold. Again, these are residualized payments because I have controlled for bank, month and other account observables. Each point in Figure 2 represents the average residualized payment amount of accounts in months where the credit card balance fell within half-open $25 intervals. Accounts immediately above the thresholds appear to pay approximately $20 more than those below the thresholds. The average payment for this sample was $459, so the effect translates to about 4.35% of the average payment.

It is possible that these results are driven by other characteristics of credit card account holders that differ discontinuously around the thresholds that affect payment behavior. I explore a few of these potential alternative explanations by plotting other characteristics across the thresholds. As discussed in Section 2, credit card issuers often set credit limits at round $1,000 thresholds, which would make credit limits potentially vary discontinuously. In other words, some borrowers below a $1,000 threshold cannot borrow as much as those above the threshold. This could be problematic for analyzing left-digit bias since presumably accounts with higher credit limits tend to be higher quality borrowers who make higher payments. In addition, consumers may accrue additional fees for incurring a balance slightly larger than their credit limit. Incurring such fees could cause consumers slightly above the $1,000 thresholds to make larger payments, which would potentially overestimate the effect of left-digit bias if their credit limit coincides with the $1,000 threshold. However, after ensuring all accounts in a $500 bandwidth around the threshold have at least a credit limit greater than $1,000 more than the threshold, credit limits appear to be relatively smooth across the threshold. Figure A1 plots analogous results to Figure 2, except with the dependent variable as the credit limit, which appears to not differ significantly across the $1,000 threshold. Also, the aforementioned restrictions ensure that accounts around the threshold will not be near their credit limit, mitigating concerns that the higher payments observed above the thresholds may be driven by avoidance of fees.[3]

Another source of concern comes from minimum payment formulas. In particular, credit card issuers often require account holders to make a minimum payment at the end of the month based on the balance accumulated on the account. Failure to make a minimum payment results in additional fees for the consumer, providing an incentive for consumers to make higher payments to avoid fees. Discontinuities in minimum fee structures around $1,000 would create identification problems for interpreting the discontinuity as left-digit bias. However, as discussed by Keys and Wang (2016), these formulas often take the form of the maximum between the percentage of the balance and interest owed and a fixed dollar amount that the payment amount cannot fall

[3]To my knowledge, credit card issuers do not set other balance-based fee structures near $1,000 thresholds besides credit limits. The existence of other fee structures around $1,000 thresholds would affect the interpretation of the discontinuities observed in this paper.

below. For the sample of revolvers considered in this paper, the minimum payment appears to be linearly related to the balance with no significant discontinuity around $1,000 thresholds. Figure A2 plots minimum payment required by the bank, which appears to be fairly smooth through the threshold. Finally, Figure A3 plots the credit score associated with the account. While it might not be expected for credit scores to vary discontinuously through the $1,000 thresholds, credit scores might reflect other characteristics of borrowers that cause them to make larger payments. Figure A3 shows that credit score of the account appears to pass through the cut-off continuously with very little variation. Throughout the entire plot, the values vary by at most five points. In each plot, the characteristics appear to pass through the cutoff continuously.

3.2 Regression Analysis

The following section reports estimates from the regression discontinuity depicted graphically in the previous section. In particular, I estimate the following locally-linear regression to quantify the discontinuity, aggregated over all of the thresholds,

$$\begin{aligned} \text{Payment}_{it} = \alpha &+ \gamma \text{Distance from Closest \$1,000 Threshold}_{it} + \beta D_{it} \\ &+ \rho \text{Distance from Closest \$1,000 Threshold}_{it} \times D_{it} \\ &+ \delta X_{it} + \varepsilon_{it} \end{aligned} \tag{1}$$

where $D_{it} \equiv \mathbb{1}\{\text{Distance from Closest \$1,000 Threshold}_{it} \geq 0\}$. Payment_{it} represents the dollar value of credit card payments made by account i in month t. As controls, X_{it}, I include the credit limit and credit score for account i in month t as well as bank and month fixed effects. Equation (1) assumes linearity on each side of the threshold, but allows the slope to vary on each side. Figures 1 and 2 suggest a quadratic term might capture the relationship between payment amount and balance on each side of the threshold more accurately. However, linearity in this case provides more conservative estimates of the effect. The results from this regression have been reported in Table 1. The first column omits controls. The second column includes bank and month fixed effects. Finally, the third column includes credit limit and credit scores. Each column results in an effect size of approximately \$20. In order to examine the differential effect of each threshold, \$1,000, ..., \$11,000, I estimate the discontinuity by each of the thresholds. In particular, I estimate the following equation,

$$
\begin{aligned}
\text{Payment}_{it} = & \sum_{j=1}^{11} \alpha_j \mathbb{1}\left\{\text{Nearest Threshold is \$j,000}\right\} \\
& + \sum_{j=1}^{11} \gamma_i \text{Distance from \$j,000 Threshold}_{it} + \sum_{j=1}^{11} \beta_j D_{itj} \\
& + \sum_{j=1}^{11} \rho_j \text{Distance from \$j,000 Threshold}_{it} \times D_{itj} + \delta X_{it} + \epsilon_{it} \qquad (2)
\end{aligned}
$$

where $D_{itj} \equiv \mathbb{1}\left\{\text{Distance from Closest \$j,000 Threshold}_{it} \geq 0\right\}$ and X_{it} has been defined similarly to Equation (1). Equation (2) assumes linearity across each side of each threshold, but allows for the slope to vary across thresholds and on each side of each threshold. Table 2 reports the results. Similar to Table 1, the first column omits controls. The second column includes bank and month fixed effects. Finally, the third column includes credit limit and credit scores. The results show that the effect varies across the thresholds. The largest coefficient appears at the \$5,000 threshold and somewhat decreases thereafter until reaching the \$10,000 threshold, where the effect size aligns more closely to the effect observed at the lower threshold amounts.

Table 1: The Impact of $1,000 Balance Discontinuities on Payment Amount

	(1)	(2)	(3)
$\mathbb{1}$ {Distance from Closest Threshold ≥ 0}	21.02***	20.98***	20.65***
	(0.282)	(0.280)	(0.274)
Current Credit Limit			0.0160***
			(0.0000506)
Current FICO			0.222***
			(0.00310)
Observations	66488179	66488179	65287755
R^2	0.001	0.005	0.046
Controls	No	No	Yes
Bank Fixed Effects	No	Yes	Yes
Month Fixed Effects	No	Yes	Yes

Estimates from the following equation:

$$\text{Payment}_{it} = \alpha + \gamma\text{Distance from Closest \$1,000 Threshold}_{it} + \beta D_{it}$$
$$+ \rho\text{Distance from Closest \$1,000 Threshold}_{it} \times D_{it} + \delta X_{it} + \varepsilon_{it}$$

where $D_{it} \equiv \mathbb{1}\{\text{Distance from Closest \$1,000 Threshold}_{it} \geq 0\}$.
Standard errors in parentheses clustered at the account level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Based on a random 10 percent sample of the Consumer Financial Protection Bureau (CFPB) Credit Card Database (CCDB). The sample is restricted to observations where accounts within a $500 window around a $1,000 threshold all have at least the same credit limit ($1,000 more than the threshold). Additionally, sample is restricted to accounts with a finance charge and balances greater than $500.

This is suggestive of an additional effect of left-digit bias at the $\$10,000$ threshold.

In addition to the effect on contemporaneous credit card payments, I explore the effect on future payments and accumulation of debt. Given the effect on contemporaneous payments, one might expect consumers to re-optimize their behavior in subsequent periods. Considering left-digit bias in terms of rational inattention models such as Reis (2006) and Gabaix (2016) would suggest that agents would recalibrate debt accumulation not just in one period. In contrast, a purely behavioral formulation of left-digit bias would not necessarily anticipate future behavior would be affected. The results in this paper suggest very little persistent effect of left-digit bias on future credit accumulation. In particular, Tables B2 and B3 estimate Equations (1) and (2), respectively, with the dependent variable of the credit card payment amount in the following month. With the exception of the $\$6,000$ threshold, the coefficients range

Table 2: The Impact of $1,000 Balance Discontinuities on Payment Amount

	(1)	(2)	(3)
$\mathbb{1}$ {Distance from Closest $1K $\geq$ 0}	19.65***	18.94***	18.89***
	(0.256)	(0.260)	(0.262)
$\mathbb{1}$ {Distance from Closest $2K $\geq$ 0}	26.81***	26.31***	26.31***
	(0.473)	(0.466)	(0.467)
$\mathbb{1}$ {Distance from Closest $3K $\geq$ 0}	25.45***	24.78***	24.80***
	(0.678)	(0.665)	(0.666)
$\mathbb{1}$ {Distance from Closest $4K $\geq$ 0}	23.64***	23.37***	23.33***
	(0.896)	(0.878)	(0.879)
$\mathbb{1}$ {Distance from Closest $5K $\geq$ 0}	29.75***	29.37***	29.15***
	(1.127)	(1.103)	(1.105)
$\mathbb{1}$ {Distance from Closest $6K $\geq$ 0}	19.22***	18.89***	18.81***
	(1.372)	(1.345)	(1.347)
$\mathbb{1}$ {Distance from Closest $7K $\geq$ 0}	11.17***	11.15***	11.18***
	(1.497)	(1.468)	(1.470)
$\mathbb{1}$ {Distance from Closest $8K $\geq$ 0}	14.50***	14.09***	13.73***
	(1.569)	(1.540)	(1.540)
$\mathbb{1}$ {Distance from Closest $9K $\geq$ 0}	10.71***	10.87***	11.09***
	(1.742)	(1.709)	(1.710)
$\mathbb{1}$ {Distance from Closest $10K $\geq$ 0}	23.04***	22.72***	22.87***
	(1.965)	(1.932)	(1.933)
$\mathbb{1}$ {Distance from Closest $11K $\geq$ 0}	9.724***	9.900***	9.843***
	(2.173)	(2.136)	(2.138)
Current Credit Limit		0.0136***	0.0118***
		(0.0000511)	(0.0000533)
Current FICO			0.598***
			(0.00330)
Observations	66488179	66488179	65287755
R^2	0.033	0.061	0.063
Controls	No	No	Yes
Bank Fixed Effects	No	Yes	Yes
Month Fixed Effects	No	Yes	Yes

Estimates from the following equation:

$$\text{Payment}_{it} = \sum_{j=1}^{11} \alpha_j \mathbb{1}\,\{\text{Nearest Threshold is \$j,000}\} + \sum_{j=1}^{11} \gamma_j \text{Distance from \$j,000 Threshold}_{it}$$
$$+ \sum_{j=1}^{11} \beta_j D_{itj} + \sum_{j=1}^{11} \rho_j \text{Distance from \$j,000 Threshold}_{it} \times D_{itj} + \delta X_{it} + \varepsilon_{it}$$

where $D_{itj} \equiv \mathbb{1}\,\{\text{Distance from Closest \$j,000 Threshold}_{it} \geq 0\}$
Standard errors in parentheses clustered at the account level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Based on a random 10 percent sample of the Consumer Financial Protection Bureau (CFPB) Credit Card Database (CCDB). The sample is restricted to observations where accounts within a $500 window around a $1,000 threshold all have at least the same credit limit ($1,000 more than the threshold). Additionally, sample is restricted to accounts with a finance charge and balances greater than $500.

from approximately \$5 to \$8, or about a quarter of the magnitude of the contemporaneous payment. Tables B4 and B5 report estimates with the amount of new purchases in the following month as the dependent variable. These results suggest little to no effect on purchase volume in the subsequent month. Overall, it appears that left-digit bias primarily affects contemporaneous accumulation of debt. Borrowers appear to be nudged in their immediate reaction to increasing levels of debt, but the effect does not seem to motivate subsequent or systemic change in future behavior through payments made in the following period or additional purchases added to the card in the following period.

In order to explore some heterogeneity of the effect, I examine the contemporaneous repayment within each self-reported income decile. Credit card issuers often ask cardholders to report their income, typically on their application. These values have been reported in the CCDB. I construct deciles based on these values and run the regression from Equation (1) separately for each income deciles. The results of these regressions have been reported in Table B6. While a strong pattern does not emerge, the effect appears to be slightly more concentrated within the top two deciles. Credit limits tend to be correlated with income levels, which could potentially explain the results. However, the third column of Table B6 shows controlling for credit limit does not affect the results substantially. Higher income borrowers likely have more liquidity to make payments enabling these consumers to make larger payments than lower income consumers. In addition, this finding appears somewhat consistent with Shah et al. (2015), which finds that lower income consumers can sometimes be less susceptible to behavioral biases. In the case of left-digit bias and credit cards, higher income borrowers may not exert the same mental energy when deciding to make payments, resulting in a higher potential for left-digit bias in their payment decision.

4 Conclusion

Analyzing monthly credit card balances and payments in a large data set covering the majority of the credit card market, I observe evidence consistent with left-digit bias in credit card repayments. In particular, I find discontinuities in credit card repayments of around \$20 near \$1,000 thresholds. The results suggest little evidence of the effect in the subsequent month on repayment and the total amount of additional purchases. Finally, I find the effect to be stronger in higher self-reported income groups.

This finding adds additional evidence to the existing literature on left-digit bias in real-world settings (Lacetera et al., 2012; Ashton, 2014). The previous empirical work has focused on shopping decisions whereas this paper finds evidence in borrowing decisions of credit card users. The existence of left-digit bias in credit card repayments contributes further evidence of behavioral biases in credit card repayment decisions (Keys and Wang, 2016). In addition, the results in this paper contributes more broadly to the empirical work on cognitive and attentional constraints in behavioral economics and psychology (DellaVigna, 2009; Kahneman and Tversky, 1974).

In this work, I focused primarily on the effect of the \$1,000 thresholds, effectively treating inattentiveness to the other digits equally. Alternatively, the salience of digits in numerical information could be decreasing in distance from the left-most digit, so that discontinuities would be observed at other round numbers as well. To some extent, this can be seen in Figure 1. Below the \$1,000 threshold, there appear to be smaller discontinuities in the payment amount around \$100 amounts. In addition, Table B3 shows a larger discontinuity at the \$10,000 amount relative to \$9,000 and \$11,000 suggesting the \$10,000 threshold may be more salient than the \$1,000 thresholds. A more flexible formulation of Equation (2) allowing decreasing salience of digits from left to right would provide more information on the form of left-digit bias observed in the data.

Finally, mounting evidence of behavioral biases among subsets of borrowers in the consumer credit card market calls for modified economic models to explain debt decisions (Zinman, 2015). Providing a uniform framework for incorporating these biases into models of credit card borrowing decisions remains a fruitful area of research and further exploration.

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A Additional Figures

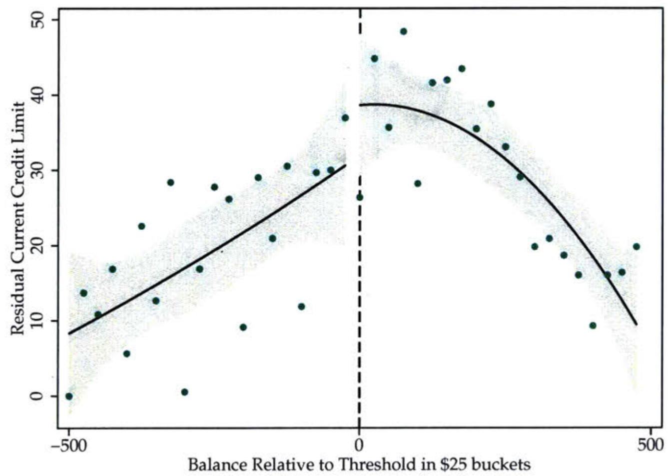

Figure A1: Credit Card Limit in Dollars

Notes: This figure plots the mean of the account's credit card limit for the month within $10 bins of credit card balances away from the a $1,000 threshold. Based on a random 10 percent sample of the Consumer Financial Protection Bureau (CFPB) Credit Card Database (CCDB). The sample is restricted to observations where accounts within a $500 window around a $1,000 threshold all have at least the same credit limit ($1,000 more than the threshold). Additionally, sample is restricted to accounts with a finance charge.

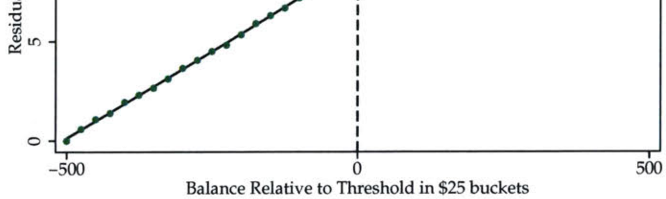

Figure A2: Minimum Payment

Notes: This figure plots the mean of the account's minimum payment required within $25 bins of credit card balances away from the a $1,000 threshold. Based on a random 10 percent sample of the Consumer Financial Protection Bureau (CFPB) Credit Card Database (CCDB). The sample is restricted to observations where accounts within a $500 window around a $1,000 threshold all have at least the same credit limit ($1,000 more than the threshold). Additionally, sample is restricted to accounts with a finance charge.

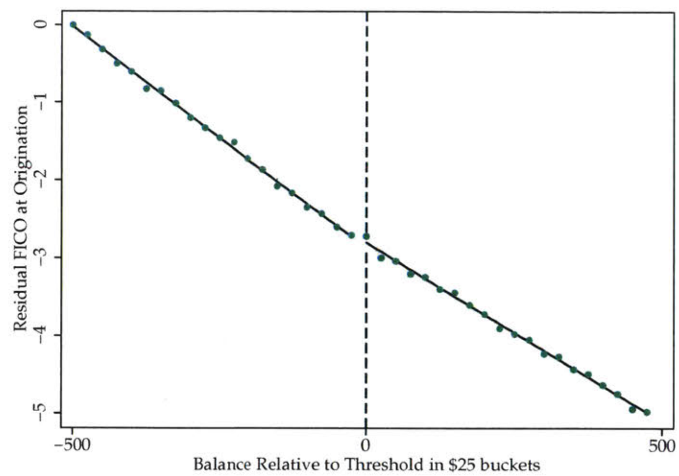

Figure A3: Credit Score At Account Opening

Notes: This figure plots the mean of the account's credit score at the time of opening within $25 bins of credit card balances away from the a $1,000 threshold. Based on a random 10 percent sample of the Consumer Financial Protection Bureau (CFPB) Credit Card Database (CCDB). The sample is restricted to observations where accounts within a $500 window around a $1,000 threshold all have at least the same credit limit ($1,000 more than the threshold). Additionally, sample is restricted to accounts with a finance charge.

B Additional Tables

Table B1: Summary Statistics

	Mean	Median	Standard Deviation
Reported income ($)	65, 037	50, 400	44, 9721
Current FICO	722	740	89
Credit limit ($)	9, 525	8, 000	8, 569
Minimum payment ($)	65	25	197
Actual payment ($)	277	100	548
Annual percentage rate (APR) %	15.7	15.0	7.5
Finance charges ($)	26	0	60
Cycle ending balance ($)	2, 594	792	4, 322

Based on a random 10 percent sample of the Consumer Financial Protection Bureau (CFPB) Credit Card Database (CCDB).

Table B2: The Impact of $1,000 Balance Discontinuities on Payment Amount in the Following Month

	(1)	(2)	(3)
$\mathbb{1}\{\text{Distance from Closest Threshold} \geq 0\}$	5.845***	5.795***	5.553***
	(0.279)	(0.278)	(0.270)
Current Credit Limit			0.0169***
			(0.0000540)
Current FICO			0.418***
			(0.00318)
Observations	61894960	61894960	60858109
R^2	0.000	0.005	0.059
Controls	No	No	Yes
Bank Fixed Effects	No	Yes	Yes
Month Fixed Effects	No	Yes	Yes

Estimates from the following equation:

$$\begin{aligned}\text{Payment}_{i,t+1} = \alpha &+ \gamma\text{Distance from Closest \$1,000 Threshold}_{it} + \beta D_{it} \\ &+ \rho\text{Distance from Closest \$1,000 Threshold}_{it} \times D_{it} + \delta X_{it} + \varepsilon_{it}\end{aligned}$$

where $D_{it} \equiv \mathbb{1}\{\text{Distance from Closest \$1,000 Threshold}_{it} \geq 0\}$.
Standard errors in parentheses clustered at the account level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Based on a random 10 percent sample of the Consumer Financial Protection Bureau (CFPB) Credit Card Database (CCDB). The sample is restricted to observations where accounts within a $500 window around a $1,000 threshold all have at least the same credit limit ($1,000 more than the threshold). Additionally, sample is restricted to accounts with a finance charge and balances greater than $500.

Table B3: The Impact of \$1,000 Balance Discontinuities on Payment Amount in the Following Month

	(1)	(2)	(3)
$\mathbb{1}$ {Distance from Closest \$1K ≥ 0}	6.233***	5.847***	5.806***
	(0.327)	(0.322)	(0.325)
$\mathbb{1}$ {Distance from Closest \$2K ≥ 0}	7.500***	7.190***	7.339***
	(0.544)	(0.527)	(0.528)
$\mathbb{1}$ {Distance from Closest \$3K ≥ 0}	7.395***	6.728***	6.635***
	(0.726)	(0.701)	(0.701)
$\mathbb{1}$ {Distance from Closest \$4K ≥ 0}	8.439***	8.281***	8.273***
	(0.918)	(0.890)	(0.889)
$\mathbb{1}$ {Distance from Closest \$5K ≥ 0}	7.335***	7.032***	6.966***
	(1.101)	(1.069)	(1.067)
$\mathbb{1}$ {Distance from Closest \$6K ≥ 0}	−5.784***	−5.481***	−5.374***
	(1.197)	(1.170)	(1.168)
$\mathbb{1}$ {Distance from Closest \$7K ≥ 0}	3.789**	3.731**	3.342**
	(1.264)	(1.242)	(1.241)
$\mathbb{1}$ {Distance from Closest \$8K ≥ 0}	7.177***	6.717***	6.628***
	(1.431)	(1.407)	(1.405)
$\mathbb{1}$ {Distance from Closest \$9K ≥ 0}	5.238**	5.304**	5.161**
	(1.668)	(1.639)	(1.637)
$\mathbb{1}$ {Distance from Closest \$10K ≥ 0}	12.46***	12.12***	12.17***
	(1.934)	(1.904)	(1.904)
$\mathbb{1}$ {Distance from Closest \$11K ≥ 0}	3.725	4.019	3.600
	(2.227)	(2.192)	(2.193)
Current Credit Limit		0.0159***	0.0137***
		(0.0000559)	(0.0000584)
Current FICO			0.699***
			(0.00344)
Observations	61894960	61894960	60858109
R^2	0.025	0.066	0.070
Controls	No	No	Yes
Bank Fixed Effects	No	Yes	Yes
Month Fixed Effects	No	Yes	Yes

Estimates from the following equation:

$$\text{Payment}_{i,t+1} = \sum_{j=1}^{11} \alpha_j \mathbb{1}\,\{\text{Nearest Threshold is \$j,000}\} + \sum_{j=1}^{11} \gamma_j \text{Distance from \$j,000 Threshold}_{it}$$
$$+ \sum_{j=1}^{11} \beta_j D_{itj} + \sum_{j=1}^{11} \rho_j \text{Distance from \$j,000 Threshold}_{it} \times D_{itj} + \delta X_{it} + \varepsilon_{it}$$

where $D_{itj} \equiv \mathbb{1}\,\{\text{Distance from Closest \$j,000 Threshold}_{it} \geq 0\}$

Standard errors in parentheses clustered at the account level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Based on a random 10 percent sample of the Consumer Financial Protection Bureau (CFPB) Credit Card Database (CCDB). The sample is restricted to observations where accounts within a \$500 window around a \$1,000 threshold all have at least the same credit limit (\$1,000 more than the threshold). Additionally, sample is restricted to accounts with a finance charge and balances greater than \$500.

Table B4: The Impact of $1,000 Balance Discontinuities on Purchase Volume in the Following Month

	(1)	(2)	(3)
$\mathbb{1}$ {Distance from Closest Threshold ≥ 0}	-0.430	-0.555	-0.929
	(0.570)	(0.567)	(0.551)
Current Credit Limit			0.0369***
			(0.000161)
Current FICO			0.540***
			(0.00717)
Observations	68850507	68850507	67568787
R^2	0.000	0.006	0.061
Controls	No	No	Yes
Bank Fixed Effects	No	Yes	Yes
Month Fixed Effects	No	Yes	Yes

Estimates from the following equation:

$$\begin{aligned}\text{Purchase Volume}_{i,t+1} = \alpha &+ \gamma\text{Distance from Closest \$1,000 Threshold}_{it} + \beta D_{it} \\ &+ \rho\text{Distance from Closest \$1,000 Threshold}_{it} \times D_{it} + \delta X_{it} + \varepsilon_{it}\end{aligned}$$

where $D_{it} \equiv \mathbb{1}\{\text{Distance from Closest \$1,000 Threshold}_{it} \geq 0\}$.
Standard errors in parentheses clustered at the account level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Based on a random 10 percent sample of the Consumer Financial Protection Bureau (CFPB) Credit Card Database (CCDB). The sample is restricted to observations where accounts within a $500 window around a $1,000 threshold all have at least the same credit limit ($1,000 more than the threshold). Additionally, sample is restricted to accounts with a finance charge and balances greater than $500.

Table B5: The Impact of $1,000 Balance Discontinuities on Purchase Volume in the Following Month

	(1)	(2)	(3)
$\mathbb{1}$ {Distance from Closest \$1K ≥ 0}	4.988***	3.982***	4.070***
	(0.873)	(0.867)	(0.878)
$\mathbb{1}$ {Distance from Closest \$2K ≥ 0}	3.344**	2.868*	3.264**
	(1.223)	(1.192)	(1.189)
$\mathbb{1}$ {Distance from Closest \$3K ≥ 0}	1.796	0.0335	0.000342
	(1.490)	(1.440)	(1.441)
$\mathbb{1}$ {Distance from Closest \$4K ≥ 0}	−1.080	−1.793	−1.543
	(1.756)	(1.689)	(1.685)
$\mathbb{1}$ {Distance from Closest \$5K ≥ 0}	−0.738	−1.899	−2.525
	(2.062)	(1.980)	(1.981)
$\mathbb{1}$ {Distance from Closest \$6K ≥ 0}	−2.801	−3.644	−3.603
	(2.404)	(2.305)	(2.297)
$\mathbb{1}$ {Distance from Closest \$7K ≥ 0}	−11.77***	−11.65***	−11.29***
	(2.760)	(2.645)	(2.636)
$\mathbb{1}$ {Distance from Closest \$8K ≥ 0}	−6.008	−7.317*	−7.828*
	(3.378)	(3.251)	(3.240)
$\mathbb{1}$ {Distance from Closest \$9K ≥ 0}	−5.968	−5.470	−5.248
	(3.605)	(3.453)	(3.439)
$\mathbb{1}$ {Distance from Closest \$10K ≥ 0}	2.785	1.209	1.271
	(4.190)	(4.026)	(4.007)
$\mathbb{1}$ {Distance from Closest \$11K ≥ 0}	−5.752	−5.862	−5.937
	(4.935)	(4.737)	(4.723)
Current Credit Limit		0.0397***	0.0383***
		(0.000165)	(0.000176)
Current FICO			0.443***
			(0.00833)
Observations	68850507	68850507	67568787
R^2	0.003	0.063	0.062
Controls	No	No	Yes
Bank Fixed Effects	No	Yes	Yes
Month Fixed Effects	No	Yes	Yes

Estimates from the following equation:

$$\text{Purchase Volume}_{i,t+1} = \sum_{j=1}^{11} \alpha_j \mathbb{1}\{\text{Nearest Threshold is \$j,000}\} + \sum_{j=1}^{11} \gamma_j \text{Distance from \$j,000 Threshold}_{it}$$
$$+ \sum_{j=1}^{11} \beta_j D_{itj} + \sum_{j=1}^{11} \rho_j \text{Distance from \$j,000 Threshold}_{it} \times D_{itj} + \delta X_{it} + \varepsilon_{it}$$

where $D_{itj} \equiv \mathbb{1}\{\text{Distance from Closest \$j,000 Threshold}_{it} \geq 0\}$

Standard errors in parentheses clustered at the account level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Based on a random 10 percent sample of the Consumer Financial Protection Bureau (CFPB) Credit Card Database (CCDB). The sample is restricted to observations where accounts within a \$500 window around a \$1,000 threshold all have at least the same credit limit (\$1,000 more than the threshold). Additionally, sample is restricted to accounts with a finance charge and balances greater than \$500.

Table B6: The Impact of $1,000 Balance Discontinuities on Payment Amount by Income Decile

	(1)	(2)	(3)
First Income Decile	24.33***	24.07***	23.97***
	(1.285)	(1.278)	(1.263)
Second Income Decile	18.05***	17.83***	17.76***
	(1.115)	(1.107)	(1.097)
Third Income Decile	19.55***	19.34***	19.52***
	(1.008)	(1.002)	(0.994)
Fourth Income Decile	19.20***	19.13***	19.52***
	(1.196)	(1.189)	(1.183)
Fifth Income Decile	21.64***	21.45***	22.05***
	(1.123)	(1.116)	(1.112)
Sixth Income Decile	21.32***	21.12***	21.57***
	(1.122)	(1.116)	(1.110)
Seventh Income Decile	21.60***	21.33***	21.79***
	(1.132)	(1.127)	(1.122)
Eighth Income Decile	23.08***	22.98***	23.89***
	(1.240)	(1.234)	(1.225)
Ninth Income Decile	27.38***	27.09***	27.47***
	(1.403)	(1.393)	(1.379)
Tenth Income Decile	31.99***	31.29***	32.63***
	(1.848)	(1.826)	(1.801)
Controls	No	No	Yes
Bank Fixed Effects	No	Yes	Yes
Month Fixed Effects	No	Yes	Yes

Estimates from the following equation:

$$\begin{aligned}\text{Payment}_{it} = \alpha &+ \gamma\text{Distance from Closest \$1,000 Threshold}_{it} + \beta D_{it} \\ &+ \rho\text{Distance from Closest \$1,000 Threshold}_{it} \times D_{it} + \\ &+ \delta X_{it} + \varepsilon_{it}\end{aligned}$$

where $D_{itj} \equiv \mathbb{1}\{\text{Distance from Closest \$j,000 Threshold}_{it} \geq 0\}$

Standard errors in parentheses clustered at the account level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Based on a random 10 percent sample of the Consumer Financial Protection Bureau (CFPB) Credit Card Database (CCDB). The sample is restricted to observations where accounts within a $500 window around a $1,000 threshold all have at least the same credit limit ($1,000 more than the threshold). Additionally, sample is restricted to accounts with a finance charge and balances greater than $500.