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How Preferences for Round Numbers Affect Choices: Stickiness and Jumpiness in Credit Card Payments*

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Abstract

We explore the effects of round number preferences in credit card payments. Payments at round numbers are very common: 70% of manual non-full credit card payments are at round numbers. Using minimum payment amounts as a natural experiment for the lower bound on payments, we show stickiness in payment amounts when the minimum payment varies in the wide interval between round number bounds yet jumpiness in payment amounts when the minimum payment varies in the narrow interval across round number bounds. Round number preferences can therefore lead to over-estimation of both inattention, *and* responsiveness, to policies. Our findings have implications for models of inattention and for policy evaluation methods.

Keywords: credit cards, round numbers, heuristic, policy evaluation

JEL Codes: D12, D14, G02, G20

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1 Introduction

In a variety of everyday settings, people face the task of choosing monetary payment amounts. Examples include small payments, such as the size of a service tip in a restaurant, through to large payments, such as contributions to a retirement saving scheme. In such cases, individuals are tasked with choosing specific values in dollars and cents. Traditional economic theory assumes that each of these choice tasks has a precise, optimal number-valued answer. However, when faced with number choices, individuals commonly choose numbers at round number values (e.g., Converse and Dennis, 2018; Sonnemans, 2006; Whynes et al., 2005; Kandel et al., 2001).

In this paper, we show that a preference towards round numbers has implications for economic models and policy evaluation. Preferences towards round numbers generate intervals of *stickiness* and intervals of *jumpiness* in choices. When faced with bounds on a choice set, in the interior interval between round numbers, within which individuals round up (or down) to the proximate round number, changes in bounds do not affect number choices (stickiness). Yet, as the bounds cross round numbers, prompting individuals to round up (or down) to the next round number, changes in bounds have large effects of number choices (jumpiness). Failure to recognize preferences for round numbers can lead to incorrect inference about inattention to state variables, and also incorrect inference regarding the effects of policy design, due to overestimating either the global stickiness or jumpiness of choice rules or policy responses.

To explore these issues, we use records of credit card payments. Credit card payments are one of the most common monetary number choices faced by a large number of individuals on a regular basis. The flexibility of credit card payment options implies that card holders who make a partial payment, which we define as a payment at or above the minimum payment but less than the full balance, face the task of choosing a specific payment amount. This context provides us with data on millions of economically relevant number choices made by individuals.

Furthermore, a feature of credit card payments provides quasi-experimental variation in bounds on the choice set. Credit card minimum payment rules imply that incremental changes in balances cause incremental variation in the lower-bound on credit card payments, sometimes resulting in minimum payment amounts due crossing round numbers. By exploiting incremental differences in minimum payment amounts, we are able to study how payment behavior changes when the lower bound increases within the interior interval between round numbers and when the lower bound breaches through round number thresholds.

Our opening contribution is to document the prevalence of round number choices in credit card payments. Among all credit card partial payments where card holders manually make payments, more than 70% of payments are at base-10 round number values. While the distribution of payment amounts is approximately log normal, the loading of mass across the distribution is heavily stacked on a few round number amounts: for example, approximately two-thirds of partial payments are accounted for by just 20 round number values. Round number payments are persistent within-individual over time and within-individual across cards, suggesting a preference for round numbers is an individual characteristic.

Our main contribution is to use variation in minimum payment amounts to show that, due to round-number payment behavior, rounding-up of payment amounts generates wider intervals of stickiness, in which payments are unresponsive to balances, interspersed with narrower intervals of jumpiness, in which payments are highly sensitive to balances. That is, observed partial payments jump upwards when the payment minimum floor sweeps upwards through a round number value. For example, when the minimum payment rule sets a payment floor between round number bounds, such as in the range \$10.01 to \$19.99, the tendency to round number payments generates an excess mass in partial payments at \$20. This payment behavior generates local stickiness in payment amounts, which are unresponsive to balances in the interior between round numbers. In contrast, when the payment floor rises from \$19.99 to \$20.01, some card holders increase payments to \$30, moving excess mass upwards to the next round-number values and thereby generating local jumpiness in payment amounts.[1]

We estimate the extent of stickiness and jumpiness in partial payment amounts within and across round number thresholds. Our main estimates show that the minimum payment just crossing a round number causes a 17% increase in the probability of payment at the next base-10 round number. In contrast, minimum payments changing within round number ranges have precisely estimated but very small effects on the probability of payment at round numbers.

[1] Among some card holders payment jump upwards to the next base-50 and base-100 pound values.

In terms of average payment amounts, our main estimates show that the minimum payment just crossing a round number (i.e., by 1 penny) causes an increase in average payments of £7.00, implying a very high marginal propensity to repay debt arising from a small increase in minimum payment.

This natural experiment demonstrates two effects which arise from rounding. First, over the range of latent payment amounts between round numbers, we observe inertia in payments. This helps to explain the inertia in payments over time which we observe in the data. A tendency to choose round numbers therefore generates excess stickiness in payment amounts as if individuals were unresponsive to changes in the state variable (in our context, the size of credit card bill). Inertia in individual behavior can arise due to rational or behavioral inattention frictions, indicating potentially sub-optimal choice behavior (Sims, 2003; Reis, 2006; Andersen et al., 2020; Bernheim et al., 2015; Steiner et al., 2017; Gabaix, 2019). Our findings suggest inertia in behavior can in some settings also be attributable to rounding payment amounts.

Second, when a latent payment amount crosses a round number boundary, we observe a jump in payments arising due to round-number payment. Hence round number payments generate a highly *discontinuous* relationship between card balances and payments. In this way, the relationship between payments and balances (on which the minimum payment is applied) is highly non-linear, with the local average treatment effect (LATE; Imbens and Angrist, 1995) of an increase in the payment floor sometimes greatly in excess, or below, the average treatment effect. The natural experiment in payment floors arising from minimum payment rules allows us to observe these two effects at work.

Rounding therefore also has implications for policy evaluation. In general, if a policy design alters the bounds of the choice set, round number payment behavior could generate locally very strong (or very weak) estimated treatment effects not due to some underlying economic relationship, but due instead to a preference for rounding. In our case study of credit card payments, the firm might draw false inference regarding the strength of relationship between minimum payment due and payment amounts. In many settings, firms or policymakers might draw false inference from rule changes that induce similar patterns in responses arising from round numbers. In this way, the round-number threshold therefore becomes a local confound in the LATE design. This is important for research design as it implies that round numbers may introduce a source of bias in LATE estimates.

More generally, the inertia and jumpiness in payment behavior arising due to round number payments has implications for optimal firm menu design (Armstrong and Chen, 2009; De Clippel et al., 2014; Grubb, 2014; Ho et al., 2017, for a review see Grubb, 2015). To draw upon a simple example: say a restaurant has a menu such that the typical bill is $36, with customers tending to round-up their payments to $40, paying a $4 tip (see Azar (2007) for a review of the literature on round numbers and tipping behavior). Now, say, the restaurant changes its menu such that the typical bill becomes $42, with some share of customers responding by paying $50, paying an $8 tip as the lower bound on the bill crosses a round-number threshold and the customer rounds-up to the next round number. The restaurant owner might interpret the doubling of the tip amount as evidence of increased customer satisfaction. However, were the menu to be modified again such that the typical bill becomes $45, with customers paying $50, the tip would fall to $5, due to inertia in payments at the nearest round number. And in exploiting round number preferences, in settings which involves might commonly round-up values, firms have an incentive to choose prices just above base-10 values in order to extract a surplus via rounding-up behavior.

Our paper is related to the broader literature on round numbers, which has three distinct strands. A first strand focuses on left-digit bias in the processing of number values, which is the tendency to focus on the leftmost digit of a number while partially ignoring other digits (Poltrock and Schwartz, 1984).[2] Lacetera et al. (2012) find left-digit bias in the processing of odometer values, leading to discontinuous drops in sale prices at 10,000-mile odometer thresholds. Shlain (2018) structurally estimates the magnitude of left-digit bias using retail pricing data, finding that consumers respond to a 1-cent increase from a 99-ending price as if it were a 15-25 cent increase.[3]

A second strand demonstrates how round numbers act as reference points. Allen et al.

[2] Other forms of bias in processing number values have also been shown in the literature, including the tendency of individuals to process small numbers on a linear scale while processing large numbers on a logarithmic scale (Roger et al., 2018) and to exhibit exponential growth bias (Stango and Zinman, 2009).

[3] Relatedly, laboratory studies have found that prices ending in a nine unit are perceived to be disproportionately smaller than prices ending in the following zero unit, e.g., 99 cents compared with $1 (Thomas and Morwitz, 2005; Manning and Sprott, 2009).

(2016) show that round numbers act a reference points for marathon finishing times. Pope and Simonsohn (2011) show how round numbers act as goals in a variety of settings. Pope et al. (2015) show that heaping of agreed house sales prices at $50,000 units can be explained by round numbers acting as focal points in sale negotiations. Bhattacharya et al. (2012) find that stock traders focus on round numbers as cognitive reference points for value, evidenced by excess buying (selling) by liquidity demanders at all price points one penny below (above) round numbers.

A third strand seeks to understand the psychology of number choices and the interaction of round numbers and "prominent" numbers. Albers and Albers (1983) presents a theory of the prominence of numbers in the decimal system in which a subset of round numbers are particularly prominent and hence more likely to be chosen. We find evidence in our credit card payments data consistent with the idea that some round numbers are more prominent than others.[4]

Our paper also relates to recent studies of decision rules used by consumers whereby consumers reduce complex problems, such as those involving marginal tax rates and credit card interest rates, to simpler problems, such as those involving average tax rates or credit card balances. Rees-Jones and Taubinsky (2020) finds evidence of consumers linearizing tax schedules using their average tax rate (known as "schmeduling", Liebman and Zeckhauser, 2004), an application of the "ironing" heuristic. Gathergood et al. (2019) show that credit card holders match the share of repayments to debts held on multiple cards to the share of balances on each card. In similar vein, rounding replaces the complex problem of choosing a precise number value with the simpler problem of choosing a number value from a grid of proximate round numbers.

The paper proceed as follows. Section 2 introduces the credit card data we use in this study. Section 3 describes round number payment behavior in the credit card sample. Section 4 explains the minimum payments natural experiment and describes the results. Section 5 discusses the implications of our results for policy design and menu design. Section 6 concludes the paper.

[4] We intend to investigate the interaction between round numbers and prominent numbers in future work drawing upon credit card payments and trades by individual investors.

2 Data

Our data source is the Argus Information and Advisory Services "Credit Card Payments Study" (CCPS). The CCPS provided detailed information on contract terms and billing records from five major credit card issuers in the UK. These issuers have a combined market share of over 40% and represent a broad range of credit card products and market segments. We have obtained monthly data covering January 2013 to December 2014 for a 10% representative sample of individuals in the CCPS who held a credit card with at least one of the five issuers. The data also allow us to link together multiple cards held by the same individual.[5]

The data include monthly-level records of spending (at the merchant category level), balances, minimum payments due and payment amounts recorded in pounds and pence. Flags are provided for delinquency and card status (open, closed, or charged-off) and also whether payments were made via automatic payment (know as Direct Debit in the UK) or by a manual payment. The dataset also includes credit scores and card open dates. The data also contain outer-digit postcode identifiers. The dataset is unbalanced, with cards opening and closing within the data period. In our analysis the unit of observation is a card-month. After initial data cleaning, the total sample includes approximately 1.2 million cards and 23.5 million card-months.[6]

2.1 Sample Selection

Our interest lies in the number values of payment amounts chosen by individuals when making a credit card payment. We therefore apply a series of sample restrictions to restrict the sample to observations where individuals face a number choice over the amount to repay in the month. For example, we exclude card-months where the card is paid in full. In such cases, the individual does not face a specific number choice of amount to repay in pounds and pence in the month

[5] Unlike other leading credit card datasets, the CCPS provides us with anonymized individual-level identifiers in addition to card identifiers. The individual identifiers allow us to link together multiple cards held by the same individual.

[6] The initial data cleaning includes (1) an exclusion of cards with imperfect information, (2) an exclusion of observations in Dec. 2014 (due to a lack of information about card bills which are issued in Jan. 2015), and (3) an exclusion of cards with closed or charged-off status.

because the amount paid is determined by the card balance.[7]

We apply the following sample restrictions in order to obtain a baseline sample for our analysis. In the first step, we drop card-months where the card has no balance and hence requires no payment. Second, we drop card-months where the payment is made by automatic payment, as this method of payment removes the need to choose a payment amount each month. Third, we drop card-months where the card is paid in full. Finally, we drop card-months where the payment is below the minimum payment due. The majority of cases where the payment is below the minimum due involve no payment being made, though in a small fraction of cases individuals make a payment less than the minimum, including some round number payments.[8] The resulting sample provided by these restrictions contains observations which we call "partial payments": payments made against a non-zero balance due, for which the individual faces a number value choice over the payment amount in the month.

The effects of the sample restrictions are shown in Table A1. Dropping card-months with no balance removes 8.7% of cards and 26.4% of observations. This restriction also causes a 1.3% reduction in total payments.[9] Dropping card-months where the card is paid by automatic payment removes a further 20.4% of cards, 26.3% of observations and 34.2% of the total payment amount. Dropping card-months where the card is paid in full further removes 19.3% of cards, 20.4% of observations and 47.4% of the total payment amount. Finally, dropping card-months where the payment made is below the minimum due removes 6.2% of cards, 2.9% of observations and 0.2% of the total payment amount. After applying the sample restrictions, the resulting sample provides approximately 45% of cards from the unrestricted sample and 24% of observations. The partial payments sample provides approximately 530,000 cards and 5.6M card-months observations. The value of payments in the partial payments sample is approximately 17% of the total payments in the unrestricted sample.

We also draw a sample of cards from the baseline sample where the card holder held two

[7] In such cases, willingness to pay is at least as high as the card balance and the exact amount the individual is willing to pay is unobserved.

[8] Perhaps surprisingly, some individuals pay below the minimum due and thereby fall delinquent because they round-down the minimum payment amount, for example making a payment of £10 when the minimum payment due is £10.50.

[9] This is due to a small number of cases in which card holders make payments to their cards even though no balance is due (i.e., they pay their account into credit).

cards in the month (Panel B in Table A1) and a further sample where the card holder held three cards in the month (Panel C). In these samples, observations are only retained in the sample if all cards held by the card holder meet the sample restrictions at the card-month level. The two-card sample restriction provides approximately 52,000 cards (hence, 26,000 individual card holders) and 534,000 card-month observations. The three-card sample restriction provides approximately 7,500 cards (2,500 individual card holders) and 63,000 card-month observations.[10]

2.2 Summary Statistics

Summary statistics for the baseline sample are shown in Table 1. The mean card credit limit is approximately £5,600 (median £4,600) with a mean Annualized Percentage Rate (APR) of 18% on purchases and 24% on cash advances. The mean balance is approximately £2,600 (median £1,600) implying card utilization at the mean is on average 52% (median 51%). The mean monthly purchase value is approximately £240, though this is highly skewed by many observations with zero purchases, the median value is only £12. The mean minimum payment due is approximately £55, approximately 2.1% of the mean balance.[11]

The mean value of payments is approximately £250. This mean payment amount is approximately 10% of the outstanding balance, and five times higher than the minimum payment due. The standard deviation of mean monthly payments is approximately twice the mean value. The payment amounts at the 25th, 50th and 75th percentile observation are each round number values, with values of £50, £100 and £200, respectively.

3 Round Number Payment Behavior

In this section we show that the distribution of payments in the baseline sample is dominated by round number payment values. We also show that round number payment behavior appears to be an individual trait, evidenced by persistence in round number payment within-individuals

[10] Among the unrestricted two-card and three-card samples, it is common for at least one card to either not have a balance, or where all cards have a balance, at least one card to be paid by automatic payment. This results in a relatively small number of observations in the two-card and three-card samples.

[11] The minimum payment is calculated as the sum of interest due plus the higher of fixed amount (e.g., £25) or a fixed percentage of the balance (e.g., 2.5%). The exact “floor” and “slope” elements of the minimum payment formula differ among cards within the sample.

over time and across multiple cards.

To begin, Figure 1 illustrates the proportion of partial payments by rightmost £-digit value in the baseline sample, with the shaded bar showing representing the proportion of payments with non-zero pence values. Strikingly, approximately 70% of payments have a last-£-digit of £0, with approximately 10% having a last-£-digit of £5. Approximately 13% of payments have non-zero pence values shown in the grey bar.

Figure 2 Panel A provides a histogram of payment amounts in the baseline sample. The bin-width for payment amounts in the histogram is 1 penny. Using the log scale on the x-axis, the distribution of partial payment amounts appears log-normal but with excessive heaping of density at round number payment amounts evident across the full range of the distribution. Density is heaped on round number amounts – such as £50, £100, and £200 – while the intervals between these round numbers see extremely low, or no, density.

Is there a mechanical explanation for this pattern? A fraction of round number payments might be attributable to minimum payment rules, which commonly include a floor at a low base-10 value, such as £10 or £20, or due to individuals rounding-up the minimum payment amount to the next available round number (though this latter behavior would arguably reflect a preference for round numbers). To illustrate such cases, Panel A colors the fraction of each type of payment within in bin, with payments exactly at a minimum, and those at a minimum rounded up to a nearest integer or a nearest multiple of 5 or 10 in blue and red, respectively. The figure shows that the majority of round number payments do not arise due to minimum payments or rounding-up the minimum payment amount to the nearest base-10 number.

Round number payments could potentially also arise indirectly from balances and spending amounts, such as individuals paying a fixed percentage of the balance or making repayments that reflect round number spending amounts. Panels B and C illustrate the distributions of balances and spending, which show much smoother distributions compared to the distribution of partial payments shown in Panel A. These distributions also exhibit some heaping at round numbers (due to, for example, the purchase of a good or service priced at a round number, or a combination of purchases that sum to a round number, or individuals paying with a preference for resulting round balances), but these heaps account for far less of the density compared with the heaps in the distribution of payment amounts. The relative scarcity of round number values in the distribution of balances and spending indicates that round number payments do not typically arise via these indirect channels.

To summarize the popularity of round number payments, Table 2 shows the top-20 payment amounts in the baseline sample. Of the top-20 values shown in the table, 17 are at base-£10 values, with three taking base-£5 values. The 17 round-number payments together account for approximately 60% of all payment values in the baseline sample.[12]

3.1 Payment Patterns Over Time and Across Cards

In this subsection, we extend the analysis to consider payment patterns over time and across multiple cards held by an individual. Results indicate that the propensity to choose round number payment amounts is persistent within-person over time and within-person across cards, suggesting that a propensity to choose round number amounts is an individual trait.

3.1.1 Payment Patterns Over Time

If the choices of round number values are an individual trait, we would expect to see persistence in round number value choices at the card level. To explore this, Table 3 illustrates the persistence of round number payments at the card level over time. The sample is restricted to observations in which the card is retained in the baseline sample in at least two consecutive months. Table 3 tabulates in rows the percentage of observations where the partial payment takes a last-digit £ value of zero at time t (where t is a month in the data period) and in columns the percentage of observations where the partial payment takes a last-digit £ value of zero at $t + 1$ (where $t + 1$ is the next calendar month in the data period).

Results show that round number payments are highly persistent: approximately 87% of cards making a round number payment continue to make a round number payment in the next month; approximately 65% of cards making a non-round number payment continue to make a non-round number payment in the next month.

[12] Table A2 repeats the analysis making separate categories for minimum payments and rounded minimum payments (i.e., payments rounding-up minimum to a nearest integer, or a nearest multiple of 5 or 10). The analysis confirms that the popularity of round number payments is not merely due to round number minimums or individuals rounding-up minimums to nearest round numbers.

Table 4 extends this analysis by showing the top-10 patterns of six consecutive payments. To do so, the sample was restricted to cards-months where the card holder made six or more consecutive partial payments.[13] The "support" column reports the percentage of cards showing each pattern in six consecutive payments.[14] Results show that the top-10 patterns of six consecutive payments are dominated by round number payments. All payment sequences shown in the table are a combination of round numbers, except payments at £25 (which is a common floor minimum-payment amount). The most common patterns are fixed payments of £100 (approximately 6% of cards), fixed payments of £50 (approximately 4% of cards), and fixed payments of £200 (approximately 2% of cards). These payment patterns are all the result of repeated, manual monthly choices over repayment amounts (as the sample is restricted to manual repayments).

3.1.2 Payments Across Multiple Cards

If round number value choices are an individual trait, we would also expect to observe a strong positive correlation in round number payments across multiple cards held by a single individual in a sample of card-months in which the individual has an opportunity to make a round number payment on each card. To explore this, Table 5 shows proportion of card-months in the baseline sample in which individuals make all last-£-digit zero payments and all last-£-digit non-zero payments across two or three cards in the same month. The sample is restricted to card-months for which we can match two or three cards to an individual in the data.

Among the sample of two-card observations, nearly 74% of observations are for payments that are either all last-£-digit zero payments or all last-£-digit non-zero payments, with individuals making a combination of one last-£-digit zero payment and one last-£-digit non-zero payment in approximately 26% of cases. In the three-card sample, approximately 60% of observations are for payments that are either all last-£-digit zero payments or all last-£-digit non-zero payments, with individuals making a combination of at least one last-£-digit zero

[13] If one card has multiple sequences of six or more consecutive partial payments with a break in the middle, we use the longest sequence provided in the baseline sample.

[14] Note that one card may contribute to more than one six-month payment patterns shown in the table when the run of consecutive partial payments is longer than six months (i.e., we extracted any six consecutive payments from a sequence.)

payment and at least one last-£-digit non-zero payment in approximately 40% of cases.

Table 6 shows the top-20 pairs of partial payments in the two-card sample for individuals making payments to two cards in the same month. The top-20 pairs of payments together account for more than 20% of all pairs of payments in the two-card sample and all of the pairs comprise only round number payments.[15]

3.2 Robustness and Sensitivity

In this subsection we present robustness and sensitivity analysis. We first examine the distribution of payment amounts in the full payments sample and the automatic payments sample. These samples show no heaping at round number payments, suggesting that round number payments arise as a result of a decision over partial payment amount in our baseline sample. We then explore whether round number payment choices are sensitive to the size of balances due (i.e., the economic magnitude of the payment decision). We also explore whether round number payment choices are sensitive to card tenure, which might arise if round number payment behavior changes as consumers gain experience of managing payments on their credit card.

3.2.1 Full Payments Sample

If individuals making payments in our baseline sample are actively choosing round number values, we should not see peaks of density at round number values in contexts where individuals do not make a number choice, such as when paying a full balance. To examine this, we compare the distribution of partial payment amounts in the baseline sample (shown in Figure 2 Panel A) to the distribution of full payment amounts. To do so, we draw observations from the third step of the sample selection in Table A1, extracting observations where the balance was paid in full.

Figure A1 illustrates the distribution of payments in the full payments sample. Given that balances arise from multiple purchases of goods and services, most of which are non-round number values, the distribution of full payments has far lower density at round number values, shown in Panel A. Some small spikes in density at round number payment amounts exist in this sample – reflecting the case that some balances are round numbers or individuals make round

[15] Table A3 repeats the analysis adding pairs including minimum payments and rounded minimum payments (i.e., payments rounding-up minimum to a nearest integer, or a nearest multiple of 5 or 10).

number payments above the balance. As shown in Panel B, fewer than 10% of payments are at round number values, with approximately 85% of payments in pence digits. The distributions of card balances and monthly spend amounts, which also exhibit some small spikes in density at round number values, are illustrated in Panels C and D. Round number payments are therefore uncommon in the full payments sample.

3.2.2 Automatic Payments Sample

When individuals adopt automatic credit card payments a monthly payment is made at a pre-set level. This level is typically the minimum payment due, the full balance, or a fixed money value. Hence, it is possible that some share of individuals adopting automatic payments also choose round number value payments. Figure A2 illustrates the distribution of payments in the sample of observations where the payment is made by automatic payment. To do so, we draw observations from the second step of the sample selection in Table A1, which identifies observations where a payment was made by automatic payment.

Figure A2 Panel A shows the distribution of automatic payments with heaping at £25, £50 and £100. (Note that £25 is one of the most common fixed (floor) minimums.) This indicates that some individuals set their automatic payment to a round number. Panel B shows that this share is approximately 10%, with three-quarters of automatic payments made in pence units, due to the large share of automatic payments covering only minimum or those paying in full. The distributions of balances and monthly spending amounts in the automatic payments sample are shown in Panels C and D of Figure A2. Round number payments are also therefore uncommon in the automatic payments sample.

3.2.3 Round Number Payments by Balance Due

Round number payments might vary with card balance. If individuals trade-off the convenience of rounding vs. precision in payment amounts, we might expect that round number value payments would increase with card balances. The proportional "cost" of rounding to a base £10 is lower at higher levels of payment. We explore whether round number payment choices vary with card balance in Figure 3 Panel A, which illustrates the proportion of payments with a last-£-digit of zero by the card balance in a binned scatter-plot. The fitted line (which is fitted through the non-binned data) illustrates that the proportion of round number value partial payments is approximately 70% across the full range of payments.[16]

3.2.4 Round Number Payments by Card Tenure

In a final sensitivity test, we explore whether round number value partial payments change with experience. We use the number of months the individual has held the credit card as a proxy measure of experience. Figure 3 Panel C illustrates the proportion of partial payments at round number values by card tenure. The line of best fit slopes slightly upwards, indicating that the likelihood of round number payments slightly increases as card tenure increases.[17]

4 Minimum Payments Natural Experiment

In this section we exploit a natural experiment in the lower-bound of the credit card partial payment choice interval arising due to minimum payment rules. As a result of minimum payment rules, incremental changes in credit card balances result in incremental changes in the minimum payment. This natural experiment allows us to estimate how partial payments respond to changes in choice intervals in the presence of a preference to round-up payments. If individuals engage in rounding behavior, there are implications for policy evaluation designs that exploit local effects of policy rules. Policy changes that induce a change in the feasible set of number values available for an individual to choose (i.e., the choice interval) might induce an apparently large treatment effect which arises purely due to rounding behavior.[18]

[16] Panel B of Figure 3 shows different categories of payments across the range of balances. The categories are: payment exactly minimum, multiple of 10, and others. The proportion of each payment category is not sensitive to balances. Figure A3 illustrates different categories of payments on balance using the unrestricted sample from Table A1. The figure shows that full payments are most common for smaller balances, with round number payments accounting for more than half of all payments in the unrestricted sample when the balance rises above £1,000.

[17] Panel D of Figure 3 plots payment categories across the range of balances, showing that the slight increase of the proportion of round number payments on card tenure is partially due to a decrease of the proportion of minimum payments.

[18] An ideal experiment to estimate the effects of rounding on partial payments would be to manipulate the set of feasible payments available to the individual, for example raising the minimum feasible payment from below to above a round number (e.g., increasing the minimum feasible payment from £9 to £11) and then observing the effect on payment amounts. While we cannot experimentally manipulate the set of minimum feasible payments available to individuals, we can exploit minimum payment rules as an ideal natural experiment.

4.1 Minimum Payment Rules

Most minimum payment amounts are calculated as the maxim of a fixed amount (the “floor”) and a percentage of the balance (the “slope”). For instance, a typical minimum payment formula might be:

$$\text{Minimum Payment} = \max(£25, 2\% \times \text{balance} + \text{interest} + \text{fees}).$$

As a consequence, the minimum payment rule places a lower bound on the feasible set of payments as a function of the balance. This provides a natural experiment in feasible payment amounts for credit card payments, as incremental differences in balance are sufficient to just-rule-out round number amounts.

For example, consider a card with the above minimum payment rule, a balance of £1,722, and interest of £15.55 due. The corresponding minimum is £49.99. However, the same card with a balance of £1,723 corresponds to a minimum of £50.01. As another example, for a month without interest and fee added, if the percentage is 2.225%, a balance of £2,247 corresponds to a minimum of £49.99 while a balance of £2,248 corresponds to a minimum of £50.01. In both examples, an change in balance increases the minimum such that round-number repayments of £50.00 are ruled out.

Figure 4 provides an example from the data. The figure illustrates how a minimum payment crossing £100 influences payment behavior. In the top panel, the red lines represent the distribution of payments when a minimum is £99 (thus a payment at £100 is still available) while the blue lines represent the distribution of payments when a minimum is £101 (thus a payment at £100 is no longer available). The bottom panel shows the difference between the red and the blue lines in the top panel (i.e., the height of a blue line minus that of a red line at each payment amount on the x-axis). As seen in the figure, when a minimum is £99 (red lines), about 13% of payments are £99 (i.e., exactly at the minimum) and about 28% of payments cluster at £100. However, when a minimum is £101 and the option to pay £100 is out of reach, about 20% of payments move to £101 (i.e., exactly at the minimum), and payments at £105 and £110 also increase approximately by absolute 4-6%. [19]

[19] Payments at £120, £150, £200, and £300 also increase by absolute 0.5-2%. We examine base-50 and base-100 round number payment behavior in Section 4.3.

The example in Figure 4 shows evidence of rounding upwards to base-10 values, and also base-5 values (i.e., £105). This jump in payment amounts suggests that the effect of a small increase in the minimum payment, here exactly £2, can be much larger than £2.

4.2 Results

4.2.1 Payments at the Next Round Number

In order to estimate an overall effect on payments of a minimum crossing a round number threshold, we first take each observation of minimum payment amount due and actual payment made for each card-month in the baseline sample, and calculate the distance (x) between the minimum payment amount due and the closest base-10 round number. Hence we calculate:

$$x = \text{Minimum Payment} - 10z,$$

where $10z$ ($z = 1, 2, \ldots, N$) is a closest base-10 £-value.

We then estimate the relationship between x and two outcomes. The first outcome is the probability of making a payment equal to the next round number, $10z + 10$ (e.g., the probability of making a payment of £60 when the minimum payment due increases through £50). The second outcomes is the average partial payment in £.

Figure 5 illustrates the main result. The figure pools all card-month observations in the baseline sample. The x-axis pools together x (Minimum Payment $- 10z$) for all integer values of z. The y-axis shows the proportion of payments in each bin that are at $10z + 10$. The plot shows two clear patterns. First, the propensity to make a payment equal to $10z + 10$ increases somewhat with x, i.e. with a higher minimum payment due. Second, there is a large jump in the probability of paying $10z + 10$ at $x = 0$. The jump in the probability of payment of $10z + 10$ when $x = 0$ represents the increased propensity to make a payment at the next round number when the previous round number is just out-of-reach (due to an incremental increase in the minimum payment). The probability of payment of $10z + 10$ jumps at $x = 0$ from approximately 8.5% to 10.5%, an increase of 2 percentage points, or approximately 25%.

Figure A4 and Figure A5 provide examples for many values of z for the baseline sample.[20]

[20] Corresponding OLS estimates are shown in Table A4.

Taking $z = 5$ as an example (the central panel in Figure A4), the proportion of payments at £60 increases steadily as the balance rises through £46, £47, £48, etc.. but jumps upwards at £50.01. In this way, when the minimum payment due increases such that a round number is rendered just out-of-reach, the proportion of payments at the next round number jumps. In the case above, the propensity to pay £60 jumps upwards when a minimum payment amount exceeds £50, providing strong evidence of base-10 rounding behavior.

We econometrically estimate the relationships shown in Figure 5 using Ordinary Least Squares regression models. Table 7 reports regression estimates fitted to the Figure 5. The econometric specification fits slopes either side of the threshold, together with a dummy variable having a value of 1 if the minimum exceeds a threshold (i.e., the x-axis variable is greater than 0 in Figure 5), otherwise 0. The table shows three econometric specifications which differ by their fit of the slopes either side of zero: linear, quadratic and cubic fits. The slope coefficients in the linear fit regression reflect the marginal propensity to make a partial payment at the next round number value when the minimum payment due increases. The slope coefficient of 0.003 in the linear model implies that a £1 increase in minimum payment due increases the probability of payment at the next round number value, $10z + 10$, by 0.3 percentage points. The coefficient on the dummy variable implies that the probability of payment at $10z + 10$ increases by 1.7 percentage points when the minimum payment due is above $10z$. Coefficient magnitudes are similar in the quadratic and cubic models. In Column 3 of Table 7, which reports results form a model conditioning for a cubic of the minimum payment, the coefficient on the threshold dummy implies a 1.5 percentage point increase in the probability of payment at the next base-10 round number when the minimum payment crosses a round-number threshold. This is a 17% increase. These estimates therefore quantify the large jump in probability of payment at the next base-10 round number when the minimum payment floor rises above the nearest base-10 round number.

4.2.2 Average Payment Amount

We also estimate the effect upon average partial payments. Figure 6 Panel A pools all card-months observations in the baseline sample, with the x-axis again pooling together x (Minimum Payment−

$10z$) for all integer values of z. In this plot the y-axis shows the average level of payments in each bin. In this case, the plot shows no clear slope relationship between x and the average level of partial payment for value of x below $x = 0$, with some evidence of an increasing relationship, though not a clear jump, for values of x higher than zero.[21]

Table 8 reports regression estimates fitted to the Figure 6 Panel A data. As in the table, the econometric specification fits slopes either side of the threshold, together with a dummy variable denoting $x > 0$ (i.e., $Minimum > 10z$). In this model the dependent variable is a level of partial payment, measured in £. Focusing on the linear model, the slope coefficient on x is positive before the round-number threshold, indicating that the level of partial payments increase as a minimum approaches to a threshold. The coefficient on the dummy variable indicating $x > 0$ is positive, taking a value of approximately 6-7 in the linear and cubic models (though this estimate is sensitive to model form, with the coefficient imprecisely defined in the quadratic-fit model). In Column 3 of Table 8, the coefficient value implies an increase in average payment amount of approximately £7 or 3% when the minimum payment due just crosses $10z$ by 1 penny.

The small effect on average payments in the baseline sample may be due to a tendency of some card holders to persistently pay exactly the minimum payment.[22] These card holders might not make an active monthly choice of payment value, but instead anchor their payment amount at exactly the minimum. Figure 6 Panel B therefore restricts the sample to payments above minimum, showing approximately £10 jump in the average payment when a minimum crosses round number thresholds.[23]

Table 9 reports regression estimates fitted to the Figure 6 Panel B data. In these estimates, the coefficient on the dummy variable is positive for all models, taking a value in the approximate range 7-12. In Column 3 (cubic fit), the coefficient value implies an increase in payment amount of about £12 or 5% when the minimum payment due just crosses $10z$ by 1 penny.

[21] Figure A6 and Figure A7 provided examples for many values of z. (Corresponding OLS estimates are shown in Table A5.)

[22] Payments exactly at minimum account for approximately 10% of all observations, with little variation in this percentage regardless of the size of minimum.

[23] A second reason for the small jump in average payments in Figure 6 Panel A is that the proportion of payments at base-50 and base-100 payments (e.g., payments at £50, 100, 150, 200) are quite large even when a minimum is small and monotonically increase as a minimum increases without jumps at many base-10 round minimums.

4.2.3 Card Holders Who Persistently Round Payments

How do payments change as the minimum increases for those card holders who persistently round-up their payments? Keys and Wang (2019) show this behaviour occurs in a sample of US credit card holders in response to a change in the minimum payment formula. Here, we show that some card holders persistently round-up payments in response to minimum payments changing due to changes in balance. To examine this, we define "persistent rounding payers" as card holders making payments at a base-10 round number nearest to the minimum in more than 50% of months with a positive balance, then restricting the baseline sample to card-months for the persistent rounding payers.[24] This sample includes approximately 270,000 observations for 18,800 cards.

In the persistent rounding-payers sample, payments jump at each threshold where a minimum crosses a base-10 round number. Figure 7 plots average payments calculated for each minimum bin with a width of 1 penny, showing that the average payment tends to jump when the minimum crosses base-10 round numbers. We estimate the jump in payments at these minimum payment discontinuities, employing a regression discontinuity design used in Lacetera et al. (2012), who show valuations of used cars drop discontinuously when mileage crosses a round number. Specifically, we conduct a regression with Equation 1.

$$Payment\ Amount_i = \alpha + f(Min_i) + \sum_{j=1}^{19} \beta_j Dummy[Min_i > j \times 10] + \gamma X_i + \epsilon_i \qquad (1)$$

In the equation, the dependent variable is a payment amount (£) in card-month i. $f(Min_i)$ is the 7th degree polynomial of minimums. X_i is a vector of card characteristics including total monthly spend, merchant and cash APR, and card utilization.[25] The coefficient vector of interest, β_j, represents the discontinuity in payments at each base-10 round number minimum threshold. Results are shown in Table 10. Coefficient estimates are positive across the distribution of round

[24] Persistent rounding payers make payments at amounts very close to the minimum. The UK Financial Conduct Authority defines systematic minimum repayments as nine or more minimum payments in 12 months while incurring interest charges, and treats such a payment pattern as an indicator of potentially problematic card holders (refer https://www.fca.org.uk/credit-card-market-study-interim-report/problem-credit-card-debt).

[25] Fixed effects for calendar months and card fixed effects are also included in additional specifications.

numbers, excepting £190, and in many cases precisely defined, reflecting the pattern seen in Figure 7.

4.3 Extension: Payments at Base-50 and Base-100 Round Numbers

4.3.1 Base-50 and Base-100 Rounding Behavior

In this section we extend out main analysis to base-50 and base-100 rounding, whereby individuals round payments to multiple of £50 or £100. Figure 4 suggests that some share of card holders round to base-50 and base-100 values, which we investigate here. We repeat our analysis using the natural experiment of variation in minimum payment amounts arising from variation in balances, whereby the minimum payment crosses a round-number value due to an incremental increase in the balance.

To estimate base-50 and base-100 rounding, we modify research design by first taking each observation of minimum payment amounts due and actual payments provided for each card-month in the baseline sample and calculating the distance, x, between the minimum payment amount due and the closest base-£50 round number (or, in a second calculation, the closest base-£100 round number). Hence we calculate:

$$x = \text{Minimum Payment} - 50z \text{ (or } 100z\text{)},$$

where $50z$ or $100z$ ($z = 1, 2, \ldots, N$) is a closest base-50 or base-100 £-value. Then, we calculate the proportion of payments at $50z + 50$ or $100z + 100$ over x.

The results are shown in Figure 8.[26] Panel A shows a jump in the proportion of payments at $50z + 50$ when the minimum payment due is above $50z$. Panel B illustrates the same effect at $100z + 100$, showing no jump in the proportion of payments at $100z + 100$ when the minimum crosses $100z$.[27] In addition, we examine how the average payments changes around $Minimum =$

[26] Corresponding OLS estimates are shown in Table A6 and Table A7.

[27] Note that the minimum thresholds of £50, £100, and, £150 together mostly account for $50z$, so in Figure A8 Panels A, B, and C, we break down Figure 8 Panel A, showing the proportion of payments at £100, £150, and, £200 around minimums of £50, £100, and £150, respectively. Figure A8 Panel A shows no jump in the proportion of £100 payments at £50. This is because the frequency of £100 payments occupy a large share in payments, even when the minimum is small. On the other hand, Figure A8 Panel B shows that the proportion of £150 payments jumps by about absolute 2% when the frequent payment amount of £100 becomes just out of the reach. Similarly, Panel C shows that the proportion of £200 payments jumps when a minimum crosses £150 by approximately absolute 2%.

$50z$ and $Minimum = 100z$. The results are shown in Figure 9 and again indicate that average payments jump upwards at the minimum payment threshold.[28]

4.3.2 Base-50 and Base-100 Round Payments and Base-10 Round Minimum Thresholds

Finally, we examine whether some share of of payments jumps upwards to round numbers of higher bases when the minimum crosses a base-10 round numbers. Specifically, we separately calculate the proportion of payments at £50, 100, 150, and 200 when a minimum crosses a base-10 round number. (Note that payments at £50, 100, 150, and 200 together account for about 70% of all base-50 round payments.) The calculation excludes card-months where a nearest base-10 round number is a base-50 round number (i.e., $10z = 50, 100, 150\ldots$) in order to exclude the effect of base-50 and base-100 rounding.

Figure 10 show the results. Panels A to D show the increase in payments at £50, £100, £150 and £200 respectively. Discontinuities at the base-10 minimum payment threshold are seen in each case. We econometrically estimate the jump seen in Figure 10, with results shows in Table A11 - Table A14 which show positive coefficients on the above-threshold dummies.

This analysis therefore shows that the increase in average payments when the minimum crosses a base-10 round number is in part attributable to payments jumping upwards to round number of higher bases, such as base-50 and base-100. These effects accentuate the increase in average payments arising from round number payment choices.

4.3.3 Change in Payment Distribution at Round Minimum Thresholds

The analysis so far indicates that the average level of payments jumps when the minimum crosses round numbers. However, policy makers may also concern the distribution of a variable of interest rather than the average level of the variable.

The clear jump in the proportion of payments at a next base-10 round number seen in Figure 5 implies that the distribution of payments in our data substantially changes when

Panel D shows the proportion of £200 payments around a minimum of £100, confirming no jump seen in Figure 8 Panel B. Corresponding OLS estimates are provided in Table A8.

[28] Corresponding OLS estimates are shown in Table A9 and Table A10. In both tables, the coefficient on the above threshold dummy is imprecisely defined in quadratic- and cubic-fit models while linear-fit model indicates a 3% jump in payments at Base-50 round number thresholds and a 7% jump in payments at Base-100 round number thresholds.

the minimum crosses base-10 round number minimum thresholds. In order to examine this, we draw payments for each minimum bin with a width of £2 and calculate a divergence in the payment distribution between each of two adjacent bins.[29] Specifically, as a measure of divergence, we calculate the sum of absolute distance between two cumulative payment distributions according to Equation 2.[30]

$$Divergence_i = \int \mid F(x|i-2 < Min < i) - F(x|i < Min < i+2) \mid dx, \quad (2)$$

where x represents a logarithm of payment amount, i is a minimum threshold, and $F(x)$ is the cumulative distribution function. (In short, the divergence measure quantifies the total area between two cumulative payment distributions.)

The results are shown in Figure 11. The each bar in the figure represents a divergence in payment distributions between two adjacent minimum bins. For example, a bar height at 50 on the x-axis represents a divergence between payment distribution for card-months where $minimum = 48.01 - 49.99$ and that for card-months where $minimum = 50.01 - 51.99$. The red bars represent a divergence for base-10 round number minimum thresholds. The figure indicates three things. First, the divergence is larger for base-10 round number thresholds than for interior intervals between round numbers, indicating that there is a large distributional change in payments at base-10 round number thresholds. Second, the divergence is larger at base-50 round number thresholds. This is because base-50 round number payments occupying a large share just drops. Third, the large divergence at base-10 round thresholds is less obvious after a minimum exceeds 100, indicating that card holders' rounding behavior, at least in part, shifts to higher-base rounding when the digit of a minimum changes.

5 Discussion

In this section we discuss two implications of rounding behavior. These relate to interpretation of inertia in consumer behavior and estimation of local average treatment effects (Imbens and

[29] The bin-width of £2 was chosen to have sufficient number of observations in all bins. If we use £1 bin instead, we see a moderately large divergence at base-5 round minimum threshold.

[30] The measure is equivalent to the Wasserstein distance or the earth mover's distance for one dimensional variable.

Angrist, 1995).

5.1 Inertia and Inattention

Round number payment behavior generates local inertia in payment amounts. In our descriptive analysis of payment behavior, a significant share of card holders make persistent payments at a fixed round number £-value. As shown by our discontinuity estimates, the marginal propensity to partial payments between round number values is non-monotonic. A preference for paying round number amounts can therefore generate apparent intervals of inertia in payment behavior, with card holders apparently unresponsive to changes in minimum payment, and hence changes in balance, in the interval between round number minimum payments.

Interpreted in isolation, this inertia might be taken as a signal that the individual is unresponsive to parameters of the choice decision, such as the credit card minimum payment, or implicitly the credit card balance. However, our estimates show that this unresponsiveness to state variable(s) is only a local effect *within* the interval between round numbers. A preference for rounding can therefore be interpreted as an local inattention friction. This is similar to the notion of a localized optimization friction in Chetty (2012), who studies local optimization frictions at the intensive and extensive margins of labor supply choices.

5.2 Local Average Treatment Effects

Conversely, round number payment behavior also generates narrow intervals of jumpiness in payments when the minimum payment due crosses a round number - with payment amounts jumping upwards as individuals round-up to base-10, or base-50 and base-100 multiples. Again, interpreted in isolation, this jumpiness might be taken as a signal that the individual is exceptionally responsive to parameters of the choice decision. However, our estimates show that this high level of responsiveness to state variable(s) is only a local effect *across* round numbers threshold.

The combination of stickiness and jumpiness in payment behavior has implications for policy evaluation in the presence of rounding behavior. In general, with round number preferences in settings in which individuals make a choice over number amounts, if a policy design alters the bounds of the choice set, round number payment behavior could generate locally very strong (or very weak) estimated treatment effects not due to some underlying economic relationship, but due instead to a preference for rounding. In this way, round number payment behavior might generate a local confound in the LATE design. This is an important consideration for research designs in contexts where individuals make free number choices.

6 Conclusion

In this paper we examine round number payment behavior. Round number payment behavior is of interest to economic analysis because it generates intervals of stickiness and intervals of jumpiness in response to a state variable. Failure to recognize preferences for round numbers can lead to incorrect inference about inattention to state variables, and also incorrect inference regarding the effects of policy design, due to overestimating either the stickiness or jumpiness of choice rules or policy responses.

We study preferences for round numbers using records of credit card payments. The flexibility of credit card payment amounts implies that card holders who make a partial payment which we define as a payment at or above the minimum payment but less than the full balance, face the task of choosing a specific payment amount. We showed that more than 70% of credit card partial payments are at base-10 round number values. While the distribution of payment amounts is approximately log normal, the loading of mass across the distribution is heavily weighted on a few round number amounts.

We also exploit a natural experiment in minimum payment amounts. This natural experiment demonstrates two effects which arise from rounding. First, over the range of latent payment amounts between round numbers, we observe inertia in payments. This helps to explain the inertia in payments over time which we observe in the data. A tendency to choose round numbers generates excess stickiness in payment amounts as if individuals were unresponsive to changes in the state variable (in our context, the size of credit card bill). Inertia in individual behavior can arise due to inattention frictions, indicating potentially sub-optimal choice behavior (Gabaix, 2019). Our findings suggest inertia in behavior can also be attributable to limited attention arising from the convenience of rounding payments.

Second, when a latent payment amount crosses a round number boundary, we observe a jump in payments arising due to round-number payment. Hence round number payments generate a highly *discontinuous* relationship between card balances and payments. In this way, among the sample of round-number payments, the relationship between payments and balances (on which the minimum payment is applied) is discontinuous, with the local average treatment effect of an increase in the payment floor sometimes greatly in excess, or below, the average treatment effect. The natural experiment in payment floors arising from minimum payment rules allows us to observe these two effects at work.

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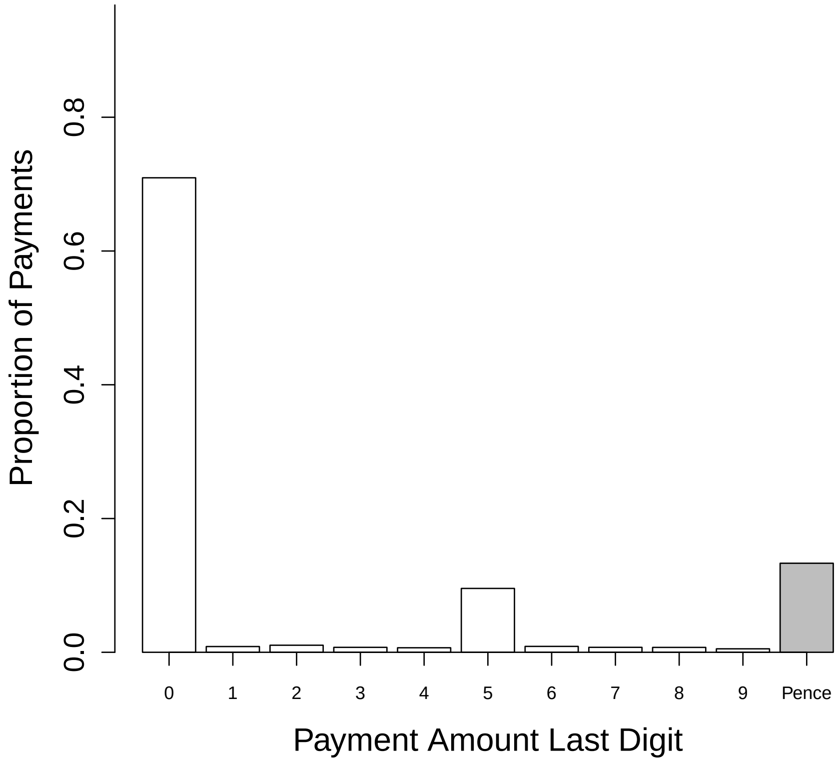
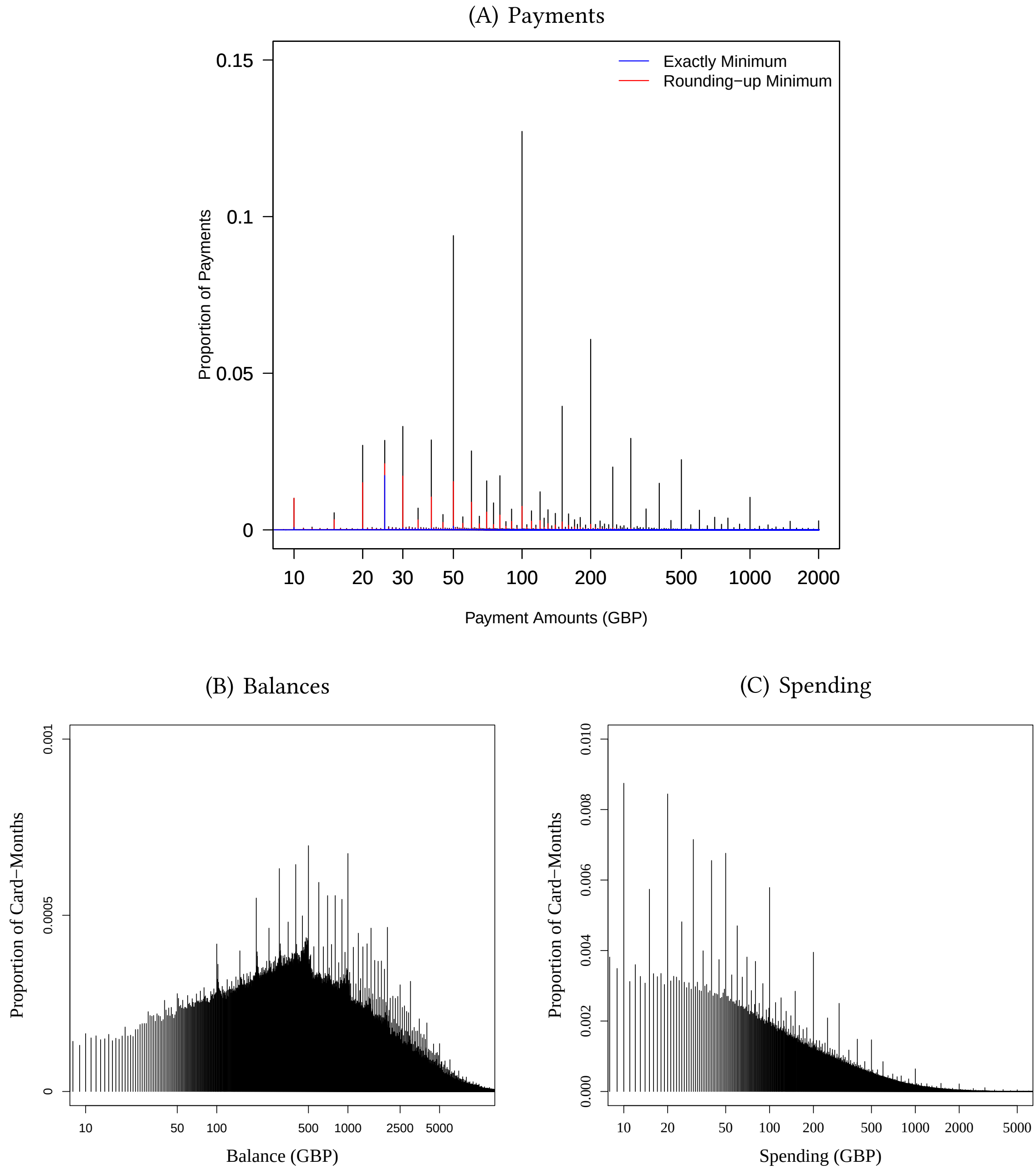
Figure 1: Righttmost £-Digit Payment Amounts in the Baseline Sample



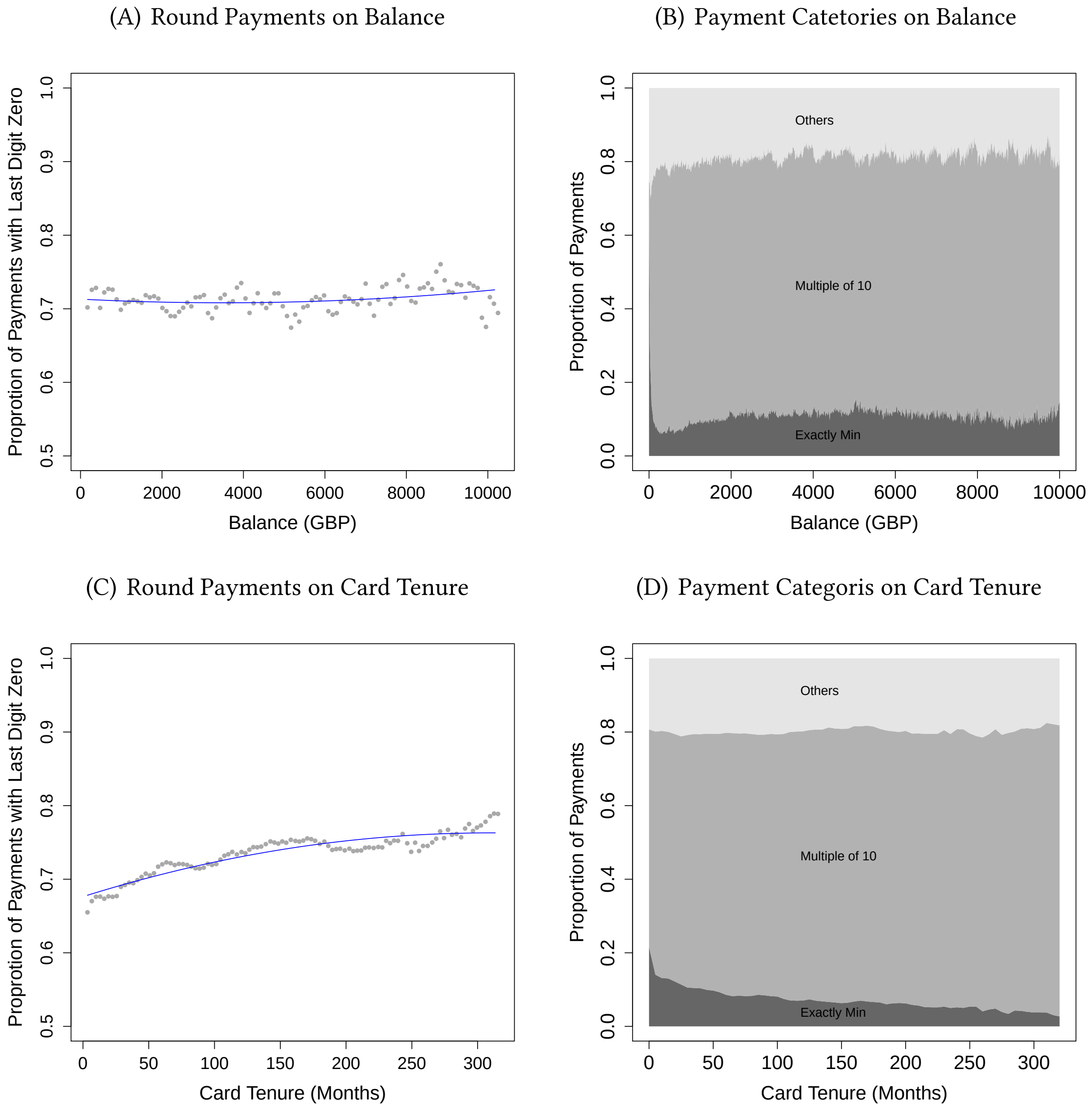
Note: Figure illustrates the distribution of rightmost £-digit integer-value payment amounts in the baseline sample. Grey bar contains all non-integer-value payments. Baseline sample. For sample selection details see Section 2.

Figure 2: Payments, Balances, and Spending in the Baseline Sample



Note: Figure illustrates the distribution of payments, balance and spending in the baseline sample. In Panel A, the bin width is 1 penny. The blue parts represent minimum payments and the red parts represent rounded minimum payments (i.e., payments rounding-up minimum to a nearest integer, or a nearest multiple of 5 or 10). In Panels B and C, the bin width is 1 pound. For sample selection details see Section 2.

Figure 3: Sensitivity of Round Payments to Balance and Card Tenure



(A) Round Payments on Balance

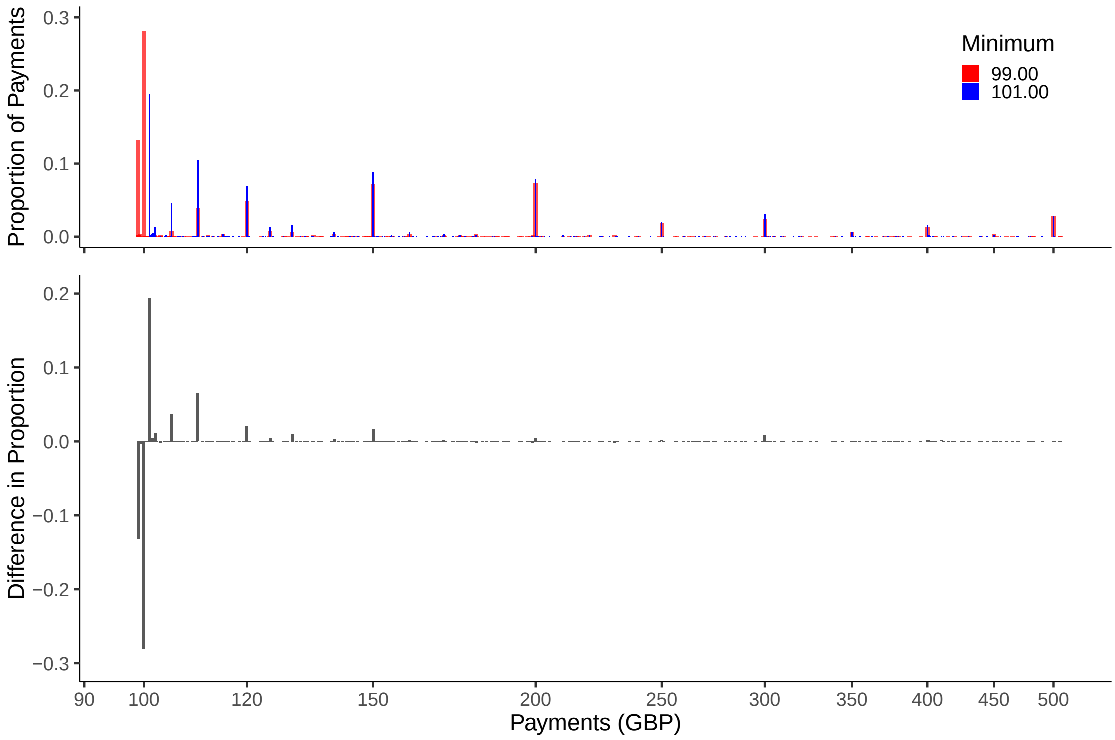
(B) Payment Catetories on Balance

(C) Round Payments on Card Tenure

(D) Payment Categoris on Card Tenure

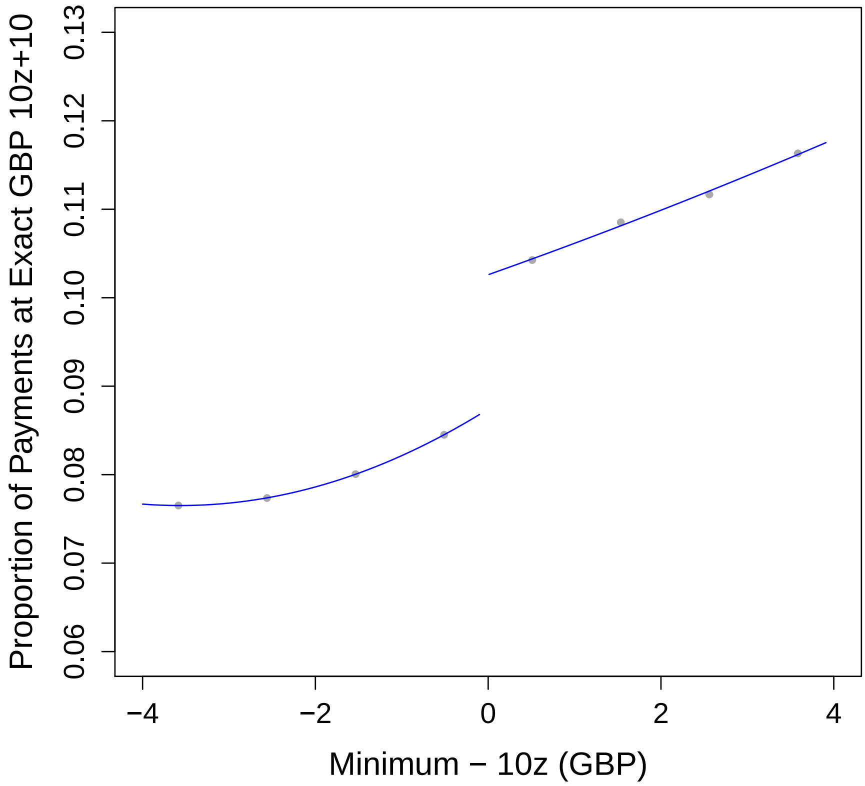
Note: Left-side figures illustrate the proportion of payments with a last integer digit amount of zero by card balance and card tenure. Right-side figures illustrate the proportion of payments in each of three mutually exclusive and exhaustive categories: payments at exactly the minimum payment due, payments in multiples of 10 pounds, and other payments. For sample selection details see Section 2.

Figure 4: Comparison of Payment Distributions for Minimums at £99 and £101



Note: Figure illustrates the distribution of payments for card-months with minimum payments of exactly £99 and card months with minimum payments of exactly £101. In the top panel, the red lines represent the distribution of payments when a minimum is £99.00 while the blue lines represent the distribution of payments when a minimum is £101.00. The red lines are slightly wider than the blue lines just for making a comparison visually easier. The bottom panel shows the difference between the red and the blue lines at a given payment amount (i.e., the height of a blue line minus the height of a red line). For illustration purpose, the x-axis is truncated at 500 (the 85th percentile value). The baseline sample restricted to minimums due of £99 or £101. For additional sample selection details see Section 2.

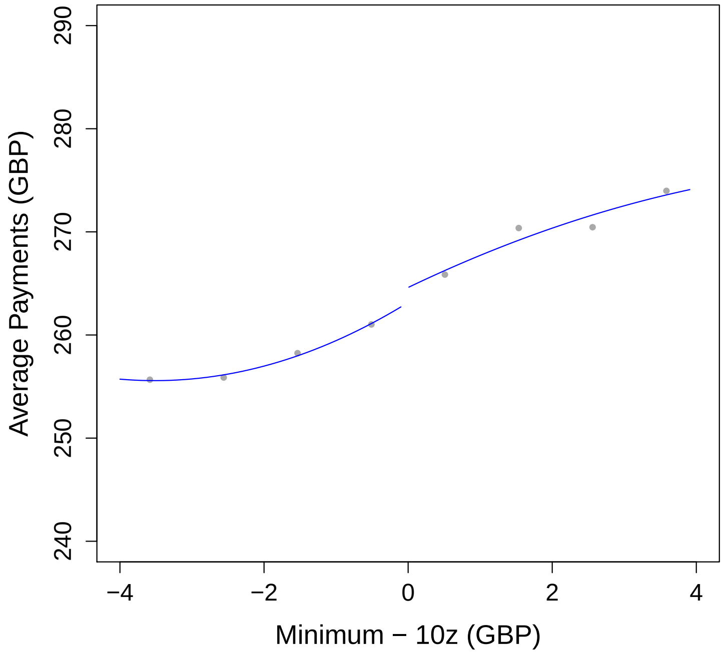
Figure 5: Round Number Payments and Minimum Payments (Baseline Sample)



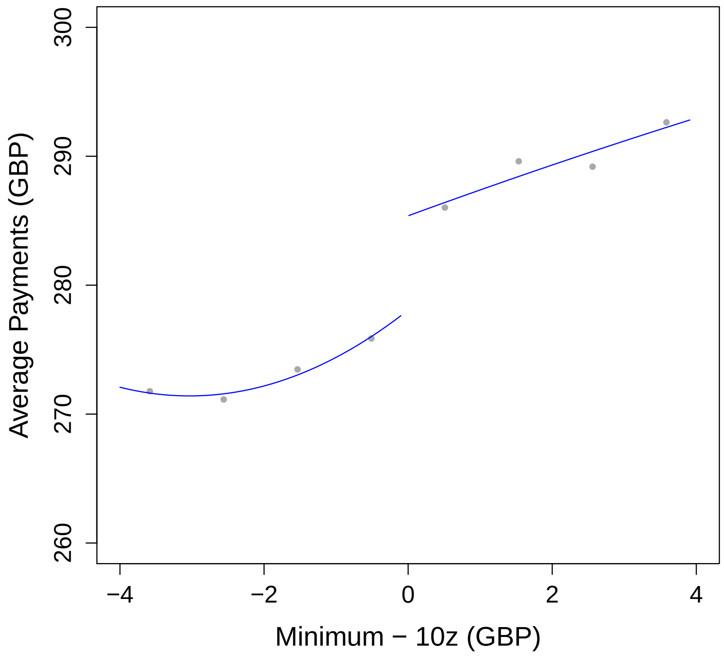
Note: Figure illustrates the proportion of payments at the next base-10 round number by distance from a base-10 round number minimum. Binned scatter plot with quadratic line of best fit, either side of zero.

Figure 6: Average Payment Amounts and Minimum Payments

(A) Baseline Sample

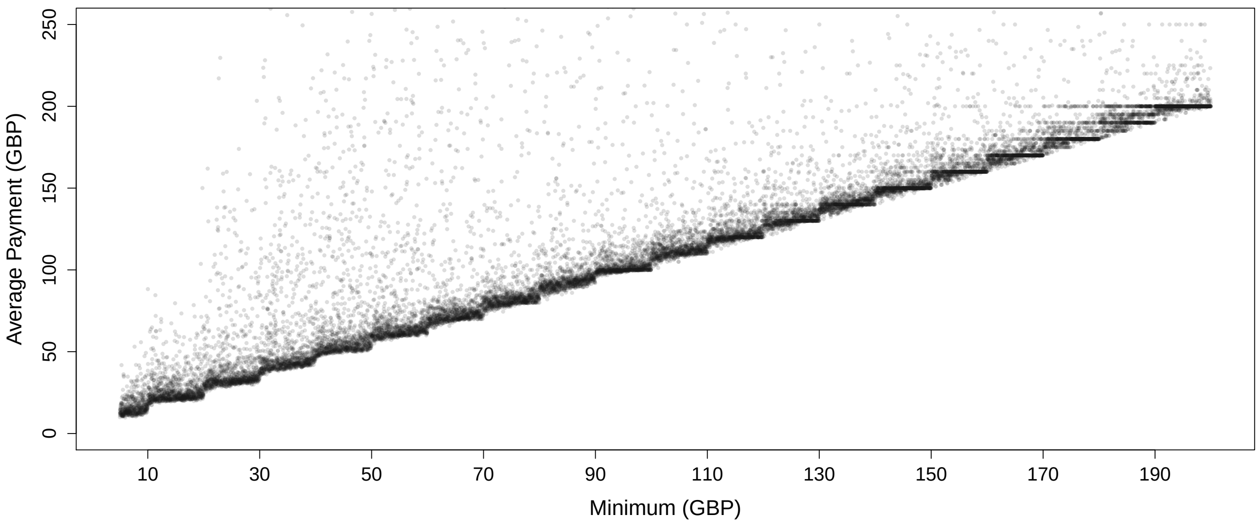


(B) Payments above Minimum



Note: Figure illustrates average payment amount by distance from a base-10 round number minimum. Binned scatter plot with quadratic line of best fit, either side of zero. Panel A includes the baseline sample, panel B restricts the sample to payments above minimum.

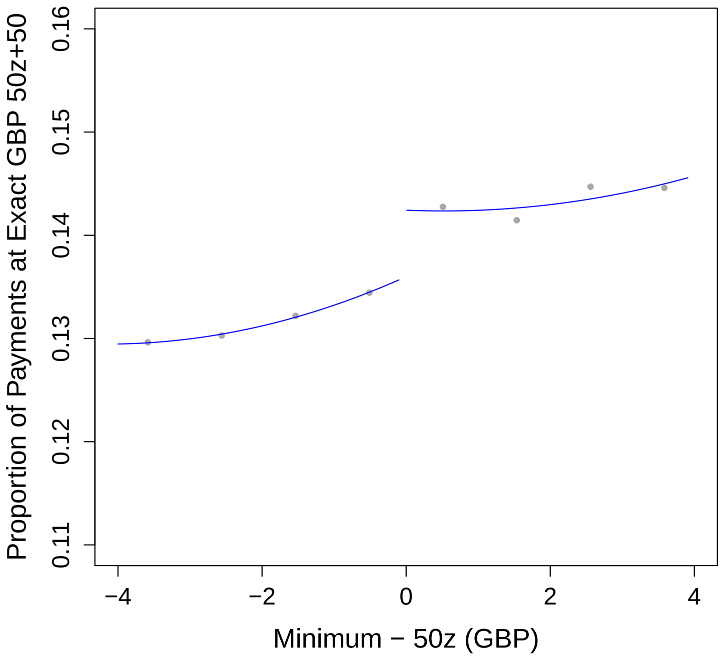
Figure 7: Discontinuity in Average Payments at Base-10 Minimum Thresholds
(Rounding Payers Sample)



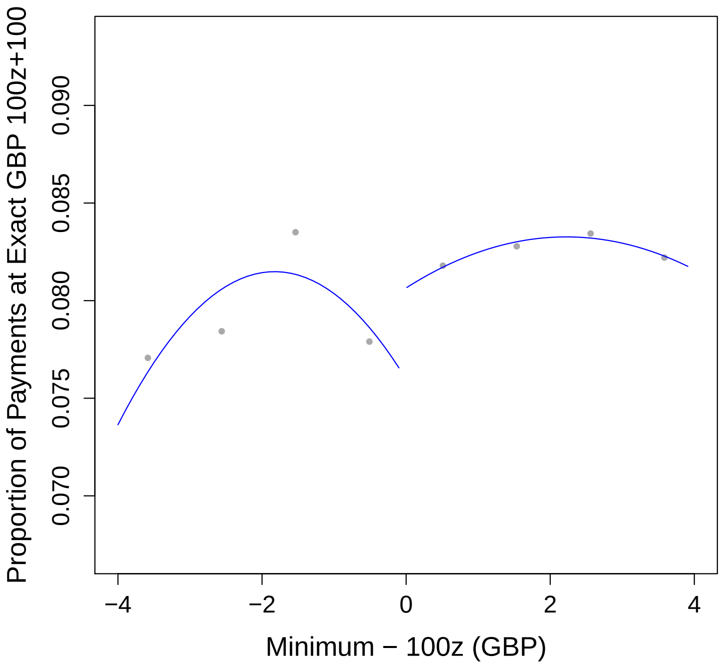
Note: Figure shows the average payment on minimum. The average payment is calculated for each bin of minimums with a bin width of 1 penny. Extreme values (about 4% of all bins) are not shown for illustration purpose.

Figure 8: Base-50 and Base-100 Round Number Payments and Minimum Payments

(A) Base-50 Rounding



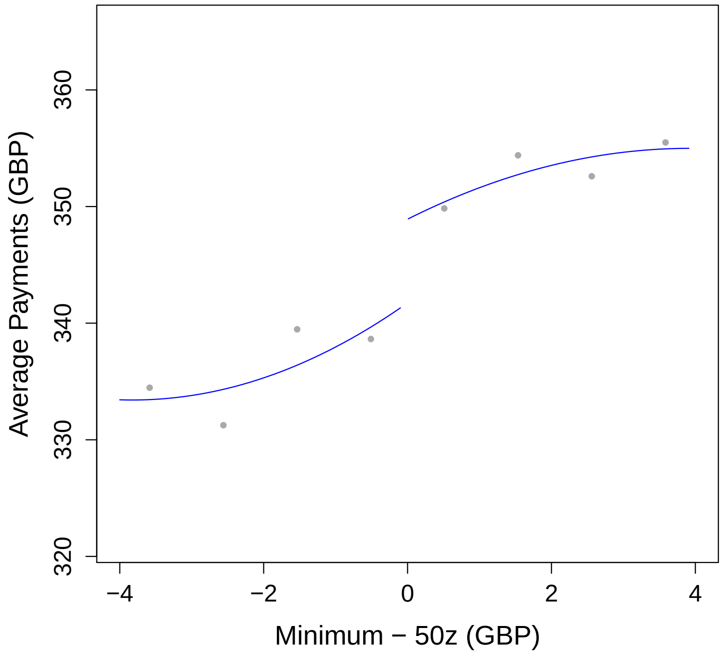
(B) Base-100 Rounding



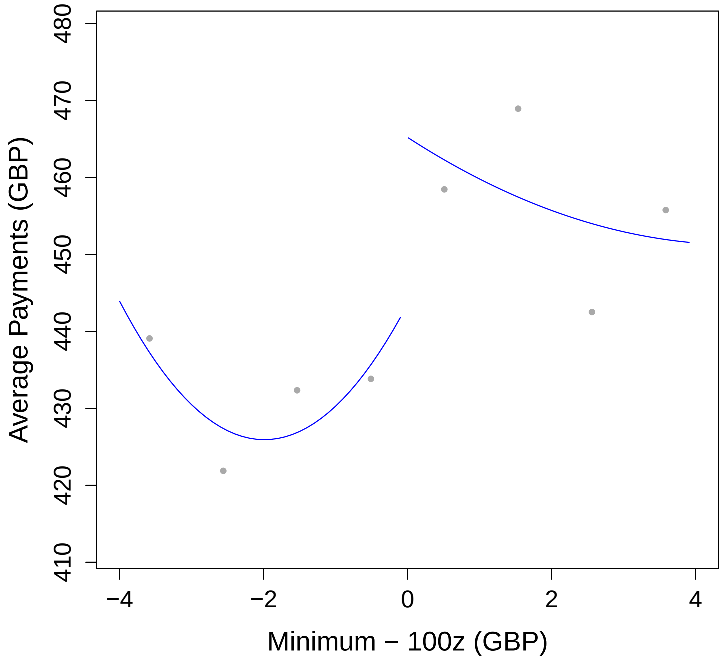
Note: Figure illustrates the proportion of payments at the next highest round number (base-50, base-100) by distance from a round number payment (base-50, base-100 round number). Binned scatter plot with quadratic line of best fit, either side of zero. Panel A shows results for base-50 numbers in the baseline sample. Panel B shows results for base-100 numbers in the baseline sample.

Figure 9: Average Payment Amounts Around Base-50 and Base-100 Minimum Payments

(A) Base-50 Rounding

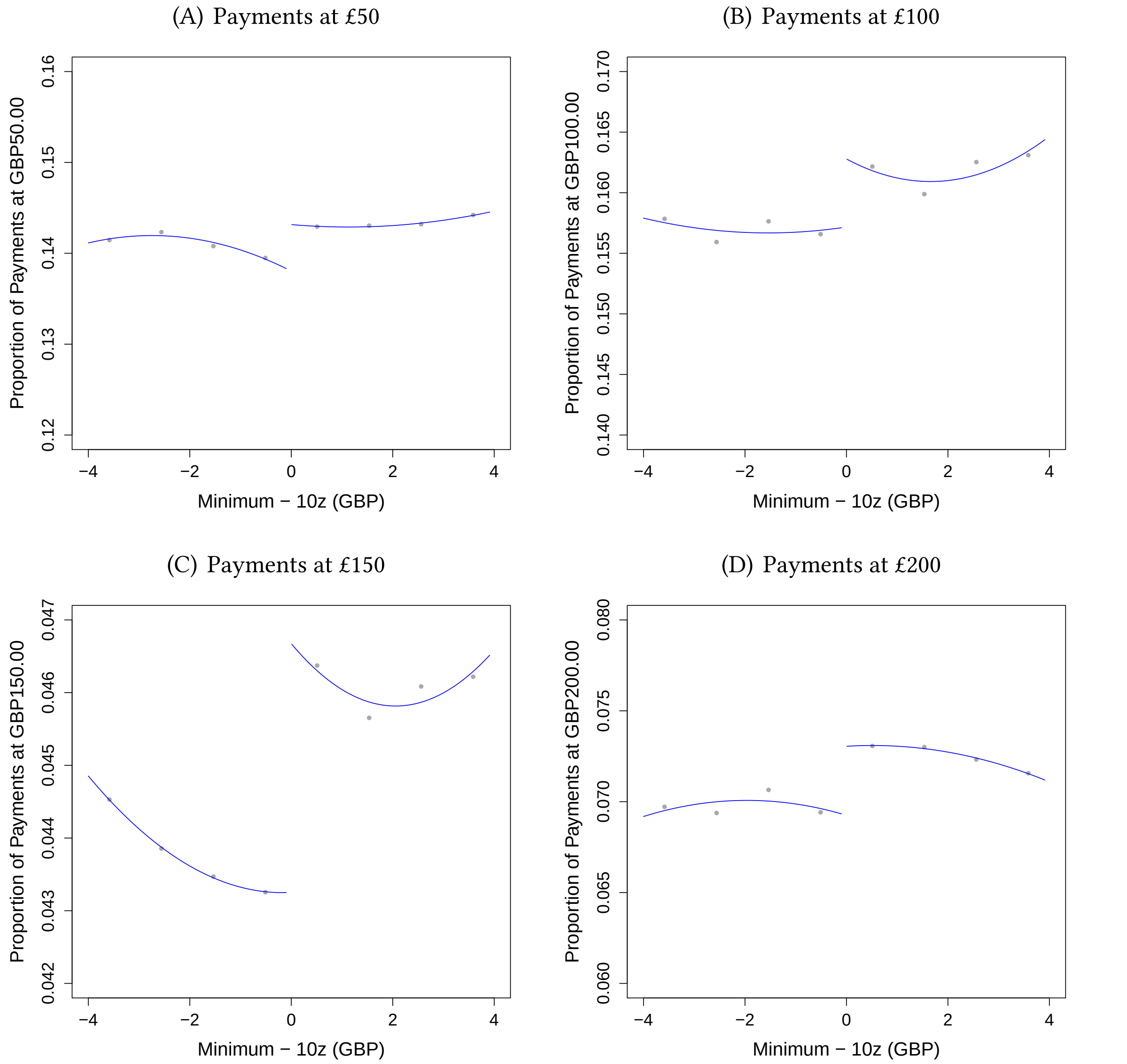


(B) Base-100 Rounding



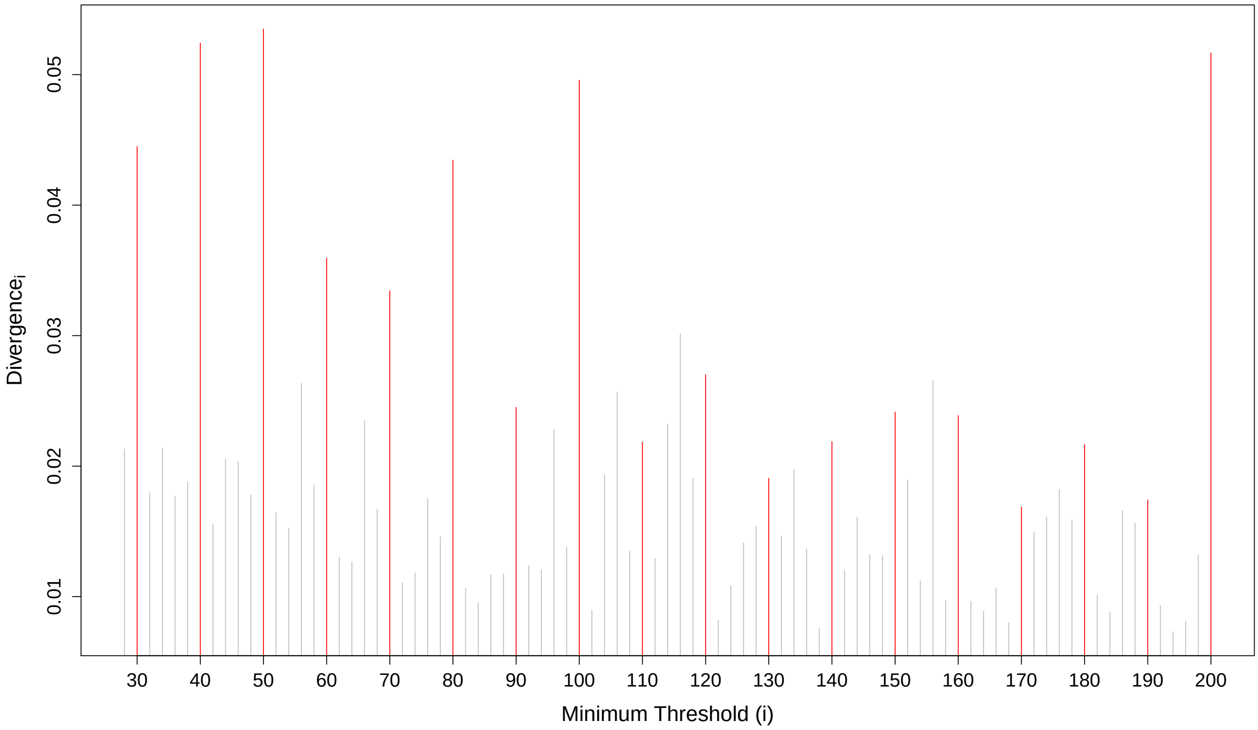
Note: Figure illustrates average payment amounts by distance from a round number payment (base-50, base-100 round number). Binned scatter plot with quadratic line of best fit, either side of zero. Panel A shows results for base-50 numbers in the baseline sample. Panels B shows results for base-100 numbers in the baseline sample.

Figure 10: Payments at £50, 100, 150, and 200 around Base-10 Round Minimum Thresholds



Note: Figure illustrates the proportion of payments at by distance from a base-10 round number minimum. Binned scatter plot with quadratic line of best fit, either side of zero.

Figure 11: Divergence in Payment Distributions between Two Adjacent Minimum Bins



Note: Figure shows the Wasserstein distance in payment distribution between two adjacent bins divided by a minimum threshold, i. The bin-width is £2. For example, a bar at 50 on the x-axis represents a divergence between payment distribution for card months where $minimum = 48.01 - 49.99$ and that for card months where $minimum = 50.01 - 51.99$. The red bars represent a divergence for base-10 round number minimum thresholds. The divergence measure quantifies the total area between two cumulative payment distributions (see Equation 2). The calculation was done up to the minimum of £200 (the 95th percentile). Card months with an integer minimum and those with a repayment more than £2,635 (the 99th percentile) were excluded from the analysis.

Table 1: Baseline Sample Summary Statistics

	Mean	S.D.	25th	Median	75th
Minimum	54.21	62.30	18.00	32.00	67.23
Balance	2,558.48	2,704.53	706.78	1,636.56	3,426.29
Credit limit	5,575.85	4,011.40	2,500.00	4,600.00	7,750.00
Utilization	0.52	0.35	0.20	0.51	0.86
Merchant APR	0.18	0.08	0.17	0.18	0.22
Cash APR	0.24	0.05	0.23	0.25	0.28
Monthly purchase	238.49	587.64	0.00	12.17	233.41
Payment	247.42	564.41	50.00	100.00	200.00

Note: Table reports summary statistics for the baseline sample. The unit of observation is an card-month. Minimum is the minimum payment due in the card-month. Utilization is balance divided by credit limit. APR denotes Annualized Percentage Rate. Payment is the payment amount made in the card-month.

Table 2: Top 20 Payment Amounts in Baseline Sample

Payment (GBP)	Proportion (%)	Cumulative Proportion (%)
100	0.13	0.13
50	0.09	0.22
200	0.06	0.28
150	0.04	0.32
30	0.03	0.35
300	0.03	0.38
40	0.03	0.41
25	0.03	0.44
20	0.03	0.47
60	0.03	0.49
500	0.02	0.52
250	0.02	0.54
80	0.02	0.55
70	0.02	0.57
400	0.01	0.58
120	0.01	0.60
1000	0.01	0.61
10	0.01	0.62
75	0.01	0.62
35	0.01	0.63

Note: Table reports the 20 most frequent payment amounts in the baseline sample. Unit of observation is an card-month. Table A2 repeats the analysis making separate categories for minimum payments and rounded minimum payments (i.e., payments rounding-up minimum to a nearest integer, or a nearest multiple of 5 or 10). For sample selection details see Section 2.

Table 3: Transition Matrix:
Round and Non-Round Number Payments

		t+1	
		Last Digit Zero	Last Digit Non-Zero
t	Last Digit Zero	86.92	13.08
	Last Digit Non-Zero	34.90	65.10

Note: Table reports transition matrix for adjacent months in times in the baseline sample. Unit of observation is a pair of consecutive card-months. Sample consists of 4,628,444 card-months of 415,127 cards with a partial payment for a least two consecutive months. For sample selection details see Section 2.

Table 4: Top 10 Consecutive 6-Month Payment Sequences

Sequence	Support (%)
100,100,100,100,100,100	5.56
50,50,50,50,50,50	3.80
200,200,200,200,200,200	1.69
25,25,25,25,25,25	1.29
30,30,30,30,30,30	1.06
150,150,150,150,150,150	1.03
20,20,20,20,20,20	0.97
100,50,50,50,50,50	0.87
40,40,40,40,40,40	0.83
200,100,100,100,100,100	0.80

Note: Table reports the 10 most frequent series of six month payment amounts in the baseline sample restricted to spells of card-months extending to at least six sequential months. Sample consists of 3,741,077 card-months of 271,461 cards making a partial payment for six or more consecutive months and never using automatic payment. For sample selection details see Section 2.

Table 5: Round Number Payments on Multiple Cards

Payments Patterns	Proportion (%)
Two Cards	
Pays All with Last Digit Zero	56.96
Pays All with Last Digit Non-zero	16.95
Other	26.09
Three Cards	
Pays All with Last Digit Zero	48.36
Pays All with Last Digit Non-zero	11.76
Other	39.88

Note: Table reports the proportion of one card holder two-card and three-card months in which the payment on all cards ended with a last integer pound value digit of zero and for which all cards ended with a last integer pound value digit other than zero, and other cases. Sample restricted to the two-card and three-card samples. For sample selection details see Section 2.

Table 6: Top 20 Pairs of Payments in Two Card Account × Month Sample

Pair of Payments (GBP)	Proportion (%)	Cumulative Proportion (%)
(100, 100)	3.76	3.76
(50, 50)	2.55	6.31
(100, 50)	2.54	8.85
(200, 100)	1.81	10.66
(150, 100)	1.30	11.96
(200, 200)	1.15	13.11
(50, 30)	0.77	13.88
(200, 150)	0.76	14.64
(150, 50)	0.72	15.36
(200, 50)	0.70	16.06
(50, 40)	0.68	16.74
(60, 50)	0.67	17.41
(300, 200)	0.66	18.07
(300, 100)	0.65	18.72
(150, 150)	0.64	19.36
(100, 60)	0.57	19.93
(30, 30)	0.57	20.50
(40, 30)	0.52	21.02
(100, 30)	0.52	21.54
(30, 20)	0.50	22.04

Note: Table reports the 20 most frequent pairs of payments in the one card holder two-card sample. Table A3 repeats the analysis adding pairs including minimum payments and rounded minimum payments (i.e., payments rounding-up minimum to a nearest integer, or a nearest multiple of 5 or 10). For sample selection details see Section 2.

Table 7: Minimum Payment Thresholds and Proportion of Payments at Next Round Number: OLS Estimates (Baseline Sample)

IV	Linear	Quadratic	Cubic
Intercept	0.086 ***	0.087 ***	0.090 ***
	(204.12)	(133.03)	(101.01)
Dummy(>Threshold)	0.017 ***	0.015 ***	0.015 ***
	(28.39)	(15.74)	(11.74)
Slope(<Threshold)^3			0.001 ***
			(4.81)
Slope(<Threshold)^2		0.000 **	0.005 ***
		(2.2)	(5.11)
Slope(<Threshold)	0.003 ***	0.005 ***	0.013 ***
	(17.88)	(6.53)	(7.01)
Slope(>Threshold)^3			-0.001 ***
			(-5.05)
Slope(>Threshold)^2		0.000 **	0.005 ***
		(-2.52)	(4.56)
Slope(>Threshold)	0.003 ***	0.005 ***	-0.004 *
	(17.3)	(6.71)	(-1.95)

Note: Table reports Ordinary Least Squares (OLS) regression estimates. Dependent variable is a dummy variable denoting payment amount at the next round number (base-10). Independent variables are the distance from the round number threshold, in pounds, above and below the threshold, plus a dummy variable denoting above the threshold. Model includes a constant term. Separate model estimates shown in which the distance from the round number threshold enters linearly, as a quadratic term, and as a cubic term. T-statistics shown in parenthesis. Card-months where a minimum is exactly the threshold were excluded from the regressions. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 8: Minimum Payment Threshold and Partial Payment Amounts: OLS Estimates (Baseline Sample)

IV	Linear	Quadratic	Cubic
Intercept	256.270 ***	259.538 ***	248.647 ***
	(297.91)	(194.14)	(136.66)
Dummy(>Threshold)	5.753 ***	2.770	6.997 ***
	(4.66)	(1.45)	(2.69)
Slope(<Threshold)^3			-2.799 ***
			(-8.82)
Slope(<Threshold)^2		1.071 ***	-16.442 ***
		(3.19)	(-8.17)
Slope(<Threshold)	-0.683 *	3.813 ***	-25.746 ***
	(-1.91)	(2.63)	(-7.05)
Slope(>Threshold)^3			1.737 ***
			(5.28)
Slope(>Threshold)^2		0.095	-10.744 ***
		(0.27)	(-5.16)
Slope(>Threshold)	3.860 ***	3.465 **	21.676 ***
	(10.4)	(2.31)	(5.76)

Note: Table reports Ordinary Least Squares (OLS) regression estimates. Dependent variable is payment amount. Independent variables are the distance from the round number threshold, in pounds, above and below the threshold, plus a dummy variable denoting above the threshold. Model includes a constant term. Separate model estimates shown in which the distance from the round number threshold enters linearly, as a quadratic term, and as a cubic term. T-statistics shown in parenthesis. Card-months where a minimum is exactly the threshold were excluded from the regressions. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 9: Minimum Payment Threshold and Partial Payment Amounts: OLS Estimates (Payments above Minimum)

Intercept	269.282 ***	273.617 ***	259.049 ***
	(290.30)	(190.08)	(132.34)
Dummy(>Threshold)	11.381 ***	7.590 ***	12.093 ***
	(8.52)	(3.66)	(4.29)
Slope(<Threshold)^3			-3.772 ***
			(-10.98)
Slope(<Threshold)^2		1.430 ***	-22.129 ***
		(3.94)	(-10.17)
Slope(<Threshold)	-1.799 ***	4.189 ***	-35.493 ***
	(-4.66)	(2.67)	(-9.01)
Slope(>Threshold)^3			2.632 ***
			(7.34)
Slope(>Threshold)^2		0.181	-16.232 ***
		(0.48)	(-7.15)
Slope(>Threshold)	4.142 ***	3.385 **	30.941 ***
	(10.26)	(2.07)	(7.56)

Note: Table reports Ordinary Least Squares (OLS) regression estimates. Dependent variable is payment amount. Independent variables are the distance from the round number threshold, in pounds, above and below the threshold, plus a dummy variable denoting above the threshold. Model includes a constant term. Separate model estimates shown in which the distance from the round number threshold enters linearly, as a quadratic term, and as a cubic term. T-statistics shown in parenthesis. Sample is restricted to payments above the minimum. Card-months where a minimum is exactly the threshold were excluded from the regressions. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

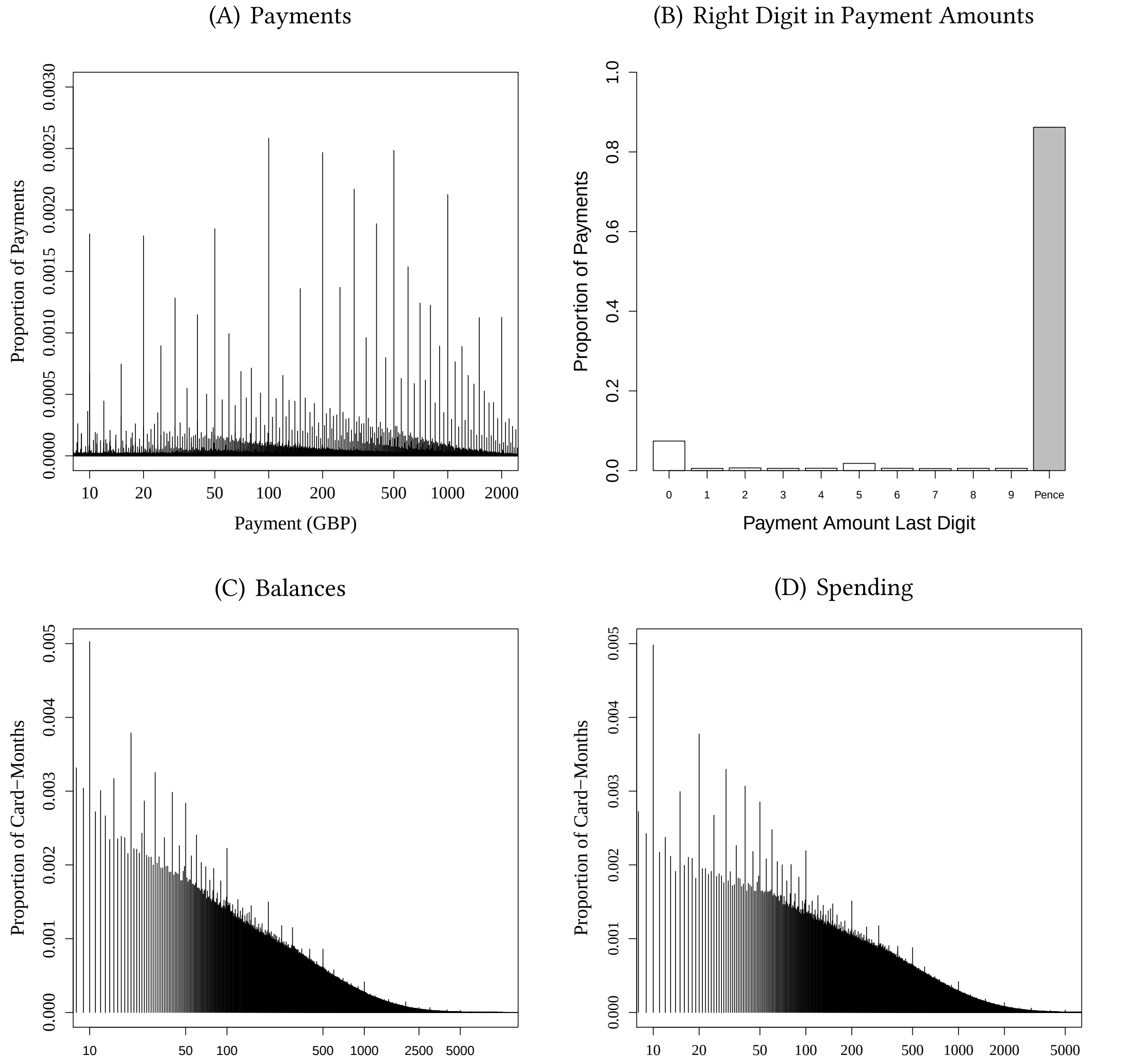
Table 10: Payment Discontinuity Estimates on Rounding Payers Sample

IV	(1)	(2)	(3)
$Dummy(Min > 10)$	5.326	5.260	1.412
	(4.793)	(4.793)	(6.359)
$Dummy(Min > 20)$	6.716	6.476	11.853**
	(4.133)	(4.134)	(5.270)
$Dummy(Min > 30)$	12.761***	12.550***	18.414***
	(3.935)	(3.935)	(4.881)
$Dummy(Min > 40)$	7.843**	7.802**	3.786
	(3.680)	(3.680)	(4.351)
$Dummy(Min > 50)$	4.904	4.707	4.467
	(4.049)	(4.049)	(4.609)
$Dummy(Min > 60)$	12.833***	12.683***	17.833***
	(4.583)	(4.583)	(5.276)
$Dummy(Min > 70)$	11.091**	10.906**	12.412**
	(5.020)	(5.020)	(5.717)
$Dummy(Min > 80)$	24.331***	24.251***	26.241***
	(5.689)	(5.689)	(6.389)
$Dummy(Min > 90)$	4.107	4.286	−2.122
	(5.741)	(5.741)	(6.350)
$Dummy(Min > 100)$	28.778***	28.718***	25.351***
	(5.957)	(5.957)	(6.564)
$Dummy(Min > 110)$	4.064	4.024	1.976
	(6.443)	(6.443)	(7.137)
$Dummy(Min > 120)$	29.075***	28.913***	37.100***
	(7.289)	(7.289)	(7.959)
$Dummy(Min > 130)$	7.154	7.037	3.809
	(8.165)	(8.166)	(8.819)
$Dummy(Min > 140)$	2.890	2.709	5.522
	(8.639)	(8.639)	(9.308)
$Dummy(Min > 150)$	25.018***	24.898***	16.744*
	(9.015)	(9.015)	(9.757)
$Dummy(Min > 160)$	8.670	8.488	9.638
	(10.750)	(10.749)	(11.509)
$Dummy(Min > 170)$	27.244**	27.177**	21.886
	(13.097)	(13.097)	(13.823)
$Dummy(Min > 180)$	26.486*	26.482*	25.602
	(14.822)	(14.822)	(15.629)
$Dummy(Min > 190)$	−49.208***	−48.678***	−44.114***
	(14.892)	(14.892)	(16.052)
7th degree minimum polynomial	Y	Y	Y
Card characteristics controls	Y	Y	Y
Calendar month FE		Y	Y
Card FE			Y
Observations	255,133	255,133	255,133
R^2	0.054	0.055	0.142
Adjusted R^2	0.054	0.054	0.080
Residual Std. Error	253.732 (df = 255102)	253.721 (df = 255080)	250.326 (df = 237748)
F Statistic	489.588*** (df = 30; 255102)		

Note: Regressions were conducted on card-months where the minimum is less than £200 (the 95th percentile) in the rounding payers sample. The negative coefficient estimate for $Dummy(Min > 190)$ is due to payments at £200 sharply increasing after the threshold of £190, decreasing the proportion of larger payments. *p<0.1; **p<0.05; ***p<0.01

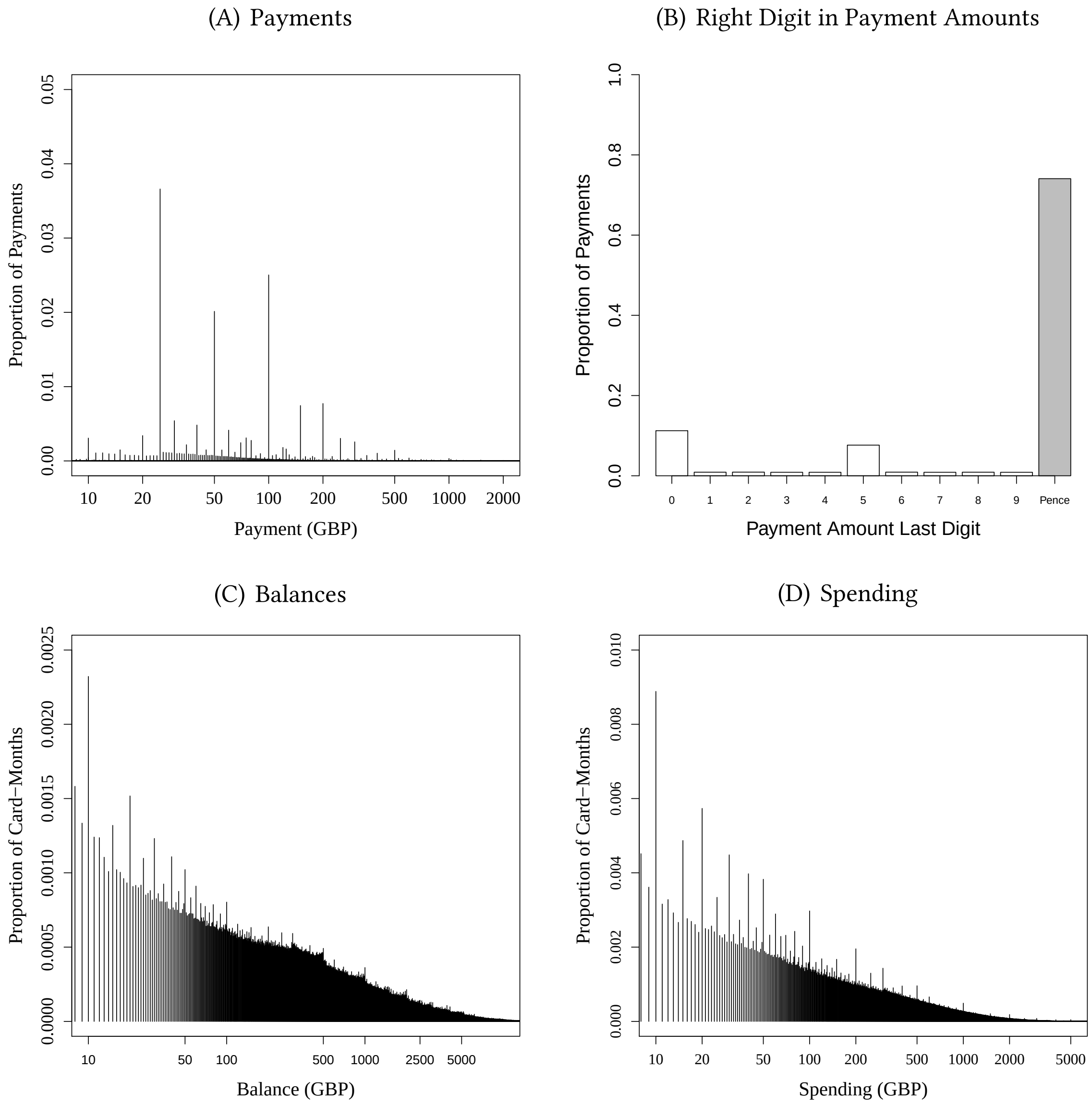
Online Only Appendix

Figure A1: Payment Amounts in the Full Payments Sample



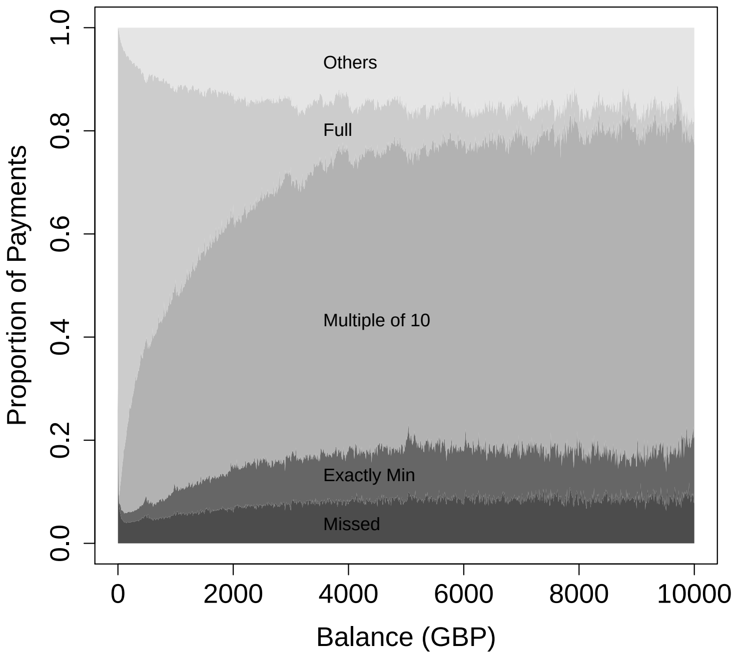
Note: Figure illustrates the distribution of payments, balances and spending amounts in the full payments sample. Panel B illustrates the distribution of rightmost £-digit integer-value payment amounts. Grey bar contains all non-integer-value payments. In Panel A, the bin width is 1 penny. In Panels C and D, the bin width is 1 pound. For sample selection details see Section 2.

Figure A2: Payment Amounts in the Automatic Payments Sample



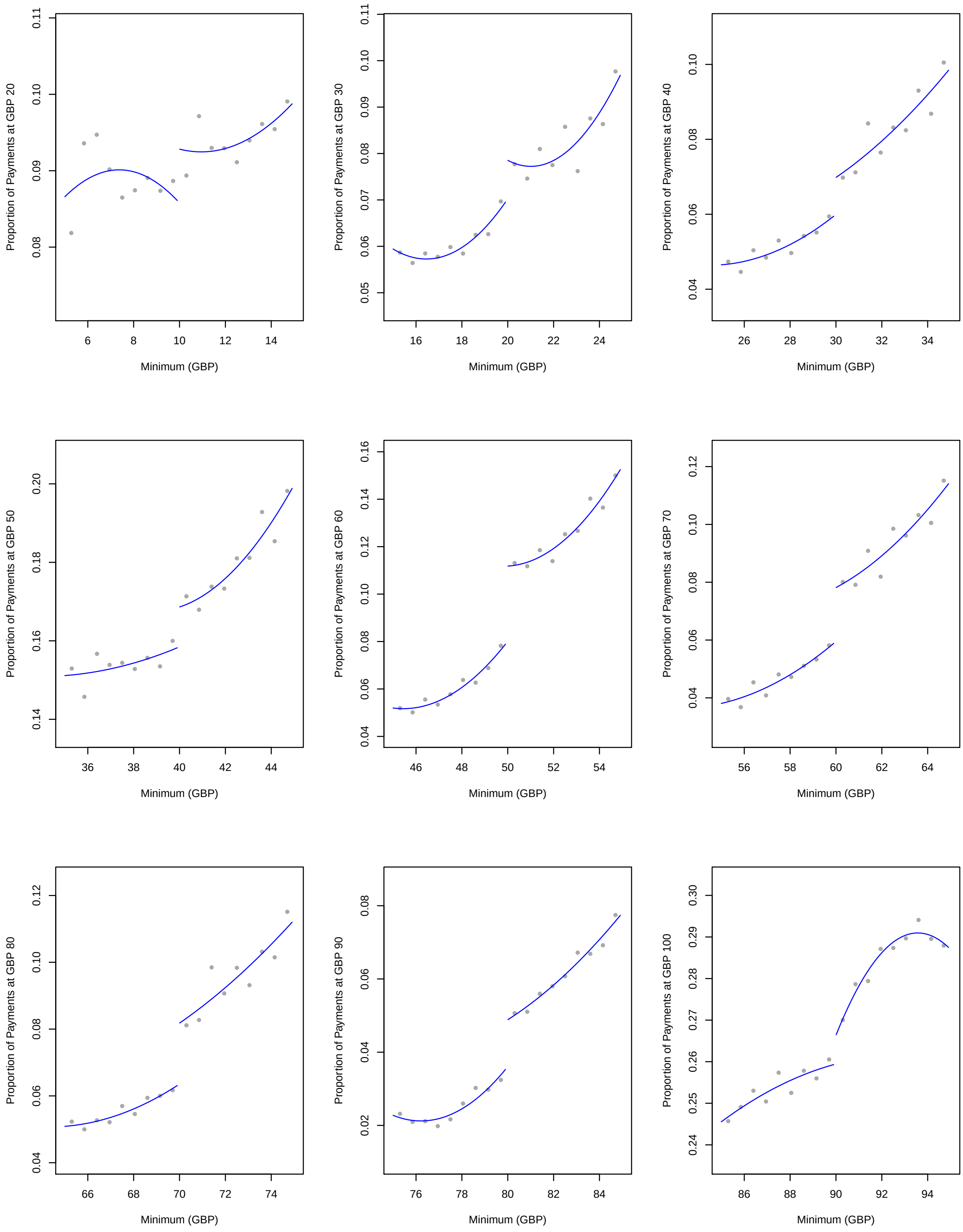
Note: Figure illustrates the distribution of payments, balances and spending amounts in the automatic payments sample. Panel B illustrates the distribution of rightmost £-digit integer-value payment amounts. Grey bar contains all non-integer-value payments. In Panel A, the bin width is 1 penny. In Panels C and D, the bin width is 1 pound. For sample selection details see Section 2.

Figure A3: Categories of Payment Amounts



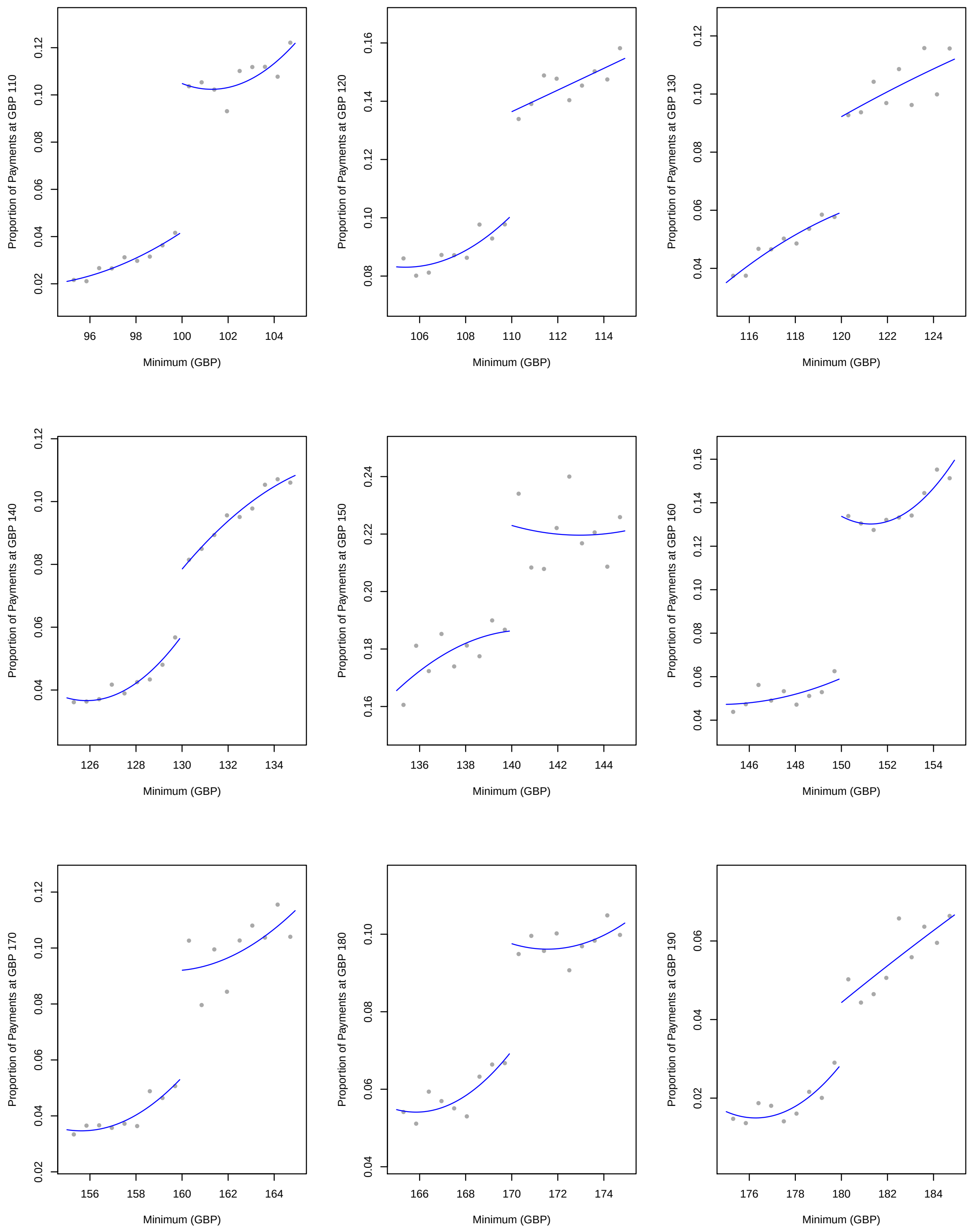
Note: Figure illustrates the proportion of payments in each of five mutually exclusive and exhaustive categories: missed payments (defined as a payment below the minimum payment due), payments at exactly the minimum payment due, payments in multiples of 10 pounds, payments of the full balance, and other payments.

Figure A4: Round Number Payment Amounts and Minimum Payments I (Baseline Sample)



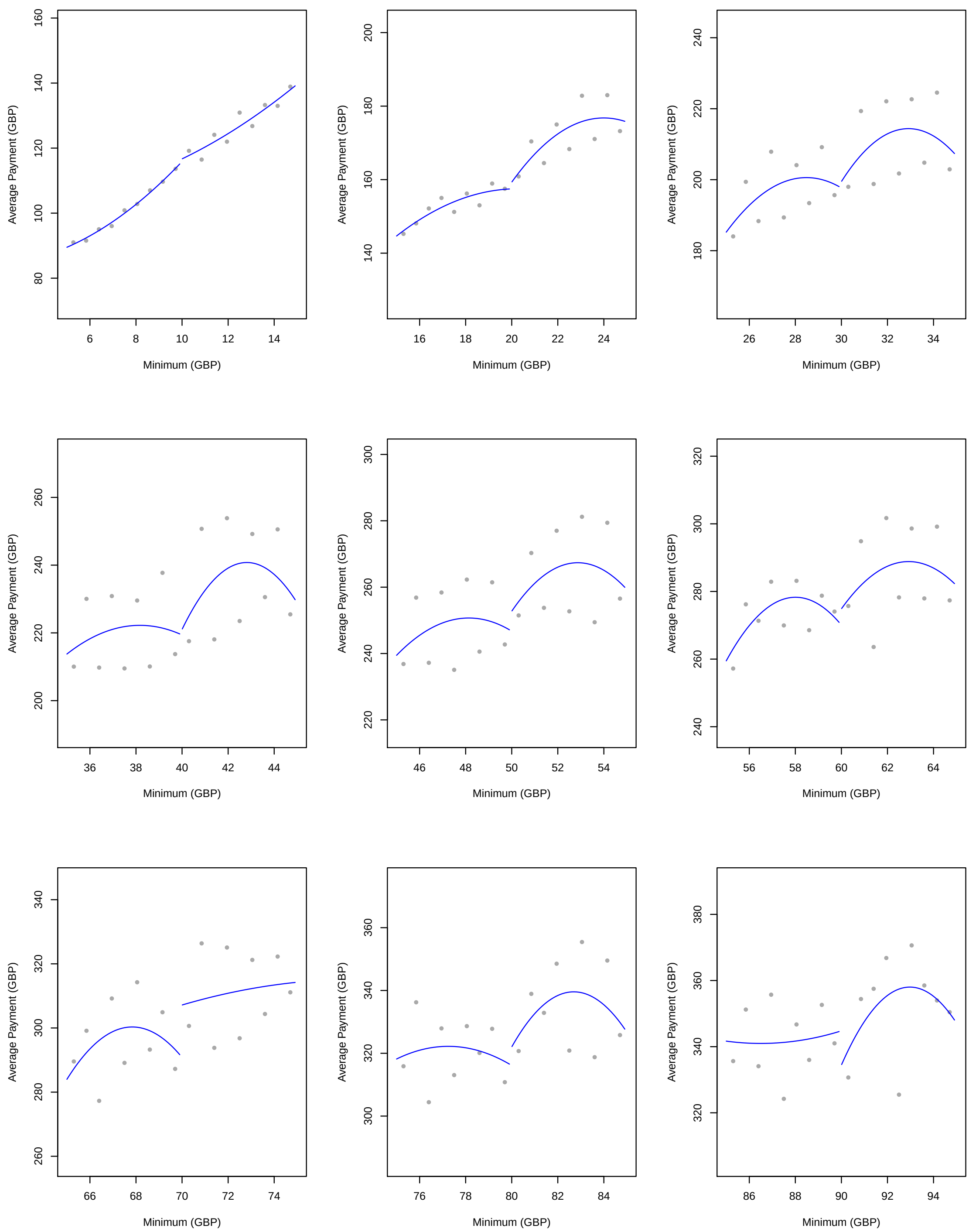
Note: Figure illustrates the proportion of payments at the next highest round number (base-10) by distance from a round number payment (base-10 round number). Binned scatter plot with quadratic line of best fit, either side of zero.

Figure A5: Round Number Payment Amounts and Minimum Payments II (Baseline Sample)



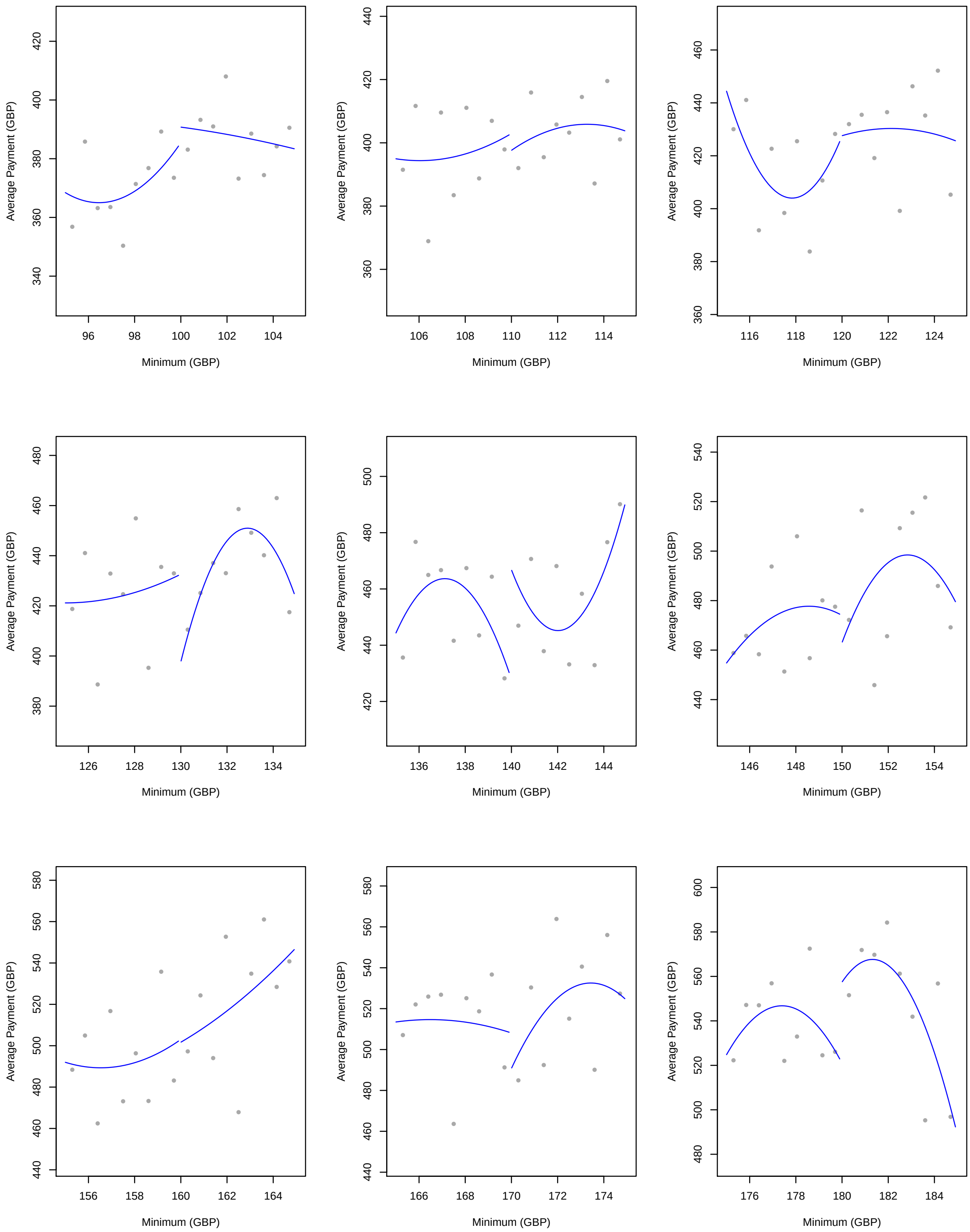
Note: Figure illustrates the proportion of payments at the next highest round number (base-10) by distance from a round number payment (base-10 round number). Binned scatter plot with quadratic line of best fit, either side of zero.

Figure A6: Average Payment Amounts and Minimum Payments I (Baseline Sample)



Note: Figure illustrates average payment amount by distance from a round number payment (base-10 round number). Binned scatter plot with quadratic line of best fit, either side of zero.

Figure A7: Average Payment Amounts and Minimum Payments II (Baseline Sample)



Note: Figure illustrates average payment amount by distance from a round number payment (base-10 round number). Binned scatter plot with quadratic line of best fit, either side of zero.

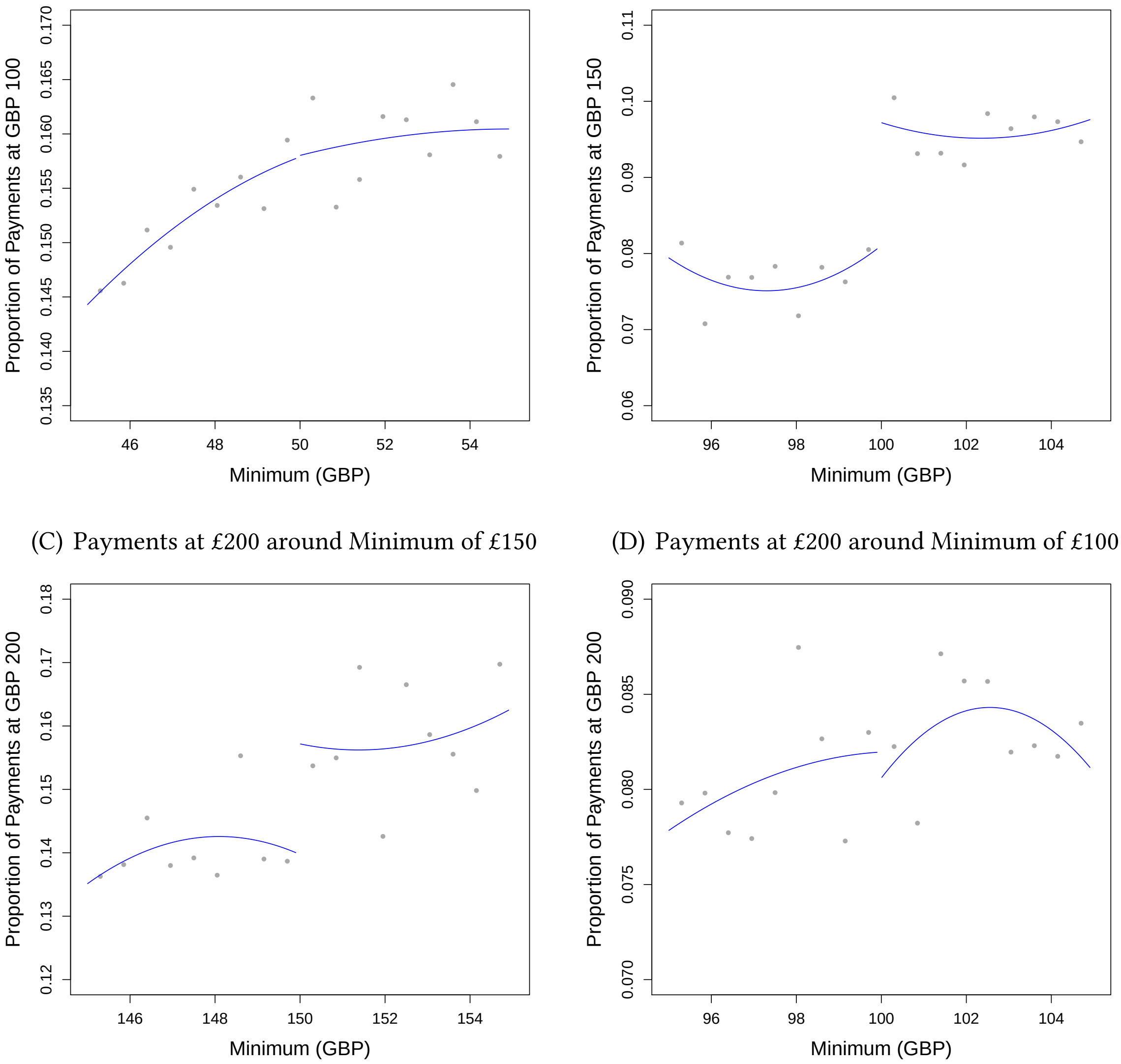
Figure A8: Base-50 and-100 Rounding

(A) Payments at £100 around Minimum of £50

(B) Payments at £150 around Minimum of £100

(C) Payments at £200 around Minimum of £150

(D) Payments at £200 around Minimum of £100



Note: Figure illustrates proportion of payments at different values by minimum payment due. Binned scatter plot with quadratic line of best fit, either side of the base-50, or base-100 number. Baseline sample.

Table A1: Sample Selection

Criterion	Cards N	%	Card Months N	%	Payment Total in GBP	%
Unrestricted Sample	1,159,480	100	23,524,898	100	8,233,866,394	100
(A) Baseline Sample						
Drop if						
No Balance	1,058,275	91.3	17,313,117	73.6	8,129,251,781	98.7
Pays via Automatic Payment	821,641	70.9	11,133,293	47.3	5,311,554,219	64.5
Pays Full	598,117	51.6	6,336,015	26.9	1,407,812,951	17.1
Pays below Minimum	526,515	45.4	5,637,154	24.0	1,394,768,308	16.9
(B) Additional Two-Card Sample						
Retain if						
Having Two Cards in the Month	52,158	4.5	533,940	2.3	105,945,297	1.3
(C) Additional Three-Card Sample						
Retain if						
Having Three Cards in the Month (4)	7,431	0.6	63,462	0.3	11,730,597	0.1

Note: Table describes sample restrictions that generate samples used in analysis. The unrestricted sample is the cleaned sample as received from Argus. Sample restrictions are applied at the card-month level. Sample A Baseline Sample is the main sample used in analysis. Samples B and C restrict the baseline sample to observations for which two card-months, or three card-months can be joined to the same card holder in the same month. Cards column shows the number of cards retained at each step. Card Months column shows the number of card-months retained at each step. Payment Total in GBP column shows the total value of payments made in the sample retained at each step.

Table A2: Top 20 Payment Amounts or Categories of Amounts in Baseline Sample

Payment (GBP)	Proportion (%)	Cumulative Proportion (%)
RM	15.44	15.44
100	11.97	27.41
Min	9.70	37.11
50	7.85	44.96
200	5.91	50.87
150	3.69	54.56
300	2.87	57.43
500	2.24	59.67
250	1.94	61.61
40	1.82	63.43
60	1.64	65.07
30	1.59	66.66
400	1.48	68.13
80	1.26	69.39
20	1.19	70.58
1000	1.04	71.62
70	1.00	72.62
120	0.92	73.54
25	0.75	74.28
75	0.69	74.97

Note: Table reports the 20 most frequent payment amounts in the baseline sample. In cases in which the payment amount is at a minimum payment, or a minimum payment rounded to the next base-10 round number, these are denoted RM and Min. "RM" represents rounded minimum payments (i.e., payments rounding-up minimum to a nearest integer, or a nearest multiple of 5 or 10). "Min" represents payments at exactly minimum. Payments at a minimum which itself is an integer are included in "Min".

Table A3: Top 20 Pairs of Payment Amounts or Categories of Amounts in Two Card Sample

Pair of Payments (GBP)	Proportion (%)	Cumulative Proportion (%)
(RM, RM)	11.27	11.27
(Min, Min)	4.76	16.02
(Min, RM)	5.27	21.29
(100, 100)	3.38	24.67
(RM, 100)	2.20	26.87
(100, 50)	2.09	28.96
(50, 50)	1.99	30.95
(RM, 50)	1.92	32.87
(200, 100)	1.64	34.51
(150, 100)	1.14	35.65
(200, 200)	1.10	36.75
(RM, 200)	0.88	37.63
(Min, 100)	0.79	38.42
(RM, 150)	0.76	39.18
(RM, 40)	0.75	39.93
(RM, 30)	0.71	40.64
(Min, 50)	0.69	41.33
(200, 150)	0.69	42.02
(300, 200)	0.63	42.65
(300, 100)	0.62	43.27

Note: Table reports the 20 most frequent pairs of payments in the one card holder two-card sample. In cases in which the payment amount is at a minimum payment, or a minimum payment rounded to the next base-10 round number, these are denoted RM and Min. "RM" represents rounded minimum payments (i.e., payments rounding-up minimum to a nearest integer, or a nearest multiple of 5 or 10). "Min" represents payments at exactly minimum. Payments at a minimum which itself is an integer are included in "Min".

Table A4: Minimum Payment Thresholds and Proportion of Payments at Next Round Number: OLS Regression Discontinuity Estimates (Baseline Sample)

IV	Payment=20 around 10	Payment=30 around 20	Payment=40 around 30
Intercept	0.074 ***	0.053 ***	0.043 ***
	(48.92)	(26.83)	(23.36)
Dummy(<Threshold)	0.014 ***	0.012 ***	0.014 ***
	(8.26)	(5.66)	(6.93)
Dummy(>Threshold)	0.018 ***	0.019 ***	0.024 ***
	(10.12)	(8.91)	(11.74)
Slope(<Threshold)	0.000	0.002 ***	0.003 ***
	(-1.05)	(7.14)	(8.83)
Slope(>Threshold)	0.001 ***	0.004 ***	0.006 ***
	(3.92)	(11.98)	(17.22)
IV	Payment=50 around 40	Payment=60 around 50	Payment=70 around 60
Intercept	0.133 ***	0.043 ***	0.043 ***
	(40.98)	(20.22)	(15.22)
Dummy(<Threshold)	0.024 ***	0.032 ***	0.014 ***
	(6.71)	(12.62)	(4.34)
Dummy(>Threshold)	0.032 ***	0.062 ***	0.031 ***
	(8.69)	(24.44)	(9.77)
Slope(<Threshold)	0.002 ***	0.006 ***	0.004 ***
	(2.84)	(12.24)	(9.37)
Slope(>Threshold)	0.006 ***	0.008 ***	0.007 ***
	(10.65)	(16.74)	(14.87)
IV	Payment=80 around 70	Payment=90 around 80	Payment=100 around 90
Intercept	0.056 ***	0.029 ***	0.221 ***
	(16.06)	(10.09)	(29.15)
Dummy(<Threshold)	0.005	0.002	0.04 ***
	(1.38)	(0.71)	(4.83)
Dummy(>Threshold)	0.024 ***	0.018 ***	0.054 ***
	(6.13)	(5.72)	(6.51)
Slope(<Threshold)	0.003 ***	0.003 ***	0.003 ***
	(4.6)	(5.57)	(2.63)
Slope(>Threshold)	0.006 ***	0.006 ***	0.004 ***
	(10.5)	(11.75)	(3.43)

Note: Table reports Ordinary Least Squares (OLS) regression estimates. Dependent variable is a dummy variable denoting payment amount at the next round number (base-10). Independent variables are the distance from the round number threshold, in pounds, above and below the threshold, plus a dummy variable denoting above the threshold. Model includes a constant term. Card-months where a minimum is exactly the threshold were excluded from the regressions. *p<0.1; **p<0.05; ***p<0.01

Table A5: Minimum Payment Thresholds and Partial Payment Amounts:
OLS Regression Discontinuity Estimates (Baseline Sample)

IV	Payment around 10	Payment around 20	Payment around 30
Intercept	114.103 ***	159.811 ***	204.852 ***
	(255.89)	(209.04)	(165.29)
Dummy(>Threshold)	1.186 *	4.898 ***	4.012 **
	(1.89)	(4.42)	(2.23)
Slope(<Threshold)	5.332 ***	2.611 ***	2.493 ***
	(33.65)	(9.87)	(5.85)
Slope(>Threshold)	4.604 ***	3.324 ***	1.648 ***
	(29.67)	(11.7)	(3.58)
IV	Payment around 40	Payment around 50	Payment around 60
Intercept	226.056 ***	254.171 ***	280.237 ***
	(134.15)	(112.87)	(98.68)
Dummy(>Threshold)	8.683 ***	7.939 **	4.183
	(3.56)	(2.43)	(1.02)
Slope(<Threshold)	1.356 **	1.562 **	2.131 **
	(2.32)	(2.01)	(2.16)
Slope(>Threshold)	1.529 **	1.614 *	1.347
	(2.44)	(1.93)	(1.28)
IV	Payment around 70	Payment around 80	Payment around 90
Intercept	302.57 ***	320.932 ***	344.115 ***
	(84.96)	(74.15)	(67.66)
Dummy(>Threshold)	8.293	12.405 **	3.942
	(1.61)	(1.99)	(0.54)
Slope(<Threshold)	1.842	-0.552	0.236
	(1.49)	(-0.37)	(0.13)
Slope(>Threshold)	1.095	1.444	2.215
	(0.83)	(0.91)	(1.19)

Note: Table reports Ordinary Least Squares (OLS) regression estimates. Dependent variable is payment amount. Independent variables are the distance from the round number threshold, in pounds, above and below the threshold, plus a dummy variable denoting above the threshold. Model includes a constant term. Card-months where a minimum is exactly the threshold were excluded from the regressions. *p<0.1; **p<0.05; ***p<0.01

Table A6: Minimum Payment Thresholds and Proportion of Payments at Next Base-50 Round Number: OLS Estimates (Baseline Sample)

IV	Linear	Quadratic	Cubic
Intercept	0.136 ***	0.138 ***	0.140 ***
	(96.66)	(62.74)	(46.56)
Dummy(>Threshold)	0.006 ***	0.004	0.006
	(2.98)	(1.21)	(1.38)
Slope(<Threshold)^3			0.000
			(0.91)
Slope(<Threshold)^2		0.001	0.004
		(1.23)	(1.1)
Slope(<Threshold)	0.002 ***	0.005 **	0.010 *
	(3.48)	(2.05)	(1.65)
Slope(>Threshold)^3			-0.001 *
			(-1.9)
Slope(>Threshold)^2		0.000	0.006 *
		(-0.07)	(1.86)
Slope(>Threshold)	0.001	0.001	-0.010
	(1.04)	(0.32)	(-1.61)

Note: Table reports Ordinary Least Squares (OLS) regression estimates. Dependent variable is a dummy variable denoting payment amount at the next round number (base-50). Independent variables are the distance from the round number threshold, in pounds, above and below the threshold, plus a dummy variable denoting above the threshold. Model includes a constant term. Card-months where a minimum is exactly the threshold were excluded from the regressions. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table A7: Minimum Payment Thresholds and Proportion of Payments at Next Base-100 Round Number: OLS Estimates (Baseline Sample)

IV	Linear	Quadratic	Cubic
Intercept	0.081 ***	0.079 ***	0.078 ***
	(38.05)	(23.65)	(17.07)
Dummy(>Threshold)	0.002	0.002	0.008
	(0.52)	(0.44)	(1.16)
Slope(<Threshold)^3			0.000
			(-0.37)
Slope(<Threshold)^2		-0.001	-0.003
		(-0.95)	(-0.52)
Slope(<Threshold)	0.001	-0.002	-0.006
	(0.98)	(-0.68)	(-0.61)
Slope(>Threshold)^3			-0.001
			(-1.35)
Slope(>Threshold)^2		-0.001	0.006
		(-0.71)	(1.21)
Slope(>Threshold)	0.000	0.003	-0.009
	(-0.07)	(0.68)	(-0.97)

Note: Table reports Ordinary Least Squares (OLS) regression estimates. Dependent variable is a dummy variable denoting payment amount at the next round number (base-100). Independent variables are the distance from the round number threshold, in pounds, above and below the threshold, plus a dummy variable denoting above the threshold. Model includes a constant term. Card-months where a minimum is exactly the threshold were excluded from the regressions. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table A8: Minimum Payment Thresholds and Round Number Payments (Base-50 and Base-100 Rounding): OLS Regression Discontinuity Estimates (Baseline Sample)

IV	Payment=100 around 50	Payment=150 around 100	Payment=200 around 150	Payment=200 around 100
Intercept	0.159 ***	0.077 ***	0.099	0.083 ***
	(91.75)	(34.04)	(1.36)	(37.11)
Dummy(>Threshold)	-0.001	0.018 ***	-0.003	0.000
	(-0.5)	(5.54)	(-0.02)	(0.00)
Slope(<Threshold)	0.003 ***	0.000	0.001	0.001
	(4.58)	(0.49)	(0.57)	(1.09)
Slope(>Threshold)	0.001	0.000	0.001	0.000
	(1.24)	(0.09)	(0.71)	(0.18)

Note: Table reports Ordinary Least Squares (OLS) regression estimates. Dependent variable is a dummy variable denoting payment amount at the next round number (base-50 or base-100). Independent variables are the distance from the round number threshold, in pounds, above and below the threshold, plus a dummy variable denoting above the threshold. Model includes a constant term. Card-months where a minimum is exactly the threshold were excluded from the regressions. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table A9: Base-50 Minimum Payment Threshold and Partial Payment Amounts: OLS Estimates (Baseline Sample)

IV	Linear	Quadratic	Cubic
Intercept	337.235 ***	342.929 ***	328.876 ***
	(110.9)	(72.1)	(50.63)
Dummy(>Threshold)	8.985 **	5.056	14.120
	(2.04)	(0.74)	(1.51)
Slope(<Threshold)^3			-3.522 ***
			(-3.18)
Slope(<Threshold)^2		1.830	-20.312 ***
		(1.56)	(-2.87)
Slope(<Threshold)	0.604	8.339	-29.286 **
	(0.48)	(1.63)	(-2.27)
Slope(>Threshold)^3			1.292
			(1.09)
Slope(>Threshold)^2		0.585	-7.482
		(0.47)	(-1)
Slope(>Threshold)	3.268 **	0.822	14.388
	(2.45)	(0.15)	(1.06)

Note: Table reports Ordinary Least Squares (OLS) regression estimates. Dependent variable is payment amount. Independent variables are the distance from the round number threshold, in pounds, above and below the threshold, plus a dummy variable denoting above the threshold. Model includes a constant term. Card-months where a minimum is exactly the threshold were excluded from the regressions. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table A10: Base-100 Minimum Payment Threshold and Partial Payment Amounts: OLS Estimates (Baseline Sample)

IV	Linear	Quadratic	Cubic
Intercept	429.205 ***	450.259 ***	423.219 ***
	(57.65)	(38.74)	(26.68)
Dummy(>Threshold)	31.117 ***	17.345	27.494
	(2.87)	(1.03)	(1.20)
Slope(<Threshold)^3			-6.870 **
			(-2.50)
Slope(<Threshold)^2		6.846 **	-36.179 **
		(2.36)	(-2.08)
Slope(<Threshold)	-1.157	27.623 **	-45.174
	(-0.37)	(2.20)	(-1.43)
Slope(>Threshold)^3			4.444
			(1.50)
Slope(>Threshold)^2		2.434	-25.201
		(0.78)	(-1.35)
Slope(>Threshold)	-1.812	-11.957	34.317
	(-0.55)	(-0.89)	(1.02)

Note: Table reports Ordinary Least Squares (OLS) regression estimates. Dependent variable is payment amount. Independent variables are the distance from the round number threshold, in pounds, above and below the threshold, plus a dummy variable denoting above the threshold. Model includes a constant term. Card-months where a minimum is exactly the threshold were excluded from the regressions. *p<0.1; **p<0.05; ***p<0.01

Table A11: Base-10 Minimum Payment Thresholds and Proportion of Payments at £50: OLS Estimates (Baseline Sample)

IV	Linear	Quadratic	Cubic
Intercept	0.140 ***	0.139 ***	0.140 ***
	(183.72)	(118.61)	(87.90)
Dummy(>Threshold)	0.002 **	0.005 ***	0.004 *
	(2.10)	(2.85)	(1.78)
Slope(<Threshold)^3			0.000
			(0.57)
Slope(<Threshold)^2		0.000	0.001
		(-0.59)	(0.46)
Slope(<Threshold)	-0.001 *	-0.001	0.000
	(-1.66)	(-0.98)	(0.13)
Slope(>Threshold)^3			0.000
			(0.09)
Slope(>Threshold)^2		0.001 **	0.000
		(2.14)	(0.26)
Slope(>Threshold)	0.001	-0.002 *	-0.002
	(1.64)	(-1.67)	(-0.58)

Note: Table reports Ordinary Least Squares (OLS) regression estimates. Dependent variable is a dummy variable denoting payment amount at £50. Independent variables are the distance from the round number threshold, in pounds, above and below the threshold, plus a dummy variable denoting above the threshold. Model includes a constant term. Separate model estimates shown in which the distance from the round number threshold enters linearly, as a quadratic term, and as a cubic term. T-statistics shown in parenthesis. Card-months where a minimum is exactly the threshold were excluded from the regressions. The estimates were done up to $10z = 30$. *p<0.1; **p<0.05; ***p<0.01

Table A12: Base-10 Minimum Payment Thresholds and Proportion of Payments at £100: OLS Estimates (Baseline Sample)

IV	Linear	Quadratic	Cubic
Intercept	0.155 ***	0.156 ***	0.149 ***
	(237.25)	(154.13)	(108.66)
Dummy(>Threshold)	0.005 ***	0.006 ***	0.012 ***
	(5.86)	(4.22)	(6.19)
Slope(<Threshold)^3			-0.002 ***
			(-6.90)
Slope(<Threshold)^2		0.000	-0.010 ***
		(1.57)	(-6.54)
Slope(<Threshold)	-0.001 ***	0.001	-0.017 ***
	(-4.33)	(0.46)	(-6.14)
Slope(>Threshold)^3			0.000
			(0.33)
Slope(>Threshold)^2		0.001 **	0.000
		(2.32)	(0.06)
Slope(>Threshold)	0.001 ***	-0.002	-0.001
	(3.19)	(-1.46)	(-0.28)

Note: Table reports Ordinary Least Squares (OLS) regression estimates. Dependent variable is a dummy variable denoting payment amount at £100. Independent variables are the distance from the round number threshold, in pounds, above and below the threshold, plus a dummy variable denoting above the threshold. Model includes a constant term. Separate model estimates shown in which the distance from the round number threshold enters linearly, as a quadratic term, and as a cubic term. T-statistics shown in parenthesis. Card-months where a minimum is exactly the threshold were excluded from the regressions. The estimates were done up to $10z = 80$. *p<0.1; **p<0.05; ***p<0.01

Table A13: Base-10 Minimum Payment Thresholds and Proportion of Payments at £150: OLS Estimates (Baseline Sample)

IV	Linear	Quadratic	Cubic
Intercept	0.043 ***	0.043 ***	0.043 ***
	(122.12)	(79.20)	(58.85)
Dummy(>Threshold)	0.003 ***	0.003 ***	0.003 ***
	(6.78)	(4.21)	(2.58)
Slope(<Threshold)^3			0.000
			(0.88)
Slope(<Threshold)^2		0.000	0.001
		(0.62)	(0.97)
Slope(<Threshold)	-0.001 ***	0.000	0.001
	(-3.60)	(-0.29)	(0.69)
Slope(>Threshold)^3			0.000
			(0.21)
Slope(>Threshold)^2		0.000	0.000
		(0.29)	(-0.16)
Slope(>Threshold)	0.000	0.000	0.000
	(0.02)	(-0.28)	(0.08)

Note: Table reports Ordinary Least Squares (OLS) regression estimates. Dependent variable is a dummy variable denoting payment amount at £150. Independent variables are the distance from the round number threshold, in pounds, above and below the threshold, plus a dummy variable denoting above the threshold. Model includes a constant term. Separate model estimates shown in which the distance from the round number threshold enters linearly, as a quadratic term, and as a cubic term. T-statistics shown in parenthesis. Card-months where a minimum is exactly the threshold were excluded from the regressions. The estimates were done up to $10z = 130$. *p<0.1; **p<0.05; ***p<0.01

Table A14: Base-10 Minimum Payment Thresholds and Proportion of Payments at £200: OLS Estimates (Baseline Sample)

IV	Linear	Quadratic	Cubic
Intercept	0.069 ***	0.069 ***	0.068 ***
	(162.96)	(105.12)	(76.11)
Dummy(>Threshold)	0.004 ***	0.002 ***	0.004 ***
	(5.99)	(2.62)	(2.86)
Slope(<Threshold)^3			0.000 *
			(-1.82)
Slope(<Threshold)^2		0.000	-0.002 *
		(0.00)	(-1.79)
Slope(<Threshold)	0.000	0.000	-0.003 *
	(-1.10)	(-0.28)	(-1.78)
Slope(>Threshold)^3			0.000
			(-0.16)
Slope(>Threshold)^2		0.000 **	0.000
		(-2.28)	(-0.22)
Slope(>Threshold)	0.000	0.001 *	0.001
	(-1.40)	(1.87)	(0.60)

Note: Table reports Ordinary Least Squares (OLS) regression estimates. Dependent variable is a dummy variable denoting payment amount at £200. Independent variables are the distance from the round number threshold, in pounds, above and below the threshold, plus a dummy variable denoting above the threshold. Model includes a constant term. Separate model estimates shown in which the distance from the round number threshold enters linearly, as a quadratic term, and as a cubic term. T-statistics shown in parenthesis. Card-months where a minimum is exactly the threshold were excluded from the regressions. The estimates were done up to $10z = 180$. *p<0.1; **p<0.05; ***p<0.01