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The Red, the Black, and the Plastic: Paying Down Credit Card Debt for Hotels, Not Sofas

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Abstract. Using transaction data from a sample of 1.8 million credit card accounts, we provide the first field test of a major prediction of Prelec and Loewenstein's theory of mental accounting: that consumers will pay off expenditure on transient forms of consumption more quickly than expenditure on durables. According to the theory, this is because the pain of paying can be offset by the future anticipated pleasure of consumption only when money is spent on consumption that endures over time. Consistent with this prediction, we found that repayment of debt incurred for nondurable goods is an absolute 10% more likely than repayment of debt incurred for durable goods. The strength of this relationship is comparable to an increment in 15 percentage points in the credit card annualized percentage rate. Our results have not only managerial implications for the structuring of financial transactions (e.g., that credit card customers should be given the option of paying off specific purchases) but also more general implications for exploiting variations in the pain of paying in incentive schemes aimed at customers and employees.

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1. Introduction

The assumption of fungibility is an essential feature of standard consumer theory. Consumers are assumed to purchase what they value most and to pay for their purchases using the least costly options for payment. What a person pays for should not affect how he or she pays for it (e.g., via cash or credit), and how money is obtained should not affect the way it is spent. Research on mental accounting (Thaler 1999) challenges these assumptions. There is, by now, a large body of empirical research documenting violations of fungibility, showing that people like to pay for different types of purchases in different ways and that people like to spend money arising from different sources or stored in different ways differently (for a discussion of the assumption of fungibility in standard economics, see Thaler 1985).

Most of the early research on mental accounting involved surveys and hypothetical choice studies. O'Curry and Strahilevitz (2001) found that, compared with ordinary income, windfall gains, including winnings from long-shot lotteries, are more likely to be spent on hedonic, as opposed to utilitarian, goods. Thaler and Johnson (1990) report the phenomenon, since well documented (Keasey and Moon 1996, Weber and Heiko 2005, Ackert et al. 2006), that gamblers are more willing to take risks after a recent gain because they feel they are playing with house money. Heath and Soll (1996) find that when consumers purchase an item that is prototypical of an expense category, they are subsequently less likely to purchase other items in that category, which they attribute to nonfungibility between mental accounts.

A number of field studies have subsequently documented diverse violations of fungibility [for a recent review, see Zhang and Sussman 2018]. Virtually all of these focus on the question of whether money that is framed as coming from or designated as being earmarked for a specific category of consumption is, in fact, spent on that category [as discussed by Thaler 1985]. Kooreman (2000), in an early field study, found that the marginal propensity to consume child clothing out of child benefits is higher than out of other income. Beatty et al. (2014), using a regression discontinuity analysis, find that the UK winter fuel payment, a cash grant, is disproportionately spent on heating. Hastings and Shapiro (2017), using a data set of grocery transactions that includes information about payment medium, find that Supplemental Nutrition Assistance Program payments are disproportionately spent on food, relative to cash income. Milkman and Beshears (2009) find that a grocery coupon provided by an online retailer leads to a much greater increase in spending on food than that which is predicted by standard economic theory. Finally, whereas all the studies just reviewed relied on observational field data, Abeler and Marklein (2017) conducted a field experiment in which patrons of a wine restaurant were given a coupon good for either any usage or for wine. Customers given the wine coupon spent more on wine than those given the coupon earmarked for any usage, and both groups spent more on their overall meal. Both results violate fungibility (given that virtually all patrons of the wine restaurant would have spent at least the value of the coupon on wine).

We used data from a large data set on credit card spending to test a major prediction of a theory of mental accounting proposed by Prelec and Loewenstein (1998): that consumers will be more motivated to pay off expenditure on more transient forms of consumption more quickly than expenditure on durables. We provide the first field test of this theoretical prediction using transaction and repayment data from a sample of 1.8 million credit card accounts. In line with the predictions of Prelec and Loewenstein (1998), we find that people are an absolute 10% less likely to pay off and, hence, more likely to pay interest on durable items, such as vehicles, clothes, and education, compared with nondurable items, such as grocery products, gas, hotel accommodation, and restaurants. This result holds in analyses comparing repayments across individuals and also analyses comparing changes in repayments within individuals over time (with individual fixed effects). As a complement to the judgments of hypothetical scenarios presented in Prelec and Loewenstein (1998), our field data are the first evidence that debt aversion varies as a function of the nature of the associated consumption and the first evidence regarding preferences for the relative timing of consumption and payment.

Prior research has examined patterns of behavior involving credit cards using diverse research methods and data sources. For example, in incentivized laboratory experiments, Amar et al. (2011) found that consumers were more likely to spend on credit cards with the lowest balance rather than, as cost minimization would suggest, the lowest rate of interest. Stewart (2009) [see also Navarro-Martinez et al. 2011 and Keys and Wang 2016] examined, using both credit card repayment data and an experiment, whether consumers anchor repayments on minimum payment amounts that are currently included on all credit card statements. Gathergood et al. (2019) [see also Stango and Zinman 2015 and Ponce et al. 2017] examine how consumers split repayments across debts held over multiple cards. All three contributions show that consumers tend not to minimize interest costs when allocating repayments across cards, and Gathergood et al. (2019) show that this arises because consumers tend to split the ratio of repayments across their cards in approximate proportion to the ratio of revolving balances instead of paying down the highest interest rate debt first as economic logic would predict. Using detailed transaction data from a relatively affluent and financially sophisticated online panel of 917 households, Stango and Zinman (2009) found that the median household pays $500 per year in credit card costs and could avoid more than half these costs with minor changes in behavior. In contrast to these prior contributions, this paper is, to the best of our knowledge, the first to use credit card data to test for a violation of fungibility as well as the first to test a key prediction of the Prelec and Loewenstein (1998) model using field data. Rather than examining the impact of credit balances and annualized percentage rates (APRs) on card repayment, here we examine the impact of the specific type of consumption financed with a credit card on the likelihood of fully paying off the credit balance on the card.

Beyond providing support for a key prediction of Prelec and Loewenstein (1998), our results have implications for the designers of financial products. In particular, if customers have a preference for paying down certain types of consumption ahead of others, customers may value payment options that allow them to prioritize payments against certain spending types. Credit card issuers currently report customer card balances with manual and automated payment options at various levels of payment (including minimum payment or full payment), but customers might also benefit from options that allow them to identify the balance due by the spending it represented and then pay for specific items. The research reported here suggests that given such an option, consumers would be more prone to pay off debt incurred for nondurable than for durable consumption and that doing so might well decrease the pain they experience from paying off their credit cards. More generally, managers should look for ways to reduce customers' and workers' pain of paying to enhance the value of incentives that they provide. For example, if customers find it painful to pay for shipping on purchases, a promotional offer could be framed as paying for or providing free shipping as opposed to a discount from the price of the product itself. Or, if gas prices are high and consumers find it painful to pay for their daily commute, a wellness program that provided incentives in the form of gas cards might be more effective than one that paid the same amount in cash despite the compelling economic logic favoring cash that can be spent in a maximally flexible fashion.

2. Background

Prelec and Loewenstein (1998) propose a double mental accounting model in which people establish mental accounts to link the *pleasure* of the consumption of an item with the *pain* of paying for it. In their model, every act of consumption evokes painful consideration of its cost, and every act of payment is buffered by (typically) pleasurable thoughts about the consumption that the payment is financing. The key assumption of the model, dubbed *prospective accounting*, is that people only care about future costs and benefits: for each transaction, people offset the pain of repayments against future consumption and offset the pleasure of consumption against the pain of future repayments. Prospective accounting predicts, for example, that a vacation paid for ahead of time will be more enjoyable because, as there are no payments in the future, it feels as if it is free. Likewise, it predicts that paying for the vacation after one returns is especially painful because, given that the vacation has already happened, it feels as if one is paying for nothing. Purchase and repayment decisions are therefore contingent on the expected sequence of consumption and payment utilities. When a good is not fully paid off or when a transaction is made in multiple payments, the pleasure of its consumption is undermined by painful thoughts regarding the remaining payments. Hence, consumers would be inclined to prepay for a product rather than accumulate the debt.

However, the attractiveness of prepayments is not the same for all types of consumption in the double mental accounting model. People are happier to pay interest on durable goods because the pain of paying interest is offset by their anticipated future consumption from the durable good. But for nondurable goods that are consumed immediately, as in the vacation example, there is no future consumption to offset the pain of paying interest. Hence, people have a stronger preference for prepaying debt associated with nondurable goods compared with durable goods.

Figure 1 illustrates the interaction between the magnitude of hedonic benefits of prepayment and the durations of the utility flow. The top panels represent the utility flow obtained when prepaying (left) and postpaying or leasing (right) a nondurable item with high utility, such as the vacation. The bottom panel illustrates the equivalent utility flow for a durable item, such as a clothes dryer. The shaded area indicates the net utility derived from consumption after subtracting the disutility associated with the future payments. The vertical bars record the net disutility of payments after subtracting the utility related to future consumption.

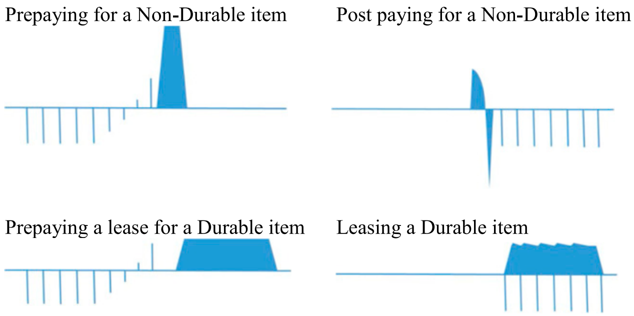
When the payment schedule for the vacation is shifted into the future, there is a large hedonic fall at the very end of the vacation because there are only payments to look forward to. In contrast, there is little psychological cost to delaying the payments for the clothes dryer because the dryer delivers sufficient residual utility over its lifetime. So the mental account approach predicts a strong tendency to accelerate payment for items whose utility declines over time. Note that consumers may also prefer not to pay in advance for durable goods so that they can maintain the ability to withhold payments for durable goods that later break down (Patrick and Park 2006).

Prelec and Loewenstein (1998) show, for instance, that although prepayment would greatly enhance the quality of a vacation experience, it would have a small or negligible influence on the hedonics obtained from the use of a clothes dryer. In one of their studies, they described two scenarios to 91 visitors to the Phipps Conservatory in Pittsburgh. In the first scenario, the visitors were asked to imagine they were planning a one-week vacation to the Caribbean, six months from now, that will cost \$1,200. They could finance the vacation by either six monthly payments of \$200 before the beginning of the vacation or six monthly payments of \$200 after returning. About 60% of respondents chose the earlier payments. However, in the second scenario, when they were asked to imagine that they were planning to purchase a clothes washer and dryer that will cost \$1,200 and that they could finance it by either six monthly payments of \$200 before the machine arrives or by six monthly payments beginning after it arrives, 84% of visitors opted to postpone the payments.

In summary, to keep mental accounts in the black, people are prone to accelerate payments for items whose utility declines over time (nondurables) but will be less motivated to do so with items whose utility persists over time (durables). Mental accounting may act at the time of repayment, encouraging people to repay debt on nondurable items when they receive their bill, or it may at the time of purchase so that people avoid spending on nondurable items they cannot immediately afford because they anticipate the greater pain of repaying. Either way, the prediction is the same. People should be more likely to repay debt incurred on nondurable items. To test this prediction, we consider different spending and repayment patterns in which individuals might link their propensity to repay their credit card bill to the type of consumption that created the bill.

We begin by analyzing repayment patterns in new credit card accounts that begin with no debt and incur spending of a single purchase type only—durable or nondurable—during the month. Using a classification proposed by Kuchler (2013), we categorize spending into durable and nondurable purchases from 25 underlying merchant categories of expenditure. Kuchler

Figure 1. (Color online) Impact of Prepayment (Left) or Postpayment (Right) on the Hedonics of Consumption and Payment for a Nondurable Good (Top) and a Durable Good (Bottom)



Source. Redrawn from Prelec and Loewenstein (1998).
Notes. The shaded area is experienced utility of consumption, and the bars are the experienced disutility of the payments as predicted by the mental accounting model (Prelec and Loewenstein 1998).

(2013) lists short-run consumables and other nondurable spending categories. We used this list to assign our merchant category codes to durable and nondurable categories. For example, airlines are classified as nondurable, and electric appliance stores are classified as durable. We test the sensitivity of our results to reclassification of categories that might arguably contain both durable and nondurable items. In response to a reviewer's comments, we also ran a consumer survey of 501 UK residents, measuring the durability of 152 goods and services from the 25 merchant categories. These ratings lead to a durable/nondurable classification that is very similar to Kuchler's (2013).

We evaluate how the nature of the spending increases or decreases the likelihood of full repayment of the debt. Regression analysis shows that individuals who spend on nondurable goods are almost 10 percentage points more likely to pay the bill in full at the end of the month. Durable goods are often big-ticket items, so we control for the size of the credit card balance using a fifth-order polynomial and also conduct separate regressions across samples by quartile of the balance amount. This result also holds when additional controls are added to the regression specification, including characteristics of the credit card account (including the APR and credit limit) and controls for matched socioeconomic characteristics of the postcode of the cardholder obtained from census data. The postcode-level control variables allow us to control, albeit imperfectly, for differences in socioeconomic characteristics (e.g., incomes) that might determine credit card repayment behavior.

We then expanded our analysis to evaluate repayment behavior of accounts that show spending on both durables and nondurables within the month. Specifically, we quantify how the probability of full repayment is related to the proportion of total spending of each type within the month. Results show the same effect as in the single purchase type analysis, the coefficient estimates implying that a switch from the percentage of purchases in the nondurable category from 0% to 100% increases the likelihood of full repayment of the credit card bill by 15 percentage points. This result is again robust to the inclusion of controls for account balance amount, credit card account characteristics, and socioeconomic characteristics.

In subsequent analyses, we expand the data sample to include older credit card accounts and again conduct analysis of months of data in which accounts incur spending of a single purchase type and multiple purchase types. These samples provide multiple observations of spending and repayment undertaken by the same individual over time. With these data, we are able to estimate models that include random and fixed effects. The inclusion of individual fixed effects allows us to control for individual-specific time-invariant unobserved heterogeneity, which might drive differences in repayment behaviors across individuals, such as differences in permanent incomes or IQ. These models allow us to control for unobserved heterogeneity across individuals, such as an underlying propensity to repay an account in full (which might correlate with the type of spending). We find that our central result is robust to the inclusion of either random effects or individual fixed effects.

Unfortunately, conducting a field experiment on the question this paper addresses would be difficult, if not impossible, because we cannot experimentally assign debts accruing from spending on durable or nondurable goods to a sample of credit card holders in real-world data. Although Prelec and Loewenstein (1998) examined closely related questions by presenting experimental subjects with hypothetical scenarios, in real-world data, we are limited to observing naturally occurring variation in spending over time, which has inevitable limitations. Specifically, it is difficult to definitely rule out potential confounds, such as individual differences that might lead to differences in repayment behavior. Our data do allow us to control for a rich set of time-varying credit card account characteristics, socioeconomic characteristics, and individual fixed effects. The inclusion of individual fixed effects allows us to allay a concern with models exploiting variation across individuals that some individuals might be inherently more likely to repay than others because of differences in time preferences, and this might also explain their tendency to purchase durables instead of nondurables. Nevertheless, our data do not allow us to account for selection into credit card spending for durable and nondurable goods. For example, individuals may be more likely to put spending on nondurable goods they intend to repay straightaway onto their credit card than they are to put spending on durable goods they intend to repay straightaway.

3. Data and Estimation Strategy

3.1. Credit Card Data

Our data source is the Argus Information and Advisory Services' credit card payments study (CCPS). The Argus data contain detailed records of credit card transactions (including spending and repayments), contract terms (e.g., APR and credit limits), and billing records (including minimum payments due and billing dates). We have a subset of data from five large UK credit card issuers. Together these issuers have a market share of more than 40%. We use a 10% representative sample of all individuals in the CCPS who held a credit card between January 2013 and December 2014 with at least one of the five issuers. This data sample provides approximately 1.8 million cards. The UK credit card market is similar to that in the United States in many respects. Visa and Mastercard are the most dominant card networks. The most widely issued credit cards are general-purpose credit cards, which offer comparable features and fee structures and often include rewards programs, teaser rate deals, and balance transfer facilities. Moreover, some UK card issuers are subsidiaries of U.S. firms (e.g., Barclaycard, Capital One, etc.).

3.2. Purchases of Durables and Nondurables

The data include detailed records of card spending incurred each month in 25 merchant-coded categories, such as restaurants/bars, food stores, and vehicles. We classify each category as durable or nondurable, closely following the classification used in Kuchler (2013). For example, airlines and hotel services are classified as nondurable, and purchases made in clothing stores and electric appliance stores are classified as durable. Table 1 provides a breakdown of the classification of the categories into the two spending types. Some spending categories might contain purchases of both durables and nondurables, such as the other retail and discount store categories. In a subsequent analysis, we test the sensitivity of our results to reclassification of categories that might contain both durable and nondurable items and to a reclassification based on consumers' judgments of durability.

3.3. Sample Selection

Our interest, in this paper, is in the relationship between types of credit card spending and subsequent repayment behavior. The unit of analysis is a month of data in which we observe the spending and repayment on an account. We therefore first restrict the sample to months in which (a) spending is incurred on the account in either the durable or nondurable type (or both), (b) the account has a balance due that is above the obligatory minimum repayment, (c) the account does not show a balance transfer to another credit card account.[1] After applying these sample restrictions, we focus our analysis on samples of the data in which the relationship between spending and repayment can be most cleanly analyzed. We used two main samples.

The first sample includes only the first month of data for new credit card accounts in which all the spending is on either durable or nondurable purchases. This is the cleanest sample for our analysis because the sample exhibits no prior history of spending or repayment behavior and accounts can be cleanly separated by spending type. We use a dummy variable to label observations as either durable-spend or nondurable-spend months. We call this sample the *single-purchase-type sample*, which provides 21,671 month observations.

The second sample also restricts data to only the first month for new credit card accounts but includes months in which the account incurs durable and nondurable spends in addition to the single-purchase-type months (hence, this sample includes the aforementioned first sample). For this sample, we calculate the share of spending on durable purchases and the share of spending on nondurable purchases (which together sum to one). We term this the *multiple-purchase-type sample*, which includes 58,404 month observations. Summary data for spending incurred in the first and second samples are shown in Tables 1 and 2.

In additional analysis, we extend the sample to include all months, not just the first month. Hence, we construct single-purchase-type and multiple-purchase-type samples that include repeated observations from the same account. Theses samples include accounts for which we have records of between a single month and many years. This substantially increases the sample size, with 154,000 observations of single-purchase-type months and 130,000 observations of multiple-purchase-type months. However, this represents a less clean sample for analysis because these accounts have histories of spending and repayment that may decouple mental accounts on the part of the cardholder (i.e., people may no longer be able to remember what they spent the money on when they are repaying their bill). Summary data for spending incurred in these samples are shown in Tables A-1 and A-2 of Online Appendix A.

Apart from differing in the number of observations, the four samples we draw show some differences in the level and composition of spends. The monthly spend on the new accounts single-purchase-type sample is lower than that of the new accounts multiple-purchase-type sample (£660 versus £745), a difference also seen in the sample of all accounts in Tables A-1 and A-2 in Online Appendix A (£320 versus £420). The nondurable spending category with the highest mean spend, travel agencies, is the same across single and multiple samples (for new and all accounts), and in the multiple-purchase-type sample, mean spending on airlines is notably higher.[2] In each sample, spending on durables is broadly spread across categories. As

Table 1. Descriptive Statistics for Purchase Amounts for the First Purchase for New Accounts: Single-Purchase-Type Sample

Merchant category	Frequency	Mean	Standard deviation	p25	p50	p75
Nondurables						
Airlines	601	£931.12	£1,119.47	£208.75	£547.06	£1,194.87
Auto rental	258	£263.60	£411.43	£73.29	£140.69	£286.90
Hotel/motel	754	£526.41	£895.42	£90.00	£220.14	£500.00
Restaurants/bars	632	£233.44	£821.13	£24.65	£49.65	£95.40
Travel agencies	1,885	£1,450.72	£1,224.57	£511.91	£1,140.87	£2,040.00
Other transportation	561	£485.63	£1,059.86	£40.90	£100.00	£322.77
Drug stores	125	£63.73	£173.20	£15.75	£25.00	£51.57
Gas stations	1,331	£90.35	£245.46	£34.46	£51.00	£80.08
Mail orders	465	£230.69	£419.24	£29.50	£71.80	£235.31
Food stores	2,450	£113.14	£295.09	£23.59	£54.32	£112.56
Other retail	1,897	£457.90	£1,052.26	£29.99	£79.99	£363.00
Recreation	771	£422.19	£771.18	£65.00	£150.00	£405.60
Subtotal	11,730	£501.78	£957.17	£40.05	£102.27	£466.00
Durables						
Department stores	485	£458.81	£921.34	£55.79	£142.82	£458.32
Discount stores	294	£191.40	£243.60	£44.99	£119.98	£263.93
Clothing stores	1,433	£170.40	£317.94	£37.00	£71.98	£150.00
Hardware stores	687	£1,017.68	£1,594.09	£72.06	£331.56	£1,230.90
Vehicles	1,200	£2,080.72	£2,282.94	£299.98	£1,100.00	£3,184.50
Interior furnishing stores	783	£1,113.82	£1,528.05	£234.00	£575.00	£1,248.45
Electric appliance stores	1,028	£660.03	£811.64	£196.49	£419.99	£855.75
Sporting goods/toy stores	510	£471.72	£784.74	£56.00	£155.34	£499.46
Healthcare	414	£1,237.53	£1,573.06	£150.00	£414.50	£2,000.00
Education	191	£1,283.57	£1,640.86	£168.00	£775.00	£1,700.00
Professional services	1,257	£672.93	£852.91	£179.04	£410.00	£825.30
Repair shops	16	£1,019.63	£1,273.31	£97.05	£491.39	£1,388.14
Other services	1,643	£831.82	£1,485.23	£60.50	£222.50	£947.12
Subtotal	9,941	£854.70	£1,435.33	£81.41	£290.64	£931.25
Single purchase total	21,671	£663.67	£1,213.18	£50.99	£167.95	£687.76

Notes. Single-purchase total shows the monthly spending for the single-purchase-type sample of monthly observations belonging to new credit card accounts. p25, 25th percentile; p50, median; p75, 75th percentile.

we show in Table 3, the socioeconomic characteristics of cardholders who contribute observations to each sample are very similar across samples.

3.4. Census Data Socioeconomic Controls

The data include geocodes, allowing us to match socioeconomic controls from the UK National Census records. The data are geocoded at the four-digit UK postcode level.[3] We match the following variables: (a) the median house price within the locality based on self-reported evaluations of selling prices, (b) self-reported median net weekly income, and (c) the proportion of households within the locality with children enrolled in education who receive free school meal vouchers. The final measure is commonly used in the United Kingdom as an indication of social insurance dependency. Because of some missing postcodes within the credit card data set, in the single-purchase-type sample, we can match 70% of months to census records (107,384 of 154,924 months), and in the multiple-purchase-type sample, 69% (194,214 of 282,997 months). The addition of these variables to the data set allows us to partially control for differences in credit card repayment arising from differences in socioeconomic characteristics.

3.5. Summary Statistics

Summary data for spending amounts in each of the 25 categories in the first month single-purchase-type sample are shown in Table 1. The sample comprises 21,671 observations. For nondurable spending, the most common purchase category is food stores; for durable spending, the most common purchase category is clothing stores. Mean spending totals approximately £664, with median spending of £168. Table 2 shows the summary statistics for purchases in the multiple-purchase-type sample. Summary statistics for single-purchase-type and multiple-purchase-type samples, including all accounts (not just new accounts), are shown in Tables A-1 and A-2 of Online Appendix A. Table 3 summarizes the socioeconomic variables for the four samples (new accounts single-purchase-type, new accounts multiple-purchase-type, all accounts single-purchase-type, all accounts multiple-purchase-type).

Table 2. Descriptive Statistics for Purchase Amounts for the First Purchase for New Accounts: Multiple-Purchase-Type Sample

Merchant category	Frequency	Mean	Standard deviation	p25	p50	p75
Nondurables						
Airlines	2,559	£1,176.40	£1,106.75	£412.81	£850.90	£1,571.49
Auto rental	1,138	£917.37	£1,082.72	£215.78	£540.18	£1,183.42
Hotel/motel	5,282	£959.71	£992.49	£311.00	£652.96	£1,257.84
Restaurants/bars	12,572	£796.63	£890.66	£237.12	£525.02	£1,025.39
Travel agencies	4,982	£1,445.37	£1,193.59	£563.55	£1,127.27	£1,973.36
Other transportation	5,888	£835.91	£960.92	£219.61	£523.17	£1,092.10
Drug stores	4,954	£834.38	£861.93	£275.70	£583.23	£1,084.79
Gas stations	14,894	£735.42	£853.47	£201.51	£470.37	£941.65
Mail orders	3,812	£807.45	£889.52	£218.38	£544.95	£1,066.45
Food stores	23,087	£668.35	£821.68	£166.94	£408.22	£849.35
Other retail	16,867	£806.69	£950.35	£216.22	£513.00	£1,030.25
Recreation	6,394	£866.70	£910.35	£272.23	£591.46	£1,133.69
Subtotal	45,304	£689.94	£930.20	£129.02	£365.98	£867.72
Durables						
Department stores	6,084	£919.96	£974.92	£295.14	£624.05	£1,170.77
Discount stores	4,052	£821.51	£841.83	£286.94	£581.33	£1,052.89
Clothing stores	14,563	£742.01	£822.92	£206.72	£485.90	£964.81
Hardware stores	7,124	£1,109.67	£1,197.62	£341.06	£743.07	£1,408.39
Vehicles	4,700	£1,481.26	£1,642.09	£412.14	£887.19	£1,959.05
Interior furnishing stores	5,656	£1,228.85	£1,275.01	£413.24	£825.02	£1,557.05
Electric appliance stores	5,887	£1,031.85	£1,059.91	£354.99	£700.93	£1,344.82
Sporting goods/toy stores	5,611	£864.47	£881.34	£275.52	£594.87	£1,129.82
Healthcare	2,332	£1,101.77	£1,190.37	£325.59	£679.67	£1,425.71
Education	866	£1,102.37	£1,181.63	£344.00	£793.01	£1,404.02
Professional services	5,617	£1,049.22	£1,091.03	£355.20	£725.98	£1,352.74
Repair shops	236	£1,125.72	£1,123.40	£349.27	£844.68	£1,449.76
Other services	11,158	£988.92	£1,161.31	£275.02	£633.79	£1,236.14
Subtotal	39,685	£848.82	£1,117.68	£199.64	£477.17	£1,021.74
Multiple purchases total	58,404	£735.09	£1,058.35	£122.85	£362.22	£893.76

Notes. Multiple-purchase total shows the monthly spending for the multiple-purchase-type sample of monthly observations belonging to new credit card accounts. Note that the multiple-purchase-type sample includes the single-purchase-type sample described in Table 1. Because cardholders can consume products in more than one category during the month, frequencies for each category do not add to the month observations displayed in the multiple-purchases total. p25, 25th percentile; p50, median; p75, 75th percentile.

The summary statistics are very similar across these samples.[4]

4. Econometric Model

Our main interest lies in estimating whether the propensity of credit card holders to repay a credit card bill incurred in a given month relates to the type of purchases made in that month.

We begin by estimating the following baseline model:

$$P(Repay_{i,t} = 1) = \alpha + \beta_1 Nondurable_{i,t} + \beta_2 APR_{i,t} + \beta_3 Credit\ Limit_{i,t} + \beta_4 Tenure_{i,t} + \beta_5 Utilization_{i,t} + \psi \boldsymbol{X}_{i,t}, \quad (1)$$

where *Repay* is a one/zero dummy variable that takes a value of one if at least 90% of the bill is repaid within the following month (the period in which payment of the bill becomes due). We used the 90% threshold to take into account the possibility of people paying the bill by rounding down to the nearest tenth or hundredth and failing to pay the exact amount, although our analysis is robust to variations in this arbitrary choice. The variable *Nondurable* describes the purchases made on the account. In estimates based on the single-purchase-type sample, this variable is a one/zero dummy variable taking a value of one if the month contains nondurable purchases and a value of zero for durable purchases. In the multiple-purchase-type sample, this variable is the proportion of purchases (as a proportion of the total monthly spend) on nondurables.

The additional variables in the model that act as control variables (all measured at the month level) are the annualized percentage rate on card purchases (*APR*), the credit limit on the credit card account (*Credit Limit*), the age of the account in years (*Tenure*), and a measure of utilization (*Utilization*). Account utilization is measured as the ratio of the account balance (before repayment is made) over the credit limit. Hence, a

Table 3. Descriptive Statistics of Cardholders' Socioeconomic Characteristics for the Samples Under Study

	Number of cardholders	Number of accounts	Mean	Standard deviation	p25	p50	p75
New accounts single-purchase-type sample							
Median house price, £	14,766	14,851	203,261.50	103,940.20	133,622.90	182,269.40	241,094.10
Free school meals, %	14,766	14,851	12.97	7.01	7.83	11.57	16.68
Weekly household income, £	14,766	14,851	742.29	155.42	626.54	719.58	837.01
New accounts multiple-purchase-type sample							
Median house price, £	38,010	38,481	206,902.10	105,695.60	135,989.00	185,029.90	244,892.20
Free school meals, %	38,010	38,481	12.77	6.98	7.65	11.44	16.52
Weekly household income, £	38,010	38,481	749.99	156.83	631.34	726.35	847.48
All accounts single-purchase-type sample							
Median house price, £	64,478	66,021	204,339.10	105,353.00	135,034.20	184,025.80	241,339.10
Free school meals, %	64,478	66,021	12.35	6.72	7.44	11.01	15.82
Weekly household income, £	64,478	66,021	746.44	155.47	630.00	721.99	839.18
All accounts multiple-purchase-type sample							
Median house price, £	104,643	108,050	207,050.30	107,419.00	136,933.60	185,437.60	243,501.40
Free school meals, %	104,643	108,050	12.34	6.77	7.39	11.00	15.84
Weekly household income, £	104,643	108,050	750.68	156.74	631.78	725.22	846.84

Notes. Socioeconomic data were obtained by matching cardholders' postcodes to the UK National Census records. Data matched include the median house price within the locality based on self-reported evaluations of selling prices, self-reported median net weekly income, and the proportion of households within the locality with children enrolled in education who receive free school meal vouchers. Because of some missing postcodes within the credit card data set, descriptive statistics in the table correspond to 68% of the total number of cardholders in the data set whose month observations met the selection criteria imposed. p25, 25th percentile; p50, median; p75, 75th percentile.

utilization value of 0.5 indicates a balance on the account at a value of half the credit limit.

The model also includes additional controls [captured by the vector $\boldsymbol{X}$ in Equation (1)]: calendar month fixed effects to control for seasonal differences in patterns of spending and repayment (e.g., the months of November and December are more likely to include purchases of seasonal gifts). The vector also includes the socioeconomic control variables, which are measured at the geocode level (which contains a cluster of account × months).

We also add to the model controls for the value of the credit card bill. These are important controls; as a result of the lumpiness of durable purchases, accounts with durable purchases typically have higher total purchases than those with nondurable purchases, and hence, these accounts might naturally have a lower likelihood of being repaid in full. As a first approach, we control for the total purchase amount, allowing for a flexible relationship between purchase amount and the probability of repayment using a fifth-order polynomial. As a second approach, we split the sample into quartiles of the total amount of durable purchases and estimate models on each quartile on observations separately while continuing to include the fifth-order polynomial of the total purchase amount as controls in the model.[5]

We estimate our main models as linear probability models. We also present estimates based on random effects and fixed effects models. These account for correlations among repeated measures of the same credit card account holder within the data set.

5. Results

5.1. Single-Purchase-Type Sample

Results from our main model estimates of Equation (1) for the single-purchase-type sample are shown in Table 4. Column (1) shows estimates from a model that includes only a one/zero dummy variable indicating whether purchases in the month were nondurable and a constant term. Hence, the reference group is months of account data that contain durable purchases only. The coefficient on the nondurable purchase dummy is 0.197 (95% confidence interval [CI] [0.184, 0.210]) and indicates that people are almost an absolute 20 percentage points more likely to pay their bill in full when the bill comprises monies spent on nondurable purchases. Columns (2) and (3) add the controls for the fifth-order polynomial in purchase amount, calendar month fixed effects, and card characteristics. As expected, with the addition of controls for the purchase amount in column (2), the R^2 of the model increases substantially, and the coefficient on the nondurable dummy variable reduces in absolute magnitude. The coefficient on the nondurable dummy is 0.097 (95% CI [0.084, 0.106]) and indicates that people are almost an absolute 10 percentage points more likely to pay their bill in full when the bill comprises monies spent on nondurable purchases.

Table 4. Estimated Likelihood of Repaying Full Balance: Single-Purchase-Type Sample for New Accounts

	All observations			Sample split by quartiles of purchase amount			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	OLS	OLS	OLS	OLS quartile 1 (£5.02–£81.41)	OLS quartile 2 (£81.42–£290.64)	OLS quartile 3 (£290.65–£931.25)	OLS quartile 4 (£931.26–£17,000)
Nondurable = 1	0.197***	0.0966***	0.0955***	0.0422***	0.139***	0.0992***	0.0372***
	(0.00667)	(0.00571)	(0.00564)	(0.00883)	(0.0131)	(0.0139)	(0.00918)
Merchant APR (%)			0.00615***	0.00326***	0.00730***	0.00837***	0.00893***
			(0.000343)	(0.000471)	(0.000791)	(0.000894)	(0.000750)
Credit limit (£1,000)			0.00242*	−0.000805	0.00740**	0.00255	0.000143
			(0.00129)	(0.00195)	(0.00304)	(0.00371)	(0.00367)
Utilization (%)			−0.00152***	−0.00723***	−0.00176*	−0.00229***	−0.000782**
			(0.000217)	(0.00222)	(0.00102)	(0.000449)	(0.000352)
Account age (years)			0.126***	0.00449	0.162***	0.281***	0.298***
			(0.0123)	(0.0167)	(0.0289)	(0.0310)	(0.0263)
Amount purchase (£1,000)		−1.036***	−0.919***	29.37**	9.604	−56.08*	−0.264***
		(0.0163)	(0.0197)	(13.21)	(61.99)	(29.39)	(0.0629)
Amount purchase $(£1{,}000)^2$		0.459***	0.419***	−1,619*	−93.55	198.2*	0.0907***
		(0.0114)	(0.0118)	(843.0)	(755.9)	(107.8)	(0.0264)
Amount purchase $(£1{,}000)^3$		−0.0821***	−0.0756***	38,230	291.3	−339.2*	−0.0136***
		(0.00273)	(0.00274)	(23,613)	(4,430)	(191.3)	(0.00468)
Amount purchase $(£1{,}000)^4$		0.00619***	0.00571***	−421,664	−97.45	280.1*	0.000904**
		(0.000252)	(0.000251)	(298,838)	(12,515)	(164.5)	(0.000358)
Amount purchase $(£1{,}000)^5$		−0.000162***	−0.000150***	1.752×10^6	−601.2	−89.57	-2.19×10^{-5}**
		(7.67×10^{-6})	(7.62×10^{-6})	(1.396×10^6)	(13,677)	(54.90)	(9.63×10^{-6})
Constant	0.421***	0.759***	0.681***	0.659***	0.264	6.413**	0.287***
	(0.00491)	(0.00557)	(0.0160)	(0.0744)	(1.951)	(3.093)	(0.0559)
Observations	21,671	21,671	21,671	7,676	5,317	4,223	4,455
Observations *Nondurable* = 1	11,730	11,730	11,730	5,191	2,832	1,737	1,970
R^2	0.039	0.325	0.344	0.033	0.077	0.100	0.106
Month fixed effects	No	No	Yes	Yes	Yes	Yes	Yes

Notes. The sample is restricted to new accounts and includes months in which purchases were related to only one merchant code (there are 25 codes). All models are linear probability models in which the outcome takes the value of one when the repayment–purchase ratio is greater than 0.9 and otherwise takes a value of zero. Models (4)–(7) split the sample into four quartiles based on purchase amount. For instance, all purchases included in Model (4) had a monthly balance higher than £5.02 and up to £81.41. Quartile cutoff values were defined based on the value of durable purchases. Reference category: durable goods. Standard errors in parentheses. OLS, ordinary least squares.

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

To gauge the quantitative importance of the coefficient estimates, Figure 2 plots the predicted probability of repayment from the model estimates in Table 4 (column (3)). The circles indicate the predicted probability, and bars indicate 95% CIs. In the top panel, the whole sample bars show that nondurable-spending-type months have a predicted probability of repayment of approximately 60% compared with approximately 50% for accounts in the durable category. This 10-percentage-point difference is large in economic terms. A natural economic comparison is to the increase in APR, which would generate an equivalent increase in the predicted probability of bill repayment. We make this comparison based on the estimated coefficient on the *APR* variable in the model, which allows us to make a correlational comparison.[6] Using the estimates from column (3) of Table 4, a 15-percentage-point increase in APR would be needed to deliver the equivalent increase in likelihood of card repayment.

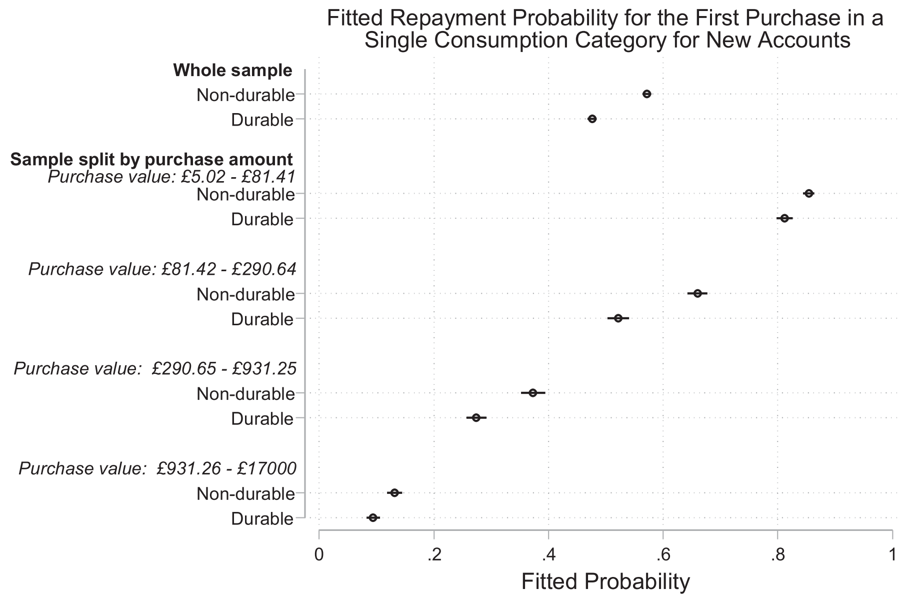
The lower part of Figure 2 breaks down the predictions by quartiles of purchase value. Coefficient estimates are shown in columns (4)–(7) of Table 4. Across the quartiles, the predicted probability of repayment is higher for spends on nondurable goods, with the difference in predicted probability ranging from approximately 0.04 to 0.14.

Table B-1 in Online Appendix B shows results with the addition of socioeconomic controls. The coefficients on the nondurable dummy variable are very similar to those in Table 4.

5.2. Multiple-Purchase-Type Sample

Table 5 shows results from the main model estimates of Equation (1) for the multiple-purchase-type sample. In

Figure 2. Fitted Probabilities of Full Repayment Based on Linear Probability Models (See Table 4, Columns (3)–(7)), Evaluated at the Mean of the Other Covariates



Note. Lines span 95% confidence intervals.

these models, the *Nondurable* variable measures the proportion of the spends in the month that are of the nondurable type.

The coefficient for the *Nondurable* variable is 0.239 (95% CI [0.229, 0.249]) and implies that as the share of nondurable purchases increases from 0% to 100%, people are almost exactly an absolute 24 percentage points more likely to pay their bill in full for nondurable purchases. As in the estimates in Table 3, with the inclusion of controls in columns (2) and (3), the value of this coefficient falls in magnitude. The coefficient value of 0.149 (95% CI [0.140, 0.158]) in column (3) indicates that a switch in the proportion of the total monthly spending in the nondurable category from 0% to 100% increases the likelihood of full repayment by almost exactly 15 percentage points. Again, this is a large effect in economic terms. Using the coefficient estimates in column (3), the effect of switching spending on nondurable purchases from 0% to 100% is equivalent to a 21-percentage-point increase in the card APR. Figure 3 shows the size of the difference of the predicted probability of repayments of durable and nondurable purchases.

The pattern of coefficient estimates on the control variables resembles that in Table 4. The likelihood of full repayment of the credit card bill is increasing with the APR and credit limit but falling with account utilization.

Columns (4)–(7) of Table 5 present estimates by quartile subsamples. As before, the coefficients on the nondurable variable are positive and precisely defined in each specification, with the coefficient values implying an increase in the likelihood of repayment of between 5 and 22 percentage points from a switch in the proportion of the spend in nondurable purchases from zero to one. Table B-2 in Online Appendix B presents estimates from the same set of models as Table 5 with the inclusion of socioeconomic control variables. The pattern in the coefficient estimates is as before.

5.3. Alternative Classification of Purchase Categories

To test whether our results depend on the classification of purchases used, we perform two additional robustness tests. First, as discussed earlier, some purchase categories might contain both durable and nondurable items. Therefore, we reestimate the main results, reclassifying these items into the opposite purchase type. Specifically, we flip the classification of the following categories: from nondurable to durable, other retail and from durable to nondurable, professional services, other services, and discount stores. Online Appendix C replicates the main results (Tables C-3 and C-4) for this alternative classification. Our findings remain consistent with the main results.

Second, although our sample does not contain business credit cards, it is possible that some cardholders use a personal credit card for business expenses. Such expenditure is likely to be nondurable spending that is reimbursed by the cardholder's employer and, hence, likely to be repaid quickly. To control for this, we reestimated the main models omitting the following categories, which are those most likely to contain business expense: hotel/motel, travel agencies, airlines, and

Table 5. Estimated Likelihood of Repaying Full Balance: Multiple-Purchase-Type Sample for New Accounts

	All observations			Sample split by quartiles of purchase amount			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	OLS	OLS	OLS	OLS quartile 1 (£5.02–£81.41)	OLS quartile 2 (£81.42–£290.64)	OLS quartile 3 (£290.65–£931.25)	OLS quartile 4 (£931.26–£17,000)
Nondurable (proportion)	0.239*** (0.00488)	0.152*** (0.00448)	0.149*** (0.00441)	0.0454*** (0.00820)	0.171*** (0.00946)	0.219*** (0.00883)	0.105*** (0.00762)
Merchant APR (%)			0.00697*** (0.000249)	0.00372*** (0.000411)	0.00684*** (0.000480)	0.00787*** (0.000520)	0.00878*** (0.000618)
Credit limit (£1,000)			0.00745*** (0.000914)	0.00128 (0.00173)	0.0102*** (0.00188)	0.0123*** (0.00185)	0.00786*** (0.00233)
Utilization (%)			−0.00199*** (0.000140)	−0.00530*** (0.00175)	−0.00163*** (0.000538)	−0.00185*** (0.000244)	−0.00136*** (0.000245)
Account age (years)			0.143*** (0.00976)	0.0150 (0.0149)	0.139*** (0.0195)	0.217*** (0.0207)	0.259*** (0.0231)
Amount purchase (£1,000)		−0.855*** (0.0111)	−0.696*** (0.0132)	21.00* (12.15)	68.64* (37.90)	2.353 (14.58)	−0.183*** (0.0495)
Amount purchase (£1,000)^2		0.389*** (0.00820)	0.325*** (0.00839)	−1,076 (759.2)	−844.2* (457.5)	−7.114 (53.25)	0.0500** (0.0221)
Amount purchase (£1,000)^3		−0.0730*** (0.00207)	−0.0613*** (0.00208)	23,187 (20,873)	4,913* (2,656)	7.491 (94.05)	−0.00645 (0.00413)
Amount purchase (£1,000)^4		0.00577*** (0.000201)	0.00485*** (0.000200)	−235,712 (259,915)	−13,768* (7,438)	−2.133 (80.48)	0.000403 (0.000330)
Amount purchase (£1,000)^5		−0.000158*** (6.36×10^{-6})	−0.000133*** (6.31×10^{-6})	912,643 (1.197×10^6)	14,925* (8,063)	−0.484 (26.76)	-9.71×10^{-6} (9.21×10^{-6})
Constant	0.334*** (0.00341)	0.682*** (0.00446)	0.568*** (0.0107)	0.691*** (0.0694)	−1.638 (1.205)	0.00857 (1.541)	0.259*** (0.0411)
Observations	58,404	58,404	58,404	10,585	15,185	18,672	13,962
R^2	0.040	0.219	0.245	0.033	0.063	0.087	0.084
Month fixed effects	No	No	Yes	Yes	Yes	Yes	Yes

Notes. Table 5 replicates Table 4 specifications for the sample in which months with both consumption types are included in the sample. All models are linear probability models in which the outcome takes the value of one when the repayment–purchase ratio is greater than 0.9 and otherwise takes a value of zero. Models (4)–(7) split the sample into four quartiles based on purchased amount. For instance, all purchases included in Model (4) had a monthly balance higher than £5.02 and up to £81.41. Quartile cutoff values were defined based on the value of durable purchases. Reference category: proportion of the total month spending on durable goods. Standard errors in parentheses.

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

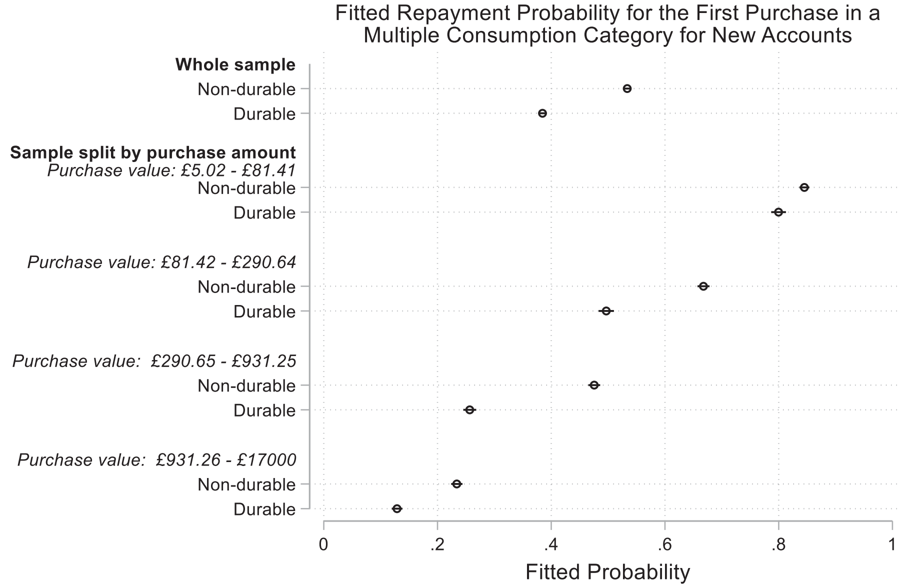
other transportation. Online Appendix D replicates the main results (Tables D-1 to D-6). Our findings remain consistent with the main results.

We also estimate models using the underlying merchant codes, which are classified into durable and nondurable expenditure. Online Appendix E (Tables E-1 to E-4) shows the estimated marginal effects for each individual merchant code. The size of these effects can be observed in Figures 4 and 5. Figure 4 displays the probability of full repayment of each nondurable merchant code and, as a point of comparison at the bottom of the figure, the probability of full repayment over all *durable* expenditures. Figure 4 shows that every nondurable expenditure is more likely to be repaid in full than the average over all durable expenditures. Figure 5 displays the probability of full repayment of each durable merchant code and, as a point of comparison at the bottom of the figure, the probability of full repayment over all nondurable expenditures. Figure 5 shows that every durable expenditure is less likely to be repaid in full than the average over all nondurable expenditures. Hence, our main result that individuals are less likely to pay down durable spending is not driven by only a few categories.

5.4. Using Durability Measures from a Consumer Survey

As an alternative approach to classifying items as durable and nondurable, we undertook a consumer survey on the platform Prolific Academic in which 501 recruited individuals were asked to rate the durability of items on a one to seven scale. We obtained from Argus the approximately 500 next-level-down items that feed into the 25 categories used in the analyses herein and asked survey respondents to rate the durability of these individual items. Several of the items received from Argus made reference to company names (e.g., for the merchant code "airlines," we have American Airlines, British Airways, Japan Airlines, etc.). There were 126 airlines companies, 80 hotels, and 24 auto rental

Figure 3. Fitted Probabilities for Full Repayment Based on Linear Probability Models (See Table 5, Columns (3)–(7)), Evaluated at the Mean of the Other Covariates



Note. Lines span 95% confidence intervals.

companies. After aggregating such items, we ended up with 274 items to test. However, some of these items were exceptionally rare, with purchase frequencies of less than 1 in 1,000 in the national accounts. After excluding these rare cases, we retained and tested 152 items. These 152 categories cover 95% of the weights used in the 2014 UK consumer price inflation indices. We used the following question format.

We gave each of 501 respondents recruited from Prolific Academic (and restricted to UK nationals living in the United Kingdom) a list of these 152 of 500 next-level-down spending categories (e.g., “an airline ticket”) and had them evaluate the degree to which the item was a durable or nondurable. Figure 6 shows the survey instructions and first two spending categories (the ordering of the categories was randomized across subjects). Some few people did not provide scores to some items in the survey because they were not required to evaluate all items if they did not want to. But 500 people replied to at least 95% of the survey items.

From these responses, we calculated weighted-average durability scores for the 25 merchant categories, applying expenditure weights from the UK national accounts and reclassified the 25 merchant categories as durable or nondurable items. Our survey design and steps in analysis were preregistered with details of the methods (https://aspredicted.org/f9iu4.pdf) and results shown in Online Appendix G.

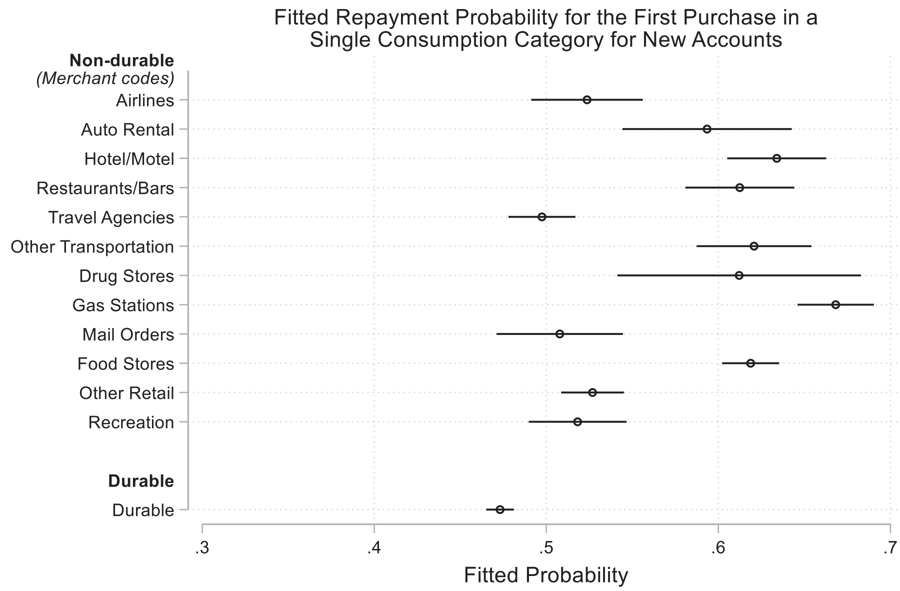
The durable/nondurable classification from the consumer survey was very close to the original classification based on Kuchler (2013), with the exceptions being healthcare, professional services, other services, mail orders, and other retail. To test the sensitivity of our results, we reestimated the main models using durability scores from the survey responses. The regression tables in Online Appendix G are in keeping with our earlier analysis for both the single-purchase-type and multiple-purchase-type samples.

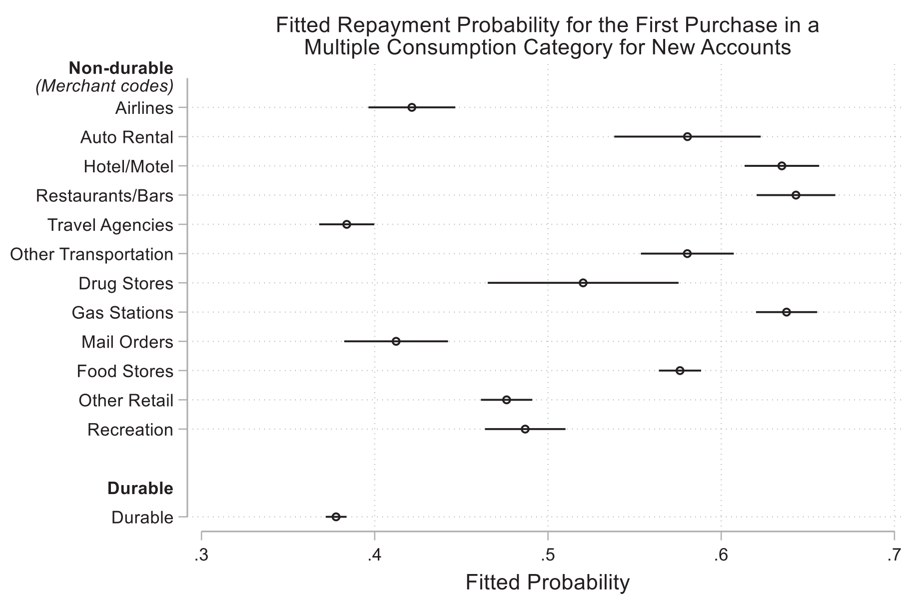
5.5. Controlling for Characteristics of Other Cards

We also test whether our results are robust to controlling for balances due on other cards held by the individual at the same time. Drawing from the same universe of data, Gathergood et al. (2019) show that consumers tend adopt a repayment heuristic when making intratemporal choices over allocating payments across cards due within the same month. Instead of paying down the highest interest rate debt first, as economic logic would predict, consumers tend to split the ratio of repayments across their cards in approximate proportion to the ratio of revolving balances, which Gathergood et al. (2019) describe as the application of a “balance-matching heuristic.”

We draw the subsample of observations from our main sample in which individuals hold two or more cards concurrently within the same month with positive balances due.[7] The resulting sample differs from that used in Gathergood et al. (2019), who design their analysis to focus on partial repayment of revolving debts, restricted to cases in which consumer face interest payments, in contrast to our focus on full repayment.[8] We first replicate our main models on this sample (without adding controls for additional cards), for completeness including socioeconomic controls in the regression specification. Table F-1 in Online Appendix F shows that the

Figure 4. Fitted Probabilities of Full Repayment Based on Linear Probability Models (See Tables E-1 and E-2, Column (1)), Evaluated at the Mean of the Other Covariates





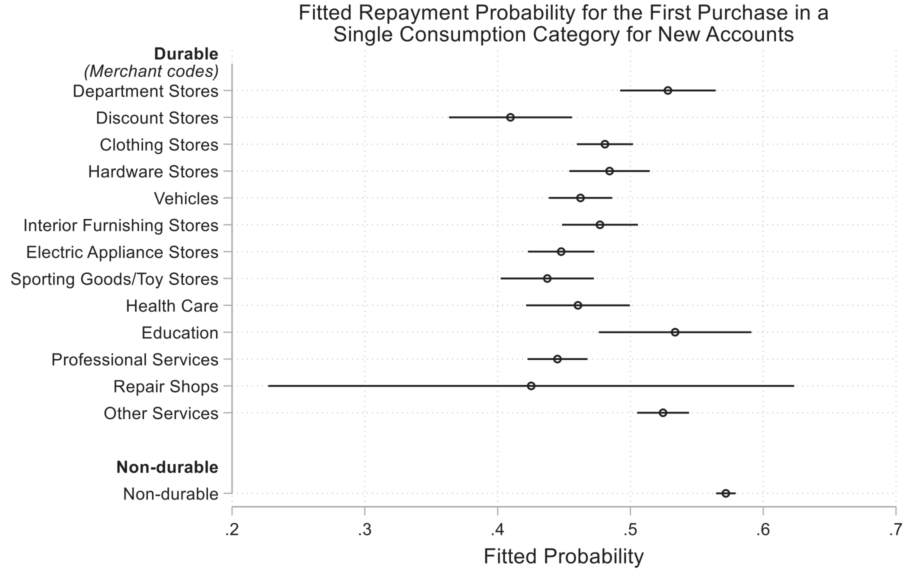
Note. Lines span 95% confidence intervals.

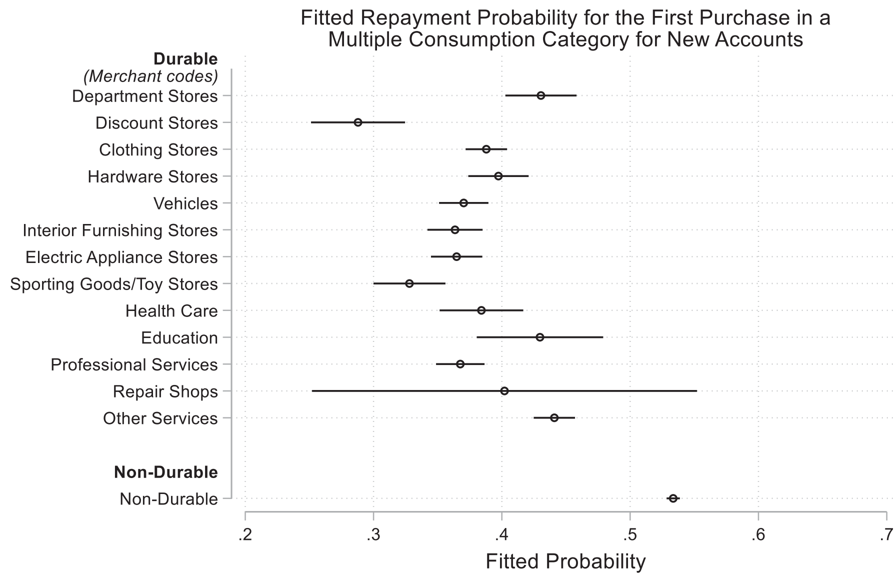
coefficients on the nondurable variables are very similar to those obtained using the main samples.

In Tables F-2 to F-5 in Online Appendix F, we then expand the econometric specification by adding control variables drawing on characteristics of the other cards held. We first control for the number of cards held. In a series of additional models, we then control for the balance on other cards, the ratio of the balance of the first card to the total balance on all cards (to control for balance matching across cards), and additional specifications, including dummy variables for whether the first card has the highest utilization among all cards, lowest utilization among all cards, highest balance among all cards, and finally, lowest balance among all cards. We do not include all these measures in a single specification because they are highly correlated.[9]

Results show that the coefficients on the nondurable variables are unchanged from those in the earlier models. The coefficients on the multiple-card variables are consistent with consumers being more likely to pay down the card with the highest balance. The coefficient on the ratio of balance on the first card to balances on all cards is positive and statistically significant at the 1% level, implying a higher balance on the current card increases the likelihood of full repayment. The coefficients on the other variables show that when the first

Figure 5. Fitted Probabilities for Full Repayment Based on Linear Probability Models (See Tables E-3 and E-4, Column (1), of Online Appendix E), Evaluated at the Mean of the Other Covariates.





Note. Lines span 95% confidence intervals.

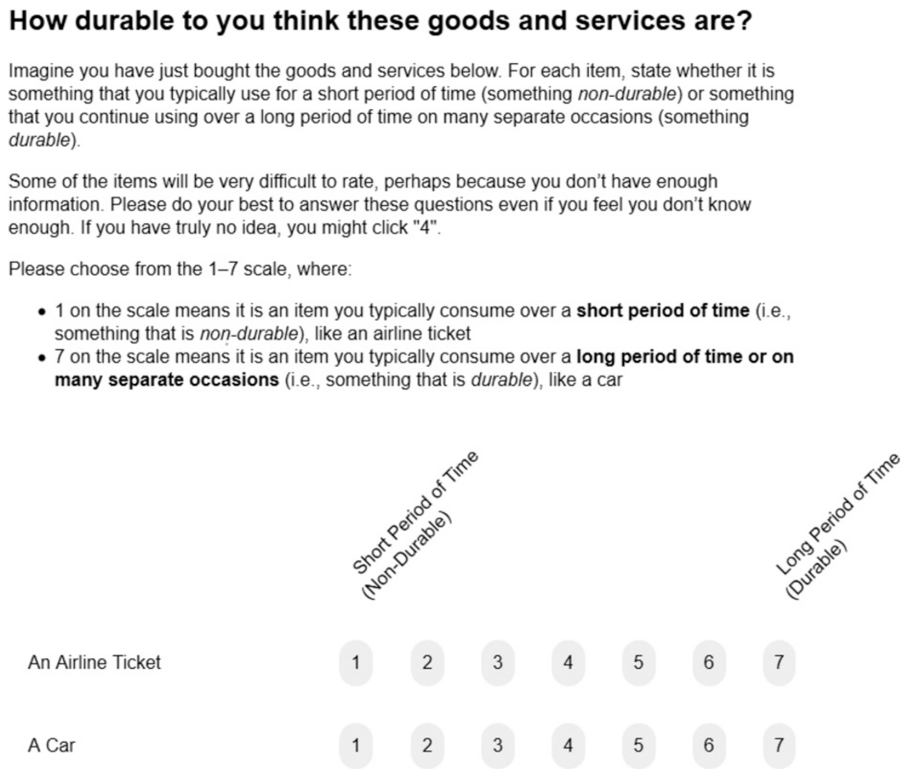
card has the highest balance or utilization (which correlates), the card is more likely to be repaid in full, and conversely, when the first card has the lowest balance or utilization, it is less likely to be repaid in full. From this analysis, we conclude that repayment behavior appears to be driven by both intertemporal mental accounting and also the application of intratemporal heuristics.

5.6. Older Account Samples

Next, we widened the sample to older accounts, incorporating months of data that include single and multiple purchase types. In these wider samples, we see multiple observations of the same account over different months. Therefore, we are able to estimate models with individual-level random and fixed effects.

Table 6 shows results from a single-purchase-type sample of older accounts. We report specifications without controls (column (1)), with the inclusion of a fifth-order polynomial in purchase amount (column (2)), and with the inclusion of additional controls and month fixed effects (column (3)). Columns (4)–(6) repeat these three specifications with the addition of socioeconomic controls. The sample size is smaller because these controls are available only for 69% of the data. Columns (7)–(9) again repeat these specifications with the addition of individual fixed effects. The sample size decreases in these specifications because only accounts that contribute

Figure 6. (Color online) Question Format Used in the Consumer Survey for the Classification of Items into Durables and Nondurables



How durable to you think these goods and services are?

Imagine you have just bought the goods and services below. For each item, state whether it is something that you typically use for a short period of time (something *non-durable*) or something that you continue using over a long period of time on many separate occasions (something *durable*).

Some of the items will be very difficult to rate, perhaps because you don't have enough information. Please do your best to answer these questions even if you feel you don't know enough. If you have truly no idea, you might click "4".

Please choose from the 1–7 scale, where:

- 1 on the scale means it is an item you typically consume over a **short period of time** (i.e., something that is *non-durable*), like an airline ticket
- 7 on the scale means it is an item you typically consume over a **long period of time or on many separate occasions** (i.e., something that is *durable*), like a car

	Short Period of Time (Non-Durable)					Long Period of Time (Durable)
An Airline Ticket	1	2	3	4	5	6	7
A Car	1	2	3	4	5	6	7

at least two months are retained in the account fixed effects models.

Results show that, consistently across all model estimates, the coefficient on the nondurable purchase type dummy is positive with a tight CI. Based on the fullest specifications incorporating controls (columns (3), (6), and (9)), the coefficient on the nondurable dummy implies switching from durable to nondurable purchases raises the likelihood of repayment by between 0.7 and 3.0 percentage points, a smaller range of magnitude than that found in the earlier analysis of new accounts. The coefficient estimates on the covariates are in keeping with those returned in previous models: the propensity to repay an account in full increases with APR and reduces with the credit limit and card utilization.

Table 7 reports results from the multiple-purchase-type sample. The sample here is again much larger because of the higher prevalence of accounts with purchase of more than one consumption type. Across all model estimates shown in Table 7, the coefficient on the proportion of the total monthly spending on purchases of the nondurable type is positive and precisely defined. Depending on the model specification, the coefficient varies between 1.0 and 4.0 percentage points. Hence, the propensity to repay accounts in full increases with nondurable purchases among older accounts even when conditioning for account random and fixed effects.

6. Conclusions

Research on mental accounting has extensively probed violations of the commonly assumed fungibility of money and has convincingly argued that the labeling of mental budgets, the allocation of money, and the sources of income can have an important influence on consumers' choices (Prelec and Loewenstein 1998, Thaler 1999). Much of the early evidence, however, came from studies using judgments of hypothetical spending and repayment scenarios and from nonrepresentative samples of young adults.

Subsequent empirical investigations of mental accounting have shifted toward observational field studies (Kooreman 2000, Milkman and Beshears 2009, Beatty et al. 2014) as well as one experimental field study (Abeler and Marklein 2017). However, most of these studies have focused almost exclusively on the issue of labeling—that is, of whether earmarking payments for particular purposes affects the way they are spent even when individuals would naturally spend more on the category of consumption than the amount of the earmarked payments.

In this paper, we use credit card data to test a specific prediction of a theory of mental accounting proposed by Prelec and Loewenstein (1998): whether debt incurred on consumables is more likely to be paid off more rapidly than debt incurred on durables. Analyzing data on credit

Table 6. Estimated Likelihood of Repaying Full Balance: Single-Purchase-Type Sample for All Accounts

	Random effects			Random effects (+ socioeconomic controls)			Fixed effects		
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Nondurable = 1	0.0403***	0.0243***	0.0249***	0.0383***	0.0223***	0.0230***	0.0116***	0.00717***	0.00708***
	(0.00162)	(0.00159)	(0.00156)	(0.00194)	(0.00191)	(0.00188)	(0.00201)	(0.00201)	(0.00201)
Merchant APR (%)			0.0103***			0.00875***			0.00280***
			(0.000153)			(0.000187)			(0.000372)
Credit limit (£1,000)			–0.00285***			–0.00255***			0.00643*
			(0.000379)			(0.000444)			(0.00357)
Utilization (%)			–0.00323***			–0.00334***			–0.000726***
			(9.49×10^{-5})			(0.000115)			(0.000156)
Account age (years)			0.00484***			0.00461***			–0.0111***
			(0.000137)			(0.000155)			(0.00171)
Amount purchase (£1,000)		–0.357***	–0.211***		–0.348***	–0.208***		–0.145***	–0.120***
		(0.00543)	(0.00640)		(0.00646)	(0.00766)		(0.00742)	(0.00927)
Amount purchase $(£1{,}000)^2$		0.110***	0.0817***		0.107***	0.0792***		0.0555***	0.0503***
		(0.00380)	(0.00378)		(0.00447)	(0.00447)		(0.00539)	(0.00552)
Amount purchase $(£1{,}000)^3$		–0.0153***	–0.0123***		–0.0146***	–0.0115***		–0.00875***	–0.00816***
		(0.000853)	(0.000833)		(0.000984)	(0.000969)		(0.00124)	(0.00125)
Amount purchase $(£1{,}000)^4$		0.000937***	0.000776***		0.000859***	0.000698***		0.000555***	0.000525***
		(7.15×10^{-5})	(6.96×10^{-5})		(8.10×10^{-5})	(7.94×10^{-5})		(0.000107)	(0.000107)
Amount purchase $(£1{,}000)^5$		-2.03×10^{-5}***	-1.71×10^{-5}***		-1.79×10^{-5}***	-1.48×10^{-5}***		-1.20×10^{-5}***	-1.15×10^{-5}***
		(1.96×10^{-6})	(1.90×10^{-6})		(2.18×10^{-6})	(2.13×10^{-6})		(2.99×10^{-6})	(2.99×10^{-6})
Median house price (£)				1.32×10^{-8}	7.37×10^{-9}	-1.04×10^{-9}			
				(2.30×10^{-8})	(2.14×10^{-8})	(2.05×10^{-8})			
Free school meals (%)				–0.306***	–0.276***	–0.194***			
				(0.0268)	(0.0250)	(0.0240)			
Weekly household income (£)				-2.44×10^{-5}	-8.17×10^{-6}	6.07×10^{-6}			
				(1.77×10^{-5})	(1.65×10^{-5})	(1.58×10^{-5})			
Constant	0.782***	0.870***	0.694***	0.844***	0.914***	0.738***			
	(0.00154)	(0.00172)	(0.00402)	(0.0124)	(0.0116)	(0.0119)			
R^2							0.001	0.014	0.016
Observations	154,924	154,924	154,924	107,384	107,384	107,384	93,957	93,957	93,957
Number of accounts	95,461	95,461	95,461	66,021	66,021	66,021	34,494	34,494	34,494
Month fixed effects	No	No	Yes	No	No	Yes	No	No	Yes

Notes. The sample includes all accounts and months in which expenses were related to only one merchant code (there are 25 codes). All models are linear probability models in which the outcome takes the value of one when the repayment–purchase ratio is greater than 0.9 and otherwise takes a value of zero. Models (1)–(6) are random effects models, and Models (7)–(9) are fixed effects models that control for unobserved account heterogeneity. Reference category: durable goods. Standard errors in parentheses.

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Table 7. Estimated Likelihood of Repaying Full Balance: Multiple-Purchase-Type Sample for All Accounts

	Random effects			Random effects (+ socioeconomic controls)			Fixed effects		
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Nondurable (proportion)	0.0469***	0.0316***	0.0357***	0.0433***	0.0288***	0.0329***	0.0172***	0.0117***	0.0117***
	(0.00138)	(0.00137)	(0.00133)	(0.00165)	(0.00164)	(0.00160)	(0.00160)	(0.00159)	(0.00159)
Merchant APR (%)			0.0126***			0.0111***			0.00475***
			(0.000113)			(0.000137)			(0.000235)
Credit limit (£1,000)			–0.00220***			–0.00236***			0.00957***
			(0.000335)			(0.000392)			(0.00236)
Utilization (%)			–0.00322***			–0.00328***			–0.000854***
			(6.69×10^{-5})			(8.18×10^{-5})			(0.000103)
Account age (years)			0.00659***			0.00628***			–0.00743***
			(0.000125)			(0.000140)			(0.00128)
Amount purchase (£1,000)		–0.343***	–0.165***		–0.323***	–0.159***		–0.153***	–0.122***
		(0.00397)	(0.00459)		(0.00471)	(0.00550)		(0.00498)	(0.00613)
Amount purchase (£1,000)^2		0.118***	0.0700***		0.107***	0.0647***		0.0630***	0.0560***
		(0.00292)	(0.00287)		(0.00341)	(0.00338)		(0.00380)	(0.00387)
Amount purchase (£1,000)^3		–0.0181***	–0.0114***		–0.0159***	–0.0101***		–0.0109***	–0.0100***
		(0.000692)	(0.000669)		(0.000791)	(0.000772)		(0.000929)	(0.000933)
Amount purchase (£1,000)^4		0.00121***	0.000780***		0.00102***	0.000658***		0.000763***	0.000708***
		(6.10×10^{-5})	(5.86×10^{-5})		(6.83×10^{-5})	(6.63×10^{-5})		(8.44×10^{-5})	(8.44×10^{-5})
Amount purchase (£1,000)^5		-2.83×10^{-5}***	-1.84×10^{-5}***		-2.31×10^{-5}***	-1.50×10^{-5}***		-1.81×10^{-5}***	-1.69×10^{-5}***
		(1.73×10^{-6})	(1.66×10^{-6})		(1.91×10^{-6})	(1.84×10^{-6})		(2.48×10^{-6})	(2.48×10^{-6})
Median house price (£)				8.53×10^{-8}***	7.40×10^{-8}***	5.10×10^{-8}***			
				(1.96×10^{-8})	(1.83×10^{-8})	(1.71×10^{-8})			
Free school meals (%)				–0.365***	–0.356***	–0.228***			
				(0.0232)	(0.0216)	(0.0203)			
Weekly household income (£)				-5.23×10^{-5}***	-1.95×10^{-5}	1.34×10^{-5}			
				(1.52×10^{-5})	(1.42×10^{-5})	(1.33×10^{-5})			
Constant	0.699***	0.812***	0.606***	0.784***	0.865***	0.637***			
	(0.00133)	(0.00154)	(0.00316)	(0.0107)	(0.01000)	(0.00997)			
R^2							0.001	0.017	0.021
Observations	282,997	282,997	282,997	194,214	194,214	194,214	184,673	184,673	184,673
Number of accounts	159,100	159,100	159,100	108,050	108,050	108,050	60,776	60,776	60,776
Month fixed effects	No	No	Yes	No	No	Yes	No	No	Yes

Notes. Table 7 replicates Table 6 specifications, but months with multiple consumption categories or merchant codes are added to the sample (there are 25 codes). All models are linear probability models in which the outcome takes the value of one when the repayment–purchase ratio is greater than 0.9 and otherwise takes a value of zero. Models (1)–(6) are random effects models, and Models (7)–(9) are fixed effects models that control for unobserved account heterogeneity. Reference category: proportion of the total month spending on durable goods. Standard errors in parentheses.

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

card usage and repayment behavior provided by five UK credit card issuers, we provide strong support for this prediction of the theory. In a series of analyses that are based on different subsets of the data, including both new and older credit card accounts, and that incorporate different configurations of controls, including random effects and individual fixed effects, we find that this effect of purchase type on the propensity to repay is strong and robust. Repayment of nondurable goods is an absolute 10% more likely than repayment of durable goods. The size strength of this relationship is comparable to an increment of 15 percentage points in the credit cards' APR—an economically large relationship. We hope these results will motivate a deeper investigation of the mental accounting implications on consumer choice.

Although our evidence provides support for the prediction it was intended to test, inevitably, there are limitations to our analysis. One is that there was some arbitrariness in the division of spending categories used to catalog the nature of consumption. We carefully chose our original classification based on the previous literature, and this was the first and only classification we have tested. After the initial analysis we conducted and report here, we ran tests designed to assess the robustness of the estimated effects under alternative classification schemes. Unfortunately, however, we do not have data on the exact product or service purchased in an individual transaction. Furthermore, we were unable to filter the impact of other important determinants of repayment behavior, such as the sources of income or the locations of funds cardholders use for repayment, because of data constraints. These may be other dimensions of credit card spending and repayment decisions in which mental accounting might be relevant. Our analysis, however, attempts to reduce these concerns by controlling for differences in socioeconomic status, using proxies of income deprivation in the area surrounding the cardholder postcode, and by controlling for unobserved (time constant) heterogeneity among cardholders.

These results have diverse implications for managerial decision making. First, focusing specifically on credit cards, they point to potential new innovations that could give credit cards a strategic advantage. Repayment options currently are focusing on the amount to be repaid, with typical options being the minimum amount to avoid a penalty charge, the last statement balance, or the full current balance. The results just presented suggest, however, that credit card issuers could potentially attract customers by offering repayment options that permit repayment of specific purchases as opposed to amounts. This would increase the tightness of coupling of purchases and payments, which, according to Prelec and Loewenstein's (1998) model, should increase the pain of paying for goods and services but decrease the pain of paying off the credit card. Similar strategies could be employed for other financial instruments via, for example, the partitioning of spending and savings accounts (see Loewenstein et al. 2012). Second, and more generally, the notion of pain of paying, reinforced by these new findings, could have diverse implications for the delivery of incentives. In many situations, managers are interested in increasing the impact of incentives, for example, for employees or customers, and in these situations, the value of incentives could be enhanced by delivering them in the form of earmarked payments aimed at expenses for which individuals find it painful to pay. For example, although, from an economic perspective, customers should be indifferent to whether a discount is applied to an overall purchase or to some specific component of that purchase (e.g., the cost of the good itself, taxes, or shipping), customers may find some of these components more painful to pay for than others, and firms could benefit from framing a discount as being applied to those components. Likewise, special bonus rewards provided to employees for engaging in specific behaviors, such as engaging with a wellness program or achieving high rates of customer satisfaction, could again be targeted to paying off expenses that employees dislike paying for—for example, dental insurance premiums, parking, or other commuting costs. As these examples suggest, managers have barely begun to take advantage of the diverse opportunities available for exploiting variability in the pain of paying across both situations and people (see Rick et al. 2008).

In sum, our analysis provides a new, theoretically grounded data point in a growing body of empirical research documenting systematic violations of the predictions of standard consumer theory in ways predicted by theories of mental accounting.

Acknowledgments

The Argus Credit Card Payments Study data that support the findings of this study are not publicly available. We have posted all of the code used to generate the figures and tables in the paper, including files that allow researchers to create a simulated data set on which the code will run. If you would like to view the reproduction of our results using this code on the Argus CCPS data, please contact us to organize a supervised visit to our local network.

Endnotes

[1] Specifically, under restriction (a), we remove month observations in which the account holder makes no transactions, withdraws cash using the card, pays utility bills, or undertakes a classification unclassified in the merchant code data. These transactions fall outside the mental accounting framework we consider here. Under restriction (b), we also excluded all months with a total purchase amount lower than £5 during the preceding month as balances equal to or less than this quantity that need to be repaid in full because of the required minimum policy. Ignoring such transactions is not problematic if small, routine expenses, such as coffee or lunch, are habitually not booked, emulating the organizational practice of allocating small expenditures to a petty cash fund that is not under scrutiny (Thaler 1999). Under restriction (c), we also excluded months in which a balance transfer occurred on the account because balance transfers reflect substitution

of debts to other credit cards. We also excluded months in which repayments were made automatically by direct debit.

[2] This might be as expected if holiday purchases made via travel agents commonly occur in the same cycle as purchases of airline tickets to holiday destinations.

[3] There are approximately 3,000 UK four-digit postcodes, and each contains, on average, 9,000 individual addresses or 0.03% of all UK addresses.

[4] This suggests that our four samples are very similar in terms of average socioeconomic cardholder characteristics. However, we are only able to match socioeconomic variables based on postcode for 68% of the cardholders in the data.

[5] We split the sample by quartiles of the total value of durable purchases instead of splitting the sample by the total value of all purchases to avoid generating quartiles that contain account × month observations with nearly all observations of durable or nondurable purchases only.

[6] One caveat to this exercise is that, in our data, we do not have random variation in APR. For studies exploiting quasi-experimental variation in APR or random variation, see Gross and Souleles (2002), Bertrand et al. (2010), and Alan and Loranth (2013).

[7] Our universe of data contains records from five UK credit card issuers. Although these issuers comprise more than 40% of the UK market by number of cards, we cannot see all cards held by all individuals in our sample. Therefore, we necessarily restrict our sample by more than if we had data on all cards in the United Kingdom.

[8] Specifically, Gathergood et al. (2019) restrict their sample to observations in which individuals, holding fixed total monthly repayments, have scope to reallocate payments across cards to minimize interest charges. They restrict the sample to months in which the individual (i) carries revolving debt on all cards, (ii) faces different interest rates on the cards, (iii) pays at least the minimum balance due on all cards, and (iv) does not pay all cards down in full. These restrictions allow the authors to analyze whether individuals are minimizing their interest charges. In the current analysis, we restrict to observations in which the individual begins the month *not* revolving any debt (so that we can link spending and repayment). Hence, the samples used in this paper and those in Gathergood et al. (2019) are mutually exclusive.

[9] Gathergood et al. (2019) design their analysis to distinguish which, from a set of candidate repayment heuristics based on these variables, best explain consumer repayment behavior across multiple cards. They use two approaches: one based on a goodness-of-fit criterion to determine which heuristic is closest, on average, to the observed allocation of payments across cards and a second based on determining which heuristic best fits on an observation-by-observation basis. Our econometric implementation of these heuristics as control variables in Online Appendix F, while delivering results in keeping with those from Gathergood et al. (2019), does not, therefore, exactly match the econometric techniques used in that paper.

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