Zwick Center for Food and Resource Policy
Working Papers Series
No. 13

Payment choice with consumer panel data*

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September 18, 2012

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We thank the Consumer Payments Research Center at the Federal Reserve Bank of Boston for support for this project, and for useful advice. The seminar audience at the Economics of Payments VI Conference hosted by the Bank of Canada provided helpful feedback. We thank the Zwick Center for Food and Resource Policy at the University of Connecticut for data. We also thank Adam Rabinowitz, Sarojini Rao, Hanbing Zhang and Mingli Chen for excellent research assistance.

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Preliminary!

Abstract

We exploit scanner data to track payment choice for grocery purchases for a large panel of households over three years. We particularly focus on the role of expenditure size in determining payment choice. While the use of a long panel for these purposes is novel, the introduction of household fixed effects has little effect on our estimates.

Introduction

Over the past several decades, the U.S. payments system has shifted from paper payment instruments, cash and check, to digital instruments, debit cards and credit cards. This shift is important since digital payments are typically regarded as superior in most dimensions: they are faster and cheaper to process, and they are easier to track and less subject to crime. The shift to digital payments is far from complete however, as cash and check still play a large role in the economy, particularly in some sectors.

A number of studies aim to identify the determinants of payment choice. However, doing so is often hampered by data constraints. It is difficult to track the payments of individual households, particularly with regard to cash. One method for tracking payment choice is to survey consumers retrospectively such as in Schuh & Stavins (2010) and Koulayev, Rysman, Schuh & Stavins (2012), which use a survey that asks consumers about payment use over the previous month. However, this method makes it difficult to study the determinants of each individual choice, or why choice varies across shopping trips. Another method is to ask survey participants to fill out a diary of payment behavior, such as in Fung, Huynh & Sabetti (2011) and Rysman (2007). This is an important contribution, although Jonker & Kosse (2009) raises questions about how accurate these surveys are, showing that the daily number of transactions in 7 day surveys is significantly less than in one day surveys, suggesting a form of "diary fatigue." A solution to this problem is to obtain data directly from consumer bank accounts so consumers are passive, such as in White (1975), Cho & Rust (2012), Stango & Zinman (2012) and Dutkowsky & Fusaro (2011). However, these typically provide no information on how the consumer uses cash, and consumers may use multiple accounts for transactions, some of which may not show up in the available transaction record.

The idea behind this paper is to leverage an existing scanner data set to obtain transaction-level data on payment choice. We focus on grocery purchases. Nielsen maintains a panel of households that tracks in great detail their purchase choices of grocery products. These types of data are common for marketing studies. It turns out that Nielsen also tracks the payment method of each purchase, and we obtained those data for this paper. To our knowledge, no previous academic study has used such data.

Our data has important limitations. First, we observe only grocery purchases, a small subset of any household's budget. However, groceries are an important touchpoint for payment choice, and have been a focus of the payments industry. Also, the method that Nielsen Homescan used for tracking payments is not perfect for our purposes, as we essentially cannot distinguish between debit and credit use. But importantly, we can distinguish between cash, check and card, and we observe transaction size, which is the focus of the paper. We discuss further limitations below.

Scanner data has important advantages over alternatives. Most importantly, we observe individual household decisions continuously for a period of three years, something that no existing diary data set can come close to matching, and we observe which member of the household made each purchase. We observe important demographics such as household size and income.

A closely related paper is Klee (2008). Klee also uses scanner data to study payment choice. Her data set is drawn from the cash register of a grocery chain. As a result, she cannot observe the identities of the purchasers, and thus cannot track consumers over time in any way. She accounts for consumer demographics by using census data on the neighborhoods of the stores. This contrasts with our paper, where we observe consumer demographics directly and can account for unobserved heterogeneity using panel techniques such as fixed effects. In addition, our study covers packaged food shopping from a wide array of retailing channels, not just a single store. Like us, Klee cannot distinguish between debit and credit, although she can distinguish signature and PIN-based card transactions.

We find that transaction size is an important determinant, with consumers using cash for almost all of the smallest transactions, and cards and to a certain extent checks for larger transactions. Surprisingly, we find that accounting for household and even shopper fixed effects has relatively little effect on this relationship, supporting the approach of Klee (2008). Similarly, the importance of expenditure size is robust to accounting for state dependence via lagged dependent variables.

We also use the data to characterize the extent of single-homing, that is, how much do consumers concentrate payments on a single payment method as opposed to spread them across methods. The extent of single-homing is an important issue for merchants as they decide what mechanisms to accept, and is an important issue in the literature on two-sided markets (see Rochet & Tirole, 2006; Rysman, 2009). As in Rysman (2007), we find substantial single-homing. Although relatively few households use a single payment instrument exclusively, most focus a substantial share of their payments on a single instrument.

Despite this evidence on single-homing, households sometimes switch their favorite payment choice. Although this happens rarely, the length of our panel means we can study this topic as well. We find that changes in income predicts changes in payment choice, particular higher income leads to more card use.

In addition to our specific findings, we conclude that this type of scanner data is a useful, unexplored source of information on payment choice.

2 Data

We draw our data set from the Home-Scan database maintained by the A.C. Nielsen company. It covers three years from 2006-2008 for 16 Designated Marketing Areas, which are geographical regions somewhat larger than the average Metropolitan Statistical Area, and are meant to denote television markets.

Participating households receive a UPC scanner that they use to scan all of their grocery purchases, which provides the basic source of the data set. In addition, they receive a keypad device that they use to record purchases of products without UPC codes, such as fruit. They also enter their payment choice on this device. Consumers send in receipts as well, which Nielsen uses to verify the consumer's purchase behavior. Consumers are supposed to report all purchases of food that is purchased to consume at home.

We obtain this data set through the Zwick Center for Food and Resource Policy at the University of Connecticut. They obtained the data for purposes of studying the demand for calorie rich consumer packaged foods, and thus obtained all shopping trips that include at least one of the following seven product categories: ready-to-eat breakfast cereals; candy; gum; salty snacks; fruit; nuts; and carbonated soft drinks. Thus, if a consumer stops in to buy only a container of milk, we will not observe that shopping trip. Presumably, almost any large shopping trip will include one item from the one of the categories. We ignore this selection issue in what follows.

We make use of whether the consumer uses cash, check or a card. The card category combines debit and credit. In fact, the survey asks households to record whether they use cash, check, a credit card or a debit card. Unfortunately, the survey instruction booklet tells them to record any card transaction that uses a signature as credit, which would include signature debit transactions. Indeed, in our data, the share of credit transactions is much higher than one would expect based on other data sources. If consumers well-understood this instruction, we could study the choice between PIN and signature, as in Klee (2008). However, we are not particularly interested in this distinction, and furthermore, signature and PIN are labeled as "credit" and "debit" in the entry device, so we suspect that many signature debit transactions were recorded as PIN. Indeed, the share of (what the recorder calls) credit transactions is much higher than other sources would suggest for grocery stores, but not enough to account for all signature transactions. The result of all of this is that we combine debit and credit transactions and simply study the choice of cash, check and card. In fact, household use of debit and credit cards for transactional purposes are similar (see Koulayev et al., 2012) and furthermore, we are particularly interested in the use of digital payments relative to paper payments, which we can still study in this environment. [1]

Overall, we observe 1.6 million transactions. Unfortunately, payment choice is missing on about a 10% of these. Standard analysis does not identify any systematic differences between shopping trips with and without payment information. [2] We lose more observations to other missing data. Our final data set use 1.34 million transactions.

We observe consumer demographics, such as household income, household composition, race, age of each member, education of male and female adults, DMA, and home-ownership status. We also observe demographic weights. For each shopping trip, we observe the date, the shopper, the total expenditure, the payment method, the type of store (grocery market, convenience store or non-food store, such as Target) and indicators for whether the shopper used a loyalty card or coupons. We further observe a store identifier for 1,400 retail shops. Transaction size includes any items that the consumer buys at the register, including non-food items. Transaction size does not include any cash back that the consumer may withdraw from their bank account if purchasing with a debit card.

Our data set contains 13,574 households. While there is turnover in the panel, we can track most households for a substantial amount of time. The unweighted mean number of shopping trips is 98.8, the median is 84 and the 10th percentile household still makes 24 trips. The median date between the first and last trip is 149.5 weeks apart. That is, the median household appears in the data set for the entire three-year panel. Even the 10th percentile makes trips 46 weeks apart.

Figure 1 shows a histogram of the number of shopping trips in a month that we see in our data set. The mean is 3.87, and the median is 3, so our data set shows that households make shopping trips slightly less than once a week. This might be a little low for several reasons. First, we only observe shopping trips that fall into at least one of our food categories. We do not know how many observations we miss as a result. Second, we have dropped a portion of our observations because payment information is missing. There may also be an issue with survey participants who do not track every grocery trip. Naturally, Nielsen acts to minimize compliance problems.

Table 1 reports basic market shares for each payment type, using population weights. We find that cards used for 45.5% of transactions, cash for 47.8% and check used for 6.7%. These numbers indicate higher cash usage than for the economy as a whole – for comparison see Koulayev et al. (2012), not surprising for the grocery industry. Cards are much higher by value, 57.1%, with cash at 32.7 and check at 10.2. The use patterns vary substantially with transaction size. Figure 2 breaks up transaction value into 20 bins with equal numbers of transactions in each. The figure shows the percentage of transactions by each payment choice by transaction size. The x-axis labels the lower bound of each bin. So we can see that for transactions below $4 (the bin labeled 0.01), 92% of transactions are in cash. This number changes dramatically with higher values. For the upper fifth of transactions (more

[1] The survey asks "credit users" to indicate their network choice – Visa, MasterCard, American Express or Discover. These might be independently interesting, and also, since American Express and Discover do not market debit cards (either signature or PIN), it gives us a bit of information on when consumers use credit versus debit. However, Visa and MasterCard still dominate the credit market, so we do not pursue this further.

[2] A regression of an indicator for unknown payment type on the log of transaction size generates a coefficient of 0.004. This coefficient is statistically significant (as one would expect with 1.6 million observations), but it is economically insignificant.

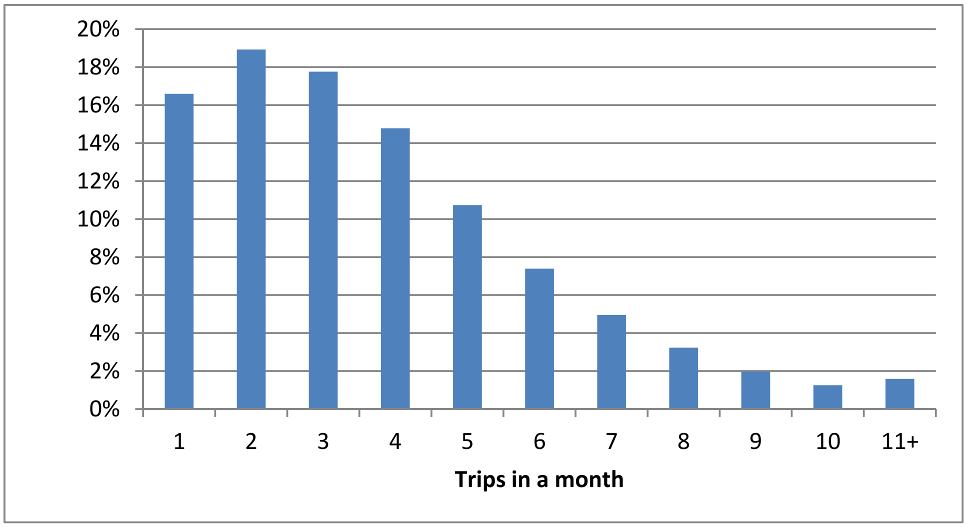

Figure 1: Frequency of number of trips in a month.

	Transactions	Value	Average Expenditure
Cash	47.87%	32.67%	$35.26
Check	6.65	10.2	$70.20
Card	45.48	57.14	$64.91

Table 1: Use shares.

than \$80.43, the last 4 bins), more than 60% of transactions are by card, around 15% of transactions are by check and 25% or less of transactions are by cash.

Table 2 analyzes payments by type of store. We observe four types of stores: grocery stores, non-food stores (such as gas stations and department stores), convenience stores (such as 7-11, and including drug stores such as CVS) and "other" stores. Most purchases, 58%, are at grocery stores, with convenience stores and the other category splitting most of the rest. Average transaction values are very similar across the stores, between \$53 and \$56 except for the other category. Payment methods look similar at grocery and convenience stores, around 40% for cash and 50% for card. Cash use is dramatically higher on non-food stores, perhaps driven by gas stations. The other category falls in between.

Payment choice is strongly related to income. To show this, we compute for each household the average income and the share of payments that went to each payment choice. Just using the average household income may miss some element of how income relates to payment choice, but note that 60% of households never change income in our data, and 90% of households have a lifetime standard deviation in income of less than \$12,500. We divided households into 20 bins based on income, with equal numbers of households in each bin. For each bin, we calculate the average share of each payment instrument.[3]

[3]We do this computation in two steps, first averaging by household and then averaging over households, in order to weight each household equally in our final result. We could compute payment choice by income

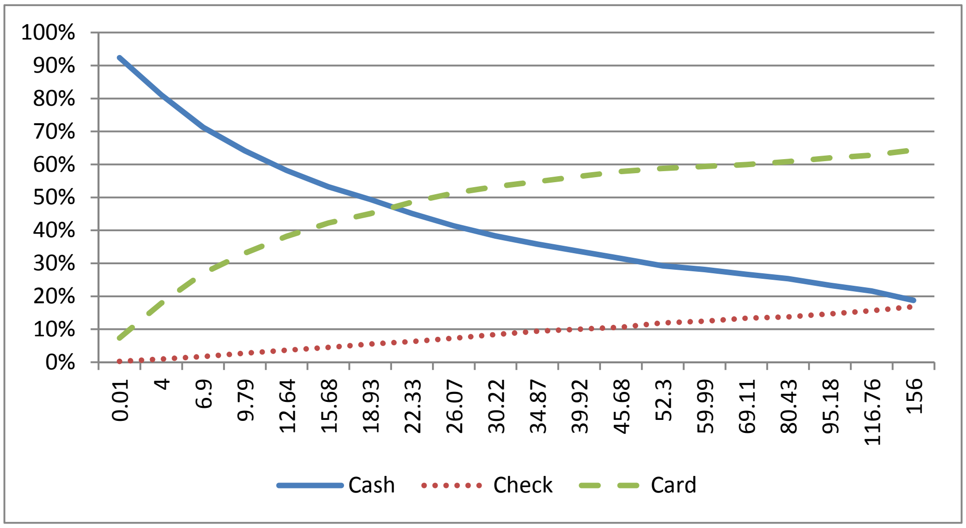

Figure 2: Pay type by transaction size.

	% of transactions	transaction value	% cash	% check	% card
Grocery	57.98	$53.05	39.97	9.77	50.26
Non-food	19.31	$55.99	53.36	6.86	39.79
Convenience	2.79	$54.80	39.73	8.66	51.61
Other	19.91	$45.93	44.41	6.38	49.20

Number of observations: 1,341,226

Table 2: Pay type by type of store.

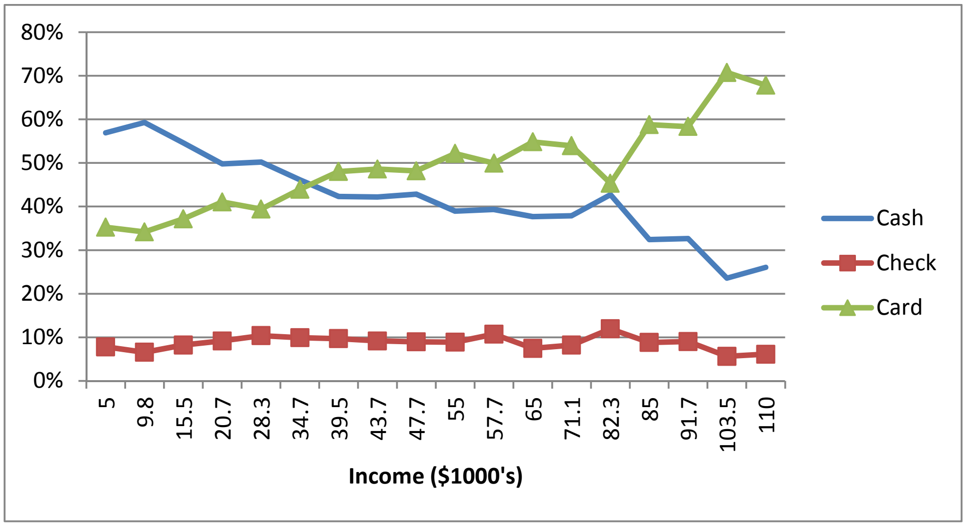

Figure 3: Pay type by household income.

Results are in Figure 3. We see that low income households rely heavily on cash, but that this declines quickly with income. By $35,000, households prefer cards to cash, with very wealthy households putting as much as 70% of transactions on card. Check stays fairly constant, hovering around the 9% mark.

Previous work, such as Koulayev et al. (2012), has shown that education is an important predictor of payment choice. That is true in the current data set as well. Here, we calculate the share that each payment instrument gets for each household, along with the highest educational level achieved by the male in each household. We then compute the average share for each payment instrument, by education level. If no male is present, we code it as *missing*. The result appears in Figure 4. We see that college and post-college degree households are much heavier users of cards than low education households, who lean much more heavily on cash. How much of this outcome is due to education and how much is due to income is delayed until the regression results. Check appears non-monotonic, although the changes are not large, ranging from 4% to 9%.

The data set tracks gender, which provides some interesting results not available in other data sets. For this analysis, we focus on households with a male and a female adult, 45% of our data. Within this group, women perform 70.3% of the shops. We compute the share to each payment instrument by household and shopper gender, and then we calculate the difference in shares between the male and female within each household. Table 3 reports the average difference and standard deviation. We see relatively small average differences. Males devote 5.2 percentage points more to cash, whereas females use 2.6 percentage points more for check and card each. But notice that the standard deviations around these numbers are very large. For instance, the standard deviation for the difference in cash market shares is 26.7 percentage points. Thus, in many households, men and women use payment instruments in very different ways, although the direction of these effects is not consistent across households. Of course, it may be that men and women do different types of shops,

directly, but this would overweight households that made many purchases.

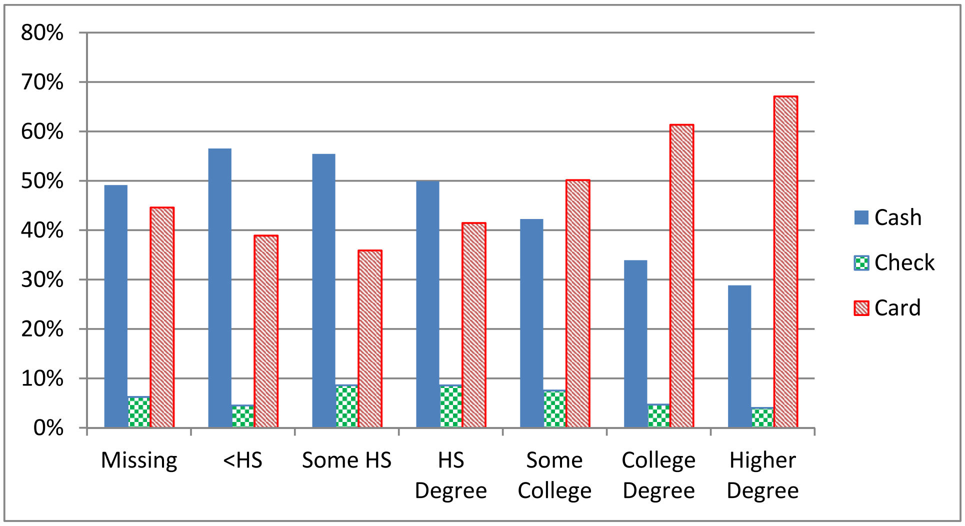

Figure 4: Pay type by highest educational attainment of the male head-of-household.

	Difference	Standard Deviation
Share of cash	-0.052	0.267
Share of check	0.026	0.151
Share of card	0.026	0.267

Table 3: Difference between shares that men and women in the same house devote to payment instruments.

so that the proper controls will limit the importance of gender differences. We defer this discussion for the regression analysis.

3 Single-homing

An important empirical question for the payments card market is the extent of single-homing. Consumers that single-home use only one payment type. In contrast, multi-homing consumer use multiple types of payments. Single-homing is important because merchants must accept the payment type of single-homing consumers in order to have them as customers. If the payment type is proprietary, such as with networks such as Visa and American Express, the payment network has market power over the merchant for access to single-homing consumers. Single homing plays an important role in theoretical discussions of competition between platforms in two-sided markets. For example, see Armstrong (2006) and Rochet & Tirole (2006).

We cannot observe consumers avoiding stores because they do not accept a payment type, a behavior that perhaps best captures the notion of single-homing. Furthermore, practically every grocery retailer accepts cash, check and cards. However, we are still

	Percent of Population					
	5%	10%	25%	50%	75%	90%
favorite pay type	51.35	55.55	68.25	84.82	95.38	100
favorite two pay types	87.8	93.5	98.6	100	100	100

Number of obsevations: 13,574

Table 4: Single-homing behavior

interested in the extent to which households focus their spending on a single payment type. Beyond the single-homing interpretation, these results are useful for interpreting what is to follow. Previously, Rysman (2007) takes a similar approach to studying single-homing on credit card networks among credit card purchases.

We calculate the percent of payments that each household puts on each payment type, and determine the household's favorite payment type. We then treat the percent of payments on the favorite type as the variable of interest, and compute how it is distributed across the population. Thus, if there were no heterogeneity, all households would pick cards as their favorite type, and place 48.1% of payments on cards.

In practice, we find substantially more single-homing type behavior. Table 4 reports the percent of households that put less than some percent of payments on their favorite payment choice. For instance, we see that only 5% of the population puts less than 51.35% of their payments on their favorite payment type. Similarly, 10% of the population puts less than 55.55% on their favorite choice. The higher percentages are striking: 50% of households put more than 84% of their transactions on a single pay type, and 10% put all of their transactions on a single pay type. We can do a similar analysis at the level of the shopper rather than the level of the household. Results are similar – 50% of shoppers put 87.5% or more of their transactions on a single pay-type.[4]

If we extend our analysis to the favorite two payment types, we find that 85% of the population prefers cash and card to any other combination. Also, 75% of households put more than 98% of their transactions on their favorite two types, and 95% of the population puts more 87% on their favorite two types. Thus, we find that households rarely use more than two payment types.

Having said that, we rarely see households literally use a single payment instrument for 100% of their shopping trips. This result is interesting both because it moderates our conclusion about single-homing and because it means that we can proceed with an estimation strategy based on household fixed effects and within variation. Obviously, households that use only one payment instrument for every shop will drop out of a fixed-effects regression, but this is rarely the case. Table 5 presents the percentage of households that either always or never use a payment instrument. Because we are interested in both the population average for these numbers and in understanding the role of household fixed effects in estimation, we report these numbers both with and without using population weights. We see that only 8% of the population (6.8% of our data) always uses cash and that 4.7% (5.1% of our data)

[4]Formally, the data set provides the gender of the shopper, not the identity of the shopper. Thus, we condition on the shopper gender in this exercise. Since households with multiple shoppers typically contain one female and one male, we treat observing the shopper gender as if we were observing the shopper identity.

% HHs	Cash	Check	Card
Always use	6.84	0.17	3.83
Weighted	8.31	0.15	3.64
Never Use	5.08	61.26	10.45
Weighted	4.71	64.71	11.32

Table 5: Percent of population that always or never uses an instrument.

	None	Cash	Check	Card
Favorite by Quarter		41.23	6.6	52.16
With cut-off at 80%	33.6	29.49	2.75	34.16

Table 6: Share as favorite for a household-quarter.

never uses cash. Similarly for cards, 3.6% always use a card and 11.3% never use a card. Also, less than 1% always use a check. The one large number we observe is that 64% of the population never uses a check.

4 Switching

The previous section shows that households are likely to concentrate their payments on a single payment instrument. Does the extent of this concentration remain constant over the life of the household, or do they switch among favorites over time? A unique feature of observing such a long and continuous panel is the ability to analyze switching behavior within the household. This section presents some simple statistics, and the next section introduces regression analysis on this topic.

In order to study switching, we must choose a time period over which to define a favorite payment card. We choose a period of one quarter. For each household-quarter in the data, we compute the share the household places on each of cash, check and card. The instrument with the highest share is the household favorite. The share of each as favorite appears in Table 6. The shares are 41.23% for cash, 6.6% for check and 52.16%, similar to the per-transactions shares, although with less weight on checking.

We construct a transition matrix for the favorite payment choice of the month. The results appear in Table 7. In this table, each row sums to 100 and each element in the row provides the probability of ending in that column, given the household started in that row. For instance, the first row indicates that a household that chose cash in one quarter has a 86.43% chance of choosing cash again the next period. There is a 1.88% chance that check will be the favorite. Since the diagonals are high, these tables indicate that switching is relatively rare. For instance, a household that chooses *card* has about a 90% chance of choosing card again, which means that on average, it will keep card as the favorite for 10 quarters, or 2.5 years. For cash, the average is 7.2 quarters and for check, it is only 4.3 quarters.

Table 7 does not capture the extent to which households typically return to choices they

	Cash	Check	Card
Cash	86.43	1.88	11.70
Check	11.68	77.41	10.91
Card	8.72	1.09	90.19
Total	41.22	6.54	52.25

Table 7: Transition matrix for favorite payment instrument by household-quarter.

	Cash	Check	Card
Cash	52.13	1.48	46.39
Check	9.01	46.96	44.03
Card	5.36	0.65	93.99
Total	9.41	1.23	89.35

Table 8: Transition matrix for favorite payment instrument by household-quarter, among households that chose *card* two periods ago.

made in the past. In fact, there is substantial persistence of the choices of consumers over time. In order to explore this possibility, Table 8 presents the transition matrix for the subset of households that chose card two periods ago. Indeed, we see that households that chose card two periods ago are substantially more likely to switch to choose card this period than the general set of households. That is, the card column is higher in Table 8 than in Table 7. A household that goes from card to cash has 46.39% chance of switching back to card, whereas the unconditional probability of choosing card having chosen cash before is only 11.7%. Thus, households exhibit persistence over time in their choices.[5]

Rather than look at period-to-period switches, this persistence suggests that we should look at the lifetime switching of each household. For each household, we record the number of switches the household makes. We present a histogram of the results in Figure 5. A first striking result is that more than 60% of households never switch their favorite instrument. However, although the median number of switches is 0, the mean is 0.97, the 75th percentile is 2 and the 90th percentile is 3. Therefore, over three years of data, we observe non-trivial changes in payment choice across households. We can imagine several sources of such changes. The data set is well-suited to study demographic changes, such as changes in income and employment status. We study these topics in the regression analysis below. Other important issues that we do not attempt to address might be learning or social effects.

Before going forward, we might be concerned that our methods overstate the amount of switching. For instance, a household that hovers around putting 50% of spending on a card and 50% on cash may generate many switches in our method, although its behavior is changing very little. To consider this possibility, we recompute the statistics above, but

[5] A benefit of our data set is that it provides enough observations to do this sort of conditional analysis. For instance, we observe 51,862 household-quarters with three sequential months of data that chose card two months ago. The row in Table 8 with the least number of observations, the row representing households that went from card two periods ago to check one period ago, still has 646 observations in it.

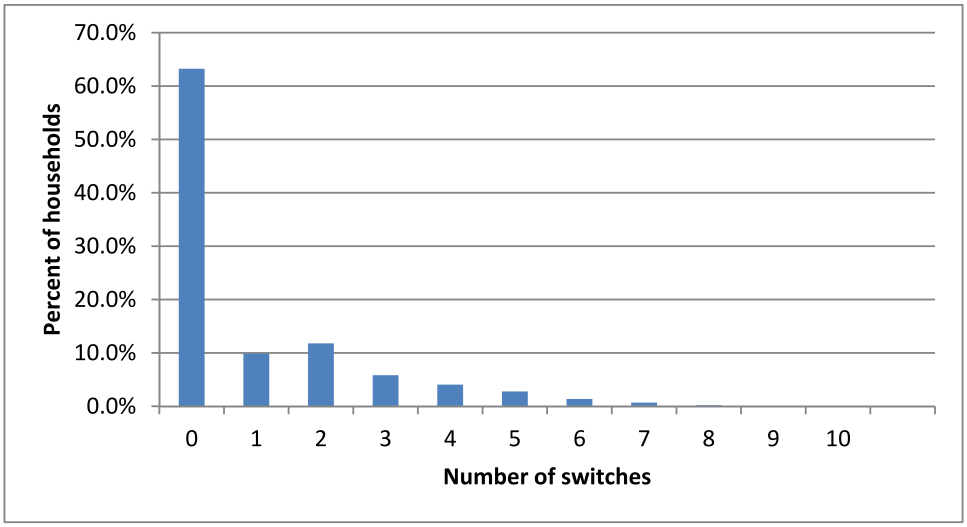

Figure 5: Number of switches of favorite payment instrument per household.

	None	Cash	Check	Card
None	64.06%	12.55	2.89	20.50
Cash	14.99	83.74	0.16	1.11
Check	37.29	1.33	59.81	1.57
Card	18.96	0.92	0.09	80.03
Total	33.58	29.44	2.69	34.29

Table 9: Transition matrix for favorite payment instrument by household-quarter. If no instrument gets 80%, the favorite is *none*.

define a payment instrument to be a favorite only if it garners at least 80% of the share. Households that put less than 80% of their spending on all of the instruments choose *none* as their favorite. The shares of each as a favorite appear in Table 6.

The transition matrix appears in Table 9. Here, it appears that there is more switching in the sense that the diagonal of the table is lower, implying holding times of 2.5 to 6 quarters. However, we see that the off-diagonals among cash, check and card are extremely small. There is less than a 2% chance that a household that chooses cash, check or card will switch to one of the other two instruments. Almost all of the switching is from one of the instruments to the choice of *none*. This suggests that households make large changes in their payment instrument use only infrequently. Furthermore, it would be wrong to think that households switch to *none* and then randomly to one of the other instruments. If they switch, it is back to the same instrument as before. To show this, Table 10 recomputes Table 9 for the population that chose card two periods ago. From *none*, they have a 45.27% chance of picking none again, a 51.33% chance of picking card and less than a 3.5% chance of picking cash or check, much less than the unconditional probability of switching from none to cash or check.

Overall, this exercise suggests that switching is limited. We also wish to see how this

	None	Cash	Check	Card
None	45.27%	3.22	0.18	51.33
Cash	53.10	21.00	0.00	25.90
Check	42.06	0.61	22.74	34.59
Card	13.16	0.41	0.03	86.40
Total	19.63	1.1	0.08	79.19

Table 10: Transition matrix for favorite payment instrument by household-quarter, among households that chose *card* two periods ago. If no instrument gets 80%, the favorite is *none*.

computation affects the histogram in Figure 5. To do so, we define a household to have switched its favorite payment choice if its current favorite instrument is different than the last favorite instrument it chose, as long as it chose an instrument within the last 6 quarters. To give several examples, suppose a household switches back and forth between *none* and *card* throughout the data set (again, we define an instrument as a favorite if it garners 80% of the share for a quarter). We code this household as never having switched. Suppose a household picks a sequence of *card*, *none*, *none*, *cash*. When the household picked cash, its last favorite instrument was card, so under our definition, the household has switched once, from card to cash. If the household had picked *none* 6 or more times in a row, we would not record this as a switch since we would code the household as has having no "last favorite instrument" after the 6th choice of *none*. A household that picked *check*, *cash*, *none*, *check* would have two switches.

The resulting histogram appears in Figure 6. This figure indicates substantially less switching than in Figure 5. We find that almost 85% of households never switch their favorite instrument. Less than 1% of households make more than 2 switches. Thus, while Figure 5 suggests that switching is at least somewhat prevalent, Figure 6 shows that when we focus on large changes in behavior over time, there is remarkably little.

5 Regression Analysis

We are interested in the determinants of payment choices, particularly the effect of transaction size. We are interested in controlling for individual heterogeneity via fixed effects, which has not been explored in previous work. However, discrete choice models are non-linear and applying fixed effects in panel data to non-linear models runs into the well-known incidental parameters problem (for example, see Baltagi, 2003).[6] One solution to this problem is to use the conditional logit model of Chamberlain (1980). However, this faces two problems from

[6]Interestingly, the typical statement is that household fixed effects are biased in non-linear estimation unless the researcher observes many observations per household. Since we observe weekly data for three years, we observe many observations per household. However, we wish to identify fixed effects for each payment type for each household. We observe relatively few households with substantial use of all three instruments. For example, consider a household that almost always uses card payment. We have enough data to consistently estimate the fixed effect for card use relative to cash use, but not enough to identify the fixed effect for check relative to cash. Thus, we proceed as if we are afflicted with the incidental parameters problem, although we have more observations per household than usual, and indeed, there may be a sub-set of the dataset for which the incidental parameters problem does not apply.

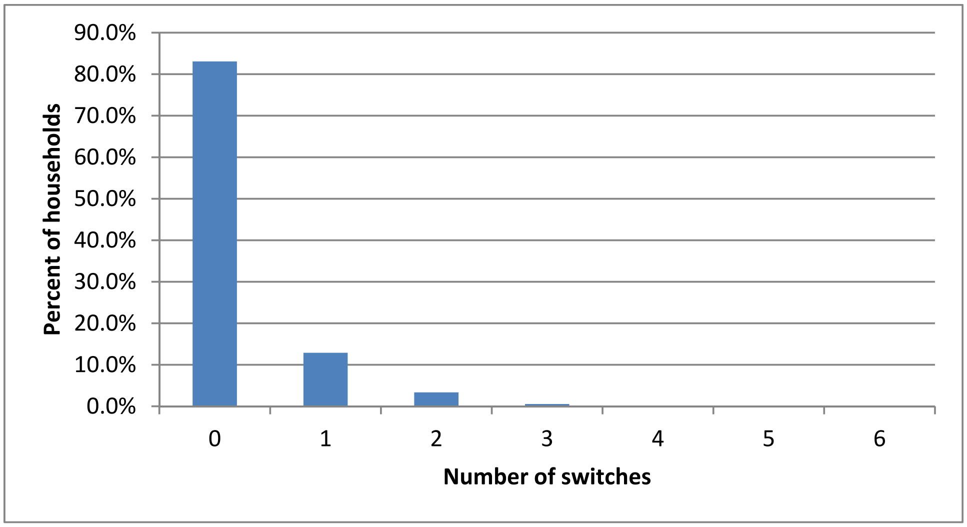

Figure 6: Number of switches of favorite payment instrument per household, allowing households to choose no favorite.

our perspective. First, it is numerically challenging to handle anything but binary choice, and our model has three choices. Second, the conditional logit model does not identify the fixed effects and thus it is difficult to use to analyze magnitudes and marginal effects. We can potentially solve the first problem by dropping check-users from our data set, so we have a binary choice. But we are very much interested in the economic magnitudes of our estimates, so the second problem is important. Thus, we proceed by analyzing linear models. Angrist (2001) argues in favor of using linear models in the case of limited dependent variables, since linear models properly identify the conditional expectation function, which is often the primary object of interest.

5.1 Payment choice

We begin with a multivariate linear probability model. That is, we treat an indicator for whether the household used an instrument on a shopping trip as a linear function of explanatory variables. We perform this regression separately for each of the three payment types. In our first regression, we use only one explanatory variable, the log of the total expenditure. We perform this regression with and without household fixed effects.

Results appear in Table 11. As expected, transaction size has a negative effect on the likelihood of using cash, a positive effect on the likelihood of using check, and a strong positive effect on the likelihood of using a card. Surprisingly, introducing household fixed effects has little effect on the results. The effect of transaction size declines, and the declines are each statistically significant. However, the economic magnitudes are not large. The decline for check is the largest, 28%. The parameter on transaction size declines by only 17% and 13% for cash and card respectively. Thus, there is substantial within-household variation in payment choice in response to transaction size, even in the face of the evidence supporting single-homing in Table 4. We also experiment with a random effects specification in the last row of Table 11. Interestingly, the results are almost numerically identical to

	Cash	Check	Card
OLS			
ln(expenditure)	-0.176	0.043	0.133
	(0.0003)	(0.0002)	(0.0004)
Within HH			
ln(expenditure)	-0.147	0.031	0.116
	(0.0003)	(0.0002)	(0.0003)
Fraction of variance in FE	50.3%	53.2%	54.8%
Random Effect			
	-0.147	0.031	0.116
	(0.0003)	(0.0002)	(0.0003)

Note: Dependent variable is an indicator for the use of a payment instrument, with separate regressions for each instrument. Standard errors are in parenthesis. Fixed and random effects models use the household as the group identifier. The number of

Table 11: Linear probability models without demographic explanatory variables.

the fixed effects specification. These results suggest that the fixed effects are essentially orthogonal to transaction size.

In the next regression, we add explanatory variables. We can divide the explanatory variables into two groups: variables that vary by year, such as household demographics, and variables that vary by trip, such as store type and the day of the week. For demographic explanatory variables, we add male and female education levels, race indicators, designated marketing area of the household, employment status of the male and female, household income, household size (in terms of number of people), and whether the house has a pet. Each variable is entered as a set of dummy variables for categories used in the data set. For shopping-trip variables, we use the day of the week, the year, the type of store and the gender of the shopper, again entered as dummies. We again perform linear regression for each payment instrument separately, with and without household fixed effects. When we use household fixed effects, we drop all of the demographic explanatory variables.[7] Adding explanatory variables causes the coefficient on expenditure to move towards the fixed effects estimate. That is to be expected, since the explanatory variables control for the some of the heterogeneity captured by the fixed effect. Thus, the difference between the OLS and fixed effects estimate is even smaller when including explanatory variables.

While the main focus of the paper is on the effect of transaction size, it is also interesting to look at the effect of other explanatory variables. There are many variables, so in order to make the presentation more manageable, we break up the results into two sets, those that

[7]Surprisingly, almost all of the household explanatory variables vary within the household over the three years for at least a few households, even the indicator for race. Thus, we do not necessarily have to drop those variables in the fixed effects context. We return to these variables below.

	Cash	Check	Card
OLS			
ln(expenditure)	-0.160	0.040	0.120
	(0.0004)	(0.0002)	(0.0004)
Within HH			
ln(expenditure)	-0.145	0.030	0.115
	(0.0003)	(0.0002)	(0.0003)
Fraction of variance in FE	50.4%	53.2%	54.9%
Random Effect			
	-0.145	0.030	0.115
	(0.0003)	(0.0002)	(0.0003)

Note: Dependent variable is an indicator for the use of a payment instrument, with separate regressions for each instrument. Standard errors are in parenthesis. Fixed and random effects models use the household as the group identifier. The number of observations is 1,341,226.

Table 12: Linear probability models with demographic explanatory variables.

vary by year and those that vary by trip. We include the demographic variables only in the regression without fixed effects, so there are three columns of results in Table 13 (one for each payment instrument) and six columns in Table 14 (one for OLS and one for fixed effects, for each instrument). The OLS results in Table 13 and Table 14 are from the same regression, but are split across two tables.

We begin with the OLS results, that is Table 13. First, we can see that income has a negative effect on cash usage, and positive effect on check usage and an even more positive effect on card usage. Employment by the male head of household has little effect on payment choice, with seeming non-monotonicities in the change from less than 30 hours to more than 35 hours of work. Education by the female or male leads to dramatically larger card use, mostly at the expense of cash. Also, younger men and women use cards more, with both cash and check-use increasing in age. For household size, we focus on the empirically relevant range from 1 to 5. Cash use increases in household size, and card use falls, while check use remains close to constant. Blacks use cash and check relatively more than whites, while Asians use cards relatively more. Renters also use cash more than home-owners, a results that is consistent with our results in income and education.

Now we turn to the trip-specific variables, which appear in Table 14. The year 2008 sees slightly increased card use relative to cash and check. Note that 2008 is the first full year of recession, and this result may reflect consumers using their credit lines. Is it striking that the effect of gender switches sign when we introduce household fixed effects. That is, women appear less likely use cards overall, but when we look within a household, women are more

		Cash			Check			Card		
HH income	$5,000-$7,999	0.007	(0.006)		-0.004	(0.004)		-0.003	(0.006)	
(excl: <$5,000)	$8,000-$9,999	0.016	(0.006)	*	0.011	(0.004)	*	-0.026	(0.006)	*
	$10,000-$11,999	0.036	(0.006)	*	-0.001	(0.004)		-0.035	(0.006)	*
	$12,000-$14,999	-0.021	(0.005)	*	0.002	(0.003)		0.019	(0.006)	*
	$15,000-$19,999	-0.052	(0.005)	*	0.019	(0.003)	*	0.033	(0.005)	*
	$20,000-$24,999	-0.051	(0.005)	*	0.014	(0.003)	*	0.036	(0.005)	*
	$25,000-$29,999	-0.077	(0.005)	*	0.022	(0.003)	*	0.055	(0.005)	*
	$30,000-$34,999	-0.080	(0.005)	*	0.030	(0.003)	*	0.050	(0.005)	*
	$35,000-$39,999	-0.100	(0.005)	*	0.028	(0.003)	*	0.072	(0.005)	*
	$40,000-$44,999	-0.099	(0.005)	*	0.015	(0.003)	*	0.084	(0.005)	*
	$45,000-$49,999	-0.113	(0.005)	*	0.014	(0.003)	*	0.099	(0.005)	*
	$50,000-$59,999	-0.108	(0.005)	*	0.009	(0.003)	*	0.098	(0.005)	*
	$60,000-$69,999	-0.120	(0.005)	*	-0.005	(0.003)		0.124	(0.005)	*
	$70,000-$99,999	-0.139	(0.005)	*	0.000	(0.003)		0.139	(0.005)	*
	$100,000 & Over	-0.149	(0.005)	*	-0.021	(0.003)	*	0.170	(0.005)	*
Male Employment	Not Employed	-0.245	(0.004)	*	-0.067	(0.003)	*	0.312	(0.005)	*
(excl: no male	Under 30 Hours	-0.199	(0.004)	*	-0.085	(0.003)	*	0.284	(0.004)	*
head or unknown)	30-34 Hours	-0.161	(0.004)	*	-0.067	(0.003)	*	0.227	(0.005)	*
	35+ Hours	-0.203	(0.004)	*	-0.056	(0.002)	*	0.259	(0.004)	*
Male Education	Grade School	0.072	(0.005)	*	0.0001	(0.003)		-0.072	(0.005)	*
(excl: no male	Some High School	0.127	(0.003)	*	0.024	(0.002)	*	-0.151	(0.003)	*
head or unknown)	Graduated HS	0.096	(0.002)	*	0.012	(0.001)	*	-0.109	(0.002)	*
	Some College	0.054	(0.002)	*	0.027	(0.001)	*	-0.081	(0.002)	*
	Graduated College	0.018	(0.001)	*	0.014	(0.001)	*	-0.031	(0.002)	*
Female Education	Grade School	-0.027	(0.006)	*	-0.045	(0.004)	*	0.072	(0.007)	*
(excl: no female	Some High School	-0.031	(0.004)	*	-0.041	(0.003)	*	0.072	(0.004)	*
head or unknown)	Graduated HS	-0.077	(0.004)	*	-0.019	(0.002)	*	0.096	(0.004)	*
	Some College	-0.115	(0.003)	*	-0.020	(0.002)	*	0.135	(0.004)	*
	Graduated College	-0.137	(0.003)	*	-0.028	(0.002)	*	0.165	(0.004)	*
	Post College Grad	-0.156	(0.004)	*	-0.028	(0.002)	*	0.183	(0.004)	*
Male Age (years)		0.003	(0.0001)	*	0.001	(0.00003)	*	-0.004	(0.0001)	*
Female Age (years)		0.001	(0.0001)	*	0.001	(0.00003)	*	-0.002	(0.0001)	*
Pet Owner	Dog	0.008	(0.001)	*	0.009	(0.001)	*	-0.017	(0.001)	*
(excl: no pet)	Cat	0.001	(0.001)		0.007	(0.001)	*	-0.008	(0.001)	*
	Other	0.032	(0.001)	*	0.010	(0.001)	*	-0.042	(0.001)	*
Household size	2	0.046	(0.001)	*	-0.008	(0.001)	*	-0.038	(0.001)	*
(excl: 1)	3	0.053	(0.002)	*	-0.006	(0.001)	*	-0.047	(0.002)	*
	4	0.076	(0.002)	*	-0.004	(0.001)	*	-0.072	(0.002)	*
	5	0.103	(0.002)	*	0.002	(0.001)		-0.105	(0.002)	*
	6	0.090	(0.003)	*	-0.018	(0.002)	*	-0.072	(0.003)	*
	7	0.178	(0.005)	*	-0.032	(0.003)	*	-0.146	(0.006)	*
	8	0.177	(0.007)	*	0.035	(0.005)	*	-0.212	(0.008)	*
	9	0.107	(0.011)	*	0.195	(0.007)	*	-0.302	(0.012)	*
Race	Black	0.104	(0.001)	*	0.104	(0.001)	*	-0.090	(0.001)	*
(excl: White)	Asian	-0.041	(0.002)	*	-0.041	(0.002)	*	0.065	(0.002)	*
	Other	0.045	(0.002)	*	0.045	(0.002)	*	-0.040	(0.002)	*
Rent	Rent	0.044	(0.001)	*	-0.016	(0.001)	*	-0.028	(0.001)	*
(excl: Own home)	Other	0.035	(0.003)	*	-0.002	(0.002)		-0.033	(0.003)	*

Notes: 1,341,220 observations. Standard errors are in parenthesis. We do not report dummies for DMA code (a region indicator) and male industry of occupation. Trip-specific variables appear on a separate table.

Table 13: Demographic explanatory variables from the linear probability model.

likely to use a card than their spouse. Household fixed effects eliminate households with only one adult from the gender result, so this result may reflect that married households are more likely to hold credit cards. Most of the day-of-the-week effects shrink considerably under the fixed effects specifications, suggesting that households do not change their card use with the day, but rather that different households typically shop on different days.

		Cash OLS			Cash FE			Check OLS			Check FE			Card OLS			Card FE		
ln(expenditure)		-0.160	(0.0004)	*	-0.145	(0.0003)	*	0.040	(0.0002)	*	0.030	(0.0002)	*	0.120	(0.0004)	*	0.115	(0.0003)	*
Year	2007	-0.004	(0.001)	*	-0.004	(0.001)		-0.011	(0.001)		-0.012	(0.0004)		0.015	(0.001)		0.016	(0.001)	
(excl: 2006)	2008	-0.006	(0.001)	*	-0.006	(0.001)	*	-0.023	(0.001)	*	-0.023	(0.0004)	*	0.029	(0.001)	*	0.029	(0.001)	*
Store Type	Non-food	0.052	(0.001)	*	0.044	(0.001)	*	-0.008	(0.001)	*	-0.010	(0.0005)	*	-0.043	(0.001)	*	-0.034	(0.001)	*
(excl: Food)	Drug	-0.015	(0.002)	*	-0.021	(0.002)	*	-0.017	(0.001)	*	-0.023	(0.001)	*	0.033	(0.002)	*	0.044	(0.002)	*
	Other	-0.008	(0.001)	*	-0.005	(0.001)	*	-0.028	(0.001)	*	-0.026	(0.0005)	*	0.036	(0.001)	*	0.031	(0.001)	*
Shopper Gender	Female	-0.016	(0.001)	*	-0.021	(0.001)	*	0.019	(0.001)	*	0.015	(0.001)	*	-0.003	(0.001)	*	0.006	(0.001)	*
Day of Week	Mon.	-0.014	(0.001)	*	-0.009	(0.001)	*	-0.0005	(0.001)		0.001	(0.001)		0.014	(0.001)	*	0.007	(0.001)	*
(excl. Sun.)	Tue.	-0.019	(0.001)	*	-0.012	(0.001)	*	0.0002	(0.001)		0.001	(0.001)		0.019	(0.001)	*	0.010	(0.001)	*
	Wed.	-0.016	(0.001)	*	-0.012	(0.001)	*	0.0002	(0.001)		0.002	(0.001)	*	0.015	(0.001)	*	0.011	(0.001)	*
	Thu.	-0.009	(0.001)	*	-0.009	(0.001)	*	0.004	(0.001)	*	0.003	(0.001)	*	0.004	(0.001)	*	0.006	(0.001)	*
	Fri.	-0.005	(0.001)	*	-0.005	(0.001)	*	0.0005	(0.001)		0.001	(0.001)		0.005	(0.001)	*	0.004	(0.001)	*
	Sat.	0.003	(0.001)		0.0003	(0.001)		0.005	(0.001)	*	0.0002	(0.001)		-0.008	(0.001)	*	-0.0004	(0.001)	

Notes: 1,341,220 observations. Standard errors are in parenthesis. Household demographic variables appear in a separate table.

Table 14: Trip-specific variables from the linear probability model.

It is interesting to contrast these results with those in Klee (2008). The demographics results in Table 13 may differ because we observe household demographics whereas Klee (2008) uses census data near to stores to infer demographics. The trip-level variables may differ because Klee (2008) cannot track identities thus cannot use household fixed effects.

5.2 State dependence

The emphasis so far has been on persistent household heterogeneity. Another important issue may be state dependence, the notion that once a household makes a choice, they are likely to choose it again. That is, a household may not have a long-term persistent preference for cash, but having chosen cash, it is likely to do so again. Here, we focus on a transaction-by-transaction measure instead of the long-term decision-making discussed in Section 4. We do so by including the lagged dependent variable as a regressor. That is, if we are estimating a linear probability model for the choice of cash, we include a dummy variable for having chosen cash on the previous trip as a regressor. To the extent that the coefficient on this variable is positive, we learn that state dependence is an important determinant of payment choice.

When combined with household fixed effects, the lagged dependent variable becomes endogenous by construction, as discussed in Arellano & Bond (1991). However, this endogeneity problem is mitigated as the number of observations per household rises. The estimator proposed in Arellano & Bond (1991) is envisioned for cases with around 10, or often fewer, observations per household. We typically observe 150 observations per household. Implementing the estimator for the case of large T is challenging because the number of instrumental variables increases in T, so matrices can become unmanageably large. But more importantly, the endogeneity problem that they seek to address should not be important in our application. Thus, we do not implement the Arellano-Bond estimator, and proceed as if there was no endogeneity problem.

In Table 15, we present the results of instrument-by-instrument linear probability models. For each of the three payment instruments, we estimate by OLS including the full set of demographic and trip-specific variables, and with household fixed effects including only trip-specific variables. We include the lagged dependent variable in each regression. We report only the coefficients on the lagged dependent variable and the log of expenditure. The other coefficients are similar to those in the previous subsection. The lagged dependent variable is always positive and significant, indicating a role for state dependence. Adding household fixed effects drastically reduces the importance of the lagged dependent variable, dividing the coefficient by about 8. In contrast, the coefficient on expenditure changes little from adding fixed effects. Also, comparing Table 15 and Table 13 shows that coefficient on expenditure changes little from adding the lagged dependent variable. Furthermore, expenditure size appears to be more important than state dependence in determining choice. At least for cash and card, the coefficient on expenditure is substantially larger than that on state dependence. Note that log expenditure has a mean of 3.4 and a standard deviation of 1.12, both larger than the lagged dependent variable (a dummy variable). Thus, reasonable rescaling of the expenditure effect would still lead to the conclusion that the expenditure size is more important than state dependence in determining instrument choice.

	Cash		Check		Card	
	OLS	FE	OLS	FE	OLS	FE
ln(expenditure)	-0.134	-0.145	0.030	0.030	0.099	0.115
	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0003)
lag Choice	0.448	0.055	0.540	0.071	0.513	0.068
	(0.0007)	(0.0008)	(0.0007)	(0.0009)	(0.0007)	(0.0008)

Notes: Number of observations: 1,327,646. FE results include household fixed effects and trip-specific variables. OLS result includes demographic and trip-specific variables. Lag Choice is a dummy for whether the household made the same choice in the previous shopping trip. Thus, in the Cash column, Lag Choice is a dummy if the household chose *cash* in the previous trip. Standard errors are in parenthesis.

Table 15: Linear probability model with lagged dependent variable.

5.3 Determinants of switching

In this section, we look at the effects of changes in demographic variables on payment-instrument choice. There are some limits as to what we can find in this exercise given how rare switching appears to be in Section 4. We focus on two variables, household income and male employment. We focus on male employment rather than female employment because we believe that the decision for women to work is more complicated and often endogenous to other life events. Obviously, there is limited variation in these variables in a three-year panel, especially as they are collected only once per year. However, in a data set as large as ours, some variation exists.

First, consider the amount of variation in income. Note that we observe income as a categorical variable, as in Table 13. For these purposes, we recode income as a continuous variable by assigning each household the mid-point of the bin in which their income level falls. Consider the difference between the maximum and minimum income reported by households. In our data, 60.29% report no change in income over three years. Obviously, a regression with household fixed effects will not make use of these observations for identifying the effect of household income. However, the 75th percentile reports a difference of \$12,500, and the 90th percentile reports \$25,000. Thus, in a data set with more than 13,000 households, there is sufficient variation to identify the coefficient on household income.

There is less variation in employment status. The data set reports employment as a categorical variable with five values: Male not present or employment unknown, unemployed, less that 30 hours, 30-35 hours, and greater than 35 hours. In the population, 90.76% report no change in male employment status. However, 1,175 households report multiple values of this variable (7.76% using population weights) and 81 observations report three categories, a different category in each year. While we should be concerned about the level of variation, there is perhaps enough here to proceed with estimation.

In order detect the effect of changes in these variables on payment choice, we utilize a regression similar to Table 14. We introduce household income (treated as a continuous variable) and dummy variables for each employment category into a regression with household fixed effects. Thus, only within-household variation identifies the coefficients on

		Cash			Check			Card		
ln(expenditure)		-0.145	(0.0003)	*	0.030	(0.0002)	*	0.115	(0.0003)	*
HH income		-0.0002	(0.0002)		-0.001	(0.0001)	*	0.001	(0.0002)	*
Male Employment	Not Employed	0.011	(0.004)	*	-0.003	(0.002)		-0.007	(0.004)	
(excl: no male	Under 30 Hours	0.006	(0.005)		0.004	(0.003)		-0.010	(0.005)	
head or unknown)	30-34 Hours	0.008	(0.005)		0.008	(0.003)	*	-0.016	(0.005)	*
	35+ Hours	0.013	(0.004)	*	0.006	(0.002)	*	-0.019	(0.004)	*

Notes: 1,340,220 observations. Other trip specific variables are unreports. All regressions include household fixed effects. * indicates 99% significance.

Table 16: Household demographics from the linear probability model with household fixed effects.

income and employment status. The regression also contains all of the variables that vary by trip (all of the variables in Table 14).

Results appear in Table 16. First of all, we note that the coefficient on transaction size is similar to Table 14. There is no effect of income on cash use, but income causes increased card use at the expense of check. The magnitude is reasonably high as income is entered in level. For example, an increase in income of \$10,000 increases the probability of card use by 7.52 percentage points.[8] The coefficients on employment status for cash are unclear, as they appear non-monotonic, with low values for unemployment and full employment, and higher values for partial employment. We interpret this similar to the finding of no effect of income on cash. Surprisingly, the results for check and card are the opposite of income. The trend in the coefficients on employment indicate a positive effect of employment on check use, whereas the trend for the cards is negative, so employment leads to less card use. However, keep in mind that the magnitude of the changes for employment is not large. In fact, while the coefficients on unemployment and full employment are significantly different from zero, they are not significantly different from each other with 95% confidence (this test has a p-value of 0.85). Even if we accept the coefficients, they indicate that switching from unemployment to full employment raises card use by only 1.2 percentage points. Note that as employment and income increase, households simultaneously gain access to new credit cards and need consumer credit less, so these trends can be rationalized. But, overall we conclude that raising employment status and income simultaneously tends to increase card use at the expense of check, with little effect on cash use.[9]

[8] The actual parameter is 0.000752, which appears at 0.001 in Table16 since we report only up to the third digit.

[9] Note that income and employment status should be correlated within a household, but results are similar when we drop one or the other from our regression. Also, it is clear from our wording that we interpret the effects in Table 16 as causal. That is because we do not believe that payment choice affects changes in income or employment, at least not at this scale. There may still be problems with causal interpretations. For instance, if someone anticipates that their employment status will change, they may change payment choice in anticipation, which would dilute the effects we seek to estimate.

6 Conclusion

We explore the use of household-level scanner data for learning about choices over payment instruments. Relative to other studies of payment choice, our panel is large, long and very detailed, although it focuses on only a subset of shopping behavior, namely grocery stores. We show substantial single-homing behavior within the choices of cash, check and card, and show that that there is only limited switching of favorite payment choices over time. We explore how heterogeneity in payment choice is related to demographic variables such as income and education.

Our study highlights the importance of expenditure size in determining payment choice. We show that the coefficient on expenditure size changes little even when accounting for panel data features, such as household heterogeneity and state dependence, accounted for by household fixed effects and lagged dependent variables respectively. The robustness of the result on expenditure size is surprising, and suggests that the prevalence of cash use is common across the population, and is not due to some subset of consumers with particular preferences. This result provides guidance to policy-makers interested in such topics as encourage digital payments or interchange fee regulation.

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