Payment choice with Consumer Panel Data

Michael Cohen
Stern School of Business

Marc Rysman
Boston University *

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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.

1 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, 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 Kouyalev, 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 Cho & Rust (2012), Stango & Zinman

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(2012) and Dutkowsky & Fusaro (2011). However, these typically provide no information on how the consumer uses cash.

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. Nielson 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 Nielson 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 only observe grocery purchases. However, groceries are an important touchpoint for payment choice, and have been a focus of the payments industry. Also, the method that Nielson 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 in the data set. 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 all food shopping, 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).

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.

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. Nielson 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 Nielson uses to verify the consumer's purchase behavior.

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 obesity, 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 of these items. 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). 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 Kouyalev 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 1.8 million transactions. Unfortunately, payment choice is missing on about a third of these. Standard analysis does not identify any systematic differences between shopping trips with and without payment information. Thus, we focus on the 1.3 million transactions that indicate payment choice.

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

[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.

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 panel. Even the 10th percentile makes trips 46 weeks apart.

These numbers suggest surprisingly few trips per week. There are several explanations. 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 about a third of our observations because payment information is missing. There may also be a an issue with compliance in the sense of survey participants who do not track every grocery expenditures. Naturally, Nielson acts to minimize compliance problems.

Overall, we find cards used for 48.1% of transactions, cash for 43.4% and check used for 8.5%. These numbers indicate higher cash usage than for the economy as a whole – for comparison see Kouyalev et al. (2012), not surprising for the grocery industry. The use patterns vary substantially with transaction size. Figure 1 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 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 1 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.

Now do income, gender, demographics

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

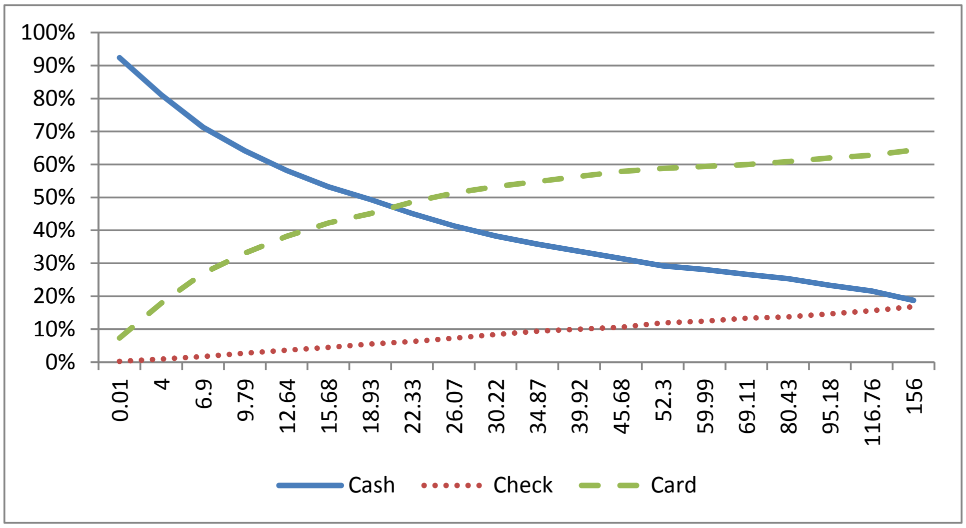

Figure 1: Pay type by transaction size

	% 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 1: Pay type by type of store

	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 2: Single-homing behavior

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 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 2 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.[2]

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

[2]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 3: Percent of population that always or never uses an instrument.

every shopping trip. 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 3 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) 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. In contrast however, we observe that 64% of the population never uses a check. We exploit this feature below to focus on the card versus cash choice in this population.

4 Payment Choice

We are interested in the determinants of payment choices, particularly the effect of transaction size. We are particularly 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).[3] In order to address this, we begin by using linear models.

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.

[3]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, 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.

	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 4: Linear probability models without demographic explanatory variables.

Results appear in Table 4. As expected, transaction size has 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 2. We also experiment with a random effects specification. Interestingly, the results are almost numerically identical to the fixed effects specification. This suggest that the fixed effects are essentially orthogonal to transaction size.

In the next regression, we add demographic explanatory variables as well as shopping trip explanatory variables. For demographic explanatory variables, we add male and female education levels, designated marketing area of the household, employment status of the male and female, household income, household size (in terms of number of people), whether the house has a pet and race. Each variable is entered as a set of dummy variables for categories used in the data set. For shopping trip variables, we use the year, the type of store and shopper gender, again entered as dummies. We again perform instrument-by-instrument linear regression with and without household fixed effects. When we use household fixed

	Cash	Check	Card
OLS			
ln(expenditure)	-0.159	0.040	0.119
	(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			
	-0.147	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 observations is 1,341,226.

Table 5: Linear probability models with demographic explanatory variables.

effects, we drop all of the demographic explanatory variables. [4] Results on expenditure appear in Table 5. Adding explanatory variables causes the coefficient on expenditure to get smaller and move towards the fixed effects estimate. Thus, the difference between the OLS and fixed effects estimate is even smaller when including explanatory variables.

The linear probability models do not capture the multinomial nature of the choice problem. However, introducing fixed effects into a multinomial choice problem in a way that addresses the incidental parameters problem is computationally very challenging. In order to address this issue, use only the subset of data that never uses a check, more than 60% of the data according to Table 3. For these households, we assume that the check option is outside of their choice set. Thus, these households make a binary choice between card and cash. For this population, we use Chamberlain's conditional logit model (Chamberlain, 1980) to address household fixed effects in a binary choice model.

The results for expenditure size appear in Table 6. This table exhibits eight regressions. The upper panel of four uses only log expenditure as an explanaotry variable, whereas the lower panel uses the large set of demographic and shopping trip observable variables that was utilized in Table 5. The first two columns use a linear probability model to predict card usage, with and without household fixed effects. Column 3 uses a logit model and column 4 uses Chamberlain's conditional logit model to handle household fixed effects. For this table, we have dropped households that exhibit no variation in their payment choice,

[4]Surprisingly, almost all of the household explanatory variables vary within the household over the three years for at least one household, even the indicator for race. Thus, we do not necessarily have to drop those variables in the fixed effects context. Unreported fixed effects estimation that includes these variables finds similar results.

	Linear		Logit	
	OLS	Fixed Effect	Logit	Conditional
No Explanatory Vars				
ln(expenditure)	0.172	0.147	0.818	1.354
	(0.001)	(0.0005)	(0.003)	(0.005)
Odds Ratio			2.266	3.872
Observations		650,201	650,179	
Explanatory Vars				
ln(expenditure)	0.157	0.144	0.810	1.336
	(0.001)	(0.0005)	(0.003)	(0.005)
Odds Ratio			2.248	3.802
Observations		650,200	650,178	

Note: Dependent variable is an indicator for card usage vs. cash. Check users are dropped. Fixed Effects and conditional logit conditions on the household. Standard errors are in parenthesis.

Table 6: Binary choice between card and cash for non-check users

so that models with and without fixed effects use the same number of observations.[5]

In the linear models, we find that the fixed effects regression reduces the coefficient on transaction size. The difference is statistically significant, but not economically important. Note that introducing explanatory variables reduces the OLS estimate and brings it closer to the fixed effects regression. The logit model provides a surprising result: Introducing fixed effects actually increases the coefficient on transaction size. We find this result difficult to interpret, and the fact that it is not supported by the linear results cautions us against putting too much weight on it. The difference is exhibited both in the parameter estimates and the odds ratio, so it is not just an issue of a non-linear transformation at different magnitudes.

Interestingly, the parameters on the other explanatory variables in the logit regressions do not change in response to the introduction of fixed effects. Table 7 exhibits the odds ratios for the estimates on variables that vary within the household for the logit regressions. For the case without explanatory variables, that is only log expenditures. For the case with explanatory variables, those variables include indicators for whether the shopper uses frequent shopping card, a coupon, a double coupon, the shopper's gender, and indicators for store type (as in Table 1 with food store excluded). The coefficients are remarkably similar across the logit and conditional logit columns, except for expenditure.

[5] Eliminating households that ever use a check reduces our data set from 1,341,226 observations to 754,909, and then eliminating households that choose only cash or only card leaves us with 650,179 observations.

	No Explanatory Vars		Explantory Vars	
	Logit	Conditional Logit	Logit	Conditional Logit
ln(expenditure)	2.266	3.872	2.248	3.802
Frequent Shopping Card			1.256	1.357
Double coupon			1.170	1.081
Coupon			1.154	1.146
Shopper Gender			1.038	1.148
Non-food store			0.823	0.783
Convenience store			1.291	1.582
Other type of store			1.211	1.299

Note: Odds ratios from binary and conditional logit on card versus cash use for explanatory variables that vary within household.

Table 7: Odds ratios from binary logit models

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