How People Pay: Evidence from Grocery Store Data

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Abstract

Although common sense and experience leads one to believe that people use cash for small purchases and checks for larger ones, empirical evidence is scant. This paper uses scanner data to examine how people pay at the grocery store. The results confirm intuition and experience – payment patterns are correlated with the number of items bought, the value of the sale and local market demographics. The value of the sale has a greater influence than the number of items bought, but both are significant. The demographic results generally agree with trends seen in earlier research using survey data.

1 Introduction

Cashiers ask consumers "how do you want to pay for that?" countless times a year. For years, consumers generally had two answers: cash and check. The rise of the use of credit cards throughout the 1980s and the takeoff of the debit card in the 1990s firmly established these as alternative options. As a result, consumers now have four answers to this question: cash, check, credit card and debit card. Indeed, everything from groceries to speeding tickets to charitable donations can be paid for using these four payment types, as indicated by recent articles in the popular press (Sapsford [2004]).

How people pay dictates how money flows through the plumbing of the US economy. While the exact dollar value of cash transactions is unknown, the dollar value of check, credit card and debit card transactions topped more than $40 trillion in 2002 (Bank for International Settlements (BIS) [2004]). The number of these payments was approximately 73 billion, which represented approximately 254 payments per capita in 2002. Checks represent the highest share of the number of and value of these payments.[1] But the substantial increase in the use of debit cards and credit cards put a dent in check's share of the number of these payments, which dropped from almost 80 percent in 1995 to only about 55 percent in 2002 (BIS [2002]).

These summary statistics show that consumers changed their payment behavior significantly over the past decade. Given this change, it becomes natural to ask what factors influence how people pay and how people substitute between payment instruments. Most of what is known about individual consumer behavior and the payment system is based on household surveys.[2] These types of studies have significant advantages. They generally have good information about family income, assets and demographics, which are excellent

[1] For an overview of check payments in the US, see Gerdes and Walton [2002].

[2] See, for example, Boeschoten [1992], Kennickell and Kwast [1997] Carow and Staten [1999], Stavins [2001], Hayashi and Klee [2003], Mester [2003], Klee [2004], Rysman [2004] and Zinman [2004].

predictors of the use and holdings of different payment instruments. For example, data from the Survey of Consumer Finances (SCF) show that debit card use increased dramatically from 1995 to 2001, from 17.6 percent of US families to 47.0.[3] But debit card use differs substantially by age group – approximately 61.8 percent of younger families used debit cards in 2001, while only 15.7 percent of older families used them.

Although these surveys offer significant insight into demographic characteristics that are correlated with use and holdings of payment instruments, these surveys lack specific information on which payment instrument consumers use at the time of an acutal exchange. For example, the SCF also indicates that approximately 37.8 percent of US families both used debit cards and had credit cards in 2001. However, the survey does not ask respondents questions regarding when they use a credit card and when they use a debit card. This information is key to understanding consumer payment behavior.[4]

The lack of information on consumer behavior at the time of the exchange has potential costs for payment system policy and for academic research. The drop in the number of check payments and the rise in the number of credit and debit card payments may have implications for overall payment system efficiency. Furthermore, in 2003, major US retailers settled a class action lawsuit against Visa and MasterCard, the two largest payment card networks, for $3 billion dollars over the fees that the networks determine and rules the card networks promulgate as conditions for accepting cards.[5] Consumer choices necessarily affect the incidence and the impact of fees to retailers and banks for

[3] The Survey of Consumer Finances surveys a cross-section of US households and is conducted every three years by the Federal Reserve in conjunction with the National Opinion Research Center at the University of Chicago. Its primary purpose is to survey families' assets and liabilites, but it contains a few questions that focus on payment systems. For details, see Aizcorbe et. al [2003].

[4] Some survey research (Boeschoten [1992], Hayashi and Klee [2003] and Rysman [2004]) does ask respondents about locations of payment use. However, even surveys that contain this information are subject to self-reporting biases, which can materially affect estimates.

[5] See In re: Visa Check/MasterMoney Antitrust Litigation, 2d. Cir., No. 96-CV-5238. Hunt [2003] offers a summary of antitrust issues in payment card networks.

transactions over the card networks. As a result, understanding consumer choices at the point of sale is necessary to inform the debate over these fees.

In addition, there exists a significant theoretical economics literature that predicts behaviors for use of media of exchange. Many of these models assume that people change behavior according to the dollar value of the sale, the opportunity cost of funds or the denomination of the currency.[6] The model results also imply that consumer preferences necessarily affects the use of the entire platform for exchange, or the acceptability of the instruments overall.[7] Understanding how these behaviors are confirmed or rejected empirically helps to shed light on new ways to extend the models.

In order to address the knowledge gap, this paper uses grocery store scanner data to investigate how people pay. Grocery store scanner data has been used extensively in other contexts, most notably to investigate price elasticities of demand for different consumer products.[8] The data used in this study are similar to that used in other studies, and were collected from a retail grocery store chain from September to November 2001. The data contain the information commonly found on most register receipts from a purchase at the grocery store. This information includes the payment type. At the grocery stores in the sample, consumers can pay with six different payment types, namely cash, check, credit card, debit card, WIC and food stamps. The first four are used generally, but the last two are associated with government food programs; thus the analysis focuses on the first four only.[9] The other data items included in the analysis are the number of items bought, the

[6] This literature is old, diverse and continuing. See, for example, Baumol [1952], Tobin [1956], Whitesell [1989], Santomero and Seater [1996], Shy and Tarkka [2002], and Lee, Wallace and Zhu [2004].

[7] The industrial organization platform competition literature is particularly interested in this question. See, for example, Rochet and Tirole [2003], Chakravorti and Roson [2004].

[8] See Chevalier et. al [2003] and Feenstra and Shapiro [2003].

[9] Although food stamps and WIC are important programs that provide necessities to the recipients and thus are important ways that people pay for food, the programs limit recipients on the types and quantities of food to purchase. In addition, the "choice" of payment instrument does not exist in the same sort of way as it does for the other payment types. For details on the food stamp and WIC programs, see Food and Nutrition Service [2004a, 2004b].

value of the sale, the number of store and manufacturer coupons and the day of the week of the transaction.

Supplementing the transaction data are census-tract level data on the demographics of the local market. The demographic information includes the median household income in a census tract, the age of the head of household, the education level, the percent of the census tract population who is married, the percent of female headed households with minor children, the percent nonwhite, the percent in urban areas or urban clusters and the percent of housing units that are owner occupied. Using the transaction data in conjunction with the census data gives a complete picture of how people pay.

Grocery store data has distinct advantages for use in studying payment behavior. There are three groups of reasons. First, the data are plentiful, accurate and represent actual exchange behavior. This necessarily helps to supplement the gaps left by relying on survey data exclusively. Second, everyone eats – a lot, often and locally. Grocery store expenditures represented 6.2 percent of personal disposable income and 16.5 percent of retail sales (excluding motor vehicle parts) in 2001. Because groceries are perishable, people choose how to pay at grocery stores all the time. According to industry data, consumers shop at grocery stores an average of twice a week.[10] Thus, the results shown represent behavior patterns for a habitual, necessary purchase. Moreover, evidence suggests that consumers shop locally for groceries.[11] Using census tract information on the demographics of the local market potentially proxies well for shopper demographics.

And third, grocery stores have an interesting role in the payment and banking system. On the technology side, grocery stores were one ofthe early adopters of debit card technology. On the consumer side, grocery stores have traditionally cashed checks for customers who applied for these privileges. In addition, grocery stores offer relatively more bank-

[10] See Food Marketing Institute [2004].
[11] See Kahn and McAlister [1997, p. 94-95].

ing and financial services to customers than other types of retailers. For example, many grocery stores chains offer in-store ATM, bank branch, and wire and remittance services, making them a unique type of retailer.

Using straightforward econometric procedures, the results clearly show that there is a correlation between payment choice and transaction characteristics including the value of the sale, the number of items bought, and the day of the week. The results show that transactions with fewer items are more likely to use cash, transactions with a greater number of items are more likely to use checks, and mid-range transactions use credit card and debit cards. The results also suggest that consumers who purchase items with a greater average value per item are more likely to use credit cards and less likely to use cash or checks. Second, the results show that the responsiveness of use with respect to these characteristics differs by instrument. Third, the results confirm the observations made in survey data research, and show that the probability of using certain payment instruments is significantly correlated with the demographics of the local market.

Importantly, there are a few caveats with the results. First, all data were stripped of potentially identifiable information. These information items include, but are not limited to, credit card and debit card numbers, loyalty card numbers, WIC and food stamp identification numbers, and check identification numbers. All demographic results are based on the second data source used in the analysis, which is 2000 census tract information from the US Census. The addresses of the retail outlets were matched with census tract level information from the US Census Bureau to proxy for demographics of the local market. Evidence suggests that people shop locally for groceries and the results presented here are under that assumption.

Second, consumers authorize debit card transactions in two different ways. Consumers can enter a PIN, or personal identification number, or consumers can sign. If a consumer enters a PIN, it is called a "PIN-based" debit card transaction, and is primarily routed over networks such as NYCE, STAR and PULSE, or the Visa and MasterCard PIN-based networks, Interlink and Maestro/Cirrus. If a consumer signs, it is called a "signature-based "debit card transaction, and is usually routed over the Visa and MasterCard credit card networks. There is no way to distinguish signature-based debit card transactions from credit card transactions in these data. Thus, the debit card results presented here are PIN debit card transactions only.

Despite these caveats, the results in this paper confirm results from earlier work on payment systems, and offer a roadmap to directions in which more research is needed. Specifically, the local demographic results are overall very consistent with those found in the consumer survey studies. Payment patterns are well predicted by demographics, and it is interesting that the simple assumptions made in this paper concerning who shops where reveal similar patterns to survey data for how people pay. The results also point to areas where many theoretical models of payment, money demand and platform competition are lacking. The data clearly show after controlling for the value of the sale, characteristics of the transaction such as the number of items bought significantly affect consumer choices of payment. Models generally do not take this affect into account, and rely solely on the value of the sale. Moreover, the data also show that the effects of the average values of items purchased and the value of the sale differs for checks and PIN debit cards. Both of these instruments are associated with checking accounts. Many models of the demand for payment and the acceptability of payment hinge on different opportunity costs for payment to explain equilibria. The results here show that these models may miss a fundamental part of the story.

The paper proceeds as follows. Section 2 gives an overview of the data. and discusses the model and the econometric issues. Section 3 describes the data and the estimation procedure. Section 4 presents the empirical results. Section 5 concludes and offers suggestions for further research.

2 Overview, model and econometric issues

2.1 Overview

In general, US consumers have four choices of how to pay for every day purchases: cash, check, credit card and debit card.[12] Consumers generally use cash, checks, credit cards and debit cards for every day purchases. Arguably, grocery store transactions represent one of the most common every day purchases. Understanding how people pay for these types of purchases will lend insight into consumer payment behavior overall.

Figure 1 shows that people pay differently according to the value of the sale. The figure presents a kernel density estimate of the probability distribution functions of the value of the sale on the population of transactions. The x axis is the value of the sale, in dollars. The y axis is the density of transactions by payment type. The data are subsetted to show only those transactions where the number of items bought is greater than two and less than 60, and where the value of the sale is greater than five dollars and less than \$150.[13]

Conditional on these restrictions, a little more than half of all transactions are below \$20. However, more than 66 percent of the cash transactions are below \$20. In contrast, approximately 26 percent of the check transactions, 31 percent of the credit card transactions and 37 percent of the debit card transactions fall below \$20. The distribution of cash transactions is also relatively concentrated at lower dollar values. The 25th to 75th percentile range for cash transactions is \$8.95 to \$25.07, while this range for check transac-

[12] Consumers also use electronic payments from a bank account, called "automated clearing house" or "ACH" payments. Consumers generally use ACH payments for mortgage, insurance and other types of recurring payments.

[13] These are also the constraints used in estimation results that follow. A more lengthy discussion follows in section 3.

tions is \$19.39 to \$58.63, a wider spread. The range for credit card transactions is \$17.22 to \$54.77, and the range for debit card transactions is \$15.01 to \$49.55. There is relatively little overlap of cash and check transactions at the low end of cash transactions and the high end of check transactions. Credit card and debit card transactions overlap with each other for a good part of their distributions. The distribution of cash transactions is the most concentrated, while the distribution of check transactions is the least.

Figure 2 shows that people also pay differently according to the number of items bought. Conditional on the restrictions, half of all transactions fall below 8 items bought. Cash transactions are relatively concentrated at lower numbers of items bought, with half of the cash transactions falling between 4 items and 11 items, the 25th and 75th percentiles respectively. The 25th to 75th percentile range for check transactions is 8 to 26 items, for credit cards, 6 to 21 items, and for debit cards, 6 to 20. It is interesting to note that these percentile ranges are almost identical for credit card and debit card transactions, although the value of the sale distributions differ slightly.

Of course, the value of the sale and the number of items bought are correlated. Items aren't free; adding items necessarily increases the value of the sale. In order to investigate these two effects contemporaneously, figures 4 through 7 present bivariate kernels of the probability distribution functions of the value of the sale. The x axis is the value of the sale, in dollars. The y axis is the number of items bought. The z axis is the density of transactions, and each graph represents a different payment type. The planes in each figure represent the approximate median value of the sale, twenty dollars, and the approximate median number of items bought, eight. The figures show that the shapes of the densities of transactions differ according to payment type. Cash transactions are very concentrated at low number of items and low value of sale. Check transactions, in contrast, have a less concentrated distribution, fanning out a bit more by the number of items bought and the value of the sale. While credit cards and debit cards have similar univariate distributions of the value of the sale and the number of items bought, the bivariate distributions show how these distributions differ. In particular, there is a relatively greater concentration of debit card transactions at lower values of the sale and items bought, while credit card transactions appear to have a broader distribution. Although these two payment instruments exhibit the closest patterns in the data, they are different to some degree, and not perfect substitutes.

2.2 The model and econometric issues

The core of the analysis investigates the factors that influence consumer payment choices between cash, check, credit card and debit card. A discrete choice model of the demand for payment is appropriate for this purpose. Following this literature, the analysis assumes that the consumer chooses the payment instrument that maximizes utility. Several transaction factors and consumer-level factors determine the utility from any particular payment instrument. The econometrician observes some of these factors, but not all of them. A portion of the unobserved factors are controlled for by the analysis. The remaining unobserved factors are summarized by an error term.

Given this structure, the specification is

$$\begin{aligned} U_{ji} &= V_{ji} + e_{ji} \\ &= b_j X_i + d_j Z_i + e_{ji}, \\ j &= 1, ..., m \text{ and } i = 1, ..., n. \end{aligned}$$

U_{ji} is consumer i's utility of using payment instrument j. The observed portion of this utility is denoted V_{ji} and the unobserved portion is denoted e_{ji}. The observed portion of utility V_{ji} includes X_i, which is a vector of the characteristics of the transaction, and b_j is a vector of payment-instrument specific coefficients to be estimated. Z_i is a vector of characteristics of the consumer and d_j is a vector of coefficients to be estimated. Whether these are considered observable or unobservable depends on the assumptions made in the various specifications described below.

The elements in X_i reflect transaction level factors that potentially affect the choice of payment. Previous theoretical and empirical research predicts that payment choice depends critically on the value of the sale. Thus, this is clearly a variable of interest. In order to capture possible nonlinear effects of the value of the sale, the value of the sale squared is also included in the specification.

In addition to the value of the sale, however, it may be possible that other factors affect payment choices. One contribution of this paper is to investigate whether this is the case. The remaining factors included in the X_i reflect possible candidates. In particular, the specification includes the number of items bought, the number of items bought squared, the number of store and manufacturer coupons and the day of the week. Results that show that the number of items bought and items bought squared are significant predictors of payment choice may lend insight into behavior based on the average value of an item, or the quantity of items associated with a transaction. In addition, the store coupons proxies for items bought on sale and are associated only with the retail chain. Sensitiveness to sales, thereby showing price sensitivity overall, may also be associated with choice of payment. In a similar vein, manufacturer coupons can be used at any grocery store, but generally, the consumer must cut them out of the newspaper before coming to the store. Sensitivities of payment choice to the number of manufacturer coupons may lend insight either into both price sensitivity and time sensitivity and how that affects the media of exchange used. Finally, significant day of the week coefficients may point to cyclicality of payment choices, which up until this point have not been documented.

Three elements of this specification are unobserved by the econometrician. Instead of observing the utility U_{ji} directly, the econometrician observes a dummy variable

$$I_{ji} = 1 \text{ if } U_{ji} > U_{-ji}, -j \neq j, j = 1, ..., m, \text{ and } i = 1, \ldots, n.$$

The second element that the econometrician does not observe is Z_i, the vector of consumer characteristics. There is no information on the demographics of the consumer, which previous research shows is a good predictor of payment choice. Moreover, there is no information on the

choice set of payment instruments for any particular consumer, which will necessarily affect the consumer's choice.

The missing Z_i do not pose an econometric problem if these unobservables are uncorrelated with observable factors that may affect payment choice. Unfortunately, it is easy to think of cases where this may not be the case. Lower average values of items bought may indicate that the consumer is shopping for a relatively low income household. Lower income households may not have all payment types available to them – they may not have access to anything but cash. These unobserved factors could potentially affect estimates. In addition, a consumer's age is one of the best predictors of whether the consumer uses a debit card – younger people report using debit cards relatively more often than older people do. But grocery store industry experts point out that employment status is correlated with the day of the week that the consumer shops.[14] People who work are more likely to shop on the weekends, and people who are not employed are more likely to shop during the week. Older individuals are more likely to be retired, and thus are more likely to shop during the week. Excluding the age factor from the analysis may tend to overstate

[14] See FMI [2004b].

the importance of the day of the week on which transaction occurred for predicting the payment choice.

In order to control for potential biases of this missing information, the analysis uses the demographics of the local market to proxy for unobserved conusmer characteristics. These characteristics include the median household income in a census tract, the distribution of the age of household heads, the education distribution in the population, the percentage of families that are married in the census tract, the percentage of families that have a female head of household with children under 18 years of age, the percentage of the population that is nonwhite, and the percentage of the tract in urban clusters.

Even with these controls, there are likely to be significant unobservable factors. The e_{ji} summarizes the random unobservable terms that the econometrician does not observe.[15] Let e_i denote the random vector for person i, where $e_i = (e_{1i}, ..., e_{mi})$. If the e_i has a joint cumulative distribution function F and probability density function f, the probability that consumer i chooses payment instrument j can be summarized as

$$\begin{aligned} \Pr(I_{ji} &= 1) = \Pr(U_{ji} > U_{-ji} \ \forall - j \neq j) \qquad (1) \\ &= \Pr(V_{ji} + e_{ji} > V_{-ji} + e_{-ji} \ \forall - j \neq j) \\ &= \Pr(e_{-ji} - e_{ji} < V_{ji} - V_{-ji} \ \forall - j \neq j) \\ &= \int I(e_{-ji} - e_{ji} < V_{ji} - V_{-ji} \ \forall - j \neq j) f\left(e_i\right) de_i \end{aligned}$$

where I is an indicator function that equals 1 if the expression in parentheses is true, and the integral is over the support of the distribution of e_i. Because there is so much individual consumer information that is unobserved, it may be the case that the specification of the error term e_i will materially affect the estimates.

[15] This discussion closely follows Train [2003].

3 Data description

The analysis in this paper is based on a scanner dataset that contains grocery store transactions for a set of 99 retail outlets. Supplementing this dataset is census-tract level statistics that contains demographic information on what is presumed to be the local market of the retail outlets.

The scanner data are comprised of over 10 million checkout transactions through the lanes over a three month period, from September to November, 2001. A few caveats about the data should be noted. Because these data were in very raw form, certain assumptions were made in order to compile the dataset. To start, a significant percentage of the cash transactions had one item only. It is most likely the case that some of these transactions represented cashier error. Including these in the estimation procedure may bias the results; as a result, these transactions were eliminated. Furthermore, a very small percentage of the transactions used multiple payment types. In these cases, the tender type with the highest associated dollar value associated with it is considered to be the tender type for the transaction. Finally, the data were trimmed on the basis of the 99th percentile of transactions in terms of the number of items bought and the value of the sale. Inspection of these transactions revealed that they were clearly outliers and could potentially bias estimates.

For computational tractability, the estimates are based on a sample. The sampling procedure is as follows. From the population of over 10 million transactions, a random sample of 100,000 observations were drawn without replacement. This process was repeated 100 times to provide 100 samples. Appendix A gives more details on the sampling procedure.

The unit of observation is a checkout transaction, which represents one customer's total purchase at the point of sale. As the data are all from one retail chain, each transaction has exactly the same information. The data contain the information commonly found on most register receipts from a purchase at the grocery store. Table 1 gives the exact definitions of all variables used in the analysis. As summarized above, these include the store number, the date of the transaction, the start time of the transaction, the end time of the transaction, the product codes for each item bought, the price for each item, the payment type, the amount of change received, the length of time of the transaction, the number of coupons (both store coupons and manufacturer coupons) and the date of the transaction. The data do not include any way to match item codes to actual items, but there is information on the general department code for the item (for example, meat, general grocery, or produce).

The second data source used in the analysis is 2000 census tract information from the US Census and the Federal Financial Institutions Examination Council. The addresses of the retail outlets were matched with census tract level information from the US Census Bureau to proxy for demographics of the local market. The definitions of the Census variables are also included in table 1.

As the first point of analysis, the data population were inspected at the lower and upper parts of the distribution of the value of the sale and the number of items bought. The graphs presented in section 2 provide intuition predicting that the percentage of transactions made with cash will be high at the lower ends of the value of the sale and the items bought distributions. Confirming intuition, cash was used in approximately 93 percent of the transactions with less than a $5 value of sale.[16] This percentage drops to 82 percent for transactions with a value of a sale greater than or equal to $5 and less than $10. Furthermore, 88 percent of the two item transactions and approximately 81 percent of the three item transactions were made with cash. The frequency of cash use for low dollar

[16] Conditional on greater than one item, as explained above.

values and low number of items shows clear preferences for tender type that depend on these factors.

The behavior at the upper ends of the items bought and the value of the sale distributions are less stark than at the lower ends, but there exists some patterns. In transactions with over $150 in the value of the sale, approximately 39 percent were paid by check, 25 percent were paid by credit card, 21 percent by debit card and 15 percent were paid with cash. In transactions with greater than 60 items 46 percent of the transactions were paid by check, just over 19 percent were paid by credit card, just under 19 percent were paid by debit card, and a little less than 17 percent were paid with cash.[17]

The descriptive statistics presented above give perspective for the remainder of the analysis. Because payment choices are almost perfectly predicted at the lower end of the items bought and value of sale distributions, transactions with less than $5 and fewer than 3 items were eliminated from the random samples and thus were not used in the estimation procedure. Similarly, transactions with greater than $150 and more than 60 items were also eliminated from the random samples. The remaining samples consisted of 6,003,113 transactions together, and ranged from 59,594 transactions to 60,348 transactions in each random sample.

Table 2 shows summary statistics for all of the random samples. The statistics reported are the averages of the statistics across the random samples: the mean of the means, the mean of the standard deviations and so on. While this is not the most technically accurate way to calculate these statistics, it does give an idea of the sample composition. Most transactions were made with cash, at approximately 53.7 percent. Checks followed, with approximately 20.4 percent of the sample, credit card transactions represent 11.3 percent,

[17] $150 and 60 items represent approximately the 99th percentile of the respective distributions after dropping the one item transactions.

and debit card transactions represent 14.5 percent.[18] The average number of items in a transaction is approximately 12.6, while the average value of the sale is $29.87. Most transactions do not have manufacturer or store coupons associated with them, but there are more transactions with store coupons than with manufacturer coupons. Most of the transactions occurrred on Saturday, and the fewest number of transactions occurred on Thursday.

The demographic results reported are "transaction weighted". Each transaction is paired with the demographics of the local market. The demographic statistics reported are with respect to the transactions. Thus, if one store has more transactions than another store, its demographics will be included more often in calculated statistics. As is evident from the table, the demographics of the sample range widely. The mean minimum median income across random samples is $20,327 and the mean maximum median household income is $117,690. This range in values shows that the transaction data potentially represents behavior from a wide range of income groups. The age statistics shows some variability as well, ranging from very young areas to others with a higher percentage of holder families. The education statistics, which are recorded for the highest education level achieved, also show significant variation. Some census tracts have very highly educated populations, while others do not. The married and female headed variables also show some variability, as does the nonwhite. The sample covers both fully urban and fully rural areas, and owner occupied statistics also vary.

These summary statistics show significant variation in both the population of transactions and the demographics of the local market. With these summary statistics in mind, the next step is to turn to the estimation results.

[18] Numbers may not sum to 100 percent due to rounding.

4 Estimation results

4.1 Binomial results

4.1.1 Baseline specification

Tables 3(a) and (b) show the baseline results for a probit specification for each payment type. In each case, the dependent variable is a zero or one, depending on whether the transaction used that particular payment type. Each row represents a different independent variable, and each set of three columns represents a different payment type. Within each set of columns, the first column is the coefficient vector and the second column is the standard error. The third column reports the marginal effect of the variable on the probability of using the payment instrument. This marginal effect is calculated as the average across all observations of the marginal derivatives for the coefficient in the case of continuous dependent variables. For dummy variables, it is calculated as the average difference between the probability of using the payment instrument of the dummy variable set to one and set to zero. In all cases, the coefficients and marginal effects reflect the choice to use a particular payment instrument, relative to the other three payment instruments.

The first row indicates that the probability of using a particular payment instrument differs according to the value of the sale. As the value of the sale increases, consumers are more likely to use checks and credit cards and less likely to use cash and debit cards. As the number of items increases, consumers are more likely to use check and credit cards and less likely to use cash and debit cards, although the coefficient on cash is not significantly different from zero at the 95 percent confidence level. The significant coefficients on the value of the sale squared and the number of items squared terms indicate that these relationships may not be linear; they give some indication of a quadratic function in these two variables. The cross term for items bought and value of sale has a significant coefficient in the cash equation, although not in the other equations.

The marginal derivatives show that the choice of payment responds relatively more to changes in the value of sale than the number of items bought. Separate calculations show that the probability of using cash is relatively inelastic with respect to the number of items bought, but relatively very elastic with respect to the value of the sale: a ten percent increase in the number of items bought implies only a 0.5 percent decrease in the probability of using cash; however, a ten percent increase in the value of the sale causes an 11 percent decrease in the probability of using cash. Interestingly, the magnitudes of the elasticities for the number of items bought is higher for the other three payment types, which shows that people change behavior relatively more with respect to the number of items bought for checks, credit cards and debit cards than they do for cash. In all cases except for check, the elasticities with respect to the number of items bought are less than half of the elasticity with respect to the value of the sale.

Both the number of store and manufacturer coupons are negatively correlated with the probability of using cash, but only the coefficient on the number of manufacturer coupons is significant. In contrast to the cash results, the number of manufacturer coupons is not a significant predictor of check use, while the number of store coupons is positively correlated with the probability of check use. The number of manufacturer coupons is positively correlated with credit card use and the number of store coupons is negatively correlated. Neither the number of manufacturer nor the number of store coupons is a significant predictor of the choice to use a debit card. Both may result from the fact that a certain percentage of consumers use cash when they are just "running to the store" for a few items, regardless of whether it is on sale. This potentially indicates that check writers are more price sensitive than people who use other forms of payment. Cash has the lowest percentage of items bought with any type of coupon, relative to the other payment types.

The elasticities in the third column indicate that payment choices are not as responsive to changes in the number of coupons as they are to the number of items bought and the value of the sale. These statistics indicate that while store coupon and manufacturer coupon use may be correlated with the use of different payment types, they are not necessarily the major factors that lead consumers to change their behavior.

The day of the week coefficients indicate that consumers are significantly less likely to use cash on Mondays, Tuesdays, Wednesdays and Thursdays, and significantly more likely to use cash on Fridays and Saturdays, relative to Sunday. In contrast, the probability of observing a check payment is lower on Sunday than on any other day of the week. None of the day coefficients is significant in the credit card equation, while all of the day coefficients are significant and negative in the debit card equation, which leads one to believe that the probability of using a debit card is highest on Sunday, the omitted day of the week. Economic theory has little to say about why the day of the week should be significant in the choice of payment. One possible hypothesis is that people use debit cards on the weekends in order to get cash back when banks are closed. However, inspection of the data shows that the percentage of debit card transactions with cash back is actually lower on the weekends than during the week. Nevertheless, it is interesting that this effect exists and points to environmental factors or buyer habits that may affect payment choice that are outside of the value of the asset criteria adopted by many theoretical models. The marginal derivatives indicate that overall, the probabilities of choosing a particular payment instrument change between roughly one and four percentage points, with the largest swings seen in checks and debit cards.

In order to investigate the robustness of the results, the model was re-estimated using the average value of an item as an independent variable instead of the value of the sale and the number of items bought. These results are not reported here. The results clearly indicate that the average value per item is relatively lower for cash transactions, and relatively higher for check, credit card and debit card transactions. Including the average value per item as an independent variable does not change the signs of the coupon coefficients, but it does change the significance of the store coupon coefficient in the cash, check and store coupon equations. The day of the week coefficients become insignificant for Monday and Tuesday in the cash equation, but few other changes are evident in these coefficients.

In sum, the results indicate that payment choices depend critically on the value of the sale and the number of items bought, and are significantly correlated with the number of store and manufacturer coupons. Furthermore, the results indicate that consumers may choose one payment type over another according to the day of the week. For the most part, these are factors that are absent from traditional models of media of exchange. However, the data show that these factors have clear affects and correlations with payment choices. Thus, these results deepen our understanding of people's interaction with the monetary economy.

4.1.2 Demographic effects

As noted above, previous research using stated preference and survey data indicates that income, age and demographics are significantly correlated with payment use. In order to test whether these factors are also evident in this sample of revealed-preference data, the analysis includes the demographics of the local market in the specification for payment choice.

As a first step, the model in tables 3(a) and (b) is re-estimated using a fixed effects model. The results are not reported. This model uses a dummy variable for each retail outlet that equals one if the transaction occurred at that particular retail outlet. The results indicate that controlling for store fixed effects materially affects the magnitude and the signs of the coefficients in the cash and credit equations, but not in the check and debit card equations. In particular, after controlling for the transaction occurring at a particular retail outlet, the coefficients on the number of items bought and the number of store coupons become significant in the cash equation. Most of the day coefficients keep the same sign when including the fixed effects, although a few change from significant to insignificant in this specification. The check estimates do not change at all after including the dummies to control for fixed effects.

In order to attempt to characterize these fixed effects, the next set of estimation results captures the effects of local market demographics. These are shown in tables 4(a) and (b). The results for the transaction characteristics are similar to those in the baseline specification; however, a few key differences should be noted. As the median household income increases in a census tract, the probability of using cash decreases; however, the coefficient is not significantly different from zero. This term does have a significant and negative coefficient in the check equation. Perhaps surprisingly, the coefficient on the median household income in a census tract is negative in the credit card equation; however, it is not significantly different from zero. A significantly different from zero coefficient may imply that a higher median tract income is correlated with a lower probability of credit card use at the grocery store. Indeed, survey data show that income is one of the best predictors of holding a credit card – a greater proportion of higher income families hold credit cards than lower income families. But, after controlling for other factors, it appears that credit card use may be negatively correlated with the income in a census tract. Finally, census tract median income is positively correlated with the probability of using a debit card. This result could point to better banking services to relatively more affluent areas, or a distinct preference of higher income individuals for debit cards at the grocery store relative to all other payment types.

The age statistics overall indicate that the probabilities of using different payment types is correlated with age. The older age groups are significantly more likely to use cash or check relative to the baseline head of household age, under 35. In contrast, the age statistics show that the age profile with respect to credit card use is nonlinear. Relative to the lowest age group, a higher proportion of families with a household head between 35 and 44 is correlated with a lower probability of using a credit card, while a higher proportion of families with a household head between 55 and 64 is correlated with a higher probability. In general, age is negatively correlated and education is positively correlated with debit card use. These results roughly agree with those found in survey data, and thus offer some evidence of preferences for payments that differ according to age.

Turning to the education results, higher education implies that the consumer is on average less likely to use cash or check, and more likely to use credit cards. The collinearity of education and income may point to why education has a significant positive coefficient, while income has a significant and negative coefficient. After controlling for education, the residual effect of income on credit card use is negative. Cash-strapped, less wealthy households may be forced to buy groceries on credit, which would be indicated by a negative coefficient in the estimation results.

The married coefficients indicates that census tracts with a higher percentage of married households are less likely to use cash and more likely to use the other three payment types. Census tracts with a higher percentage of households with a female head and children under 18 are more likely to use cash or debit cards. Census tracts with a higher nonwhite population proportion predict a lower probability of check use. The nonwhite statistics may reflect overall trends in transaction account holdings. Statistics from the Survey of Consumer Finances (SCF) indicate that approximately 75.8 percent of families with a nonwhite or Hispanic head of family have a transaction account, while 94.7 percent of white non-Hispanic families have a transaction account.[19]

The pseudo-R squared statistics for each equation indicate that only a relatively low fraction of the variation in choices of payment is explained by the chosen set of variables. This points to a need to analyze the data more closely. The analysis continues below.

4.2 Multinomial results

4.2.1 Multinomial logit results

The next set of tables reports the results from estimating a multinomial logit model using the specification in equation 1. As noted elsewhere, the multinomial logit model exhibits restrictive substitution patterns between choices, which limits its use as a gauge of substitutability for different payment instruments at the point of sale. Its advantage is its computational tractability; with the large datasets used in this paper, it is certainly an advantage.

Tables 5 (a) and (b) report the results from two specifications: the first is the baseline model and the second includes the demographics of the local market. As is the case in all multinomial discrete choice problems, the coefficients for one of the choices must be normalized to zero. In this case, the cash coefficients are normalized to zero. There are three columns under each payment type. The first reports the parameter estimate and the second reports the standard error. The third, labeled "delta "shows the effect of the parameter on the probability of using the particular payment instrument. Coefficients in multinomial choice models are difficult to interpret. Cases arise where the coefficient is negative, but the effect on the probability is positive, and vice versa. The delta shows the variable's true effect on the probability of using a particular payment instrument.

[19]Transaction accounts include checking, savings, and money market deposit accounts, money market mutual funds, and call accounts at brokerages. For details, see Aizcorbe et al [2003].

Table 5(a) reports the baseline specification results. Again, the results indicate that the probabilities of using different payment instruments is significantly correlated with the number of items bought, the value of the sale and the demographics of the local market. Interestingly, only the check transactions have a positive coefficient and delta for the number of items bought, but the value of the sale coefficients are positive for check, credit card and debit card. These results broadly agree with the unreported results above indicating that credit cards and debit cards generally have average value per item greater than other payment instruments. The number of manufacturer coupons has a positive effect on the probability of using a credit card, but a negative effect on the probability of using a check or debit card. The day of the week coeffcients are still statistically significant in many cases, showing relatively greater check use during the week and relatively higher debit card use on Sunday.

Table 5(b) reports the demographic results. The oldest age group is most likely to use checks, and least likely to use debit cards. Education is positively correlated with both types of card payments, and married families are more likely to use checks and credit cards than cash and debit cards. The percent urban in a census tract is positively correlated with both check and debit card use. This may reflect the fact that the rural areas are relatively lower income, and thus may have less access to banking services than the urban areas. The percent of owner occupied housing is negatively correlated with credit card use and significant in this specification, which is a change from the earlier estimation results. The pseudo R-squared statistic indicates that a fair amount of the variation in the dependent variable is explained by the chosen set of independent factors.

5 Conclusion

The contribution of this paper is to systematically investigate factors that influence payment choice at the point of sale. This study marks the first use of scanner data to examine how people pay. Scanner data is an excellent medium to study this problem, as it represents actual exchange behavior. The results show that people pay based on the number of items bought, the value of the sale, the day of the week and their personal demographics. The significance of these factors agree with common sense and with experience. Most people will pay for one item with cash, but many will substitute another payment instrument as the value of the sale and the number of items bought increase.

The payment system changed considerably over the past decade: debit card use increased substantially, while check use declined. Recent decisions by retailers and others to accept card payments may further change the payments landscape in the near future. The data used in this study are from 2001. Resampling in the future will help policymakers and researchers understand the changes in the payment system and whether new factors influence how people pay.

6 Appendix: Sampling procedure and statistics calculation

Computing advances in data capture and data processing creates opportunities for researchers to use more data in estimating models than was possible previously. As noted in the text, the original scanner data has 10,627,835 observations, which represents the entire population of transactions from the retail chain over the three month period. Using all 10 million observations would allow the researcher to obtain very precise estimates of population parameters. However, significant computational constraints exist for computing nonlinear models on a dataset of this size. Attempts were made to estimate some of the models on the full population; in general, these attempts failed.[20] Thus, for computational tractability, the statistics reported are based on repeated sampling and averaging of the statistics from the individual samples. This section briefly discusses the methodology behind the sampling and estimation procedures. These are based roughly on results detailed in Cochran [1977].[21]

The theory and methodology behind the sampling procedure and statistics is simple. The theory is based on repeated sampling from the same population. Repeated sampling from the same population is computationally cheap: many statistical packages offer canned procedures that perform this task well.[22] Re-estimating the models on different random samples of the same population should, in theory, provide the researcher with more precise estimates than estimates based on one random sample alone.

The first step in the estimation procedure is creating the random samples. Each random sample was created by simple random sampling of the transaction population without replacement. The sample size was 100,000 transactions. This process was repeated 100 times. Thus, the probability of any individual transaction selected for inclusion in an individual random sample is $\frac{100{,}000}{10{,}627{,}835} = 0.00944$, and the probability that any individual transaction appears in any random sample at least once is $1 - \left(1 - \frac{100{,}000}{10{,}627{,}835}\right)^{100} = 0.611$.

The second step is to eliminate overly influential and outlier transactions. As noted above, transactions were eliminated from the analysis based on the tender type, the number of items bought, and the value of the sale. These eliminations occurred after the random sampling procedure. The other option would be to eliminate these transactions before the sampling procedure. However, eliminating them after the sampling procedure allows

[20]Some simple regressions could be computed on the entire population. Nonlinear models failed miserably.

[21]Originally, the methodology was recommended in the context of household surveys for cases where "the gain in precision from ratio or regression estimates or stratification more than offsets the loss in precision due to the reduction in the size of the main sample " (Cochran, p. 327).

[22]This paper uses the PROC SURVEYSELECT procedure in SAS 8.2. It uses Floyd's ordered hash table algorithm for simple random sampling.

one to test more easily how sensitive estimation results are to these restrictions. These eliminations led to samples used in the final analysis that contain between 59,594 and 60,348 transactions.

The third step is to evaluate the econometric models. In general, models were evaluated on each random sample individually. Then, the results of the estimation procedure were then averaged across random samples, with adjustment for the number of observations in each random sample.

Summary statistics and probit results were calculated in this manner. A few adjustments that could have improved the efficiency of the estimates were not performed. Specifically, although there is a positive probability that some transactions are in more than one sample, the estimates were not adjusted for repeat observations. In addition, the standard errors of the parameter estimates were averaged across random samples. This is not completely statistically accurate. One could use the repeated observations of the standard errors to create very tight confidence bands around the averaged parameter estimates. However, the results are fairly robust using simple averaging, and the confidence bands used provide a lower bound on the significance of the results.

Table 1: Variable definitions

Variable name	Definition
Cash	Equals 1 if consumer used cash
Check	Equals 1 if consumer used a check
Credit card	Equals 1 if consumer used a credit card
Debit card	Equals 1 if consumer used a debit card
Items bought	Number of items in the transaction
Value of sale	Total value of all items in transaction, calculated as value of items plus tax minus value of coupons, where applicable, in dollars
Manufacturer coupons	Number of manufacturer coupons tendered
Store coupons	Number of store coupons tendered (associated with loyalty card)
Monday	Day of week transaction occurred
Tuesday	
Wednesday	
Thursday	
Friday	
Saturday	
Median household income[1,2]	Median household income in census tract (1999)
Age of householder	
35-44	Percent of households where householder is between 35-44 years old
45-54	Percent of households where householder is between 45-44 years old
55-64	Percent of households where householder is between 55-44 years old
65-74	Percent of households where householder is between 65-44 years old
75 and over	Percent of households where householder is over 75 years old
Education[3]	
High school	Percent of population where high school is the highest level completed.
Some college	Percent of population where either some college or an associate's degree is the highest level completed.
College	Percent of population where college or graduate school is the highest level completed.
Married	Percent of population
Female head with children under 18	Percent of households where the householder is a female with children under 18
Nonwhite[4]	Percent of population not classified as "White".
Urban	Percent of census tract living in an urban area or urban cluster
Owner occupied**	Percent of housing units in census tract that are owner occupied
N	Number of observations

Notes

1. *Includes the income of the householder and all other individuals 15 years old and over in the household, whether they are related to the householder or not.
2. *In most cases, the householder is the person, or one of the people, in whose name the home is owned, being bought, or rented.
3. *Data on educational attainment are tabulated for the population 25 years old and over. People are classified according to the highest degree or level of school completed.
4. **"White" is a person having origins in any of the original peoples of Europe, the Middle East, or North Africa. It includes people who indicate their race as "White" or report entries such as Irish, German, Italian, Lebanese, Near Easterner, Arab, or Polish.

* Indicates data source and supplied definition is from the U.S. Census Bureau, Census 2000 statistics.

** Indicates data source and supplied definition is from the Federal Financial Institutions Examination Council Census Data Software, 2000 statistics.

Table 2: Summary statistics

	Mean	Standard Deviation	Median	Min	Max
Cash	0.537	0.499	1.000	0.000	1.000
Check	0.204	0.403	0.000	0.000	1.000
Credit card	0.113	0.317	0.000	0.000	1.000
Debit card	0.145	0.353	0.000	0.000	1.000
Items bought	12.621	11.149	8.000	3.000	59.000
Value of sale	29.87	26.42	20.10	5.01	149.92
(Items bought)*(Value of sale)	637.795	1150.420	161.082	15.030	8761.308
(Items bought)^2	283.597	517.911	64.000	9.000	3481.000
(Value of sale)^2	1,590.40	2,939.68	404.09	25.10	22,475.74
Manufacturer coupons	0.185	1.209	0.000	0.000	54.909
Store coupons	1.339	3.174	0.000	0.000	78.742
Day of week					
Monday	0.138	0.345	0.000	0.000	1.000
Tuesday	0.131	0.338	0.000	0.000	1.000
Wednesday	0.135	0.342	0.000	0.000	1.000
Thursday	0.129	0.335	0.000	0.000	1.000
Friday	0.147	0.355	0.000	0.000	1.000
Saturday	0.173	0.378	0.000	0.000	1.000
Median household income	44,344	18,978	39,570	20,327	117,690
Age of head					
35-44	0.219	0.057	0.213	0.101	0.446
45-54	0.196	0.035	0.190	0.145	0.377
55-64	0.139	0.033	0.138	0.052	0.249
65-74	0.117	0.042	0.118	0.015	0.231
75 and over	0.098	0.046	0.098	0.012	0.223
Education					
High school	0.248	0.080	0.263	0.076	0.386
Some college	0.328	0.071	0.320	0.166	0.567
College	0.266	0.179	0.215	0.051	0.688
Married	0.604	0.095	0.617	0.395	0.814
Female head with children under 18	0.064	0.036	0.057	0.016	0.220
Nonwhite	0.162	0.175	0.098	0.000	0.809
Urban	0.711	0.339	0.812	0.000	1.000
Owner occupied	0.697	0.138	0.720	0.346	0.953
No. of observations	6,003,113				

Table 3(a): Baseline specification

	Cash			Check		
	Estimate	Std. error	Marginal derivative	Estimate	Std. error	Marginal derivative
Items bought	-0.005**	0.002	-0.002	0.035**	0.003	0.009
Value of sale	-0.041**	0.001	-0.014	0.020**	0.001	0.005
(Items bought)*(Value of sale)	-4.27E^{-4**}	5.91E^{-5}	-1.50E^{-4}	2.49E^{-4**}	6.25E^{-5}	6.34E^{-5}
(Items bought)^2	0.001**	8.26E^{-5}	2.74E^{-4}	-0.001	8.53E^{-5}	-1.89E^{-4}
(Value of sale)^2	2.84E^{-4**}	1.44E^{-5}	9.95E^{-5}	-1.81E^{-4**}	1.56E^{-5}	-4.61E^{-5}
Manufacturer coupons	-0.026**	0.005	-0.009	-0.001	0.005	0.000
No. of store coupons	-0.003	0.002	-0.001	0.013**	0.002	0.003
Day of week						
Monday	-0.029	0.020	-0.010	0.088**	0.023	0.022
Tuesday	-0.053	0.020	-0.019	0.126**	0.023	0.032
Wednesday	-0.049**	0.020	-0.017	0.142**	0.023	0.036
Thursday	-0.019	0.020	-0.007	0.155**	0.023	0.040
Friday	0.087	0.020	0.031	0.085**	0.022	0.022
Saturday	0.068	0.019	0.024	0.072**	0.021	0.018
Intercept	0.942**	0.018	0.330	-1.741**	0.021	-0.443
Pseudo R^2	0.1127			0.0797		
Likelihood ratio	9750.0			4949.81		

Table 3 (b): Baseline specification

	Credit			Debit		
	Estimate	Std. error	Marginal derivative	Estimate	Std. error	Marginal derivative
Items bought	-0.021	0.003	-0.004	-0.023	0.003	-0.005
Value of sale	0.030	0.001	0.005	0.025	0.001	0.005
(Items bought)*(Value of sale)	2.63E^{-4**}	7.15E^{-5}	4.72E^{-5}	0.001**	7.59E^{-5}	1.15E^{-4}
(Items bought)^2	-3.75E^{-4**}	1.03E^{-4}	-6.73E^{-5}	-4.90E^{-4**}	1.03E^{-4}	-1.07E^{-4}
(Value of sale)^2	-1.73E^{-4**}	1.70E^{-5}	-3.11E^{-5}	-2.23E^{-4**}	1.82E^{-5}	-4.87E^{-5}
Manufacturer coupons	0.036**	0.006	0.007	0.013**	0.006	0.003
No. of store coupons	-0.007**	0.003	-0.001	-0.005	0.003	-0.001
Day of week						
Monday	0.019	0.025	0.003	-0.079	0.023	-0.017
Tuesday	0.018	0.026	0.003	-0.088	0.024	-0.019
Wednesday	0.002	0.026	0.000	-0.094	0.024	-0.020
Thursday	-0.027	0.026	-0.005	-0.123	0.024	-0.027
Friday	-0.068	0.025	-0.012	-0.155	0.023	-0.034
Saturday	-0.071	0.024	-0.013	-0.104	0.022	-0.023
Intercept	-1.665	0.024	-0.299	-1.302	0.021	-0.284
Pseudo R^2	0.040			0.0234		
Likelihood ratio	1711.1			1192.0		

Table 4 (a): Demographics specification

	Cash			Check		
	Estimate	Std. error	Marginal derivative	Estimate	Std. error	Marginal derivative
Items bought	-0.015**	0.002	-0.005	0.033**	0.003	0.008
Value of sale	-0.037**	0.001	-0.012	0.022**	0.001	0.006
(Items bought)*(Value of sale)	-3.58E^{-4}**	5.91E^{-5}	-1.22E^{-4}	2.51E^{-4}**	6.27E^{-5}	6.32E^{-5}
(Items bought)^2	0.001**	8.26E^{-6}	2.69E^{-4}	-0.001	8.57E^{-5}	-1.87E^{-4}
(Value of sale)^2	2.55E^{-4}**	1.45E^{-5}	8.66E^{-5}	-1.83E^{-4}**	1.56E^{-5}	-4.62E^{-5}
Manufacturer coupons	-0.016**	0.005	-0.006	0.002	0.005	0.001
No. of store coupons	-0.006**	0.002	-0.002	0.011**	0.002	0.003
Day of week						
Monday	-0.042**	0.020	-0.014	0.079**	0.023	0.02
Tuesday	-0.066**	0.020	-0.022	0.118**	0.023	0.03
Wednesday	-0.064**	0.020	-0.022	0.133**	0.023	0.034
Thursday	-0.038	0.020	-0.013	0.142**	0.023	0.036
Friday	0.062**	0.020	0.021	0.066**	0.022	0.017
Saturday	0.045**	0.019	0.015	0.058**	0.022	0.015
Median household income	-2.75E^{-6}**	1.28E^{-6}	-9.35E^{-7}	-3.17E^{-6}**	1.44E^{-6}	-8.00E^{-7}
Age of householder						
35 to 44	0.248	0.212	0.084	0.103	0.244	0.026
45 to 54	0.608**	0.241	0.207	1.095**	0.272	0.276
55 to 64	0.378	0.278	0.129	-0.846**	0.316	-0.213
65 to 74	1.045	0.312	0.356	1.091**	0.352	0.275
75 and over	0.593	0.241	0.202	0.639**	0.272	0.161
High school	-0.092	0.218	-0.031	0.119	0.242	0.030
Some college	-0.622**	0.094	-0.212	-0.056	0.104	-0.014
College	-0.769**	0.123	-0.262	-0.609**	0.140	-0.153
Married	-0.454**	0.140	-0.154	0.426**	0.160	0.107
Female head	0.212	0.310	0.072	-0.470	0.358	-0.118
Nonwhite	0.079	0.049	0.027	-0.492**	0.057	-0.124
Urban	-0.055**	0.024	-0.019	0.110**	0.027	0.028
Owner occupied	-0.023	0.084	-0.008	0.030	0.095	0.008
Intercept	1.391**	0.114	0.473	-2.017**	0.128	-0.508
Pseudo R^2	0.138			0.090		
Likelihood ratio	11896.2			5617.1		

Table 4 (b): Demographics specification

	Credit			Debit		
	Estimate	Std. error	Marginal derivative	Estimate	Std. error	Marginal derivative
Items bought	-0.010**	0.003	-0.002	-0.013	0.003	-0.003
Value of sale	0.024**	0.001	0.004	0.019**	0.001	0.004
(Items bought)*(Value of sale)	1.04E^{-4}	7.18E^{-5}	1.75E^{-5}	3.93E^{-4}	7.57E^{-6}	8.19E^{-5}
(Items bought)^2	-2.68E^{-4**}	1.04E^{-4}	-4.49E^{-5}	-4.12E^{-4}	1.04E^{-4}	-8.58E^{-5}
(Value of sale)^2	-1.23E^{-4**}	1.72E^{-5}	-2.06E^{-5}	-1.77E^{-4}	1.82E^{-5}	-3.70E^{-5}
Manufacturer coupons	0.023**	0.006	0.004	0.001	0.006	2.60E^{-4}
No. of store coupons	-0.001	0.003	-1.37E^{-4}	-0.001	0.003	-2.29E^{-4}
Day of week						
Monday	0.04	0.026	0.007	-0.064**	0.024	-0.013
Tuesday	0.038	0.027	0.006	-0.072**	0.024	-0.015
Wednesday	0.026	0.027	0.004	-0.076**	0.024	-0.016
Thursday	0.005	0.027	0.001	-0.098**	0.025	-0.021
Friday	-0.026	0.026	-0.004	-0.120**	0.024	-0.025
Saturday	-0.031	0.025	-0.005	-0.072**	0.023	-0.015
Median household income	-3.44E^{-6**}	1.68E^{-6}	-5.77E^{-7}	5.97E^{-6**}	1.56E^{-6}	1.24E^{-6}
Age of householder						
35 to 44	-0.398	0.296	-0.067	-1.103**	0.261	-0.23
45 to 54	-0.892**	0.310	-0.149	-1.235**	0.288	-0.257
55 to 64	2.232**	0.388	0.374	0.475	0.350	0.099
65 to 74	-2.037**	0.432	-0.341	-2.279**	0.391	-0.475
75 and over	-0.805**	0.324	-0.135	-1.358**	0.296	-0.283
High school	0.353	0.316	0.059	0.923**	0.279	0.192
Some college	1.009**	0.132	0.169	1.557**	0.118	0.324
College	2.240**	0.169	0.375	1.013**	0.154	0.211
Married	1.194**	0.196	0.200	0.259	0.173	0.054
Female head	0.669	0.477	0.112	1.039**	0.407	0.217
Nonwhite	-0.121	0.073	-0.02	-0.212**	0.065	-0.044
Urban	-0.020	0.035	-0.003	0.110**	0.031	0.023
Owner occupied	-0.434**	0.113	-0.073	-0.087	0.102	-0.018
Intercept	-2.760**	0.160	-0.462	-2.003**	0.143	-0.417
Pseudo R^2	0.104			0.068		
Likelihood ratio	4434.7			3482.7		

Table 5 (a): Baseline multinomial logit

	Check			Credit card			Debit card		
	Estimate	Std. error	Delta	Estimate	Std. error	Delta	Estimate	Std. error	Delta
Items bought	0.048**	0.005	0.011	-0.028	0.006	-0.003	-0.035**	0.006	-0.004
Value sale	0.067**	0.002	-0.002	0.085**	0.002	0.001	0.075**	0.002	0.000
(Value sale * Items bought)	0.001	0.000	0.000	0.001	0.000	0.000	0.001	0.000	0.000
Items bought^2	-0.002	0.000	0.000	-0.002	0.000	0.000	-0.001	0.000	0.000
Value sale^2	0.000	0.000	0.000	-0.001	0.000	0.00	-0.001	0.000	0.000
No. of manufacturer coupons	0.057**	0.011	-0.004	0.111**	0.013	0.004	0.058**	0.014	-0.002
No. of store coupons	0.018	0.004	0.004	-0.014**	0.006	-0.002	-0.003	0.005	0.000
Day of week									
Monday	0.145	0.044	0.022	0.072	0.051	0.004	-0.102**	0.045	-0.021
Tuesday	0.258**	0.044	0.029	0.155**	0.052	0.005	-0.071	0.046	-0.027
Wednesday	0.265**	0.044	0.039	0.083	0.052	0.001	-0.121**	0.046	-0.029
Thursday	0.262**	0.044	0.047	0.023	0.053	-0.001	-0.185**	0.047	-0.032
Friday	0.053	0.043	0.041	-0.155**	0.051	-0.001	-0.335**	0.045	-0.028
Saturday	0.065	0.041	0.035	-0.160**	0.050	-0.006	-0.218	0.043	-0.017
Intercept	-2.982	0.042	-0.038	-3.053**	0.049	-0.028	-2.360**	0.042	0.064
Pseudo R^2	0.2145								
Likelihood ratio	35,884								
No. of observations	60,346								

Table 5 (b): Demographics multinomial logit

	Check			Credit card			Debit card		
	Estimate	Std. error	Delta	Estimate	Std. error	Delta	Estimate	Std. error	Delta
Items bought	0.054**	0.005	0.008	-0.001	0.006	-0.002	-0.011**	0.006	-0.004
Value of sale	0.064**	0.002	-0.001	0.073**	0.003	0.001	0.064**	0.002	0.000
(Items bought*Value of sale)	0.001**	1.16E^{-4}	-4.46E^{-5}	0.001**	1.51E^{-4}	8.05E^{-6}	0.001	0.000	0.000
(Items bought)^2	-0.002	1.60E^{-4}	-2.25E^{-5}	-0.002**	2.21E^{-4}	-1.68E^{-5}	-0.001	0.000	0.000
(Value sale)^2	-4.60E^{-4}**	2.90E^{-5}	6.14E^{-6}	-0.001**	3.60E^{-5}	-2.24E^{-6}	-0.001	0.000	0.000
No. of manufacturer coupons	0.048	0.011	-0.001	0.076**	0.014	0.003	0.029**	0.014	-0.003
No. of store coupons	0.019	0.004	0.002	0.003	0.006	-0.001	0.009	0.005	0.000
Day of week									
Monday	0.152	0.044	0.019	0.094	0.053	0.004	-0.075	0.046	-0.019
Tuesday	0.262	0.044	0.026	0.182**	0.054	0.005	-0.035	0.048	-0.025
Wednesday	0.259	0.044	0.035	0.102	0.054	0.001	-0.094	0.048	-0.027
Thursday	0.253	0.044	0.039	0.071	0.055	0.001	-0.134**	0.048	-0.029
Friday	0.050	0.043	0.029	-0.070	0.053	0.002	-0.256**	0.047	-0.024
Saturday	0.068	0.041	0.024	-0.079	0.051	-0.003	-0.143**	0.044	-0.013
Median household income	-9.46E^{-7}	2.75E^{-6}	-4.34E^{-7}	-3.48E^{-6}	3.44E^{-6}	-5.20E^{-7}	0.000	0.000	0.000
Age of householder									
35 to 44	-0.237	0.471	0.201	-0.987	0.613	0.026	-2.435**	0.527	-0.178
45 to 54	1.015	0.525	0.451	-1.711**	0.634	-0.058	-2.869**	0.577	-0.246
55 to 64	-1.927**	0.602	-0.581	4.449**	0.802	0.395	0.219	0.702	-0.102
65 to 74	-0.214	0.672	0.736	-5.931**	0.898	-0.237	-5.286**	0.789	-0.216
75 and over	1.151**	0.514	0.398	-0.833	0.660	-0.004	-2.698**	0.587	-0.278
High school	-0.208	0.455	-0.196	0.557	0.657	-0.022	1.903**	0.559	0.168
Some college	0.299	0.197	-0.351	2.581**	0.274	0.063	3.165**	0.234	0.168
College	-0.227	0.267	-0.530	4.421**	0.348	0.230	2.893**	0.309	0.078
Married	1.154**	0.308	-0.123	2.595**	0.408	0.094	1.515**	0.349	-0.035
Female head	-1.305	0.685	-0.405	0.843	1.015	0.019	2.491**	0.834	0.265
Nonwhite	-0.679**	0.108	-0.032	-0.337**	0.154	0.021	-0.554**	0.134	-0.004
Urban	0.216**	0.050	0.010	0.063	0.073	-0.012	0.227**	0.064	0.009
Owner occupied	0.109	0.182	0.097	-0.953**	0.229	-0.066	-0.252	0.200	0.017
Intercept	-3.608**	0.242	0.166	-5.495**	0.329	-0.120	-4.150**	0.284	0.039
Pseudo R^2	0.2502								
Likelihood ratio	41,869								
No. of observations	60,346								

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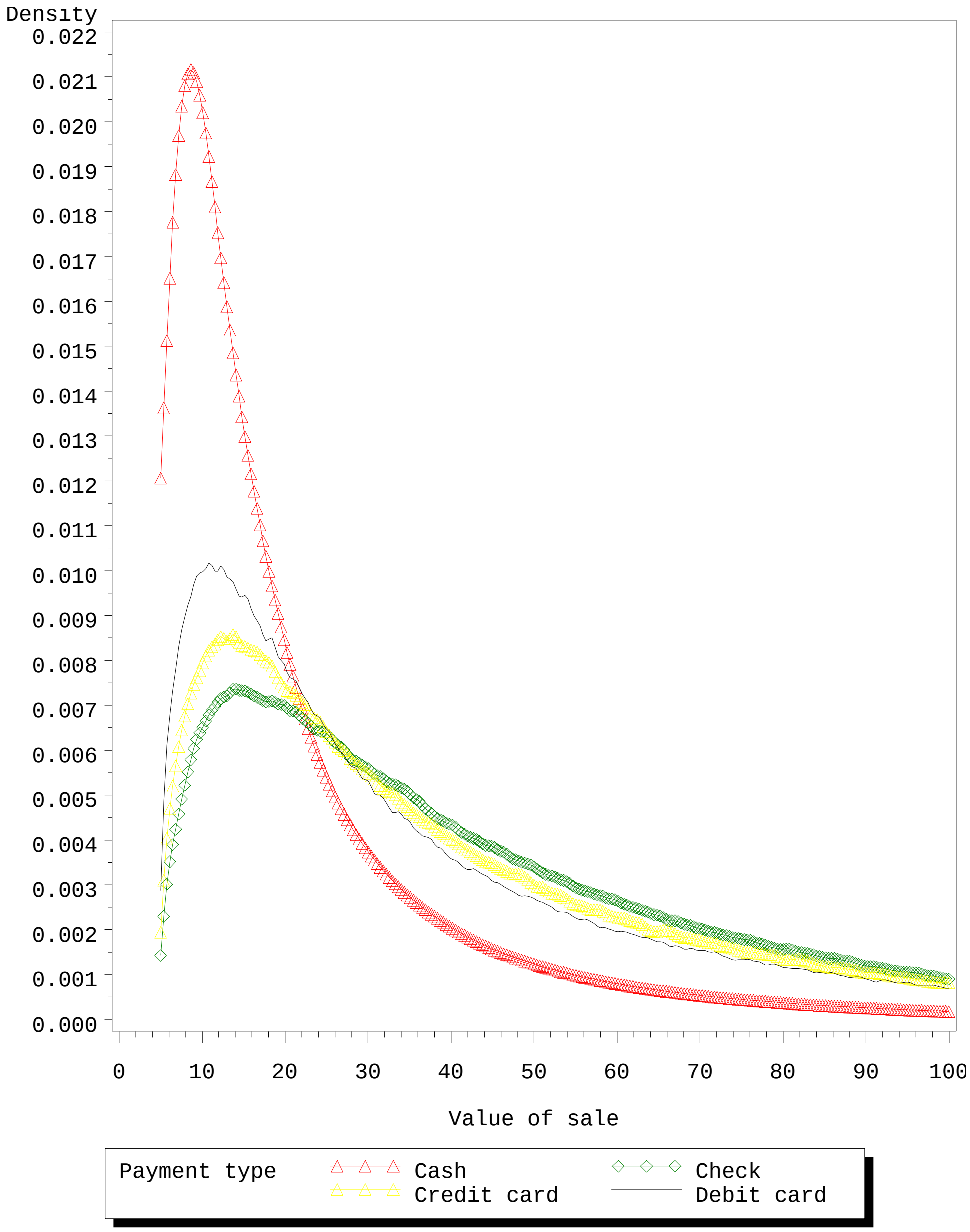

Figure 1: Kernel density estimate of value of sale probability density function

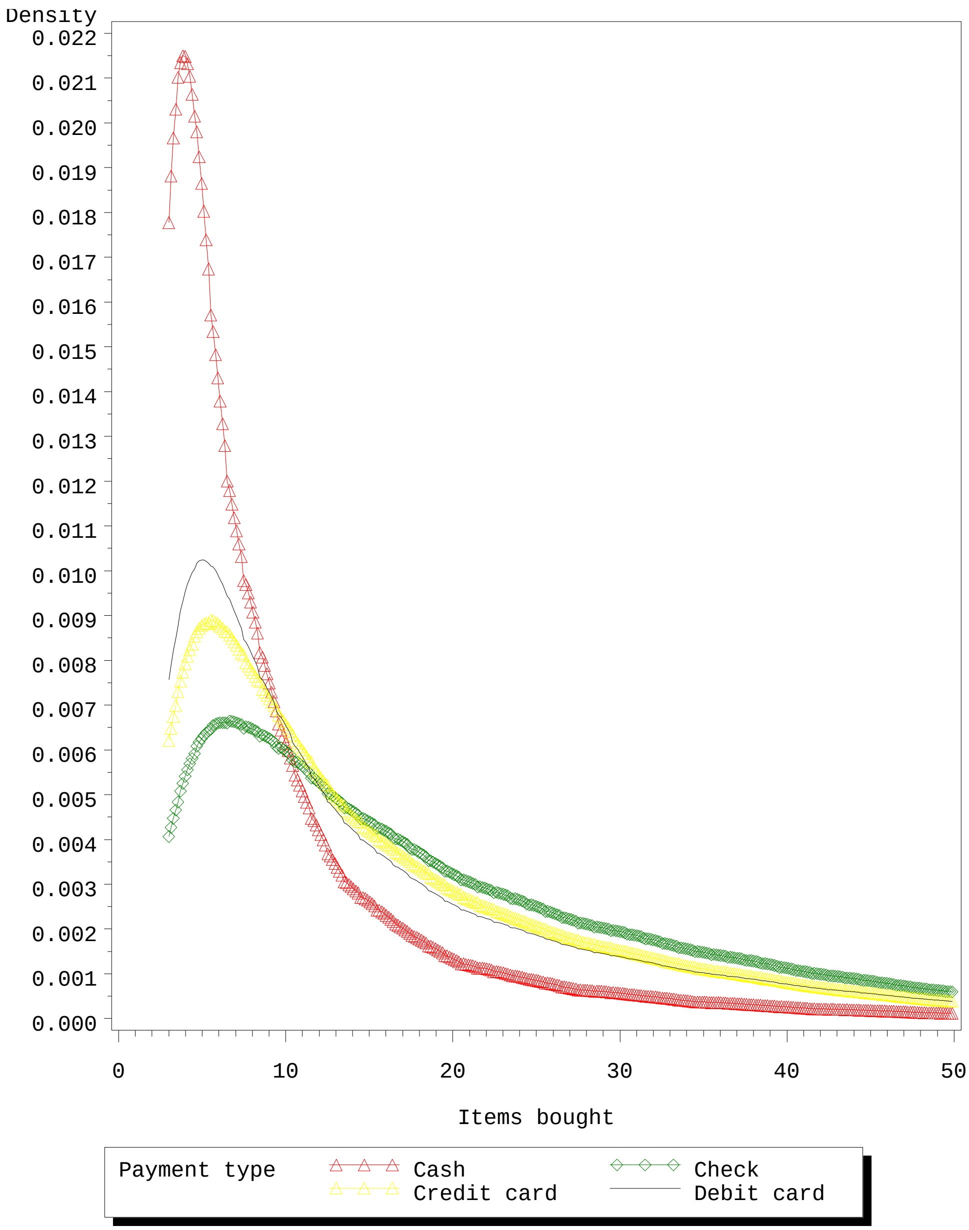

Figure 2: Kernel density estimate of items bought probability density function

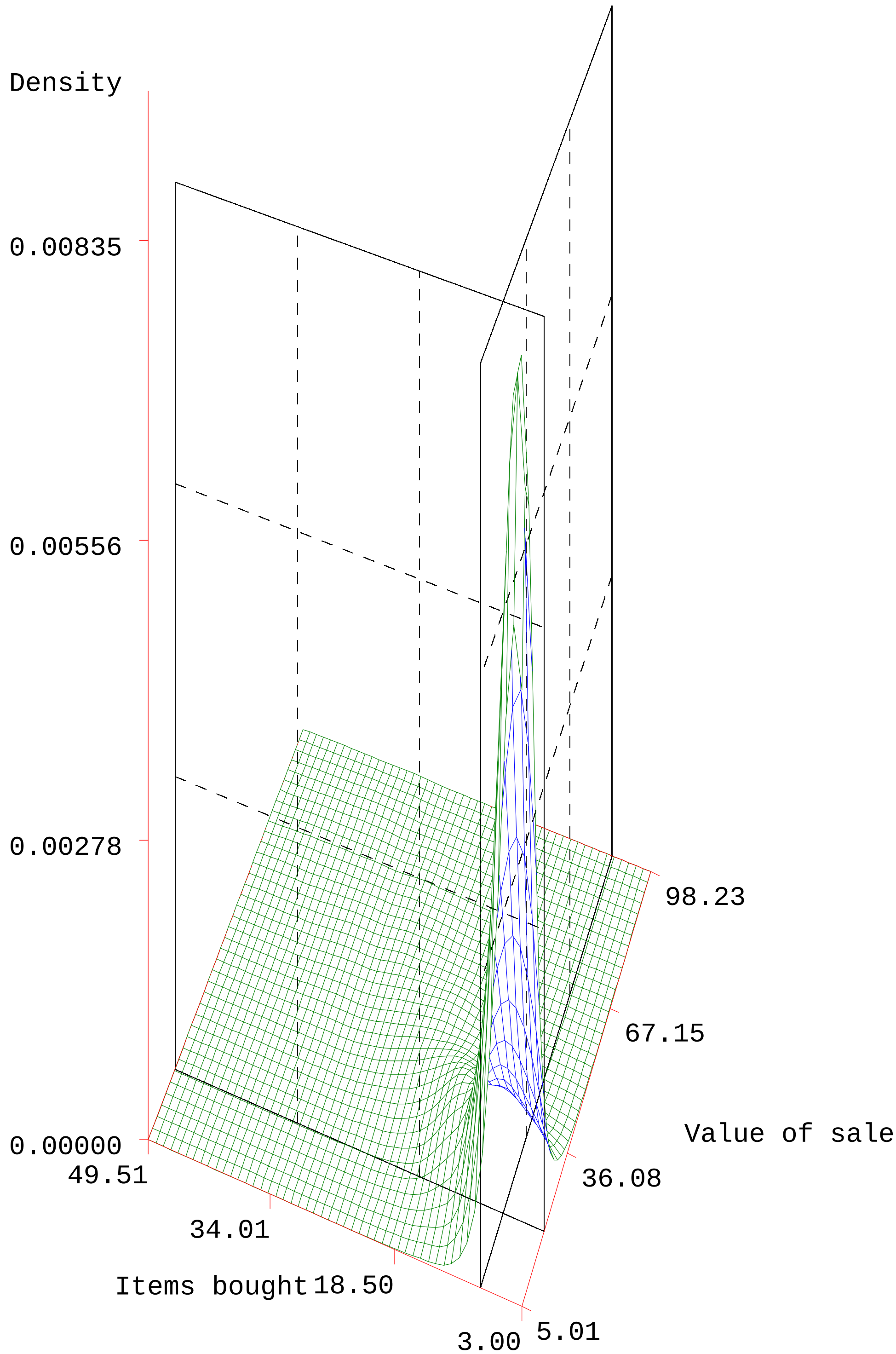

Figure 3: Bivariate kernel density estimate of value sale versus items bought – Cash

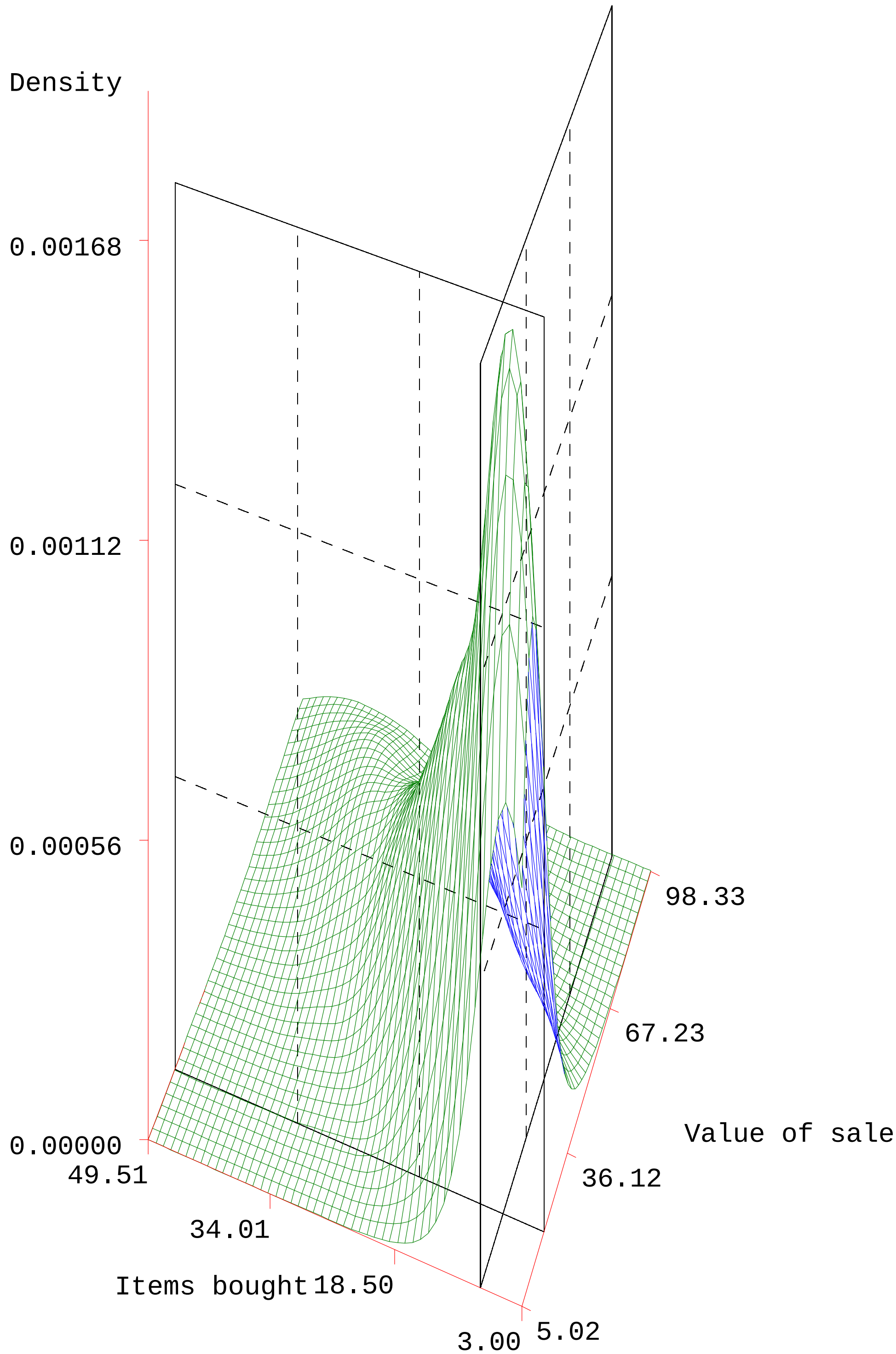

Figure 4: Bivariate kernel density estimate of value sale versus items bought – Check

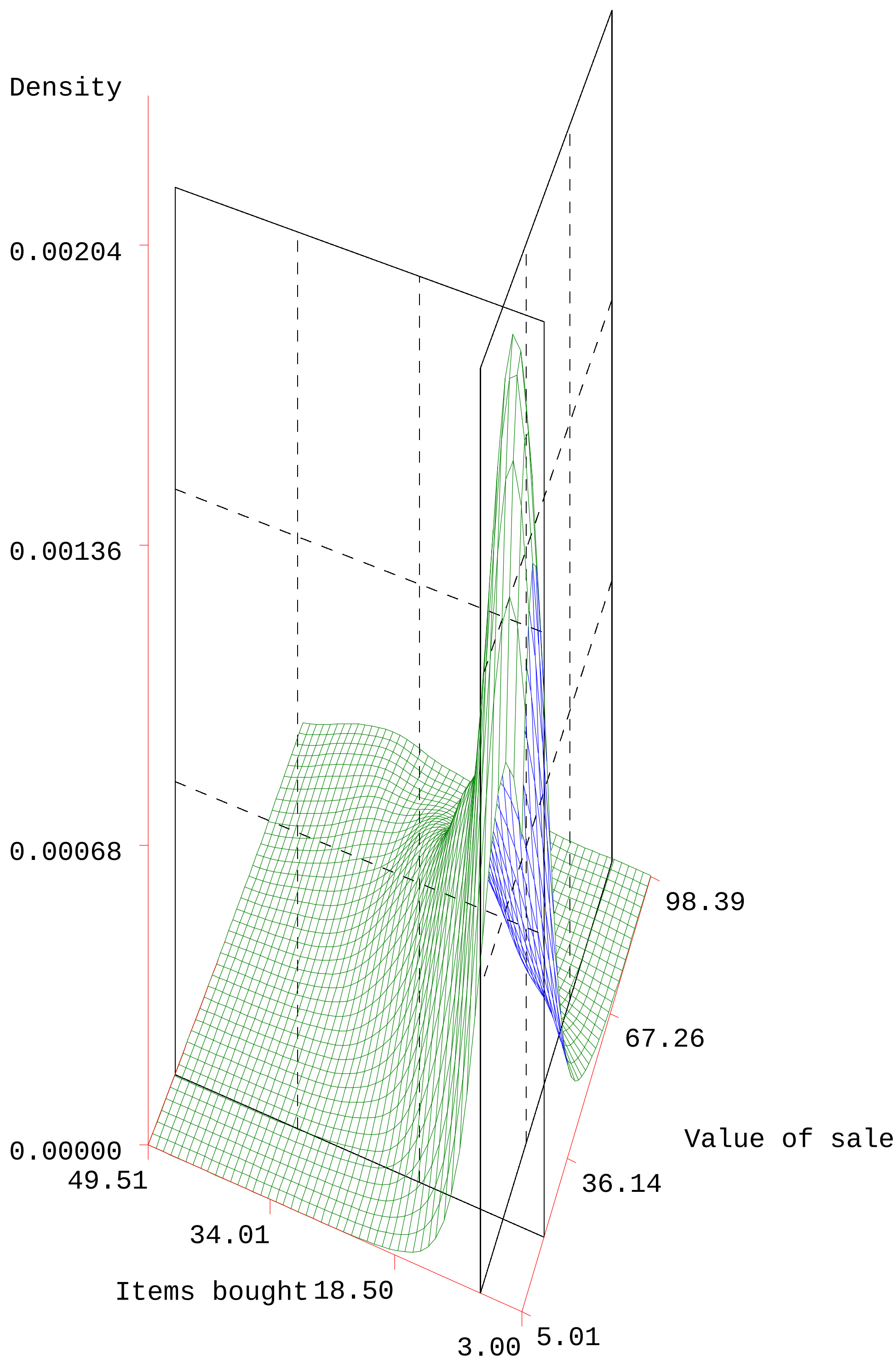

Figure 5: Bivariate kernel density estimate of value sale versus items bought – Credit card

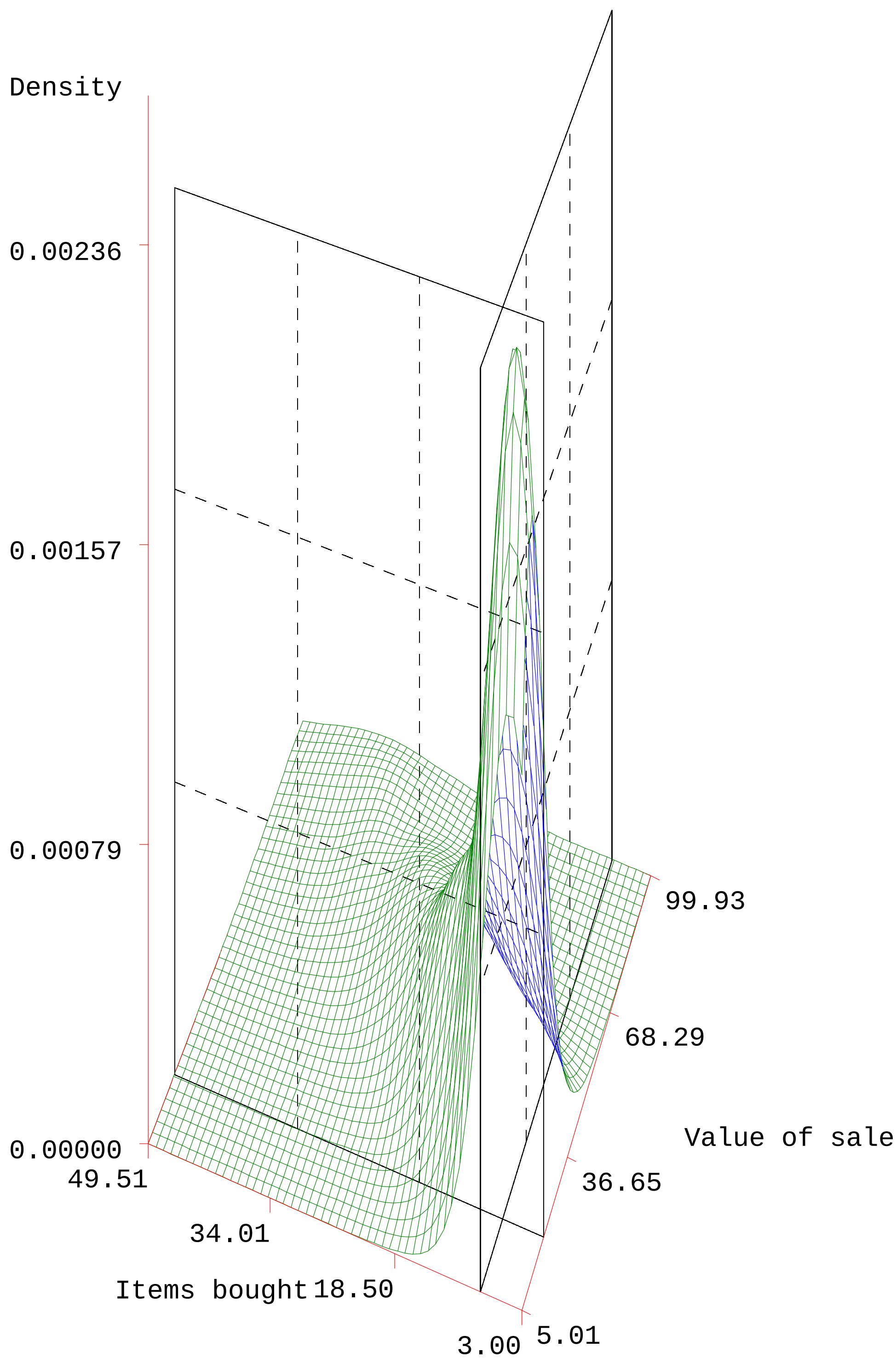

Figure 6: Bivariate kernel density estimate of value sale versus items bought – Debit card