

STATISTICAL MODEL FOR ESTIMATING THE PROBABILITY
OF USING ELECTRONIC CARDS
A STATISITICAL ANALYSIS OF SCF DATA

by

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(Under the Direction of Dr. Anand Vidyashankar)

ABSTRACT

The use of electronic banking products are increasingly important aspects of American life. Relatively little attention has been paid to the demand side of the financial service market, most importantly, consumers. To understand significant predictors to influence on the use of electronic payment instruments, we have applied stepwise logistic regression, probit regression and random effect probit model to a set of reported SCF data in U.S. and compared the results. The causal relationship between predictors and the adoption of electronic cards is investigated; a discussion of findings is given.

INDEX WORDS: Electronic Payment Instruments, Electronic Card, Smart Card, ATM Card, Debit Card, Credit Card, Survey of Consumer Finances.

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To My Tee-Hee Han and Chloe Heewon Oh

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CHAPTER 1

INTRODUCTION

1.1 OBJECTIVES OF THE STUDY

The use of electronic banking products are increasingly important aspects of American life. A growing number of consumers regularly make purchase and pay bills electronically. Credit cards, for example, are widely adopted as the second most important small dollar payments technology, at least in terms of the number of transactions (BIS, 1995). Automated teller machines (ATMs) are widely available in our everyday lives.

Information technologies play a key role in restructuring financial services industries. Recent developments in telecommunication and computer technologies have greatly reduced the cost of electronic communication. Although there are positive evidences in support of upcoming arrival of e-banking era, We should not ignore the fact that information technologies cannot change the behavior of consumers in a short time period. In spite of this fact, much of the discussion of electronic banking has emphasized on the supply side of the market (Kennickell & Kwast, 1997).¹ Relatively little attention has been paid to the demand side of the financial service market, most importantly, consumers.

¹ Most salient issues are: How and what types of are being provided by banks and other supplier of financial services? How will electronic banking affect the competitive position of banks and other financial institutions? Much of the rest of the discussion has focused on potential public policy issues, such as consumer protection and privacy concerns, and monetary policy.

1.2 RESEARCH QUESTION

It is clear that success for all payments services providers will reside in their effectiveness in understanding consumers' demand characteristics and their usage patterns. No electronic banking service can survive without consumers' support. Only four major breakthrough products have succeeded: mutual funds, credit cards, automated teller machines (hereafter, ATM), and money market funds. Only two electronic financial services are welcomed by consumers: credit cards and ATM.

In order to understand the present and the future of electronic payment banking, we need to consider such question as: What are the characteristics of current and likely future users of electronic products and services? What types of products are consumers likely to be actually willing to user?

Specifically, we are interested in the following questions: 1) What are the socio-economic characteristics of current and likely users of electronic cards? 2) What are the personal factors to influence the probability of using electronic cards?

Understanding of present and potential demand for electronic banking is critical to understanding current and future trends in the financial industry. One of the most important issue is to understand "who uses" and "why they use" questions. This paper attempts to fill a void in financial service industry researches by surveying users and their financial behavior. We try to build statistical models which may provide good estimation of the probability of using electronic payment instruments (hereafter, EPI). Logistic regression and probit regression models are used to estimate the probability of having EPI.

The next chapter presents a brief review of the burgeoning electronic banking "literature," with a focus on demand-side concerns, and provides some aggregate

perspective on the use of electronic payment instruments. Chapter III summarizes the data used in this research, gives the definitions and its descriptive statistics of electronic services used in this survey. Hypotheses are also formulated. In Chapter IV, statistical methods employed in this research are explained. Chapter V summarizes the results of statistical tests, and the final Section gives conclusions.

CHAPTER 2

LITERATURE REVIEW

2.1. OVERVIEW OF THE STRUCTURE OF ELECTRONIC PAYMENT

This section provides a brief overview of electronic payment instruments used in the United States. Electronic payments include credit cards, debit cards, ATM cards, and smart cards. Dependent variables for the analysis are the probabilities of using electronic payment instruments such as smart, ATM, debit, and credit cards.

The relative importance of electronic payments obviously increased as the relative importance of checks declined. The Electronic Payment Instruments Study (EPIS) estimated the volume and dollar value of electronic payments. This study estimated that during calendar year 2000, 29.5 billion electronic payments were originated in the United States with a volume of \$7.3 trillion (FRS, 2001).²

2.1.1 CREDIT CARD

As shown in the Table 2.1, on a transaction volume basis, credit cards were the most common electronic payment instrument used in the U.S. during the Year 2000. Credit cards accounted for 51% of all electronic payment transactions and accounted for 17% of the dollar value.

² The study was conducted by surveying the leading electronic payment processors. This study is used as a critical reference in this section.

Table 2.1: Total Estimated Volume and Dollar Value of Electronic Payments.

Electronic Payment Instrument	Transaction Volume (Millions)	Dollar Volume (\$Millions)	Average Payment Value
General purpose credit cards	12,300.2	\$1,072,555	\$87.20
Private label credit cards	2,748.6	\$162.819	\$59.24
Offline debit (signature-based)	5,268.6	\$209,980	\$39.85
Online debit (PIN-based)	3,010.4	\$138,151	\$45.89
Automated Clearing House (ACH)	5,622.0	\$5,674,851	\$1,009.40
Electronic Benefits Transfer (EBT)	537.7	\$13,744	\$25.56
Total	29,487.5	\$7,272,100	\$246.62

The share of households owning credit cards increased by 3 percent between 1989 and 1992 and 5 percent between 1992 and 1995. The number of major credit cards used also increased from 157 million to 331 million between 1984 and 1993, and in 2000 more than a billion credit cards of all types were in circulation in the United States, which means an average cardholder carries nine different cards (Kaynak and Harcar, 2001).

2.1.2 DEBIT CARD

Following credit cards, debit cards represented the second most common instrument of electronic payment. Debit cards accounted for 8.3 billion transactions and a dollar value of \$348 billion in 2000. Debit card payments have been growing quite rapidly.

Two types of debit cards are distinguished: on-line (PIN-based) and off-line (signature-based). Online debit card transactions require the customer to enter a four-digit PIN (personal identification number) as a means of authentication (as opposed to signing a sales receipt). Online debit card transactions are originated, cleared, and settled over EFT

networks (the same networks that process ATM transactions) as opposed to Visa or MasterCard's networks.

Offline debit refers to debit card transactions that require the customer's signature (rather PIN) as a means of authentication. Visa and MasterCard have the only two networks for offline debit transactions. In 1997, there were more off-line transactions than on-line, even though merchants' fees and risk are higher for off-line debit card payments.

2.1.3 SMART CARDS

A smart card is essentially a plastic card, the size of a credit card, which bears a small microprocessor. The microprocessor makes the card 'smart' and differentiates it from other plastic cards (Collins, 1999). With an embedded microprocessor, smart cards have the unique ability to store large amounts of data, carry out their own on-card functions (e.g., encryption and digital signatures) and interact intelligently with a smart card reader. Compared to conventional magnetic-stripe cards, smart cards offer enhanced security, convenience, economic benefits and multi functions. In addition, smart cards make it possible to use personalized service (Choi & Whinston, 1998).

Smart card sales could reach 1.6 billion units in 1998, up 23% from 1.3 billion units in 1997. However, American consumers tend to regard smart cards as a redundant payment mechanism when checks, credit cards and ATM cards do an adequate job for current needs (Choi & Whinston, 1998).

2.1.4 ATM CARD

Automated teller machines are instruments which enable consumers to have remote access to their bank accounts. Most on-line debit cards can only be used regionally through a merchant base that is directly linked to the relevant regional ATM network. ATM cards generally function as on-line cards, with funds authorization and transfer operating through the regional bank ATM network (Caskey & Sellon, 1994). The number of ATMs continues to grow, from 187,000 in June 1998 to 227,000 by March (Gosnell, 1999). Most banks do not simply offer ATM services to customers at the bank's ATMs; they also participate in one or more shared ATM networks (Horvitz, 1996).

2.2 OVERVIEW OF DEMOGRAPHIC CHARACTERISTICS

Information about who currently uses electronic payments and how users and non-users differ in terms of demographics and socio-economics provides greater insights into the marketers and policy makers. The existing literature suggests that consumers' preferences are not homogeneous and that demographic characteristics affect consumer choice of payment methods. For example, Mantel (2000) investigated consumers' decision about whether to use paper checks or direct debit for bill payments and found some demographic characteristics important in influencing consumers' choice of payment instruments. A study by the consulting firm Booz Allen and Hamilton (BAH, 1997) found that demographic characteristics of users are the key predictors of consumer demand for e-banking.

Using data from the 1995 SCF, Kennickell and Kwast (1997) investigated the use of various types of payment instruments by households. They found that income, assets,

age, and education influence consumers' choice of payment instruments. Carow and Staten (1999) used a survey data of consumers' gasoline purchase to examine which factors affect consumers' decision about whether to use cash, credit cards, or debit cards. They found that middle-aged consumers with less education, lower income, and fewer credit cards were more likely to use cash compared to the rest of the sample. Daniels and Murphy (1994) found that ATM usage increases with education and income, while the usage of transaction accounts decreases with age.

2.3 OVERVIEW OF PERSONAL CHARACTERISTICS

Demographic factors prove important in explaining cross-section differences in terms of the probability of using electronic cards. Recently, consumer attitudes have been found in a number of studies to make net contributions to the explanation of the variation over time in consumer spending (Ferber, 1973). According to Morgan (1958), some attitudes expressed at the beginning a year appear to be related to subsequent levels of expenditure during the year even though the effect of the major demographic variables on consumer investment expenditures have been controlled. They argued that feeling better off financially than a year ago, and expecting to be making more a year hence are both positively associated with spending on consumer investments.

Expectation toward economic condition such as interest rate, economic status in the future has been used as important indicator (Acemoglu and Scott, 1994), since consumers' attitude, pessimism or optimism, tend to influence on the macroeconomic status. By the same token, consumers' attitudes toward economy also affect their

consumption plan. It was found that there is a significant relationship between interest rates and consumer spending (Ferber, 1973).

Consumers' exposure to information is also an important factor to predict the consumption behaviors (see Moorthy etc. for a review). Product or service information influence on consumers' preference. Therefore, we can infer that consumers with optimistic attitude toward economy or more information would have more probability of using EPI.

CHAPTER 3

DATA AND HYPOTHESES

3.1 DATA DESCRIPTIONS

The data from the 2001 Survey of Consumer Finances (SCF), which includes a set of questions regarding households' use of electronic media for financial transactions and decision making, is analyzed in this research. The SCF is a triennial survey of the finances and other demographic characteristics of U.S. families³ sponsored by the Federal Reserve Board in cooperation with the Department of the Treasury. Since 1992, National Organization for Social Science and Survey Research at the University of Chicago (NORC) have collected data.

Since the SCF also collects a large amount of other data on respondents' assets, liabilities, income, expenses, use of financial services, and demographic characteristics, the survey provides a very rich source of information on not only the current usage of electronic media, but also the socio-economic characteristics of both users and nonusers.

To ensure the representativeness of the population, the SCF employs a dual sample design consisting of two parts: a standard geographically based random sample and a special over-sample of relatively wealthy families. Weights are used to combine information from the two samples to estimate the characteristics of full population. In the 2001 main survey, about 22,000 were interviewed. According to Kennickell (2003),

³ The term, families, is more comparable to the U.S. Bureau of the Census definition of "households" than to their use of "families," which excludes the possibility of one-person family.

missing data were multiply imputed using a largely covariance-based approach. The 2001 survey was conducted between May and December of that year.

3.2 VARIABLE DESCRIPTIONS AND MEASUREMENTS

The independent variables of interest in this analysis are as follows: household income, age, education level, use of financial software, two information seeking behavior for financial decisions, and two attitude variable toward economy.

Income is used as a measure of need for EPI. Income is the respondent's annual household income. To measure incomes, the SCF requested information on families' total cash income, before taxes, for the full calendar year preceding the interview. The data has been recoded into eight levels: no income to level 1; \$1 to \$20,000 to level 2; \$20,001 to \$40,000 to level 3; \$40,001 to \$60,000 to level 4; \$60,001 to \$80,000 to level 5; \$80,001 to \$100,000 to level 6; \$100,000 to \$200,000 to level 7; and over \$200,001 to level 8.

Education level is used as a measure of the households' ability to use and manage EPI. Respondents were asked to answer the highest degree they have earned. A license was excluded in the choice set. In an original data set, twelve categories are used to classify education levels. But, in the public data set, some categories are combined with similar categories, which results in only six categories. For instance, MBA degree is pooled with MA/MS degrees.

The use of financial software is selected as another measure of the household's ability to use and manage EPI. To get the information on their computer use, the interviewees were asked to answer whether they (or their spouse) use any type of software to help them with managing money. If they said "yes", it was coded "1", otherwise "5".

Age, the respondent's age, is used as a measure of experience with financial institutions. Respondents were first asked their date of birth. After that, they were asked to confirm their reconciled age by interviewers who calculated their exact age using the computer. The data has been classified into six levels: 18 to 30 to level 1; 31 to 40 to level 2; 41 to 50 to level 3; 51 to 60 to level 4; 61 to 70 to level 5; and over 71 to level 6.

Two measures (SHOPLOAN and SHOPSAV) are used as measure of information seeking behaviors. When making major decisions about credit or borrowing (or saving and investment), some people shop around for the very best terms while others don't. Respondents were asked to choose the most appropriate degree among the 5-point scale. The scale starts from "1.almost no shopping" to "5. a great deal of shopping."

Two measures are selected to estimate attitudes toward economy. In order to know their expectation for the future of economy (coded as ECON), interviewer asked a question as follows: "Over the next five years, do you expect the U.S. economy as a whole to perform better, worse, or about the same as it has over the past five years?" By the same token, respondents were asked to tell their expectation for interest rates after five years from now. The choice set consists of "1. higher," "2. lower," and "3. about the same."

On the other hand, the dependent variables in this study are as follows: smart cards, debit cards, ATM cards, and credit cards. Respondents were asked "Do you or anyone in your family living here have any such cards that you can use for a variety of purchases?" Two options, yes or no, were presented. The same type of questions was provided to respondents to know whether they use it or not. These binary variables were

coded as 1 if the answer was “yes,” and 0 if the answer was “no.” If the answer was labeled “inappropriate,” the variable was coded as missing (Stavins, 2001).

3.3 DESCRIPTIVE ANALYSIS: FREQUENCIES

For descriptive analyses, frequencies and percentages of each variable were calculated using SAS ‘proc freq’ procedure. The result is shown in Table 3.1. Among those variables, only demographic variables are of interest in this section.

As shown in the Table 3.1, about 23%, the most percentage in groups, of households has no income. The second most group is from 20,000 to 40,000. As for age, mostly distributed age group is 41 to 50. As for education, more than half of respondents had some education of grade 1 through grade 12. About half of respondents had college or beyond college degree.

While more than 80 percent of people are using credit cards, very small portion of people (3.06%) have smart cards. ATM card is the second most popular electronic payment instrument in a banking market. About 43% of people are using debit cards.

3.4. DESCRIPTIVE ANALYSIS: HISTOGRAMS

Each figure introduced in this chapter has two histograms. The upper one shows the pattern of distribution among user groups. The below one shows the pattern of distribution among nonuser groups. The height of bar is defined as the proportion of a group out of the total user group. In other words, the summation of each bar (i.e., six bars in the case of Figure 4.1) is equal to 100 percent. It is important to recognize that the height of each bar is dependent of the sample characteristics of the survey.

Table 3.1. Demographic Description.

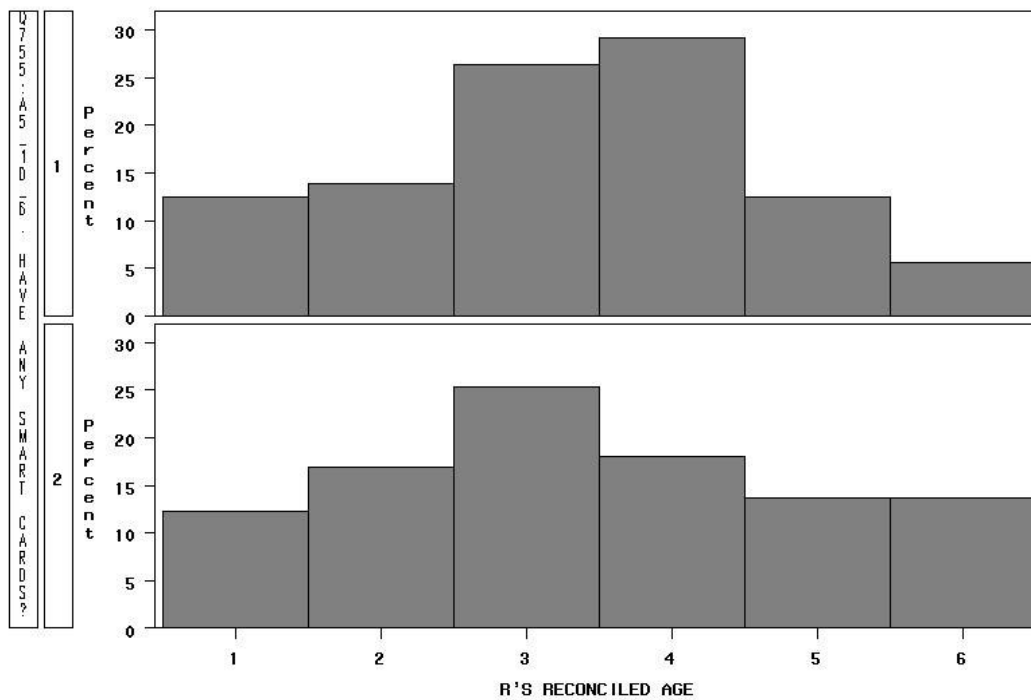
	Levels	Numbers	Percentage
Household income	no income	5,291	23.82
	1-20,000	3,258	14.67
	20,000-40,000	3,847	17.32
	40,000-60,000	2,490	11.21
	60,000-80,000	1,865	8.4
	80,000-100,000	1,164	5.24
	100,000-200,000	2,001	9.01
	Over 200,000	2,294	10.33
Age	18-30	2,744	12.35
	31-40	3,762	16.94
	41-50	5,545	24.97
	51-60	4,368	19.67
	61-70	2,796	12.59
	Over 71	2,995	13.48
Education level	0. Associate's	11,996	54.01
	1. Others	967	4.35
	2. Bachelor's	4,889	22.01
	3. MA/MS/MBA	2,417	10.88
	4. PhD/MD/JD	1,890	8.51
	11. Inappropriate	51	0.23
Attitude toward Future economy	1. Better	6115	27.53
	2. Worse	7450	33.54
	3. About the same	8645	38.92
Attitude toward Interest rate	1. Higher	14486	65.22
	2. Lower	1537	6.92
	3. About the same	6187	27.86
Shopping for loan	1. Almost no shopping	4692	21.13
	2.	1664	7.49
	3. Moderate shopping	8034	36.17
	4.	2898	13.05
	5. A great deal of shopping	4922	22.16
Shopping for saving	1. Almost no shopping	5356	24.12
	2.	2051	9.23
	3. Moderate shopping	7232	32.56
	4.	2966	13.35
	5. A great deal of shopping	4605	20.73
Use of financial software	Yes	5702	25.67
	No	16508	74.33

Have smart card	Yes	680	3.06
	No	21530	96.94
Have ATM card	Yes	15960	71.86
	No	5394	24.29
Have credit card	Yes	18088	81.44
	No	4122	18.56
Have debit card	Yes	9647	43.44
	No	11711	52.73

For instance, the height of bar group 7 takes is supposed be relatively low, since the proportion of elderly people in the population is very low. In the process of survey, respondents were allowed to choose appropriate answer among three. Users are coded as 1, Nonusers are coded as 2. Missing data is ignored in this analysis, since it has no practical meaning.

Figure 3.1. Proportion of Smart Card Users/Nonusers by Age.

1 represents users, 2 represents nonusers.



As shown in Figure 3.1, the proportion of smart card users increases as age increases from group 1 to group 4. Group 1 represents young people (from 18 to 30), and group 4 represents 41~50 old people. The proportion of smart card users is the highest at group 4. However, a decreasing trend is observed at the range of over 50s. It suggests that elderly people tend to be less familiar at smart cards.

Figure 3.2. Proportion of Credit Card Users/Nonusers by Income.

1 represents users, 2 represents nonusers.

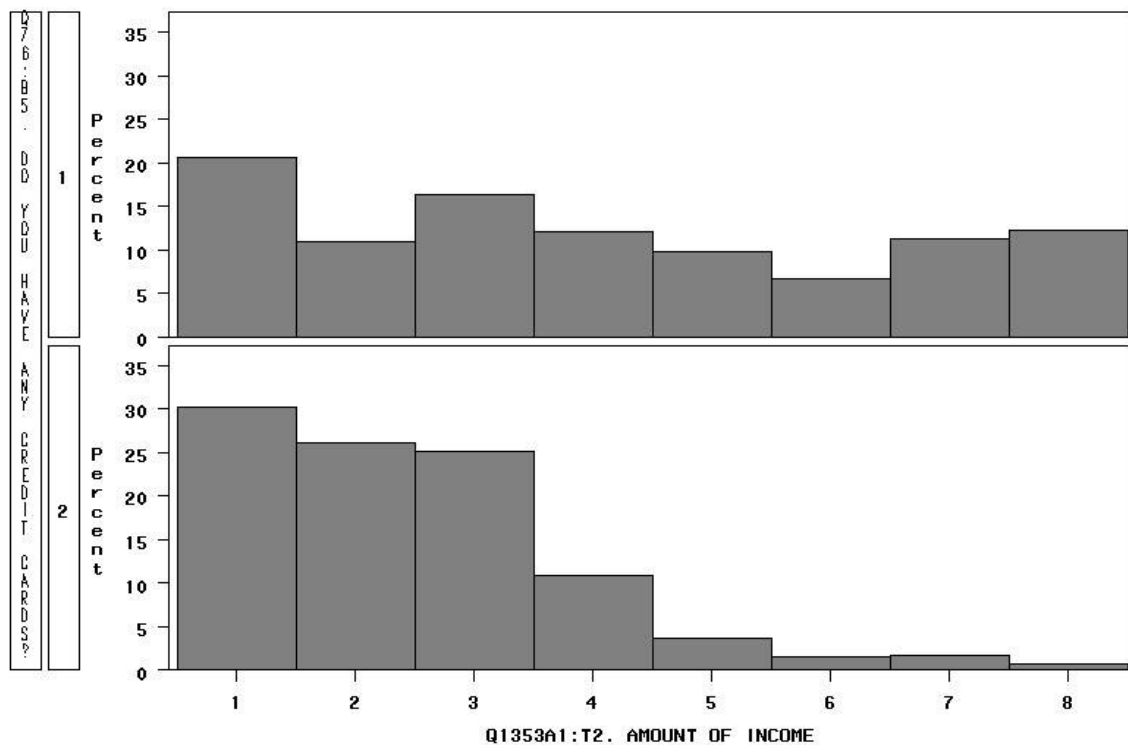
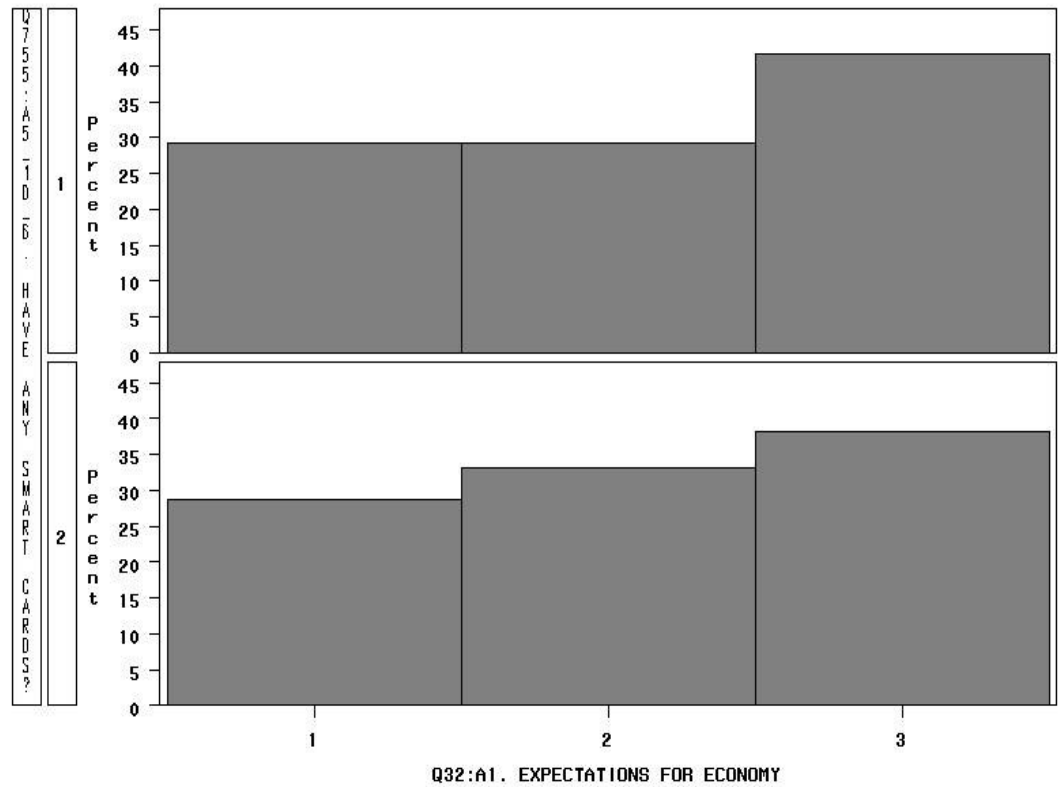


Figure 3.2 suggests that a global pattern exists in terms of the relation between the level of income and the proportion of credit card users. The below graph shows a clear decreasing pattern. In group 1, there are a lot of nonusers, however, in group 8, there are very few nonusers. It implies that older people are more likely to use credit cards.

Figure 3.3. Proportion of Credit Card Users/Nonusers by Attitude toward Economy.
1 represents users, 2 represents nonusers.



In Figure 3.3, group 1 represents people with positive attitude toward the future economy, on the other hand, group 2 represents people with negative expectation. The proportion of group 1 out of the total is 27.5, and that of group 2 is 33.5, group 3 is 38.9%. Even though some patterns seem to exist, it is hard to conclude only by using graphic information. Other histograms are placed in Appendix B. In the next section, a set of hypothesis are built to test the casual relationships between predictors and the probability of electronic card use.

3.5 HYPOTHESES

Need for electronic payment instruments (EPI)

H 1: The level of household income will be significantly related to have EPI.

H1-1: Higher income households are more likely to have EPI

Ability to Manage EPI: Human Capital Resources

H 2: The level of education will be significantly related to have EPI.

H2-1: More educated households are more likely to have EPI.

H 3: Information sources which consumers rely on (i.e., the use of computer software) will be significantly related to the likelihood that a consumer will take the use of EPI.

Experiences with Financial Institutions

H 4: The level of age will be significantly related to have EPI.

H 4.1: Older persons are more likely to have EPI.

Information seeking behavior

H 5: Information seeking behavior will be significantly related to the use of EPI.

H 5-1: Information seeking for major decisions about credit or borrowing will be significantly related to the likelihood that a consumer will take the use of EPI.

H 5-2: Information seeking for major decisions about saving and investment will be significantly related to the likelihood that a consumer will take the use of EPI.

Attitude toward economy

H 6: Attitude toward economy will be significantly related to the use of EPI.

H 6-1: Expectation for the future economy will be significantly related to the use of EPI.

H 6-2: Expectation for the future interest rates will be significantly related to the use of EPI.

CHAPTER 4

STATISTICAL MODELS

The response variable of main interest in the thesis is whether people use electronic cards or not. To attain the goal of the research, we try to build an optimal model that enables us to predict the probability of using electronic cards.

Let Y_{ijkl} represent users and nonusers of an electronic card. Then, Y_{ijkl} can be modeled as a Bernoulli random variable with following distribution.

$$Y_{ijkl} = \begin{cases} 1 & \text{with probability } \pi_{jkl} . \\ 0 & \text{with probability } (1 - \pi_{jkl}) , \end{cases}$$

where i represents customers ($i=1 \dots n$).
 j represents income groups ($j=1 \dots 8$).
 k represents age groups ($k=1 \dots 6$).
 l represents education groups ($l=1 \dots 5$).⁴

The expected value of Y_i is $E[Y_{ijkl}] = \pi_{jkl}$. We will assume that Y_{ijkl} are independent random variables for all i, j, k, l . We now model $E[Y_{ijkl}]$ and π_{jkl} using logistic and probit distributions.

However, the SCF data we use may have a correlation problem from which most social survey data suffer. If it is the case, the independence assumption does not make

⁴ For the simplicity, we suppose that there are only three predictors even though eight indicator

sense. Considering the possibility of correlation among predictors, we apply a random effect probit model to our data. In sum, the statistical methods employed in this analysis consist of two main parts: models assuming independent random variables and a model assuming possible correlation.

4.1 LOGISTIC REGRESSION

The function of simple logistic regression is:⁵

$$f(x) = \frac{e^{(\beta_0 + \beta_1 X)}}{1 + e^{(\beta_0 + \beta_1 X)}} = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X)}} = \left(1 + e^{-(\beta_0 + \beta_1 X)}\right)^{-1}.$$

Hence, $\log\left(\frac{f(x)}{1-f(x)}\right) = \beta_0 + \beta_1 X$. The function $\log\left(\frac{f(x)}{1-f(x)}\right) = \log it(f(x))$ is

called the logit function. The regression is modeled using the equation

$$\log it(f(x)) = \beta_0 + \beta_1 X.$$

The ratio of $\frac{\pi}{1-\pi}$ in the logit transformation is the definition of odds ratio. To

estimate coefficients of variables in a logit model, maximum likelihood estimation techniques is used. In our case, $\log it(\pi_{ijkl})$ is modeled.

4.2 PROBIT MODEL

By the similar reasoning, the probit equation can be derived. Probit equation can be defined using the following equation.

variables are of our interest.

⁵ For the simplicity, a simple logistic regression is mentioned. The logic can be expanded to the multiple logistic regression.

$$p = \Pr(Y = 0) = C(1 - C)F(x'\beta),$$

where p is the probability of a response.

C is the threshold response rate.

x is a vector of explanatory variables.

F is a cumulative distribution function of a normal distribution.

β is a vector of parameter estimates.

In our problem, we model $\Pr obit(\pi_{jkl})$.

4.3 RANDOM EFFET PROBIT MODEL⁶

When the assumption of independent random variables does not seem to be valid, probit model with random effect is an alternative analysis. In a random effect model it is assumed that there is natural heterogeneity across the variables and that this heterogeneity can be modeled by a probability distribution (in our case normal distribution). By using this approach, correlation can be considered in this random effect probit model. This is the example for random effect probit model:

$$\Pr obit(P(Y_{ij} = 1|u_i)) = \beta_0 + \beta_1 * X_{ij} + u_i.$$

u_i are assumed to be independent and to follow $N(0, \sigma^2_u)$. The variance, σ^2 , is used to measure the degree of heterogeneity in the probability of using electronic cards that can not be explained by independent variables. It is also assumed that, given u_i , the correlation among predictors are thoroughly explained. To conduct random effect probit models, the NLMIXED procedure which is available in SAS is used. The NLMIXED

⁶ For more information, see McCulloch and Searle (2001).

procedure attempts to maximize the likelihood directly by numerical integration methods such as adaptive Gaussian quadrature.⁷

4.4 TUKEY'S TREND TEST⁸

To investigate the differences among subgroups (i.e., low-income vs. high-income household), Tukey's trend test is employed. It is because Tukey's test is strong in terms of multiple comparisons of interval data which are used in the SCF data measurement. Furthermore, Tukey's test makes it possible to conduct all pairwise comparisons. This multiple comparison procedure enables us to compare the average effects of three or more levels of indicator variables. Using detailed information Tukey's trend test provides, we can understand which subgroups are more likely to use electronic cards. Tukey's method depends upon the standardized pairwise differences such as

$$t_{ij} = \left(\frac{\bar{y}_i - \bar{y}_j}{\hat{\delta}_{ij}} \right),$$

where i and j are the indices of two groups.

$\bar{y}_i$ and $\bar{y}_j$ are the means or Least Square-means(LS-mean) for groups i and j .

$\hat{\delta}_{ij}$ is the square-root of the estimated variance of $\bar{y}_i - \bar{y}_j$.

In Tukey's test, two means are considered significantly different by the Tukey-Kramer criterion if

$$|t_{ij}| \geq q(\alpha; k, v),$$

⁷ SUGI 27, Statistics and Data Analyses. Available at www.sas.com.

⁸ For more information, see Tukey, Ciminera, and Heyse (1985).

where $q(\alpha; k, \nu)$ is the α -level critical value of a studentized range distribution of k independent normal random variables with ν degrees of freedom.

4.5. MODEL SELECTION

4.5.1 DEVIANCE

The deviance of a model is defined as -2 times the log-likelihood of the model:

$$G^2 = -2 \log_e L.$$

As a model's ability to predict outcomes improves, the deviance decreases. On the contrary, poorly-fitting models have higher deviance. This is analogous to the residual in linear regression. The residual is $(y - \hat{y})$. By using deviance residual, the deviance can be defined as follows.

$$D = \sum_{j=1}^J d(y_j, \hat{\pi}_j)^2.$$

The distribution of the D under the assumption that the fitted model is correct in every aspect is supposed to follow chi-square with degrees of freedom equal to $J - (p + 1)$. By this fact, D is the likely ratio test statistic of a saturated model with J parameters versus the fitted model with $p + 1$ parameters (Hosmer & Lemeshow, 1989).

4.5.2 LIKELIHOOD-RATIO TEST

The likelihood-ratio test using the deviance is similar to the F test from linear regression. The likelihood test statistic has a chi-square distribution with k degrees of freedom:

$$\chi^2 = 2(\log_e L_1 - L_0),$$

where L_0 is the likelihood from the null model with no variable.

L_1 is the likelihood from the model of interest.

The likelihood-ratio test rejects the null hypothesis if the value of this statistic is too low. The decision is dependent upon the significance level of the test (Agresti, 1996; Hosmer & Lemeshow, 1989).

4.5.3. PEARSON CHI-SQUARE

Pearson chi-square test is used for a test of goodness of fit. It provides information about whether or not an observed frequency distribution differs from a theoretical distribution. Pearson chi-square is employed to test a goodness of fit in this research. Chi-square is calculated by this formula:

$$\chi^2 = \sum \frac{(O - E)^2}{E},$$

where O is an observed frequency.

E is an expected frequency, asserted by the null hypothesis.

To conduct Pearson chi-square test, the events must be mutually exclusive and each must occur at least once each time. The data used in this research satisfies these requirements (Agresti, 1996; Hosmer & Lemeshow, 1989).

4.5.4 AIC

Akaike information Criterion (AIC) is also used to evaluate the goodness-of-fit of the model. The formula of AIC is: $AIC = 2 \log \text{likelihood} + 2p$. p is the number of predictors (Hosmer & Lemeshow, 1989).

4.5.5 STEPWISE METHOD

One of the approaches to variable selection is to use a stepwise method in which variables are selected either for inclusion or exclusion from the model in a sequential fashion based on solely on statistical criteria. The stepwise approach is useful when we conduct the exploratory analysis, since it builds models in a sequential fashion and it allows for the examination of a collection of models which might not otherwise have been examined.

The reason to select a stepwise method in this research is that it provides an effective means to screen a large number of variables, and to simultaneously fit a number of logistic equations (Hosmer & Lemeshow, 1989). With the aid of the stepwise procedure, we can identify plausible interactions generated from eight main effects.

Backward stepwise regression is used in the thesis since it is a usually preferred method of exploratory analyses (Agresti, 1996; Hosmer & Lemeshow, 1989; Menard, 1995). The backward stepwise is based on a statistical algorithm which checks for the “importance” of variables, and excludes them on the basis of a fixed decision rule. The backward stepwise begins with a saturated model, eliminated variables through an iterative process, and stopped when no more variables can be excluded from the model.

The importance of a variable is defined in terms of a measure of the statistical significance of the coefficient for the variable. In logistic regression the error are assumed to follow a binomial distribution. As a consequence, the assessment of significance is based on the likelihood ratio chi-square test. Therefore, at any step in the procedure the most important variable is the one that produces the greatest change in the log-likelihood relative to a model not containing the variable (Hosmer & Lemeshow, 1989). In this analysis, we choose $p = 0.1$ as an elimination criterion, since using the $p = 0.05$ criterion may take the risk to miss the important variables in the process.

CHAPTER 5

RESULTS

5.1 LOGISTIC REGRESSION WITH NO INTERACTION MODEL

The relation between eight predictors and the probability of adopting electronic cards was analyzed using SAS ‘PROC GENMOD’ procedure. The chosen models satisfied convergence criterion.

5.1.1. PREDICTORS THAT AFFECT THE USE OF SMART CARD

Among predictors, income, age, attitude toward future economy, shopping behavior for saving, and the use of financial software are significantly related to using smart cards. As shown in table 5.1, those variables are significant at $\alpha = 0.05$ level.

Table 5.1. Deviance and Pearson Goodness-of-Fit Statistics.

<u>Criterion</u>	<u>DF</u>	<u>Value</u>	<u>Value/DF</u>	<u>Pr > ChiSq</u>
Deviance	4001	5239.4571	1.3095	<.0001 *
Pearson	4001	16606.5929	4.1506	<.0001 *

* represent “statistically significant at $\alpha = 0.05$ level.

Deviance and Pearson chi-square confirm that model fits good (p-value < .0001).

Table 5.2. Relation of Having Smart Card respect to Predictors.

LR Statistics For Type 3 Analysis			
Source	DF	Chi-Square	Pr > ChiSq
income	7	37.12	< .0001 *
age	5	22.71	0.0004 *
education	5	9.19	0.1016
attitude toward economy	2	21.42	< .0001 *
attitude toward interest rate	2	1.90	0.3860
shopping behavior for loan	4	5.28	0.2595
shopping behavior for saving	4	23.29	0.0001 *
use of financial software	1	34.12	< .0001 *

First, the need for a smart card which was measured with income was significantly related to the adoption of smart cards ($p < .0001$). Odds ratio confirms that higher income households will be more likely to have smart cards. Odds ratio estimates resulted in positive estimates, which mean that the unit increase of income is followed by the increase of likelihood to adopt smart cards. For example, other variables being constant, the one unit of increase of income from category 1 to category 2 is followed by the 0.667 increase of odds ratio

Second, the ability to manage smart cards which was measured with education levels was not significantly related to the use of smart cards. Third, experiences with financial institutions, which were measured with age, turned out to be significantly related with smart cards. The hypothesis that older people are more likely to have smart cards was confirmed by odds ratio. Older people are more likely to adopt smart cards.

Fourth, the use of computer software for financial management is a significant predictor to explain the use of smart cards. When compared to those who not use software, users are more likely to take the use of smart cards. Odds ratio is increased by 1.68 units.

In order to test a relationship between information seeking behavior and the use of smart cards, two measures were used: Information seeking for major decisions about credit or borrowing and for major decisions about saving and investment. The LR statistics for type 3 analysis support that information seeking for major decisions about saving and investment is significantly related to the likelihood that a consumer use smart cards. However, information seeking for major decisions about credit or borrowing is not significantly related to the likelihood that a consumer will take the use of smart cards.

To test the impact of attitude toward economy, two measures were used: expectation for the future economy and expectation for the future interest rates. While expectation for the future economy is significantly related to the use of smart cards, expectation for the future interest rates is not related to smart card usage. Positive attitude to the future economy increases the likelihood to use smart cards. Positive expectation for the future interest rates seems to increase the likelihood of using smart cards, but it is not significant at .05 levels.

5.1.2. PREDICTORS THAT AFFECT THE USE OF ATM CARD

All predictors except attitude toward the future economy, as shown in Table 5.4 are significant at .01 levels. The hypothesis that higher income households will be more likely to have an ATM card is supported by odds ratio. Odds ratio estimates are positive, which means that the increase of income levels is followed by the increase of odds ratio.

Table 5.3 Deviance and Pearson Goodness-of-Fit Statistics.

Criterion	DF	Value	Value/DF	Pr > ChiSq
Deviance	8032	21985.0987	2.7372	<.0001 *
Pearson	8032	32737.4031	4.0759	<.0001 *

Based on the goodness-of-fit-tests, it is confirmed that the model fits good.

Deviance criterion is satisfied (p-value < .0001), and Pearson chi-square test turns out to be significant (p-value < .0001).

Table 5.4. Relation of Having ATM Card respect to Predictors.

LR Statistics For Type 3 Analysis			
Source	DF	Chi-Square	Pr > ChiSq
income	7	68.54	< .0001 *
age	5	1243.25	< .0001 *
education	5	100.92	< .0001 *
attitude toward economy	2	1.58	0.4543
attitude toward interest rate	2	6.40	0.0407 *
shopping behavior for loan	4	25.41	< .0001 *
shopping behavior for saving	4	24.54	< .0001 *
use of financial software	1	30.67	< .0001 *

By the same token, hypothesis 2 is supported. We projected that more educated households would be more likely to have an ATM card. It is supported by positive odd ratio estimates. Experiences with financial institutions also influences on the likelihood to use the ATM card. Odds ratio estimates support that older persons are more likely to use the ATM card. However, the increase of odds ratio by the increase of one unit (10 years) is not as large as income or education.

The use of financial software, independent variable to measure information source, is significantly related to the likelihood that a consumer take the use of the ATM cards. Two measures for investigating the impact of information seeking behavior are also significant predictors to impact on the usage of the ATM cards. Based on positive odds ratio estimates, we can interpret that those who seeking information for major decision about credit or saving with more effort are more likely to use the ATM cards.

Contrary to the smart card analysis, attitude toward the future economy is not significantly related to the use of the ATM cards. Instead, expectation for the future interest rates turns out to be a significant predictor. In the analysis of smart cards, expectation for the future interest rates was not significant.

5.1.3. PREDICTORS THAT AFFECT THE USE OF DEBIT CARD

Income, age, education, attitude toward economy, shopping behavior for loan and saving, and the use of financial software are significant at .05 levels. Only attitude toward the future interest rate turns out to be insignificant.

Table 5.5. Deviance and Pearson Goodness-of-Fit Statistics.

<u>Criterion</u>	<u>DF</u>	<u>Value</u>	<u>Value/DF</u>	<u>Pr > ChiSq</u>
Deviance	8032	21985.0987	2.7372	<.0001*
Pearson	8032	32737.4031	4.0759	<.0001 *

Pearson chi-square test confirms that the model fits well (p-value < .0001) as well as a deviance criterion.

Table 5.6. Relation of Having Debit Card respect to Predictors.

LR Statistics For Type 3 Analysis			
Source	DF	Chi-Square	Pr > ChiSq
income	7	192.61	< .0001 *
age	5	1508.35	< .0001 *
education	5	71.07	< .0001 *
attitude toward economy	2	9.21	0.0100 *
attitude toward interest rate	2	0.15	0.9272
shopping behavior for loan	4	36.36	< .0001 *
shopping behavior for saving	4	14.25	0.0065 *
use of financial software	1	38.30	< .0001 *

The need for a debit card, which was measured with income, was significantly related to the adoption of debit cards. Odds ratio estimates are all positive, which means that higher income households are more likely to use debit cards.

It is supported that the ability to manage debit cards is a significant influencer on the use of debit cards. Based on the odds ratio estimates, we found strong evidence that households that are more educated are more likely to take the use of debit cards.

It is also supported that more experiences with financial institution is associated with the adoption of debit cards. Despite the odds ratio estimates are below 1, those estimates are all positive which means that the older is more likely to use a debit card.

We hypothesized that information sources that consumers rely on (i.e., the use of computer software) are significantly related to the likelihood that a consumer will take the use of a debit card. The evidence supports it, and odds ratio showed that financial software users are more likely to take the use of debit cards.

Information seeking behaviors are significantly associated with the use of debit cards. Evidence supported information seeking for major decisions about credit or

borrowing is significantly related to the likelihood that a consumer take the use of debit card. In addition, more diligent information seekers for major decisions about saving and investment are more likely to use debit cards. It is supported by the fact that all odd ratio estimates are positive. While expectation for the future economy turns out to be a significant predictor, expectation for the future interest is not significant.

5.1.4. PREDICTORS THAT AFFECT THE USE OF CREDIT CARD

All predictors of interest are significantly related to the adoption of credit cards at .01 levels.

Table 5.7. Deviance and Pearson Goodness-of-Fit Statistics.

<u>Criterion</u>	<u>DF</u>	<u>Value</u>	<u>Value/DF</u>	<u>Pr > ChiSq</u>
Deviance	4001	10866.0688	2.7158	<.0001*
Pearson	4001	26769.6435	6.6907	<.0001 *

Based on the deviance test, it is highly significant that the model fits good (p-value < .0001). Pearson chi-square test also confirms that (p-value < .0001).

All predictors of interest are significantly related to the adoption of credit cards at .01 levels. Positive odds ratio estimates support the hypothesis that higher income households will be more likely to have EPI. More educated households are more likely to use credit cards, and older people are also more prefer using credit cards. Especially, an education variable resulted in very high odds ratio estimates. For example, one unit increase of education level from master's to Ph.D.'s is associated with 18.3 increase of odds ratio, which means that highly educated people strongly prefer credit cards.

Table 5.8. Relation of Having Credit Card respect to Predictors.

LR Statistics For Type 3 Analysis			
Source	DF	Chi-Square	Pr > ChiSq
income	7	1186.72	< .0001 *
age	5	561.82	< .0001 *
education	5	940.98	< .0001 *
attitude toward economy	2	27.75	< .0001 *
attitude toward interest rate	2	24.13	< .0001 *
shopping behavior for loan	4	137.25	< .0001 *
shopping behavior for saving	4	38.49	< .0001 *
use of financial software	1	264.00	< .0001 *

Financial software users are more likely to use credit cards. More frequent information seekers for decisions about credit or borrowing are more likely to adopt credit cards. Attitude toward economy also significantly related to the use of credit cards.

5. 2. PROBIT MODEL AND COMPARISON WITH LOGISTIC REGRESSION

In this section, probit analysis is conducted to check whether the logistic regression results are consistent or not. For the comparison, the same groups of independent variables are entered into the probit model. As a result, the probit models provide very consistent results when it compared to the logistic regression outcomes.

5.2.1 EVALUATION OF GOODNESS-OF-FIT FOR PROBIT MODEL

Pearson chi-square and likelihood ratio chi-square are used to evaluate the goodness-of-fit for the four probit models. For four models, Pearson chi-square test provides that all models fit well to the data (p-value < .0001). It is noticeable that the value Pearson chi-square provides is exactly the same as the one likelihood ratio chi-

square. It is because Pearson chi-square test is asymptotically equivalent to the likelihood ratio chi-square test (Hosmer & Lemeshow, 1989)

Table 5.9 Goodness-of-Fit Tests for Probit Models.

	Statistic	Value	DF	Pr > ChiSq
Smart Card	Pearson Chi-Square	16510.2517	4001	<.0001 *
	L.R. Chi-Square	5233.7222	4001	<.0001 *
ATM Card	Pearson Chi-Square	33632.9847	8032	<.0001 *
	L.R. Chi-Square	22162.4979	8032	<.0001 *
Debit	Pearson Chi-Square	32777.8373	8032	<.0001 *
	L.R. Chi-Square	26688.0223	8032	<.0001 *
Credit	Pearson Chi-Square	50675.4601	4001	<.0001 *
	L.R. Chi-Square	10957.4375	4001	<.0001 *

5.2.2 COMPARING PROBIT MODEL TO LOGISTI REGRESSION

We are concerned with the consistency issue, “Is the result provided by logistic regression consistent?” To answer for this question, we compared two significance tests of coefficients.

As shown in Table 5.10, the chi-square values are very close to each other, as a consequence, the significance of explanatory variables are the same. The same pattern can be found in the below Table 5.11.

Table 5.10 Comparison of Logistic and Probit Model: Smart Card.

Variable	<u>Logistic Model</u>		<u>Probit Model</u>	
	Chi-Square	Pr>Chi-S	Chi-Square	Pr>Chi-S
Income	37.12	<.0001	38.23	<.0001 *
Age	22.71	<0.0004	21.27	<.0001 *
Education	9.19	0.1016	11.74	0.385
Attitude Economy	21.42	<.0001	25.39	<.0001 *
Attitude Interest rate	1.90	0.3860	0.52	0.7723
Shop for Loan	5.28	0.2595	9.00	0.0611
Shop for Saving	23.29	0.0001	23.7	<.0001 *
Software	34.12	<.0001	37.61	<.0001 *

In terms of the significance of predictors, two different statistical analyses results in the consistent outcomes. Only slight difference is observed in the case of credit cards. Attitude toward interest which is significant in the logistic regression became insignificant in probit model at $\alpha = 0.05$ criteria.

Table 5.11 Comparison of Logistic and Probit Model: Debit Card.

Variable	<u>Logistic Model</u>		<u>Probit Model</u>	
	Chi-Square	Pr>Chi-S	Chi-Square	Pr>Chi-S
Income	192.61	<.0001	294.71	<.0001 *
Age	1508.3	<0.001	1105.8	<.0001 *
Education	71.07	<.0001	47.33	<.0001 *
Attitude Economy	9.21	0.01	15.95	<.0003 *
Attitude Interest rate	0.15	0.927	2.61	0.2718
Shop for Loan	36.36	<.0001	48.55	<.0001 *
Shop for Saving	14.25	0.0065	41.92	0.0001 *
Software	38.30	<.0001	112.52	0.0001 *

Table 5.12 Comparison of Logistic and Probit Model: ATM Card.

Variable	<u>Logistic Model</u>		<u>Probit Model</u>	
	Chi-Square	Pr>Chi-S	Chi-Square	Pr>Chi-S
Income	68.54	<.0001	172.94	<.0001 *
Age	1243.2	<.0001	796.99	<.0001 *
Education	100.92	<.0001	271.59	<.0001 *
Attitude Economy	1.58	0.4543	4.36	0.1132
Attitude Interest rate	6.40	0.0407	5.65	0.0592
Shop for Loan	25.41	<.0001	43.53	<.0001 *
Shop for Saving	24.54	<.0001	51.75	<.0001 *
Software	30.67	<.0001	105.41	<.0001 *

In spite of difference, it is not appropriate to conclude that logistic regression provides inconsistent results when compared to the probit analysis. In the case of credit cards, it is confirmed that two results are highly consistent.

Table 5.13 Comparison of Logistic and Probit Model: Credit Card.

Variable	<u>Logistic Model</u>		<u>Probit Model</u>	
	Chi-Square	Pr>Chi-S	Chi-Square	Pr>Chi-S
Income	1186.72	<.0001	737.91	<.0001 *
Age	561.82	<.0001	356.71	<.0001 *
Education	940.98	<.0001	730.40	<.0001 *
Attitude Economy	27.75	<.0001	28.08	<.0001 *
Attitude Interest rate	24.13	<.0001	18.29	<.0001 *
Shop for Loan	137.25	<.0001	137.19	<.0001 *
Shop for Saving	38.49	<.0001	36.18	<.0001 *
Software	264.00	<.0001	165.89	<.0001 *

In conclusion, no evidence showing inconsistency between logistic and probit models is found. Thus, we can state that overall comparisons confirmed the reliability of causal relationship between predictors and electronic cards.

5.3. RESULTS OF TREND ANALYSIS

In Chapter 3, we proposed that higher income households would be more likely to have electronic payment instruments. Based on human capital theory, we also projected that more education households would be more likely to use EPI. Assuming that older people might have more experiences with financial institutions, we expected that older persons would more likely to take the use of EPI. To test three hypotheses, we conducted trend tests using contrasts. The null hypothesis, H_0 that there is no linear trend, was to be tested against the alternative hypothesis H_1 . The results are as follows.

5.3.1 RESULT OF TESTING “NEED FOR EPI” HYPOTHESIS

We expected that persons with higher income would have more need to use EPI. If this hypothesis is right, then a significantly positive linear trend would be detected. This hypothesis is supported regardless of types of payment methods. In every case, there is a significantly positive linearity across subgroups.

Table 5.14 Trend Test for Income Groups: Smart.

LABEL	ESTIMATE	S.E.	Chi-Square	Pr > Chi-S
Whole	2.17	0.73	8.83	0.003 *
0~200,000	1.86	0.62	9.14	0.002 *
0~100,000	0.46	0.55	0.70	0.402
0~80,000	0.53	0.17	9.79	0.001 *
0~60,000	0.16	0.24	0.45	0.503
0~40,000	0.14	0.07	4.28	0.038 *
0~20,000	0.1	0.07	1.83	0.175

In the case of smart cards, there is significant evidence supporting this hypothesis. The value of parameter estimate is positive, 2.17, and its linear trend exists across all eight groups.

Table 5.15 Trend Test for Income Groups: Debit.

LABEL	ESTIMATE	S.E.	Chi-Square	Pr > Chi-S
Whole	1.30	0.38	11.66	0.003 *
0~200,000	3.64	0.32	131.6	<0.001 *
0~100,000	3.17	0.27	142.1	<0.001 *
0~80,000	1.03	0.09	136.7	<0.001 *
0~60,000	0.86	0.11	56.48	<0.001 *
0~40,000	0.27	0.03	65.1	<0.001 *
0~20,000	0.16	0.03	21.56	<0.001 *

In terms of debit cards, a strong linear trend is observed. In the all comparisons, there are linear trend across the groups. It strongly supports the hypothesis that richer people favor debit card more than poorer people do.

Table 5.16 Trend Test for Income Groups: Credit.

LABEL	ESTIMATE	S.E.	Chi-Square	Pr > Chi-S
Whole	16.53	0.84	378.99	<0.001 *
0~200,000	10.63	0.55	362.49	<0.001 *
0~100,000	6.85	0.41	276.36	<0.001 *
0~80,000	2.25	0.12	314.03	<0.001 *
0~60,000	1.74	0.14	143.76	<0.001 *
0~40,000	0.29	0.04	55.41	<0.001 *
0~20,000	0.03	0.03	0.67	0.412

In the credit cards case, significant trends also found. The value of parameter estimate, 16.53, is larger than those of other electronic cards. Only comparison of group 1

and group 2 turns out to be insignificant. ATM cards also have linear patterns among subgroups.

Table 5.17 Trend Test for Income Groups: ATM.

LABEL	ESTIMATE	S.E.	Chi-Square	Pr > Chi-S
Whole	3.66	0.42	73.12	<0.001 *
0~200,000	3.99	0.36	117.54	<0.001 *
0~100,000	3.02	0.31	94.29	<0.001 *
0~80,000	0.87	0.09	80.37	<0.001 *
0~60,000	1.22	0.12	94.93	<0.001 *
0~40,000	0.28	0.03	63.67	<0.001 *
0~20,000	0.10	0.03	8.94	0.002 *

In conclusion, there is strong evidence supporting that higher income households are more likely to use EPI. It confirms the traditional wisdom in marketing fields. Using income factor as a predictor proves highly effective according to the information above.

5.3.2 RESULT OF TESTING “ABILITY TO MANAGE EPI” HYPOTHESIS

We inferred that using electronic cards necessarily requires the ability to manage it. This inference is followed by the hypothesis that more educated people would be more likely to use EPI. Contrary to the expectation, the results provide opposite evidence showing that less educated people tend to use EPI more frequently. This unexpected evidence was found in the case of smart cards and debit cards. On the other hand, there are tendencies supporting the positive relationship between education and the use of electronic cards in the credit and. ATM cards markets. But it is not significant across all subgroups.

Table 5.18 Trend Test for Education Groups: Smart.

LABEL	ESTIMATE	S.E.	Chi-Square	Pr > Chi-S
Whole	-22.3	0.56	1617.5	<.000 *
Asso~M.D	0.22	0.17	1.70	0.191
Asso~ Ph.D	0.28	0.20	1.98	0.159
Asso~Master	0.11	0.05	5.95	0.014 *
Asso~Bachelor	0.14	0.08	3.05	0.0891

Table 5.19. Trend Test for Education Groups: Debit.

LABEL	ESTIMATE	S.E.	Chi-Square	Pr > Chi-S
Whole	-1.53	0.96	2.53	<.000 *
Asso~M.D	-0.484	0.09	27.60	<.0001 *
Asso~ Ph.D	-0.14	0.11	1.68	0.195 *
Asso~Master	0.06	0.02	6.44	0.011 *
Asso~Bachelor	0.14	0.04	9.73	0.001 *

Using smart cards is highly related to the education level. The parameter estimate is -22.3. The negative value implies that less educated people are more likely to use smart cards. The negative relationship is also observed in the debit card market.

Table 5.20 Trend Test for Education Groups: Credit.

LABEL	ESTIMATE	S.E.	Chi-Square	Pr > Chi-S
Whole	2.06	1.11	3.43	0.063
Asso~M.D	2.76	0.19	215.82	<.0001 *
Asso~ Ph.D	2.39	0.17	185.79	<.0001 *
Asso~Master	0.69	0.04	358.22	<.0001 *
Asso~Bachelor	0.37	0.06	42.39	<0.001 *

Table 5.21 Trend Test for Education Groups: ATM.

LABEL	ESTIMATE	S.E.	Chi-Square	Pr > Chi-S
Whole	-0.07	0.98	0.01	0.941
Asso~M.D	1.33	0.10	168.04	<.001 *
Asso~ Ph.D	1.44	0.12	134.34	<.001 *
Asso~Master	0.22	0.02	68.52	<.001 *
Asso~Bachelor	0.13	0.05	6.96	0.008 *

The trend test of credit and ATM cards shows positive relationship between the education level and the usage, even though it is not universally significant across the all groups. However, after ignoring group 6, we found significantly positive linear trends supporting the hypothesis. Group 6 represents certificates in professional fields such as Nephropathy, Homeopathy, and Pharmacology. Considering this fact enables us to conclude that there are significant linear trends supporting the argument that more educated people are more likely to use EPI.

5.3.3 RESULT OF TESTING “EXPERIENCES WITH FINANCIAL INSTITUTIONS” HYPOTHESIS

Third hypothesis is based on the idea that older people would have more experience to transact with financial institutions, which means “they are more likely exposed to relatively new methods of payments. This expectation is partially by evidence trend test provided.

A significant relationship is found in the case of credit card market. In every comparison, there is a positive relation between the level of age and the probability of using credit cards.

Table 5.22 Trend Test for Age Groups: Credit.

LABEL	ESTIMATE	S.E.	Chi-Square	Pr > Chi-S
Whole	5.09	0.32	259.77	<.0001 *
18~70	1.88	0.11	292.58	<.0001 *
18~60	1.64	0.13	149.42	<.0001 *
18~50	0.45	0.04	136.05	<.0001 *
18~40	0.12	0.04	9.89	0.001 *

Table 5.23 Trend Test for Age Groups: Smart.

LABEL	ESTIMATE	S.E.	Chi-Square	Pr > Chi-S
Whole	-0.24	0.53	0.21	0.649
18~70	0.22	0.17	1.67	0.195
18~60	0.46	0.21	4.78	0.028 *
18~50	0.10	0.06	2.45	0.117
18~40	-0.11	0.07	2.26	0.133

In terms of smart cards, there is a linear trend among group 1, 2, 3 and 4. It means that the hypothesis, that older people are more likely to use smart cards, is supported, at least, among relatively younger groups.

Table 5.24 Trend Test for Age Groups: ATM.

LABEL	ESTIMATE	S.E.	Chi-Square	Pr > Chi-S
Whole	-0.07	0.98	0.01	0.941
18~70	1.34	0.10	168.04	<.0001 *
18~60	1.44	0.12	134.34	<.0001 *
18~50	0.22	0.02	68.52	<.0001 *
18~40	0.13	0.05	6.96	0.008 *

Even though there is no global linearity among subgroups, there is a positive relationship from group 1 to group 5. After ignoring the “over 70” group, we can observe an positive relationship clearly (Parameter Estimate=1.34).

However, debit cards shows opposite evidence. According to the finding, older people are less likely to use debit cards (Parameter Estimate = -8.19). The negative linearity exists across all age groups.

Table 5.25 Trend Test for Age Groups: Debit.

LABEL	ESTIMATE	S.E.	Chi-Square	Pr > Chi-S
Whole	-8.19	0.26	1007	<.0001 *
18~70	-2.32	0.09	735.5	<.0001 *
18~60	-2.37	0.11	462.7	<.0001 *
18~50	-0.43	0.03	172.08	<.0001 *
18~40	-0.30	0.03	75.73	<.0001 *

As summarized in Table 5.26, income has the positive relationship with the probability of using electronic cards. In the case of age factor, mixed evidence coexists, which means that it is inconclusive. However, as explained before, local linear trends are found among subgroups. However, the hypothesis about education is not supported by the statistical evidence which was provided by trend tests. Moreover, a clearly negative relationship was detected, which implied that less educated people are more likely to use EPI, at least smart and debit cards.

Table 5.26 Summary of Findings.

Variable	Hypothesis	Smart	Debit	Credit	ATM
Age	(+)		(-)	(+)	
Education	(+)	(-)	(-)		
Income	(+)	(+)	(+)	(+)	(+)

5.4 MODEL SELECTION: STEPWISE LOGISTIC ANALYSES

To test the hypotheses of interest, the stepwise logistic regression using backward elimination method was conducted. Eight indicator variables were entered into the full model and all interaction terms, all possible combination of predictors, were also created to be entered. The full model is expressed as follows.

$$\begin{aligned}
 y = & \beta_0 + \beta_1 * income + \beta_2 * age + \beta_3 * education + \beta_4 * econ + \beta_5 * int + \beta_6 shoploan \\
 & + \beta_7 * shopsav + \beta_8 * comuse + \beta_9 * income * age + \beta_{10} * income * edu \\
 & + \beta_{11} * income * econ + \beta_{12} * income * int + \beta_{13} * income * shoploan + \beta_{14} * income * shopsav \\
 & + \beta_{15} * income * comuse + \beta_{16} * age * edu + \beta_{17} * age * econ + \beta_{18} * age * int \\
 & + \beta_{19} * age * shoploan + \beta_{20} * age * shopsav + \beta_{21} * age * comuse + \beta_{22} * edu * econ \\
 & + \beta_{23} * edu * int + \beta_{24} * edu * shoploan + \beta_{25} * edu * shopsav + \beta_{26} * edu * comuse \\
 & + \beta_{27} * econ * int + \beta_{28} * econ * shoploan + \beta_{29} * econ * shopsav + \beta_{30} * econ * comuse \\
 & + \beta_{31} * int * shoploan + \beta_{32} * int * shopsav + \beta_{33} * int * comuse + \beta_{34} * shoploan * shopsav \\
 & + \beta_{35} * shoploan * comuse + \beta_{36} * shopsav * comuse + e
 \end{aligned}$$

The stepwise analysis began with this saturated model, eliminated variables through an iterative process, and stopped when no more variables can be excluded from the model. The elimination criterion was $\alpha = 0.1$.

5.4.1 BEST FIT LOGISTIC MODEL FOR SMART CARDS

The fitted model which was selected is as follows.

$$\begin{aligned}
 y = & \beta_0 + \beta_1 * income + \beta_2 * age + \beta_3 * education + \beta_4 * econ + \beta_5 * int + \beta_6 shopsav \\
 & + \beta_7 * comuse + \beta_8 * income * econ + \beta_9 * age * comuse + \beta_{10} * edu * comuse \\
 & + \beta_{11} * econ * int + e
 \end{aligned}$$

The chosen model satisfied convergence criterion. The test statistic for goodness-of-fit is $-2 \text{ Log } L = 5707.889$. The degree of freedom is 14, since there are 14 variables in

a model. It results in extremely p-value ($p\text{-value} < .0001$), thus stepwise logistic model proves to fit well.

As shown in Table 5.27, there are four significant interactions: income and attitude toward economy, age and financial software use, education and financial software use, and attitude toward economy and interest.

Table 5.27. Relation of Having Smart Card Respect to Predictors.

LR Statistics For Type 3 Analysis			
Source	DF	Chi-Square	Pr > ChiSq
income	7	43.73	< .0001 *
age	5	24.13	0.0003 *
education	5	3.31	0.6517
attitude toward economy	2	22.77	< .0001 *
attitude toward interest rate	2	10.13	0.0063
shopping behavior for saving	4	28.32	< .0001 *
use of financial software	1	0.000	0.9995 *
income*attitude economy	14	67.29	< .0001 *
age*software use	5	24.87	0.0001 *
edu*software use	5	17.72	0.0033 *
attitude economy*attitude interest	4	35.32	< .0001 *

Middle-income respondents who has opinions that economy will be worse in the future are less likely to use smart cards (estimated parameter of income 4 * econ 1 = -0.4668). On the contrary, middle-income people who think that economy will be better in the future are more likely to have smart cards (estimated parameter of income 4 * econ 2 = -0.6634). Among the people expecting that economy will be better, a group of respondents who think interest rate will be higher tend to use smart card more than a group expecting the interest rate will be lower.

Table 5.28. Analysis of Maximum Likelihood Estimates for Smart Cards.

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	5.7014	64.1784	0.0079	0.9292
income 1	1	0.3147	0.1196	6.9273	0.0085
income 2	1	0.1829	0.1339	1.8662	0.1719
income 3	1	-0.1598	0.1025	2.4317	0.1189
income 4	1	0.2848	0.1448	3.8652	0.0493
income 5	1	-0.3970	0.1141	12.1017	0.0005
income 6	1	0.2592	0.1852	1.9576	0.1618
income 7	1	-0.4848	0.1052	21.2507	<.0001
age 1	1	-0.1826	0.1198	2.3227	0.1275
age 2	1	0.1331	0.1082	1.5149	0.2184
age 3	1	-0.3124	0.0827	14.2666	0.0002
age 4	1	-0.2598	0.0895	8.4272	0.0037
age 5	1	-0.0101	0.1250	0.0065	0.9356
edu 0	1	-1.9147	64.1784	0.0009	0.9762
edu 1	1	-1.7194	64.1787	0.0007	0.9786
edu 2	1	-2.0643	64.1784	0.0010	0.9743
edu 3	1	-2.0540	64.1784	0.0010	0.9745
edu 4	1	-2.0288	64.1784	0.0010	0.9748
econ 1	1	-0.4349	0.1051	17.1049	<.0001
econ 2	1	0.5333	0.1328	16.1259	<.0001
int 1	1	-0.2671	0.0866	9.5160	0.0020
int 2	1	0.3222	0.1535	4.4084	0.0358
shopsav 1	1	-0.00105	0.0814	0.0002	0.9897
shopsav 2	1	-0.4555	0.0906	25.2951	<.0001
shopsav 3	1	0.1672	0.0697	5.7453	0.0165
shopsav 4	1	0.1826	0.0931	3.8460	0.0499
comuse 1	1	-0.0406	64.1784	0.0000	0.9995
income*econ 1 1	1	-0.5831	0.1379	17.8758	<.0001
income*econ 1 2	1	-0.2001	0.1513	1.7488	0.1860
income*econ 2 1	1	0.7015	0.2117	10.9862	0.0009
income*econ 2 2	1	-0.1927	0.1811	1.1326	0.2872
income*econ 3 1	1	-0.3428	0.1327	6.6764	0.0098
income*econ 3 2	1	-0.0783	0.1478	0.2802	0.5965
income*econ 4 1	1	-0.4668	0.1804	6.6944	0.0097
income*econ 4 2	1	0.6634	0.2448	7.3410	0.0067
income*econ 5 1	1	-0.0737	0.1629	0.2049	0.6508
income*econ 5 2	1	0.0589	0.1703	0.1196	0.7295
income*econ 6 1	1	-0.1325	0.2508	0.2789	0.5974
income*econ 6 2	1	0.2388	0.2971	0.6463	0.4215
income*econ 7 1	1	0.2020	0.1534	1.7329	0.1880
income*econ 7 2	1	-0.2213	0.1429	2.3970	0.1216
age*comuse 1 1	1	-0.5242	0.1156	20.5809	<.0001
age*comuse 2 1	1	-0.00062	0.1055	0.0000	0.9953
age*comuse 3 1	1	-0.1501	0.0808	3.4516	0.0632

age*comuse	4	1	1	-0.00213	0.0873	0.0006	0.9806
age*comuse	5	1	1	0.1801	0.1231	2.1414	0.1434
edu*comuse	0	1	1	-0.2716	64.1784	0.0000	0.9966
edu*comuse	1	1	1	0.6108	64.1787	0.0001	0.9924
edu*comuse	2	1	1	-0.0843	64.1784	0.0000	0.9990
edu*comuse	3	1	1	-0.0512	64.1784	0.0000	0.9994
edu*comuse	4	1	1	-0.3907	64.1784	0.0000	0.9951
econ*int	1	1	1	0.3880	0.1058	13.4471	0.0002
econ*int	1	2	1	-0.7467	0.1775	17.6875	<.0001
econ*int	2	1	1	-0.3931	0.1318	8.8979	0.0029
econ*int	2	2	1	0.2972	0.2350	1.5993	0.2060

5.42. BEST FIT LOGISTIC MODEL FOR ATM CARDS

Backward stepwise logistic regression results in a fitted equation as follows.

$$\begin{aligned}
 y = & \beta_0 + \beta_1 * income + \beta_2 * age + \beta_3 * education + \beta_4 * econ + \beta_5 * int + \beta_6 * shopsav \\
 & + \beta_7 * comuse + \beta_8 * income * shopsav + \beta_9 * income * comuse + \\
 & \beta_{10} * income * shoploan + \beta_{11} * age * comuse + \beta_{12} * age * econ + \\
 & \beta_{13} * econ * int + \beta_{14} * edu * comuse + edu * comuse + e
 \end{aligned}$$

The chosen model satisfied convergence criterion. The test statistic for goodness-of-fit is $-2 \text{ Log } L = 5707.889$. The degree of freedom is 14, since there are 14 variables in a model. It results in extremely p-value (p-value < .0001), thus stepwise logistic model proves to fit well.

Seven indicator variables, income, age, education, attitude toward future interest rate, shopping behavior for loan, shopping behavior for saving, and use of financial software, prove significant at $\alpha = 0.01$ level. Attitude toward future economy turns out to be insignificant in a fitted model. These results are the same as the previous results in the multiple logistic regression analysis. Only difference between two analyses is that the stepwise logistic regression enables us to detect interaction effects thoroughly. Stepwise logistic regression found seven statistically significant interaction variables: income and

shopping for saving, income and financial software use, income and shopping for loan, age and financial software use, and age and attitude toward future economy.

Table 5.29. Relation of Having ATM Card Respect to Predictors.

LR Statistics For Type 3 Analysis			
Source	DF	Chi-Square	Pr > ChiSq
income	7	68.54	< .0001 *
age	5	1243.25	< .0001 *
education	5	100.92	< .0001 *
attitude toward economy	2	1.58	0.4543
attitude toward interest rate	2	6.40	0.0407 *
shopping behavior for loan	4	25.41	< .0001 *
shopping behavior for saving	4	24.54	< .0001 *
use of financial software	1	30.67	< .0001 *
income*shop for saving	28	89.44	< .0001 *
income*software use	7	31.87	< .0001 *
income*shop for loan	28	109.16	< .0001 *
age*software use	5	86.46	< .0001 *
age*attitude economy	10	35.63	< .0001 *
attitude economy*interest rate	4	17.95	0.0013 *
education*software use	5	24.89	0.0001 *

Table 5.30 shows how the interactions influence the probability of using ATM cards. There is an interaction effect between the level of income and the level of shopping for saving. In the case of low-income household (income 1 in a table), active shoppers (shopsav 3 in a table) for financial information are more likely to use ATM cards (estimated parameter = 0.2428, p-value < .0001), and inactive shoppers (shopsav 1 & 2) are less likely to have ATM cards (estimated parameter = -0.1664 and -0.2835). Middle-income households with active shopping behavior (income * shopsav 3 & 4 in a table) are also more likely to take the use of ATM cards. In other words, when the level of income is fixed, more active shopping behavior tends to motivate consumers to use ATM cards.

This tendency is also observed in the case of shopping behavior for loan. When the level of income is constant, the more shopping behavior is followed by more use of ATM cards.

The interaction between education and software use causes negative impacts on the probability of using ATM cards (i.e., estimated parameter for education 1 and comuse 1 is -0.3713, p-value = 0.0002). Education 1 represents low level of education.

Table 5.30. Analysis of Maximum Likelihood Estimates for ATM Card.

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	
Intercept	5	1	-1.2538	0.0689	330.8526	<.0001
Intercept	1	1	3.5116	0.0758	2147.3459	<.0001
income	1	1	-0.0437	0.0512	0.7273	0.3938
income	2	1	-0.1697	0.0666	6.4984	0.0108
income	3	1	0.1496	0.0586	6.5295	0.0106
income	4	1	0.0745	0.0628	1.4058	0.2358
income	5	1	0.1526	0.0686	4.9431	0.0262
income	6	1	-0.1093	0.0826	1.7515	0.1857
income	7	1	-0.0784	0.0649	1.4613	0.2267
age	1	1	-0.8679	0.0611	201.6585	<.0001
age	2	1	-0.4315	0.0442	95.4662	<.0001
age	3	1	-0.3343	0.0378	78.0315	<.0001
age	4	1	0.1734	0.0388	19.9493	<.0001
age	5	1	0.3681	0.0475	59.9818	<.0001
edu	0	1	0.0385	0.0697	0.3059	0.5802
edu	1	1	0.0335	0.0985	0.1156	0.7339
edu	2	1	0.0283	0.0703	0.1618	0.6875
edu	3	1	-0.2923	0.0764	14.6552	0.0001
edu	4	1	-0.3400	0.0800	18.0589	<.0001
econ	1	1	0.0860	0.0343	6.2940	0.0121
econ	2	1	-0.0611	0.0326	3.5150	0.0608
int	1	1	-0.0667	0.0258	6.6884	0.0097
int	2	1	0.0794	0.0411	3.7420	0.0531
shoploan	1	1	0.1502	0.0453	10.9901	0.0009
shoploan	2	1	0.0178	0.0546	0.1059	0.7449
shoploan	3	1	-0.1166	0.0318	13.4093	0.0003
shoploan	4	1	-0.1144	0.0439	6.7939	0.0091
shopsav	1	1	0.1001	0.0404	6.1529	0.0131
shopsav	2	1	-0.1555	0.0514	9.1532	0.0025
shopsav	3	1	0.0400	0.0315	1.6151	0.2038
shopsav	4	1	-0.00080	0.0429	0.0003	0.9851
comuse	1	1	0.0402	0.0649	0.3843	0.5353
income*shopsav	1 1	1	-0.1664	0.0671	6.1561	0.0131
income*shopsav	1 2	1	-0.2835	0.0988	8.2263	0.0041

income*shopsav	1	3	1	0.2428	0.0585	17.2500	<.0001
income*shopsav	1	4	1	-0.00609	0.0861	0.0050	0.9436
income*shopsav	2	1	1	-0.0137	0.0853	0.0257	0.8726
income*shopsav	2	2	1	-0.2997	0.1282	5.4634	0.0194
income*shopsav	2	3	1	0.1407	0.0743	3.5886	0.0582
income*shopsav	2	4	1	-0.2281	0.1240	3.3816	0.0659
income*shopsav	3	1	1	-0.1142	0.0821	1.9362	0.1641
income*shopsav	3	2	1	0.0497	0.1066	0.2176	0.6409
income*shopsav	3	3	1	-0.0706	0.0675	1.0942	0.2955
income*shopsav	3	4	1	0.2740	0.0968	8.0188	0.0046
income*shopsav	4	1	1	0.0881	0.0958	0.8456	0.3578
income*shopsav	4	2	1	-0.00387	0.1275	0.0009	0.9758
income*shopsav	4	3	1	-0.0695	0.0780	0.7936	0.3730
income*shopsav	4	4	1	0.1366	0.1080	1.5990	0.2060
income*shopsav	5	1	1	-0.0986	0.1144	0.7422	0.3890
income*shopsav	5	2	1	0.1662	0.1458	1.2991	0.2544
income*shopsav	5	3	1	-0.0640	0.0870	0.5404	0.4622
income*shopsav	5	4	1	0.0802	0.1196	0.4503	0.5022
income*shopsav	6	1	1	0.1124	0.1568	0.5143	0.4733
income*shopsav	6	2	1	0.3114	0.1880	2.7454	0.0975
income*shopsav	6	3	1	-0.0986	0.1125	0.7683	0.3807
income*shopsav	6	4	1	-0.2150	0.1494	2.0694	0.1503
income*shopsav	7	1	1	0.00858	0.1208	0.0050	0.9434
income*shopsav	7	2	1	0.0186	0.1420	0.0171	0.8959
income*shopsav	7	3	1	-0.0393	0.0894	0.1929	0.6605
income*shopsav	7	4	1	-0.1928	0.1072	3.2327	0.0722
income*comuse	1	1	1	-0.1470	0.0462	10.1352	0.0015
income*comuse	2	1	1	0.2372	0.0582	16.6348	<.0001
income*comuse	3	1	1	-0.0489	0.0538	0.8282	0.3628
income*comuse	4	1	1	0.0237	0.0540	0.1930	0.6604
income*comuse	5	1	1	-0.1074	0.0586	3.3562	0.0670
income*comuse	6	1	1	-0.0182	0.0699	0.0677	0.7948
income*comuse	7	1	1	-0.0133	0.0539	0.0611	0.8047
income*shoploan	1	1	1	-0.0809	0.0700	1.3361	0.2477
income*shoploan	1	2	1	-0.2148	0.1049	4.1928	0.0406
income*shoploan	1	3	1	0.0107	0.0586	0.0334	0.8549
income*shoploan	1	4	1	0.4129	0.0933	19.5937	<.0001
income*shoploan	2	1	1	0.0474	0.0878	0.2920	0.5889
income*shoploan	2	2	1	0.5054	0.1327	14.5157	0.0001
income*shoploan	2	3	1	-0.1075	0.0754	2.0367	0.1535
income*shoploan	2	4	1	-0.5240	0.1199	19.1083	<.0001
income*shoploan	3	1	1	-0.1574	0.0913	2.9746	0.0846
income*shoploan	3	2	1	0.2316	0.1162	3.9714	0.0463
income*shoploan	3	3	1	-0.1281	0.0660	3.7655	0.0523
income*shoploan	3	4	1	-0.1002	0.0976	1.0540	0.3046
income*shoploan	4	1	1	0.0710	0.1120	0.4023	0.5259
income*shoploan	4	2	1	-0.3097	0.1444	4.6021	0.0319
income*shoploan	4	3	1	0.0292	0.0770	0.1438	0.7045
income*shoploan	4	4	1	0.0770	0.1081	0.5073	0.4763
income*shoploan	5	1	1	0.4797	0.1370	12.2509	0.0005
income*shoploan	5	2	1	-0.3378	0.1470	5.2795	0.0216

income*shoploan	5	3	1	-0.1312	0.0896	2.1426	0.1433
income*shoploan	5	4	1	0.1352	0.1150	1.3807	0.2400
income*shoploan	6	1	1	-0.1890	0.1811	1.0887	0.2968
income*shoploan	6	2	1	0.1793	0.1873	0.9163	0.3385
income*shoploan	6	3	1	0.0950	0.1185	0.6425	0.4228
income*shoploan	6	4	1	-0.1578	0.1539	1.0518	0.3051
income*shoploan	7	1	1	-0.0256	0.1349	0.0360	0.8495
income*shoploan	7	2	1	0.0585	0.1707	0.1176	0.7317
income*shoploan	7	3	1	-0.0479	0.0917	0.2725	0.6016
income*shoploan	7	4	1	0.3448	0.1105	9.7353	0.0018
age*comuse	1	1	1	0.2303	0.0603	14.5695	0.0001
age*comuse	2	1	1	0.3318	0.0436	58.0049	<.0001
age*comuse	3	1	1	-0.0434	0.0374	1.3409	0.2469
age*comuse	4	1	1	-0.0589	0.0380	2.4022	0.1212
age*comuse	5	1	1	-0.2245	0.0472	22.6087	<.0001
age*econ	1	1	1	-0.0181	0.0633	0.0814	0.7753
age*econ	1	2	1	-0.0660	0.0670	0.9704	0.3246
age*econ	2	1	1	0.1279	0.0569	5.0559	0.0245
age*econ	2	2	1	-0.0180	0.0532	0.1138	0.7358
age*econ	3	1	1	-0.2250	0.0472	22.7587	<.0001
age*econ	3	2	1	0.1234	0.0440	7.8446	0.0051
age*econ	4	1	1	0.0223	0.0502	0.1984	0.6560
age*econ	4	2	1	-0.00493	0.0458	0.0116	0.9142
age*econ	5	1	1	-0.0421	0.0541	0.6045	0.4369
age*econ	5	2	1	0.0817	0.0531	2.3675	0.1239
econ*int	1	1	1	-0.1361	0.0378	12.9445	0.0003
econ*int	1	2	1	0.1441	0.0600	5.7608	0.0164
econ*int	2	1	1	0.0507	0.0355	2.0367	0.1535
econ*int	2	2	1	-0.1178	0.0559	4.4479	0.0349
edu*comuse	0	1	1	-0.2006	0.0694	8.3570	0.0038
edu*comuse	1	1	1	-0.3713	0.0985	14.2179	0.0002
edu*comuse	2	1	1	-0.0588	0.0700	0.7045	0.4013
edu*comuse	3	1	1	-0.0229	0.0763	0.0903	0.7637
edu*comuse	4	1	1	-0.0928	0.0798	1.3530	0.2448

5.4.3. BEST FIT LOGISTIC MODEL FOR DEBIT CARDS

Backward stepwise logistic regression results in a fitted equation as follows.

$$\begin{aligned}
y = & \beta_0 + \beta_1 * income + \beta_2 * age + \beta_3 * education + \beta_4 * econ + \beta_5 * int + \beta_6 * shoploan \\
& + \beta_7 * shopsav + \beta_8 * comuse + \beta_9 * income * shopsav + \beta_{10} * income * comuse \\
& + \beta_{11} * income * shoploan + \beta_{12} * age * comuse + \beta_{13} * age * econ + \beta_{14} * econ * int \\
& + \beta_{15} * edu * comuse + e
\end{aligned}$$

The convergence criterion was satisfied. The test statistic for goodness-of-fit is -2 Log L = 33300.669. The degree of freedom is 15, since there are 15 variables in a model. It results in extremely p-value (p-value < .0001), thus stepwise logistic model proves to fit well. Income, age, education, attitude toward economy, shopping behavior for loan and saving, and the use of financial software are significant at $\alpha = 0.05$ levels. Only attitude toward the future interest rate turns out to be insignificant. The significance of main predictors remains unchanged.

Some obvious trends are observed. As the level of age increases, the probability of using debit cards also increases. For example, an estimated parameter for youngest groups 1 is -1.09, on the other hand, an estimated parameter for oldest groups 5 is 0.62. The same trend is also detected in the case of education. As the level of education increases, the probability to use debit cards also increases. For example, the estimated parameter for lowly-educated people (edu 2 in a table) is significantly negative (-0.20), however, the estimated parameter for highly-educated people (edu 4 in a table) is significantly positive (0.32).

It is also found that the more active shopper for loan information is less likely to use debit cards. For instance, while the estimated parameter for moderate shopper (shoploan 2) is positive (0.165), the estimated parameter for active shopper (shoploan 4) is significantly negative (-0.155).

Table 5.31 Relation of Having Debit Card respect to Predictors.

LR Statistics For Type 3 Analysis			
Source	DF	Chi-Square	Pr > ChiSq
income	7	144.88	< .0001 *
age	5	868.43	< .0001 *
education	5	56.61	< .0001 *
attitude toward economy	2	20.05	< .0001 *
attitude toward interest rate	2	1.25	0.5346
shopping behavior for loan	4	36.11	< .0001 *
shopping behavior for saving	4	12.94	0.0116 *
use of financial software	1	4.89	0.0271 *
income*shop for save	28	86.97	< .0001 *
income*software use	7	67.74	< .0001 *
income*shop for loan	28	79.47	< .0001 *
age*software use	5	43.48	< .0001 *
age*attitude economy	10	76.24	< .0001 *
attitude economy*interest rate	4	20.78	0.0004 *
education*software use	5	26.34	< .0001 *

Through the stepwise procedure, seven interaction effects are detected.

Significant interaction effects are as follows: income and shopping for saving, income and financial software use, income and shopping for loan, age and software use, age and attitude toward future economy, attitude toward future economy and future interest rate, and education and financial software use. Interesting is the interaction effect between age and attitude toward future economy. In the middle-age group (age 3 in a table), people with positive expectation (econ 2 in a table) are more likely to use debit cards (parameter value = 0.278), when it is compared to people with negative expectation (econ 1 in a table). The latter group's estimated parameter is significantly negative (-0.219).

Table 5.32. Analysis of Maximum Likelihood Estimates for Debit Cards.

Parameter	DF		Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	5	1	0.1729	0.0653	7.0045	0.0081
Intercept	1	1	3.5514	0.0731	2358.2277	<.0001
income	1	1	0.1114	0.0464	5.7600	0.0164
income	2	1	-0.1348	0.0572	5.5474	0.0185
income	3	1	-0.0202	0.0499	0.1636	0.6859
income	4	1	0.1970	0.0533	13.6763	0.0002
income	6	1	-0.2995	0.0690	18.8257	<.0001
income	7	1	-0.0907	0.0565	2.5744	0.1086
age	1	1	-1.0918	0.0392	776.9188	<.0001
age	2	1	-0.5955	0.0328	328.6890	<.0001
age	3	1	-0.3371	0.0284	141.4114	<.0001
age	4	1	0.1415	0.0318	19.7722	<.0001
age	5	1	0.6185	0.0388	254.4632	<.0001
edu	0	1	-0.0858	0.0658	1.6986	0.1925
edu	1	1	-0.2045	0.0881	5.3889	0.0203
edu	2	1	0.00502	0.0668	0.0056	0.9401
edu	3	1	0.0804	0.0716	1.2619	0.2613
edu	4	1	0.3218	0.0754	18.2061	<.0001
econ	1	1	0.1390	0.0328	17.9794	<.0001
econ	2	1	-0.0860	0.0304	7.9969	0.0047
int	1	1	-0.0297	0.0239	1.5511	0.2130
int	2	1	0.0263	0.0386	0.4618	0.4968
shoploan	1	1	0.0450	0.0407	1.2238	0.2686
shoploan	2	1	0.1655	0.0480	11.8811	0.0006
shoploan	3	1	-0.1021	0.0275	13.7959	0.0002
shoploan	4	1	-0.1551	0.0376	16.9937	<.0001
shopsav	1	1	0.0812	0.0356	5.2062	0.0225
shopsav	2	1	-0.1136	0.0437	6.7568	0.0093
shopsav	3	1	0.0545	0.0273	3.9940	0.0457
shopsav	4	1	-0.0339	0.0367	0.8567	0.3547
comuse	1	1	-0.0995	0.0616	2.6078	0.1063
income*shopsav	1	1	-0.1169	0.0664	3.0979	0.0784
income*shopsav	1	2	-0.2824	0.0899	9.8595	0.0017
income*shopsav	1	3	0.3152	0.0589	28.6725	<.0001
income*shopsav	1	4	-0.0825	0.0829	0.9890	0.3200
income*shopsav	2	1	-0.1468	0.0733	4.0104	0.0452
income*shopsav	2	2	0.1916	0.1061	3.2653	0.0708
income*shopsav	2	3	0.0291	0.0638	0.2085	0.6479
income*shopsav	2	4	-0.0954	0.1044	0.8364	0.3604
income*shopsav	3	1	0.0487	0.0722	0.4543	0.5003
income*shopsav	3	2	-0.1167	0.0904	1.6658	0.1968
income*shopsav	3	3	-0.1839	0.0579	10.0849	0.0015
income*shopsav	3	4	0.1624	0.0832	3.8088	0.0510
income*shopsav	4	1	-0.0388	0.0839	0.2145	0.6433
income*shopsav	4	2	0.1277	0.1056	1.4637	0.2263
income*shopsav	4	3	-0.0963	0.0668	2.0817	0.1491

income*shopsav	4	4	1	-0.0944	0.0924	1.0418	0.3074
income*shopsav	5	1	1	0.2035	0.0999	4.1540	0.0415
income*shopsav	5	2	1	-0.1407	0.1264	1.2406	0.2654
income*shopsav	5	3	1	-0.0695	0.0746	0.8668	0.3518
income*shopsav	5	4	1	-0.1436	0.1018	1.9887	0.1585
income*shopsav	6	1	1	-0.0954	0.1339	0.5078	0.4761
income*shopsav	6	2	1	0.3053	0.1563	3.8163	0.0508
income*shopsav	6	3	1	0.1407	0.0937	2.2545	0.1332
income*shopsav	6	4	1	-0.0253	0.1214	0.0435	0.8348
income*shopsav	7	1	1	0.0700	0.1047	0.4472	0.5037
income*shopsav	7	2	1	-0.0215	0.1195	0.0324	0.8571
income*shopsav	7	3	1	-0.1117	0.0751	2.2087	0.1372
income*shopsav	7	4	1	0.2298	0.0896	6.5719	0.0104
income*comuse	1	1	1	0.1283	0.0387	10.9969	0.0009
income*comuse	2	1	1	0.1776	0.0500	12.6073	0.0004
income*comuse	3	1	1	-0.1609	0.0449	12.8606	0.0003
income*comuse	4	1	1	0.1186	0.0457	6.7428	0.0094
income*comuse	5	1	1	-0.1259	0.0488	6.6467	0.0099
income*comuse	6	1	1	-0.0354	0.0575	0.3799	0.5377
income*comuse	7	1	1	-0.1056	0.0451	5.4946	0.0191
income*shoploan	1	1	1	0.0155	0.0707	0.0479	0.8268
income*shoploan	1	2	1	-0.0436	0.1043	0.1750	0.6757
income*shoploan	1	3	1	-0.1353	0.0579	5.4614	0.0194
income*shoploan	1	4	1	0.4351	0.0945	21.1841	<.0001
income*shoploan	2	1	1	-0.0268	0.0777	0.1194	0.7297
income*shoploan	2	2	1	0.0903	0.1166	0.6001	0.4386
income*shoploan	2	3	1	-0.0609	0.0641	0.9015	0.3424
income*shoploan	2	4	1	-0.2373	0.0994	5.6963	0.0170
income*shoploan	3	1	1	0.0624	0.0808	0.5958	0.4402
income*shoploan	3	2	1	-0.0677	0.1017	0.4434	0.5055
income*shoploan	3	3	1	-0.0218	0.0566	0.1486	0.6998
income*shoploan	3	4	1	0.0972	0.0822	1.3979	0.2371
income*shoploan	4	1	1	0.0924	0.1014	0.8309	0.3620
income*shoploan	4	2	1	-0.1407	0.1212	1.3463	0.2459
income*shoploan	4	3	1	0.0466	0.0657	0.5026	0.4783
income*shoploan	4	4	1	-0.0343	0.0923	0.1381	0.7102
income*shoploan	5	1	1	-0.1034	0.1299	0.6340	0.4259
income*shoploan	5	2	1	-0.1784	0.1239	2.0723	0.1500
income*shoploan	5	3	1	-0.0953	0.0767	1.5429	0.2142
income*shoploan	5	4	1	0.1716	0.0987	3.0185	0.0823
income*shoploan	6	1	1	0.0951	0.1536	0.3828	0.5361
income*shoploan	6	2	1	-0.2120	0.1578	1.8055	0.1790
income*shoploan	6	3	1	0.3186	0.0987	10.4242	0.0012
income*shoploan	6	4	1	-0.2135	0.1263	2.8568	0.0910
income*shoploan	7	1	1	-0.1248	0.1198	1.0852	0.2975
income*shoploan	7	2	1	0.2888	0.1521	3.6076	.0575
income*shoploan	7	3	1	0.1238	0.0779	2.5257	0.1120
income*shoploan	7	4	1	-0.1237	0.0956	1.6736	0.1958
age*econ	1	1	1	0.0266	0.0517	0.2644	0.6071
age*econ	1	2	1	-0.1800	0.0548	10.7782	0.0010
age*econ	2	1	1	0.00326	0.0475	0.0047	0.9453

age*econ	2	2	1	0.00895	0.0440	0.0413	0.8390
age*econ	3	1	1	-0.2191	0.0401	29.8646	<.0001
age*econ	3	2	1	0.2784	0.0380	53.7234	<.0001
age*econ	4	1	1	0.0248	0.0471	0.2780	0.5980
age*econ	4	2	1	0.00983	0.0420	0.0549	0.8147
age*econ	5	1	1	-0.0553	0.0548	1.0179	0.3130
age*econ	5	2	1	0.0982	0.0543	3.2746	0.0704
econ*int	1	1	1	-0.0136	0.0352	0.1483	0.7002
econ*int	1	2	1	0.0646	0.0568	1.2952	0.2551
econ*int	2	1	1	-0.0491	0.0327	2.2621	0.1326
econ*int	2	2	1	-0.0851	0.0521	2.6740	0.1020
edu*comuse	0	1	1	0.00263	0.0656	0.0016	0.9680
edu*comuse	1	1	1	-0.1705	0.0879	3.7587	0.0525
edu*comuse	3	1	1	-0.0913	0.0717	1.6243	0.2025
edu*comuse	4	1	1	-0.0996	0.0754	1.7467	0.1863

5.4.4. BEST FIT LOGISTIC MODEL FOR CREDIT CARDS

Backward stepwise logistic regression results in a fitted equation as follows.

$$\begin{aligned}
 y = & \beta_0 + \beta_1 * income + \beta_2 * age + \beta_3 * education + \beta_4 * econ + \beta_5 * int + \beta_6 * shoploan \\
 & + \beta_7 * shopsav + \beta_8 * comuse + \beta_9 * econ * int + \beta_{10} * age * econ \\
 & + \beta_{11} * edu * comuse + \beta_{12} * income * comuse + \beta_{13} * income * shoploan + e
 \end{aligned}$$

The chosen model satisfies convergence condition. The test statistic for goodness-of-fit is $-2 \log L = 15528.099$. The degree of freedom is 13, since there are 13 variables in a model. It results in extremely p-value (p-value < .0001), thus stepwise logistic model proves to fit well.

All predictors except the use of financial software are significantly related to the adoption of credit cards at $\alpha = 0.01$ levels. This finding is consistent with the one in the previous multiple logistic analysis. However, although the use of financial software was significant in the previous logistic model (p-value = 0.0001), it turns out to be insignificant (p-value=0.9899) in the stepwise logistic regression with interaction variables.

Table 5.33 Relation of Having Credit Card respect to Predictors.

LR Statistics For Type 3 Analysis			
Source	DF	Chi-Square	Pr > ChiSq
income	7	225.73	< .0001 *
age	5	499.87	< .0001 *
education	5	271.23	< .0001 *
attitude toward economy	2	28.08	< .0001 *
attitude toward interest rate	2	34.93	< .0001 *
shopping behavior for loan	4	65.58	< .0001 *
shopping behavior for saving	4	35.78	< .0001 **
use of financial software	1	0.0002	0.9899
attitude economy*interest rate	4	57.24	< .0001 *
age*attitude economy	10	107.70	< .0001 *
edu*software use	5	34.29	< .0001 *
income*software use	7	88.84	< .0001 *
income*shop for loan	28	112.04	< .0001 *

We conducted a probit regression analysis to see whether the result provided by the stepwise logistic regression is consistent or not. As shown in Table 5.35, the statistical significance remains unchanged, in spite of slight differences in coefficients' estimates.

Probit regression also shows the consistent difference that the use of financial software is not significant. Thus, we can infer that "Use of financial software" is not a truly significant indicator to explain the use of credit card. The main effect of software use may become insignificant since the interaction between income and software use and interaction between education and software use are newly identified.

Table 5.34 Probit Analysis Result for Credit Cards.

LR Statistics For Type 3 Analysis			
Source	DF	Chi-Square	Pr > ChiSq
income	7	260.48	< .0001 *
age	5	505.73	< .0001 *
education	5	322.63	< .0001 *
attitude toward economy	2	27.50	< .0001 *
attitude toward interest rate	2	32.73	< .0001 *
shopping behavior for loan	4	80.79	< .0001 *
shopping behavior for saving	4	33.70	< .0001 *
use of financial software	1	0.0003	0.9866
attitude economy*interest rate	4	56.24	< .0001 *
age*attitude economy	10	102.19	< .0001 *
edu*software use	5	50.77	< .0001 *
income*software use	7	111.08	< .0001 *
income*shop for loan	28	116.96	< .0001 *

The stepwise procedure detect five interactions: attitude toward future economy and attitude toward for future interest rate, age and attitude toward future economy, the level of education and the use of financial software, the level of income and the use of financial software, and income and shopping for loan. The interesting trend which can be derived from Table 5.36, is the men with pessimistic opinion toward future economy are more likely to use credit cards in the young age group. Age 1 represents from 20's to 30's. Their estimated parameter is 0.388. On the contrary, the same group people with optimistic opinion are less likely to use credit cards. Their estimated parameter is negative (-0.502).

Table 5.35. Analysis of Maximum Likelihood Estimates for Credit Cards.

Parameter		DF	Standard Estimate	Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	-5.1954	106.0	0.0024	0.9609
income	1	1	1.7968	10.3096	0.0304	0.8616
income	2	1	2.2196	10.3095	0.0464	0.8295
income	3	1	1.4959	10.3095	0.0211	0.8846
income	4	1	1.3308	10.3096	0.0167	0.8973
income	5	1	0.0351	10.3110	0.0000	0.9973
income	6	1	0.7924	10.3101	0.0059	0.9387
income	7	1	0.0427	10.3106	0.0000	0.9967
age	1	1	0.7629	0.0474	259.2827	<.0001
age	2	1	0.6543	0.0458	204.3995	<.0001
age	3	1	0.0102	0.0446	0.0520	0.8196
age	4	1	0.0348	0.0504	0.4761	0.4902
age	5	1	-0.7234	0.0588	151.5373	<.0001
edu	0	1	1.9838	105.5	0.0004	0.9850
edu	1	1	1.5497	105.5	0.0002	0.9883
edu	2	1	0.7692	105.5	0.0001	0.9942
edu	3	1	0.8558	105.5	0.0001	0.9935
edu	4	1	-0.3455	105.5	0.0000	0.9974
econ	1	1	0.1968	0.0407	23.4191	<.0001
econ	2	1	-0.0289	0.0404	0.5094	0.4754
int	1	1	0.0127	0.0317	0.1612	0.6881
int	2	1	0.2022	0.0480	17.7135	<.0001
shoploan	1	1	1.5609	10.3095	0.0229	0.8797
shoploan	2	1	-0.6128	28.7783	0.0005	0.9830
shoploan	3	1	0.5416	10.3095	0.0028	0.9581
shoploan	4	1	-0.7132	25.0974	0.0008	0.9773
shopsav	1	1	0.2289	0.0415	30.3386	<.0001
shopsav	2	1	0.0238	0.0623	0.1457	0.7027
shopsav	3	1	0.0356	0.0378	0.8837	0.3472
shopsav	4	1	-0.2416	0.0623	15.0534	0.0001
comuse	1	1	-1.3304	105.5	0.0002	0.9899
econ*int	1 1	1	-0.1769	0.0455	15.1342	0.0001
econ*int	1 2	1	0.3375	0.0686	24.1845	<.0001
econ*int	2 1	1	0.2369	0.0449	27.7902	<.0001
econ*int	2 2	1	-0.1443	0.0678	4.5282	0.0333
age*econ	1 1	1	0.3880	0.0619	39.2724	<.0001
age*econ	1 2	1	-0.5023	0.0665	57.0866	<.0001
age*econ	2 1	1	0.0300	0.0631	0.2254	0.6350
age*econ	2 2	1	-0.0773	0.0605	1.6298	0.2017
age*econ	3 1	1	-0.1591	0.0621	6.5608	0.0104
age*econ	3 2	1	0.0328	0.0612	0.2862	0.5927
age*econ	4 1	1	0.1021	0.0740	1.9015	0.1679
age*econ	4 2	1	0.2080	0.0669	9.6804	0.0019
age*econ	5 1	1	0.0194	0.0817	0.0566	0.8120
age*econ	5 2	1	0.1725	0.0788	4.7982	0.0285

edu*comuse	0	1	1	0.8625	105.5	0.0001	0.9935
edu*comuse	1	1	1	1.3607	105.5	0.0002	0.9897
edu*comuse	2	1	1	1.0724	105.5	0.0001	0.9919
edu*comuse	3	1	1	1.3542	105.5	0.0002	0.9898
edu*comuse	4	1	1	1.5988	105.5	0.0002	0.9879
income*comuse	1	1	1	-0.6114	0.0894	46.7466	<.0001
income*comuse	2	1	1	-0.1551	0.0828	3.5099	0.0610
income*comuse	3	1	1	-0.1460	0.0870	2.8180	0.0932
income*comuse	4	1	1	0.0645	0.0944	0.4663	0.4947
income*comuse	5	1	1	-0.5475	0.1927	8.0705	0.0045
income*comuse	6	1	1	0.4216	0.1333	10.0026	0.0016
income*comuse	7	1	1	0.7730	0.1590	23.6396	<.0001
income*shoploan	1	1	1	-0.8167	10.3096	0.0063	0.9369
income*shoploan	1	2	1	0.2184	28.7786	0.0001	0.9939
income*shoploan	1	3	1	-0.3135	10.3097	0.0009	0.9757
income*shoploan	1	4	1	0.2772	25.0978	0.0001	0.9912
income*shoploan	2	1	1	-1.3450	10.3097	0.0170	0.8962
income*shoploan	2	2	1	0.5021	28.7786	0.0003	0.9861
income*shoploan	2	3	1	-0.5063	10.3097	0.0024	0.9608
income*shoploan	2	4	1	0.6155	25.0976	0.0006	0.9804
income*shoploan	3	1	1	-1.1334	10.3097	0.0121	0.9125
income*shoploan	3	2	1	0.3668	28.7785	0.0002	0.9898
income*shoploan	3	3	1	-0.7221	10.3097	0.0049	0.9442
income*shoploan	3	4	1	0.8071	25.0976	0.0010	0.9743
income*shoploan	4	1	1	-1.0995	10.3100	0.0114	0.9151
income*shoploan	4	2	1	1.0298	28.7787	0.0013	0.9715
income*shoploan	4	3	1	-1.1347	10.3099	0.0121	0.9124
income*shoploan	4	4	1	0.5887	25.0977	0.0006	0.9813
income*shoploan	5	1	1	-0.6680	10.3110	0.0042	0.9483
income*shoploan	5	2	1	0.2921	28.7796	0.0001	0.9919
income*shoploan	5	3	1	-1.2353	10.3108	0.0144	0.9046
income*shoploan	5	4	1	0.9994	25.0980	0.0016	0.9682
income*shoploan	6	1	1	-0.9740	10.3127	0.0089	0.9248
income*shoploan	6	2	1	0.5377	28.7803	0.0003	0.9851
income*shoploan	6	3	1	-1.1248	10.3120	0.0119	0.9131
income*shoploan	6	4	1	1.2510	25.0984	0.0025	0.9602
income*shoploan	7	1	1	-0.7265	10.3138	0.0050	0.9438
income*shoploan	7	2	1	1.4309	28.7805	0.0025	0.9603
income*shoploan	7	3	1	-0.6728	10.3125	0.0043	0.9480
income*shoploan	7	4	1	-0.3956	25.1010	0.0002	0.9874

5.5 RESULTS: RANDOM EFFECT PROBIT MODEL

The full probit model with random effect in which include all independent variables of interest is as follows.

$$y = \beta_0 + \beta_1 * EDU + \beta_2 * INCOME + \beta_3 * AGE + \beta_4 * ECON + \beta_5 * INT + \beta_6 * SHOPLOAN + \beta_7 * SHOPSAV + \beta_8 * COMUSE + u$$

,where y *Probit*(probability of using smart card, ATM card, debit card, or credit card.

The SAS provides the result that optimization cannot be completed. As an alternative, reduced model is built to investigate the causal relationship between demographic variables and the probability of using electronic cards. The reduced model is

$$y = \beta_0 + \beta_1 * EDU + \beta_2 * INCOME + \beta_3 * EDU * INCOME + u ,$$

where y represents smart card, ATM card, debit card, or credit card.

The reason to choose two demographic variables is that those variables have been frequently used predictors in related fields. In following sections, we present the results of reduced probit model with random effect.

5.5.1. RANDOM EFFECT PROBIT MODEL FOR SMART CARDS

The reduced random effect probit model for smart cards is tested.

$$\text{Model: } y = \beta_0 + \beta_1 * EDU + \beta_2 * INCOME + \beta_3 * EDU * INCOME + u .$$

The fitted probit model is

$$y = 6.5207 - 0.0379 * EDU - 0.0012 * INCOME - 0.0012 * EDU * INCOME .$$

The chosen model satisfied convergence criterion. The test statistic for goodness-of-fit is $-2 \text{ Log } L = 664.4$. The degree of freedom is 3, since there are three variables in a model. It results in extremely p-value (p-value < .0001), thus random effect probit model proves to fit well.

Table 5.36. Results of Random Effect Probit Model for Smart Cards.

Parameter	Estimate	S.E.	t-value	p-value
b_0 (slope)	6.521	139.97	0.05	0.962.
b_1 (Edu)	-0.038	0.681	-0.52	0.6042
b_2 (Income)	-0.063	0.06	-1.49	0.1373
b_3 (E*I)	0.001	0.03	-0.08	0.9364

All predictors turn out to be insignificant. Only the p-value of income variable is close to $\alpha = 0.05$ level (p-value = 0.1373). Based on random effect probit model, we can state there is no significant relationship between the probability of using smart cards and demographic variables: education, income. Although we tested alternative random effect probit models which included the possible combinations of education, income and age, we did not find any model showing a significant relationship between the demographic predictor and the probability of using debit cards.

5.5.2 RANDOM EFFECT PROBIT MODEL FOR ATM CARDS

The reduced random effect probit model for ATM card is expressed as follows.

$$\text{Model: } y = \beta_0 + \beta_1 * \text{EDU} + \beta_2 * \text{INCOME} + \beta_3 * \text{EDU} * \text{INCOME} + u .$$

The fitted probit model is

$$y = 1.992 - 0.014 * \text{EDU} - 0.067 * \text{INCOME} + 0.006 * \text{EDU} * \text{INCOME} ,$$

where y is estimated probability of using ATM cards

The chosen model satisfied convergence criterion. The test statistic for goodness-of-fit is $-2 \text{ Log } L = 3530.8$. The degree of freedom is 3, since there are three variables in a model. It results in extremely p-value (p-value < .0001), thus random effect probit model proves to fit well.

Table 5.37. Results of Random Effect Probit Model for ATM Cards.

Parameter	Estimate	S.E.	t-value	P-value
b_0 (slope)	1.992	0.72	2.79	0.005 *
b_1 (Edu)	-0.014	0.03	-0.42	0.677
b_2 (Income)	-0.067	0.03	-2.29	0.022 *
b_3 (E*I)	0.006	0.01	0.81	0.416

The estimated coefficient for income level is -0.067 with standard error of 0.03. The t-test for the coefficient shows that $t = -2.29$ and $p = 0.022$, which is significant. The significant coefficient ($b_2 = -0.067$) suggests that with 1 unit increase of income level,

the odds of using ATM cards decrease by a factor $\exp(-0.067)=0.935$. The main effects of income and interaction effect are not significant.

5.5.3 RANDOM EFFECT PROBIT MODEL FOR DEBIT CARDS

The reduced random effect probit model for debit cards is tested.

$$\text{Model: } y = \beta_0 + \beta_1 * \text{EDU} + \beta_2 * \text{INCOME} + \beta_3 * \text{EDU} * \text{INCOME} + u .$$

The fitted probit model is

$$y = 6.5207 - 0.0379 * \text{EDU} - 0.0012 * \text{INCOME} - 0.0012 * \text{EDU} * \text{INCOME} ,$$

where y is estimated probability of using debit cards

The chosen model satisfied convergence criterion. The test statistic for goodness-of-fit is $-2 \text{ Log } L = 4119.0$. The degree of freedom is 3, since there are three variables in a model. It results in extremely p-value (p-value < .0001), thus random effect probit model proves to fit well.

Table 5.38. Results of Random Effect Probit Model for Debit Cards.

Parameter	Estimate	S.E.	t-value	P-value
b_0 (slope)	1.778	23.96	0.07	0.9409
b_1 (Edu)	0.086	1.15	0.07	0.9409
b_2 (Income)	-0.016	0.22	-0.07	0.9410
b_3 (E*I)	0.0004	0.05	0.07	0.9416

The result of random effect probit model for debit card shows that all demographic predictors are insignificant. Based on the result of random effect probit model, we can state that there is no significant relationship between the probability of using debit cards and demographic variables: education, income. As an alternative, we tested alternative random effect probit models which included the possible combinations of education, income and age, but we did not find any probit model which revealed a significant relationship between the demographic predictor and the probability of using debit cards.

5.5.4 RANDOM EFFECT PROBIT MODEL FOR CREDIT CARDS

The reduced model is as follows:

$$\text{Model: } y = \beta_0 + \beta_1 * \text{EDU} + \beta_2 * \text{INCOME} + \beta_3 * \text{EDU} * \text{INCOME} + u .$$

The fitted probit model is

$$y = 12.5669 - 0.3853 * \text{EDU} - 0.2374 * \text{INCOME} + 0.0297 * \text{EDU} * \text{INCOME} ,$$

where y is estimated probability of using ATM cards

The chosen model satisfied convergence criterion. The test statistic for goodness-of-fit is $-2 \log L = 2097.5$. The degree of freedom is 3, since there are three variables in a model. It results in extremely p-value (p-value < .0001), thus random effect probit model proves to fit well.

Table 5.39. The result of Random Effect Probit Model for Credit Cards.

Parameter	Estimate	S.E.	t-value	P-value
b_0 (slope)	12.56	.	.	.
b_1 (Edu)	-0.384	0.11	-3.56	0.0004 *
b_2 (Income)	-0.237	0.06	-3.68	0.0002 *
b_3 (E*I)	0.029	0.03	2.00	0.0455 *

The fitted probit model for credit cards shows that the main effects of education and income are significant at $\alpha = .05$ level. In addition, interaction between education and income proves significant at $\alpha = .05$ level. The estimated coefficient for education level is -0.384 with standard error of 0.11. The t-test for the coefficient shows that $t = -3.56$ and $p = 0.0004$, which is significant. The significant coefficient suggests that with 1 unit increase of education level (i.e., from bachelor to master degree), the odds of using credit cards decrease about 32%, since a factor $\exp(-0.384) = 0.681$.

The estimated coefficient for income level is -0.237 with standard error of 0.06. The t-test for coefficient results in $t = -3.68$, and $p = 0.0002$. The significant coefficient suggests that with 1 unit increase of income level, the odds of using credit cards decrease about 21%. However, the estimated coefficient for interaction effect between education and income is 0.029 with $p\text{-value} = 0.0455$, which means that with the 1 unit increase of an interaction level, the odds of using credit cards increase about 3%.

CHAPTER 6

CONCLUSION

This study examined the relation of socio-economic factors and the use of electronic payment methods based on the Survey of Consumer Finances data set. As expected, we found a strong evidence to support the existence of relationship between the socio-economic factors and the usage of electronic payment instruments. We used four different models to understand the probabilities of using smart cards, ATM cards, debit cards, and credit cards.

The level of income is a useful indicator to predict the adoption of four EPI. Interestingly, the level of income is significant across four models. Age is also significant across all models. It does make sense since age and income are crucial factors among socio-economic variables. Older and richer people tend to response to new way of payments in a banking market.

There are quite interesting findings in this study. The use of financial software is a strong predictor to explain the usage of EPI. Those who use software for financial management are more likely to use EPI. We can infer that technology-savvy people tend to prefer new electronic payment methods. Shopping behavior is also a strong indicator to explain the use of EPI. People who seek more financial information tend to use EPI more frequently. This type of people gives much emphasis on the value of information. Since

they have shopped more information, they can be easily familiar with electronic payment methods.

Table 6.1. Overall Summary of Findings.

Predictor	Smart card	ATM cards	Debit card	Credit cards
Income	O	O	O	O
Age	O	O	O	O
Education		O	O	O
Attitude future economy	O		O	O
Attitude future interest rates		O		O
Shop for loan		O	O	O
Shop for saving	O	O	O	O
Use of financial software	O		O	O

O = statistically significant at .05 level

When looking at each model, income, age, attitude toward future economy, shopping behavior for saving and investment, and the use of financial software are significantly related to using smart cards. For ATM cards, all predictors except attitude toward the future economy, as shown in Table 6.1 are significant at .01 levels. In the case of debit cards, Income, age, education, attitude toward economy, shopping behavior for loan and saving, and the use of financial software are significant at .05 levels. Only attitude toward the future interest rate turns out to be insignificant. The use of credit card, the most popular electronic payment method, was explained by all predictors.

However, this investigation has limitations. The logistic regression model ignored some other important factors such as ethnicity and regions. That is because Federal Reserve Board did not include in a public data set for privacy reasons. Another limitation

is that finding best-fit models are not pursued in this analysis. The reason is that the objective of this research is to test hypotheses based on theories in a related research field. Even though there are some limitations, the new findings that were presented in this study contribute to the field of marketing in banking industry and policy makers.

In our analysis, we analyzed binary data under the condition assuming independence and binomial distribution. However, in practice, it is known that observed sums and proportions often display extra-binomial variance. A common probability distribution for describing such overspread data is the beta-binomial (Skellam, 1948). When faced with proportion or binary data that exhibit extra-binomial variation, it is often necessary to consider the beta-binomial distribution as an alternative model to the more common binomial distribution (Garren, Smith, & Piegorsch, 2000). For instance, binary observations are often correlated two each other. This is the possible scenario in our survey data. Thus, in this case, it is important to test for the goodness-of-fit if the beta-binomial model fits to the data.

BIBLIOGRAPHY

- Acemoglu D., and Scott, A., (1994). Consumer Confidence and Rational Expectations: Are Agents' Beliefs Consistent with the Theory? The *Economic Journal*, Vol., 104., pp.1-19.
- Agresti, A., (1996). An Introduction to Categorical Data Analysis. John Wiley and Sons, Inc.
- Aizcorbe, A. M., Kennickell, A. B., & Moore, K. B. (2003). Recent Changes in U.S. Family Finances: Evidence from the 1998 and 2001 Survey of Consumer Finances. *Federal Reserve Bulletin*, January, 1-32.
- Arthur B. Kennickell, (2001). "Modeling Wealth with Multiple Observations of Income: Redesign of the Sample for the 2001 Survey of Consumer Finances," SCF Working paper, <http://www.federalreserve.gov/pubs/oss/oss2/method.html>
- Balto, D. A. (1998). Routing Rules of ATM Networks: The Antitrust Risks in Backbones of Electronic Commerce. *Journal of Retail Banking Services*, 20(3), 57-64.
- Booz Allen Hamilton Corporate (1997). Decreased Role of Banks in Payments.
- Carow, K. A., & Staten, M. (1999). Plastic Choices: Debit, Credit, and Cash. *Journal of Economics and Business*, 51, 409-422.
- Caskey, J. P., & Sellon, Jr., G. H. (1994). Is the Debit Card Revolution Finally Here? *Economic Review*, Fourth Quarter, 79-95.

- Choi, H. N., & DeVaney, S. A. (1995). Differences in the Use of Bank and Retail Credit Cards in the USA. *Journal of Consumer Studies and Home Economics*, 19, 381-392.
- Choi, S. Y., & Whinston, A. B. (1998). Is it Spring Time for Internet "Tulips"? Available online at <http://cism.bus.utexas.edu/works/articles/internetfirms.html>
- Collins, A. (1999). Framework for smart card use in government discussion draft issue 0.4. Available at <http://www.fipr.org/cards/cardnonsense.txt>
- Crosby, L.A., and Taylor, J.R. (1981). Effects of Consumer Information and Education on Cognition and Choice, *Journal of Consumer Research*, Vol.8 . pp.43-56.
- Danes, S. M. & Hira, T. K. (1990). Knowledge, Beliefs and Practices in the Use of credit Cards. *Home Economics Research Journal*, 18, 223-235.
- Daniels, K. N., & Murphy, N. B. (1994). The Impact of Technological Change on the Currency Behavior of Households: An Empirical Cross-Section Study. *Journal of Money, Credit, and Banking*, 26, 867-74.
- Federal Reserve Financial Services, (2001). Electronic Payment Instruments Study, Summary Report. Available online at <http://www.aba.com/NR/rdonlyres/00004b26kodjiblxexcvchub/0>
- Ferber, R., (1973). Consumer Economics, a Survey., *Journal of Economic Literature*, Vol. 11 (4), pp. 1303-1342.
- Garren, S. T., R. L. Smith and W. W. Piegorsch (2000). Reader Reaction: On a Likelihood-Based Goodness-of-Fit Test of the Beta-Binomial Model, *Biometrics* 56, 947-949.

- Gerdes, G. R., & Walton, II, J. K. (2002). The Use of Checks and Other Noncash Payment Instruments in the United States, *Federal Reserve Bulletin*, 88, 360-374.
- Gosnell, D. (1999). POS Debit Challenges ATMs. *Credit Card Management*, September, 17-20.
- Horvitz, P. M. (1996). ATM Surcharges: Their Effect on Competition and Efficiency. *Journal of Retail Banking Services*, 18(3), 57-62
- Horvitz, P. M. (1996). Preserving Competition in Electronic Home Banking. *Journal of Money, Credit, and Banking*. 28, 971-974.
- Hosmer D.W., and Lemeshow S. (1989). Applied Logistic Regression. John Wiley & Sons, New York.
- Kaynak, E., & Harcar T. (2001). Consumers' Attitudes and Intentions Towards Credit Card Usage in an Advanced Developing country. *Journal of Financial Services Marketing*, 6, 24-39.
- Kennickell, A. B.(2003) Rolling tide: Changes in the Distribution of Wealth in the U.S., 1989-2001. Working Paper. Board of Governors of the Federal Reserve System.
- Kennickell, A. B., & Kwast, M. L. (1997). Who Uses Electronic Banking? Results from the 1995 Survey of Consumer Finances," *Proceedings of the 33rd Annual Conference on Bank Structure and Competition*, Federal Reserve Bank of Chicago, May, 56-75.
- Kennickell, Arthur B. & R. Louise Woodburn (1999) "Consistent Weight Design for the 1989, 1992, and 1995 SCFs, and the Distribution of Wealth," *Review of Income and Wealth* (series 45, number 2), June 1999, pp.193-215.

- Kennickell, Arthur B. (1998) "List Sample Design for the 1998 Survey of Consumer Finances," *Federal Reserve Bulletin*, April 1998.
- Kennickell, Arthur B. (1998). Multiple Imputation in the Survey of Consumer Finances, working paper, Board of Governors of the Federal Reserve System.
- Kennickell, Arthur B. (1999) "Revisions to the SCF Weighting Methodology: Accounting for Race/Ethnicity and Homeownership," working paper, Board of Governors of the Federal Reserve System.
- Kennickell, Arthur B. (2000) "Wealth Measurement in the Survey of Consumer Finances: Methodology and Directions for Future Research," paper presented at the 2000 annual meetings of the American Association for Public Opinion Research, Portland, May.
- Kleinbaum, D., (1994). Logistic Regression: A self-learning Text. Springer-Verlag: New York.
- McCulloch, C.E. & Searle, S.R. (2000). Generalized Linear and Mixed Models. John Wiley & Song, Inc.
- Mantel, B. M., (2000). Why Don't Consumers Use Electronic Banking Products? Towards a Theory of Obstacles, Incentives, and Opportunities. Federal Reserve Bank of Chicago, Public Policy Series, No. EPS-2000-1, September., *The Nilson Report*, Oxnard, CA, No. 715.
- Medina, J. & Chau, C.T. (1998). Credit Card Usage Behavior between Anglos and Hispanics. *Hispanic Journal of Behavioral Sciences* 20, 429-47
- Min, K. (1998). Banks are Leading on ATM Surcharges, but Some Key Consumers are Retreating. *Journal of Retail Banking Services*, 20(4), 35-42.

- Moorthy, S., Ratchford, B.T., and Talukdar, D. (1997). Consumer Information Search Revisited: Theory and Empirical Analysis, *Journal of Consumer Research*, Vol. 23.
- Morgan, James N., Consumer Investment Expenditures, *American Economic Review*, Vol. 48 (5), 1958, 874-902.
- Pampel, Fred C. (2000). Logistic Regression: A Primer. Thousand Oaks: Sage.
- Roberts, C. (1998). Norwest Pushing Debit Cards towards 55% Penetration, 70% Activation, 11 uses per month. *Journal of Retail Banking Services*, 20(3), 9-14.
- Shon, T. H., & Swatman, P. M. C. (1998). Identifying Effectiveness Criteria for Internet Payment Systems. *Internet Research: Electronic Networking Applications and Policy*, 8,
- Skellam, J.G. (1948). A Probability Distribution Derived from the Binomial Distribution by Regarding the Probability of Success as Variable between the Sets of Trials, *Journal of the Royal Statistical Society, Series B* 10, 257-261.
- Stavins, J. (2001). Perspective: While More People Are Paying Electronically, Many of Us Still Cling to Checks. *Regional Review*, 4, 2-4.
- Tourangeau, Roger, Robert A. Johnson, Jiahe Qian, Hee-Choon Shin, and Martin R. Franke (1993) "Selection of NORC's 1990 National Sample," working paper, National Opinion Research Center at the University of Chicago, Chicago, IL.
- Tukey, J. W., Ciminera, J. L., and Heyse, J. F. 1985. Testing the Statistical Certainty of a Response to Increasing Doses of a Drug. *Biometrics* 41:295-301.

Wasberg, C.A., Hira, T.K., & Fanslow, A.M. (1992). Credit Card Usage and Consumer Debt Burden of Households. *Journal of Consumer Studies and Home Economics* 16, 9-32.

Weinberg, J. A. (1994). Selling Federal Reserve Payment Services: One Price Fits All? *Economic Quarterly*, 80 (4), 1-23.

Website

<http://jeff-lab.queensu.ca/stat/sas/sasman/sashtml/stat/chap39/sect32.htm>

<http://online.sfsu.edu/~efc/classes/biol710/logistic/logisticreg.htm>

<http://online.sfsu.edu/~efc/classes/biol710/logistic/logisticreg.htm>

http://www.amstat.org/sections/srms/proceedings/papers/1997_026.pdf

<http://www.federalreserve.gov/pubs/oss/oss2/2001/bull0103.pdf>

<http://www.federalreserve.gov/pubs/oss/oss2/2001/scf2001home.html>

<http://www.federalreserve.gov/pubs/oss/oss2/method.html>

<http://www.federalreserve.gov/pubs/oss/oss2/papers/asa2002.full.pdf>

<http://www.smartcardalliance.org>

<http://www.stats.gla.ac.uk/~goeran/euroworkshop/webpages/2002/slides/oliver.pdf>

<http://www2.chass.ncsu.edu/garson/pa765/logit.htm>

APPENDIX A
SURVEY QUESTIONNAIR

Need for an electronic payment instrument (EPI)

Household income:

X5702 In total, how much income from wages and salaries did you receive in all of 2000, before deductions for taxes and anything else? Did you and your family receive in all of 2000, before deductions for taxes and anything else?

Ability to Manage an EPI: Human Capital Resources

Education:

X5905(#1) What is the highest degree you have earned?

X6105(#2) What is the highest degree (he/she) earned?

Code degree

1. *Associate's; and other junior college degree
2. *Bachelor's
3. *MA/MS; and other master's except MBA
9. *MBA
4. *PhD; including post-doctorate
5. *MD; DDS; Doctor of Osteopathy
6. *Law; JD
10. Nursing degree (RN, LPN)

11. Other certificate, Chiropractic, Nephropathy, Homeopathy, Pharmacology, teaching certificate

12. Other doctorate (DVM, Doctor of Divinity, etc.)

-7. *Other

0. Inap. (/no spouse; 12 years or less of education:

X5901<12/X6101<12; did not get a degree: X5904^=1/

X6104^=1)

For the public data set, code 9 is combined with code 3; codes 5, 6, and 12 are combined with code 4; code 10 is combined with code 11

Experiences with Financial Institutions

Age:

X14 Respondent: "Reconciled age"

X19 Spouse: "Reconciled age"

In the capi program used in the survey, designated respondents were first asked their date of birth (x5907/x7003/x5908 or x6107/x7382/x6108 depending on the value of x8000). The computer calculated their age and then the interviewer asked for confirmation (x7005/x7015). At that point, a respondent could agree to the computed age, correct their birth date, or provide a different age (x8022/x104). For the designated r, this variable contains the dob age unless a different age was reported subsequently. For the r's spouse/partner, only age was asked during the household listing and date of birth was asked later in the questionnaire. However, there was no confirmation/ reconciliation built

into the program for the spouse/partner. This age variable was used in all conversions or calculations involving ages of r/s.

Information sources

Computer software use:

X6497 Do you or your (spouse/partner) use any type of computer software to help you with managing your money? Do you use any type of computer software to help you with managing your money?

1. *YES
5. *NO

Information seeking behavior

X7100 (SHOW CARD 1) When making major decisions about credit or borrowing, some people shop around for the very best terms while others don't. (What number would you be on the scale?/What number would your family be on the scale?)

1. *ALMOST NO SHOPPING
- 2.
3. *MODERATE SHOPPING
- 4.
5. *A GREAT DEAL OF SHOPPING

X7111 (SHOW CARD 1) When making major saving and investment decisions, some people shop around for the very best terms while others don't. What number would you be on the scale? What number would your family be on the scale?

1. *ALMOST NO SHOPPING
- 2.
3. *MODERATE SHOPPING
- 4.
5. *A GREAT DEAL OF SHOPPING

NOTE: See X7100 for a description of CARD 1.

Attitude toward economy

X301 I'd like to start this interview by asking you about your expectations for the future. Over the next five years, do you expect the U.S. economy as a whole to perform better, worse, or about the same as it has over the past five years?

1. *Better
2. *Worse
3. *About the same

X302 Five years from now, do you think interest rates will be higher, lower, or about the same as today?

1. *Higher
2. *Lower
3. *About the same

APPENDIX B

HISTOGRAM OF DATA

Figure B.1. Proportion of ATM Card Users/Nonusers by Income
1 represents users, 2 represents nonusers.

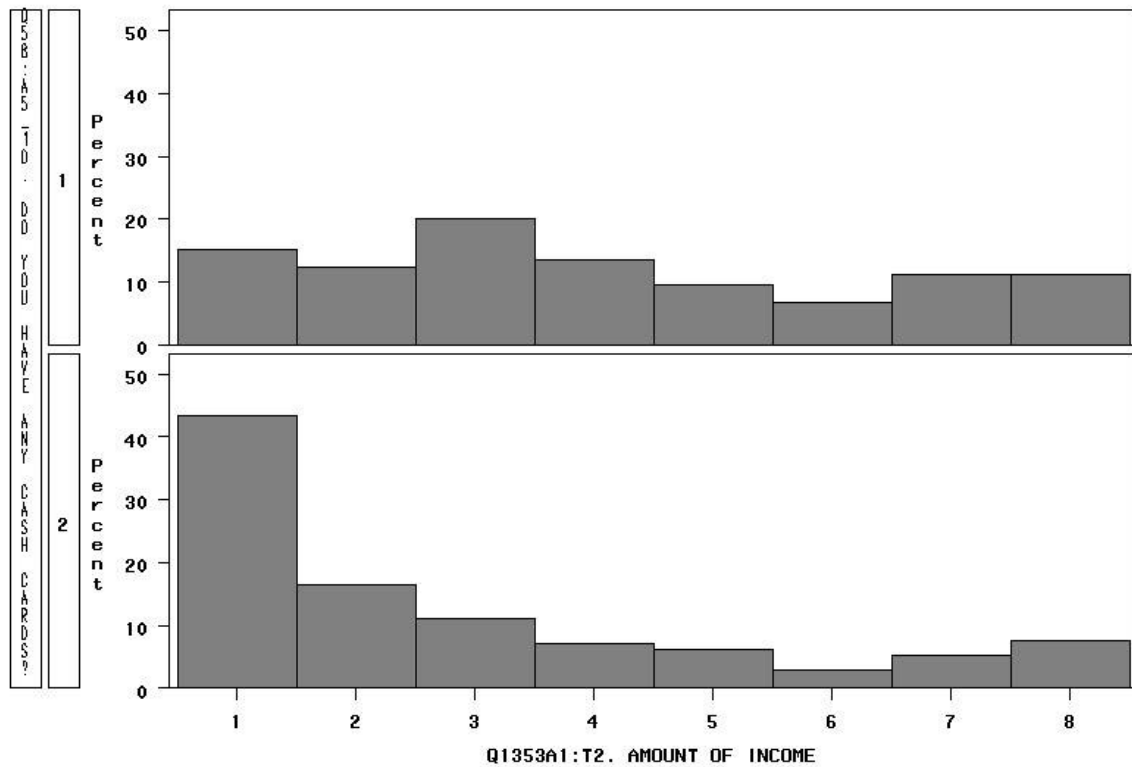


Figure B. 2. Proportion of Smart Card Users/Nonusers by Income
 1 represents users, 2 represents nonusers.

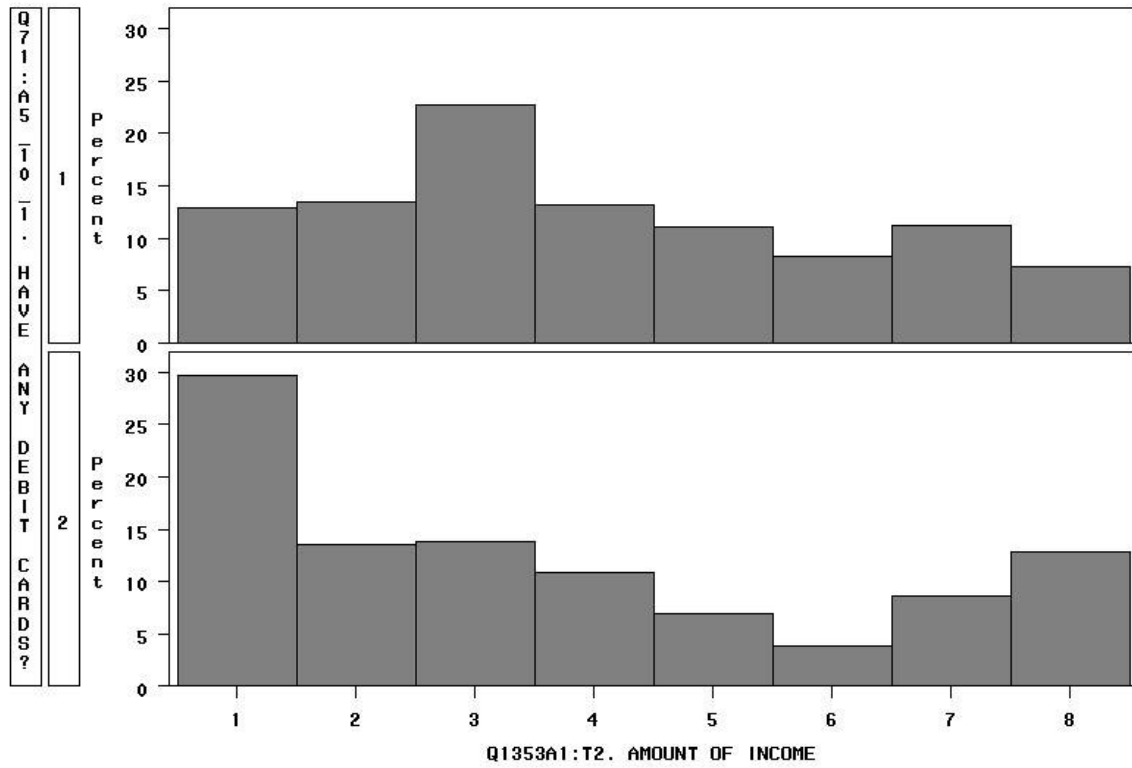


Figure B.3. Proportion of Debit Card Users/Nonusers by Age

1 represents users, 2 represents nonusers.

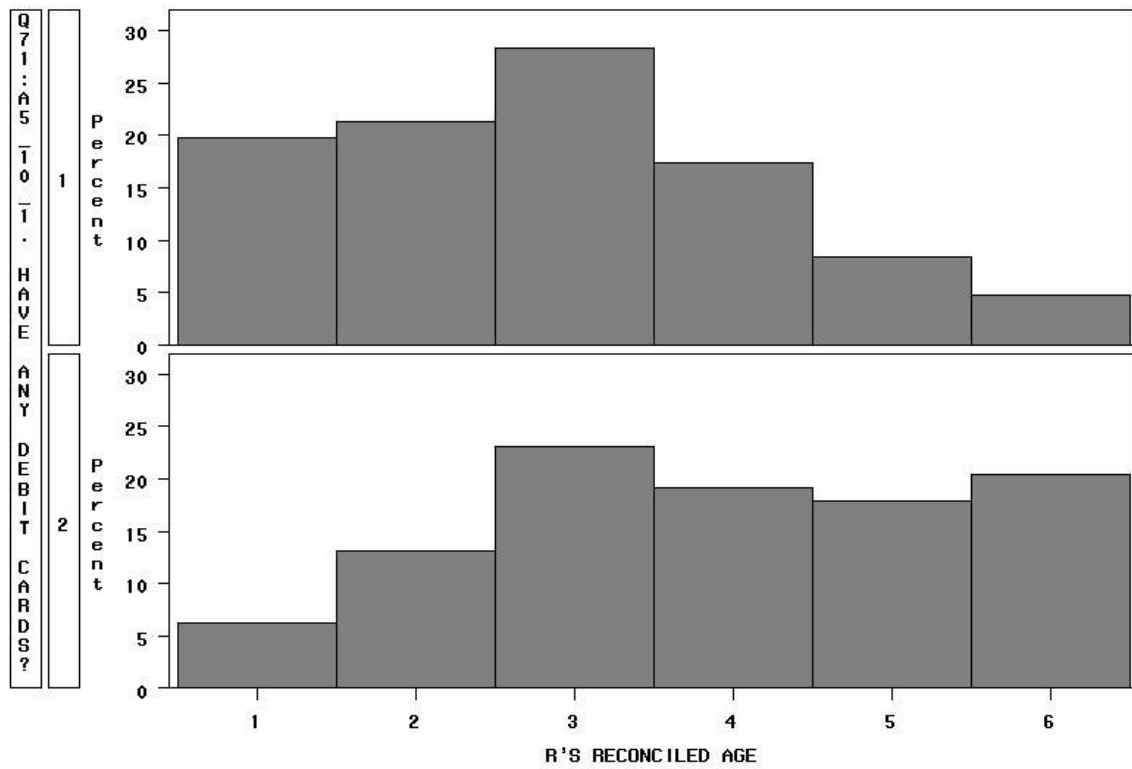


Figure B.4. Proportion of ATM Card Users/Nonusers by Age
 1 represents users, 2 represents nonusers.

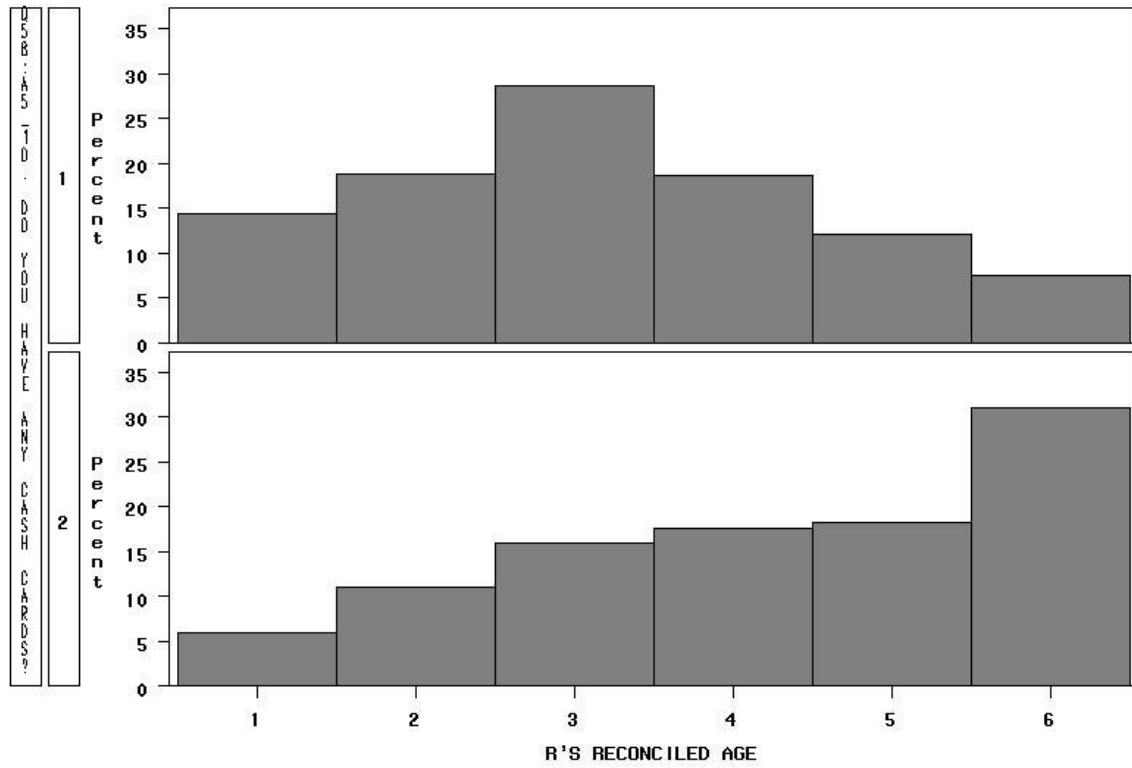


Figure B.5. Proportion of ATM Card Users/Nonusers by Shopping for Loan
 1 represents users, 2 represents nonusers.

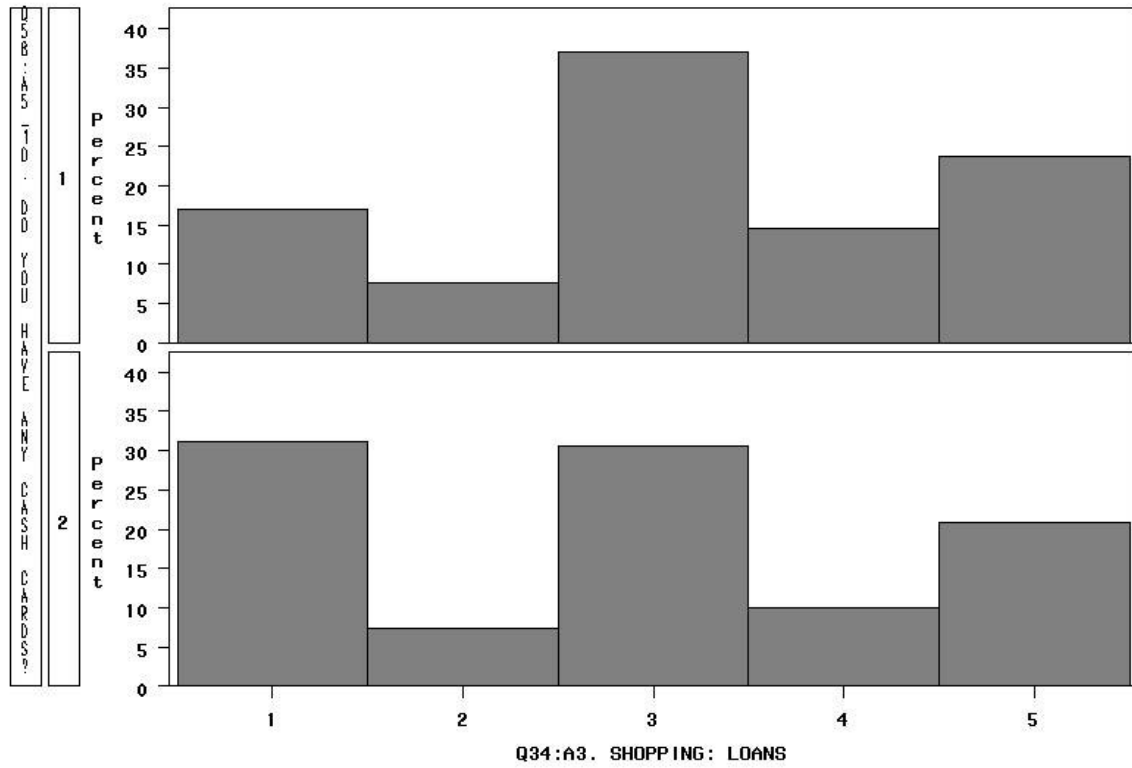


Figure B.6. Proportion of Debit Card Users/Nonusers by Shopping for Loans
 1 represents users, 2 represents nonusers.

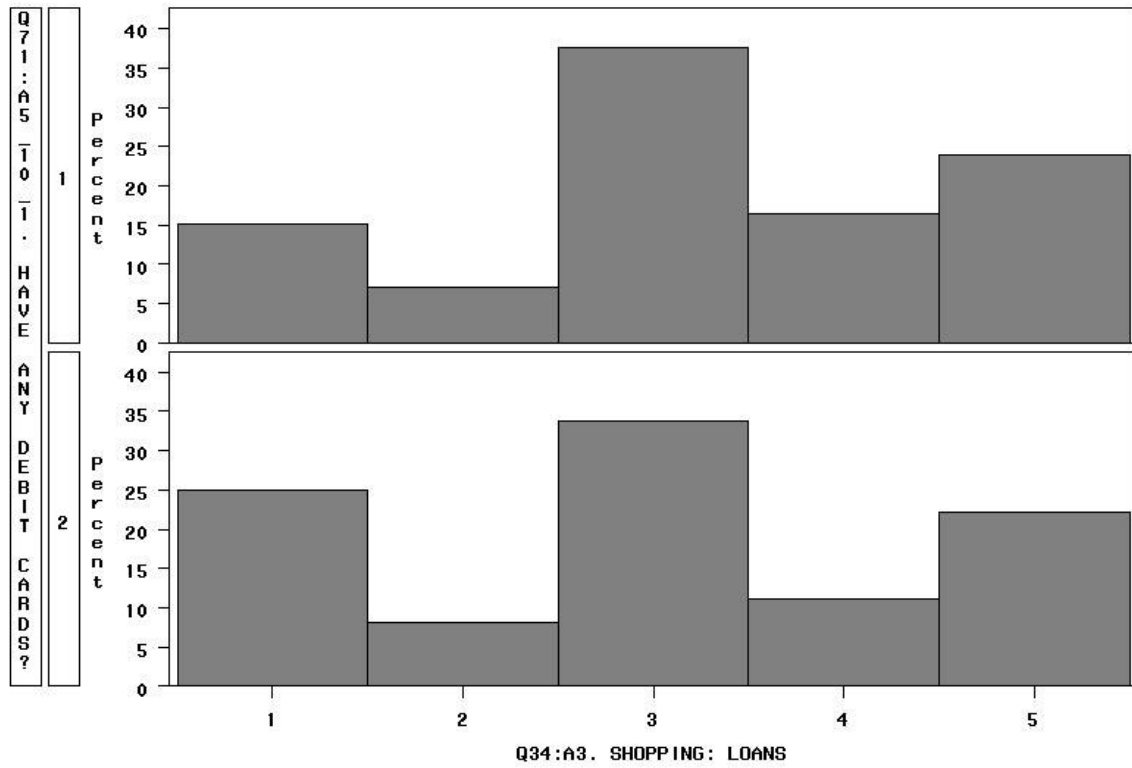


Figure B. 7. Proportion of Smart Card Users/Nonusers by Shopping for Saving
1 represents users, 2 represents nonusers.

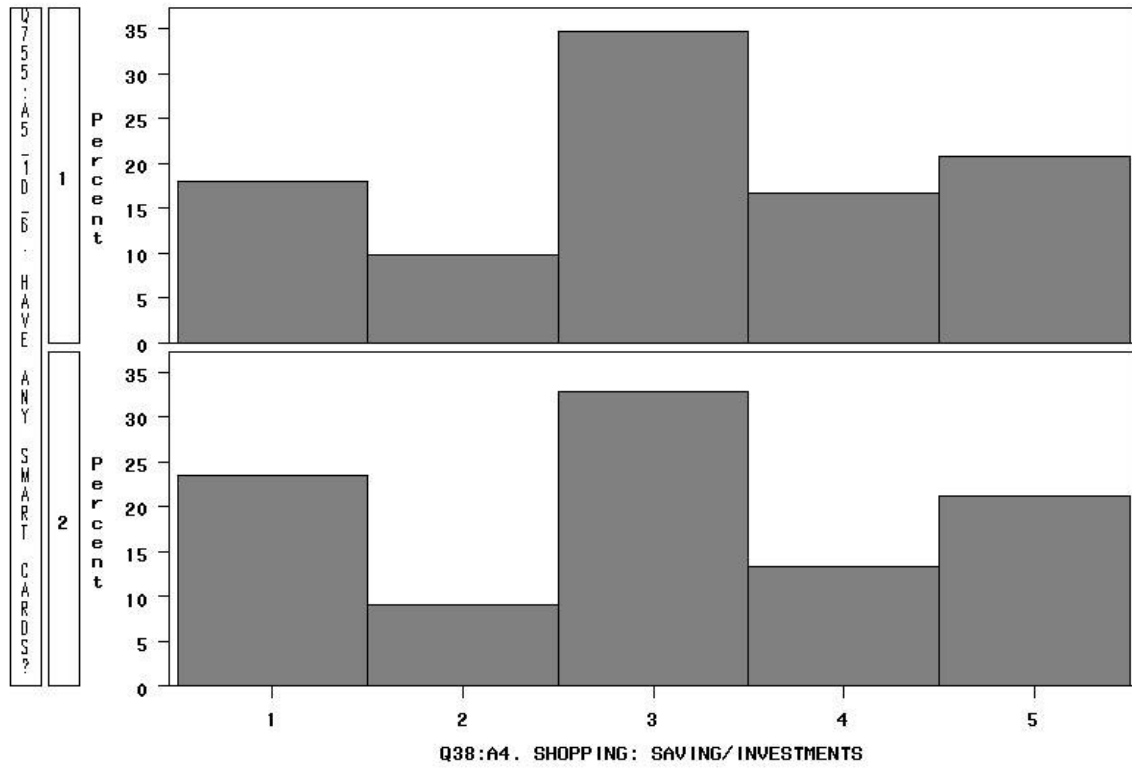


Figure B. 8. Proportion of ATM Card Users/Nonusers by Shopping for Saving
1 represents users, 2 represents nonusers.

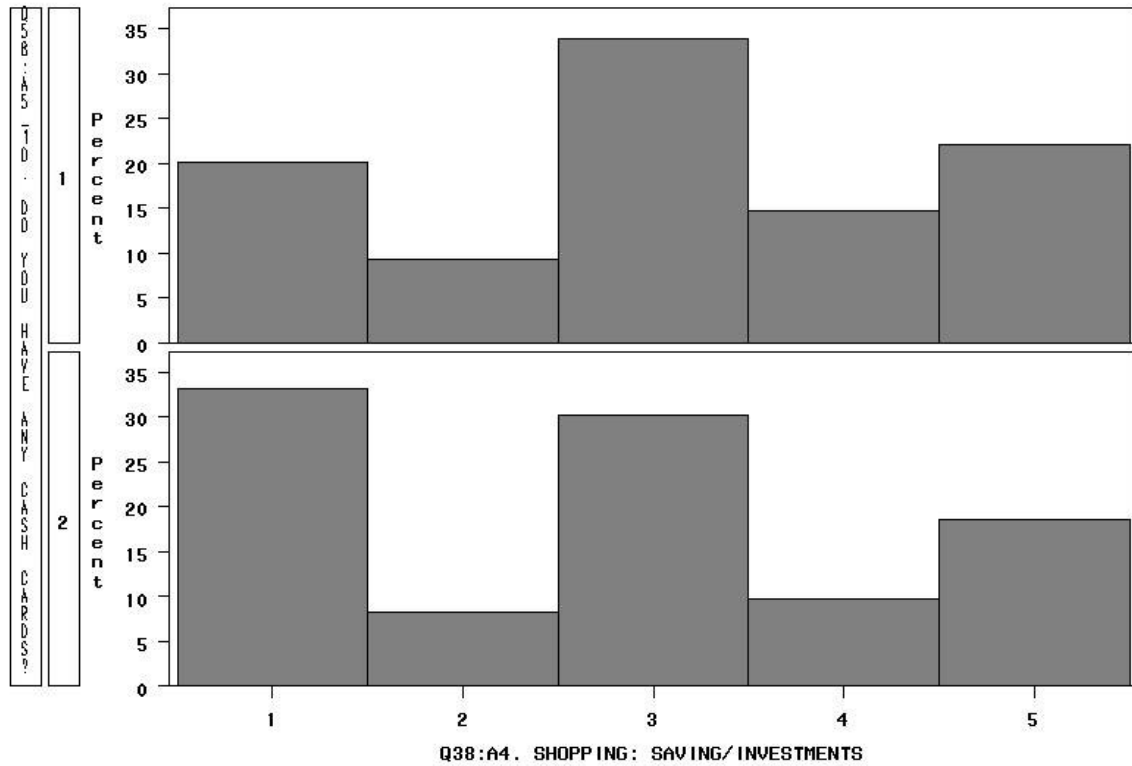


Figure B.9. Proportion of Debit Card Users/Nonusers by Shopping for Saving
1 represents users, 2 represents nonusers.

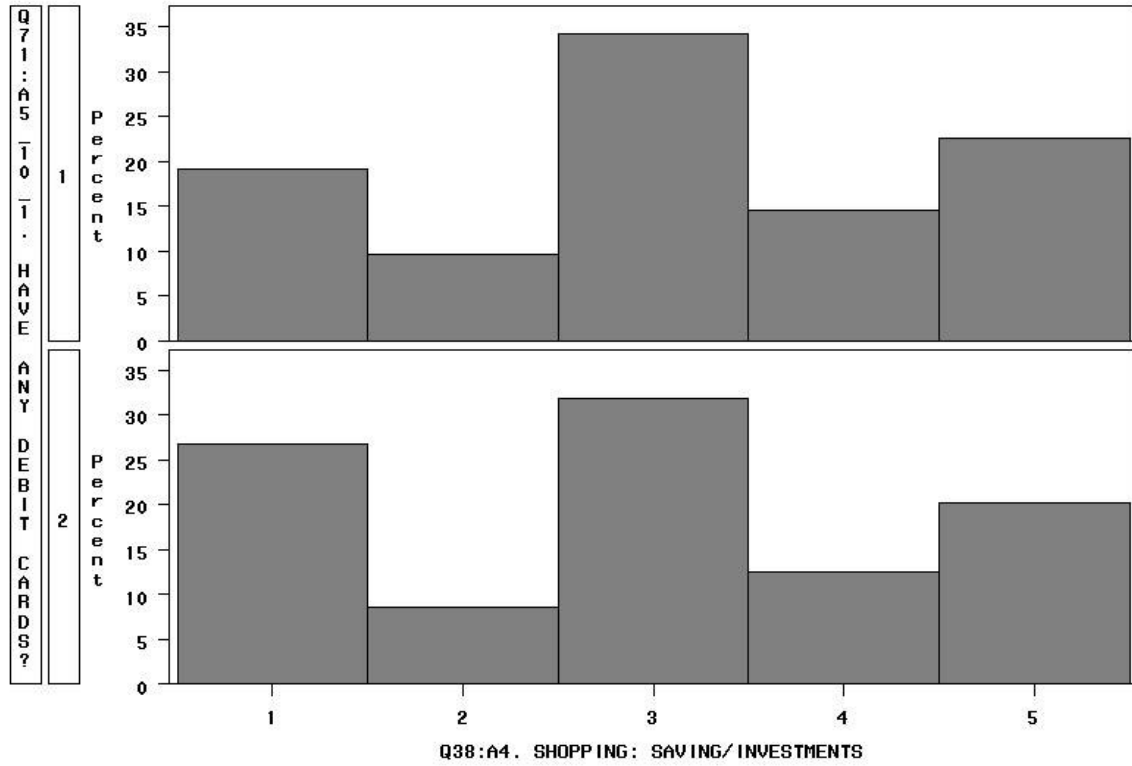


Figure B.10. Proportion of Credit Card Users/Nonusers by Shopping for Saving
1 represents users, 2 represents nonusers.

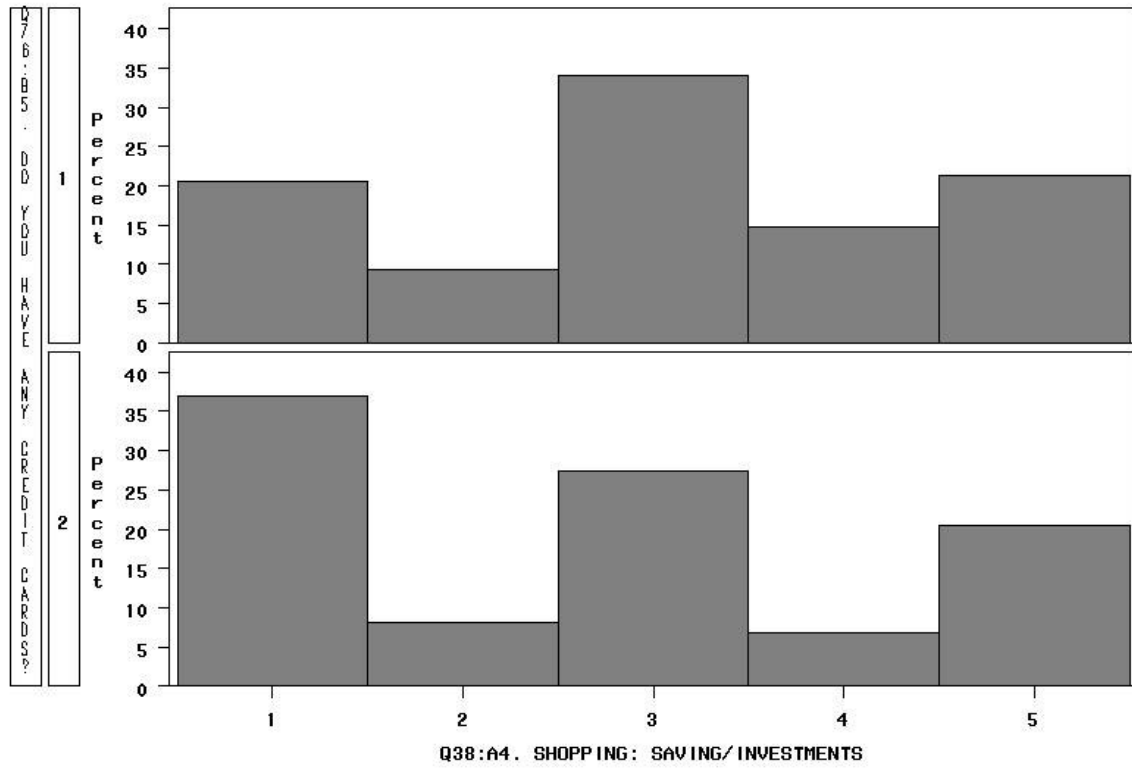


Figure B. 11. Proportion of Debit Card Users/Nonusers by Attitude toward Economy
1 represents users, 2 represents nonusers.

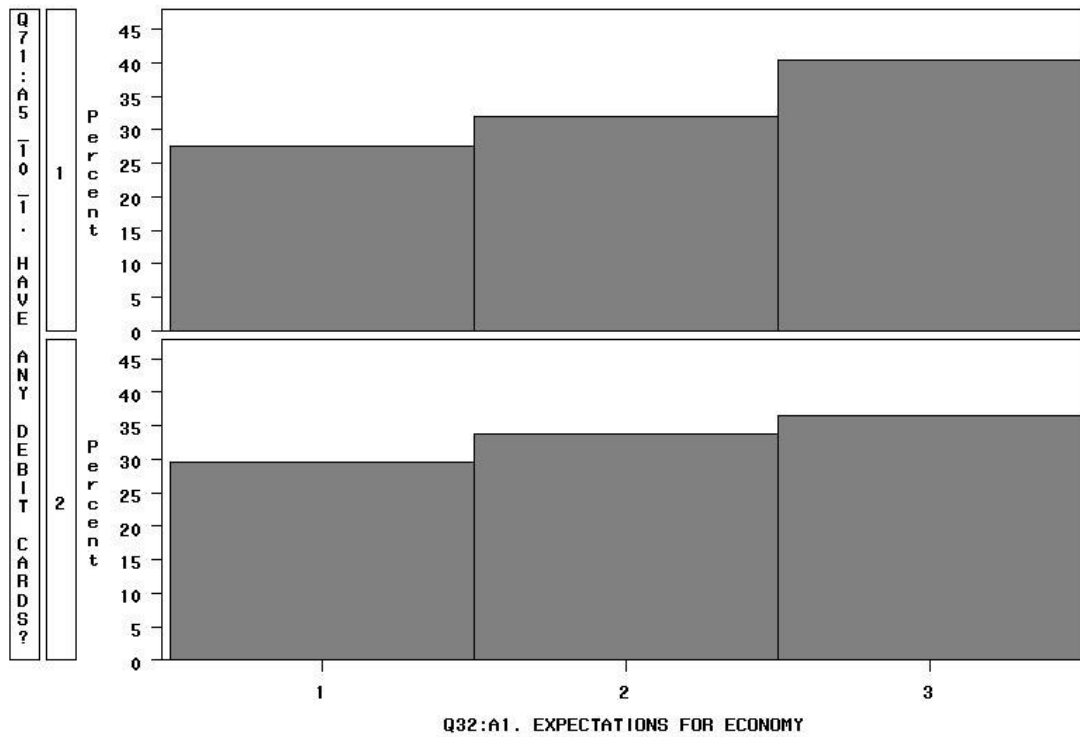


Figure B.12. Proportion of Credit Card Users/Nonusers by Attitude toward Economy
1 represents users, 2 represents nonusers.

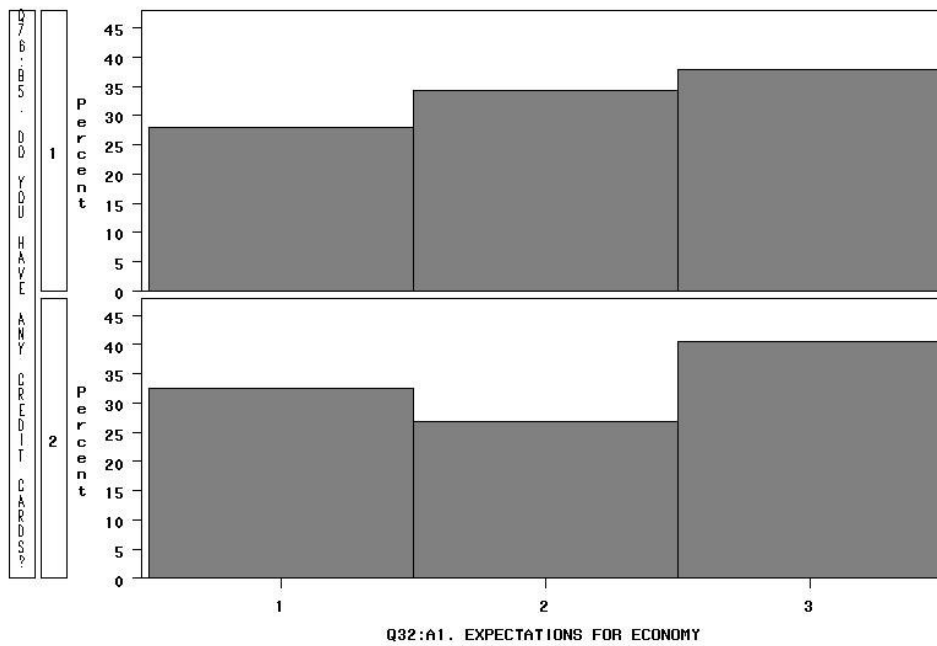


Figure B.13. Proportion of Credit Card Users/Nonusers by Attitude toward Economy
 1 represents users, 2 represents nonusers.

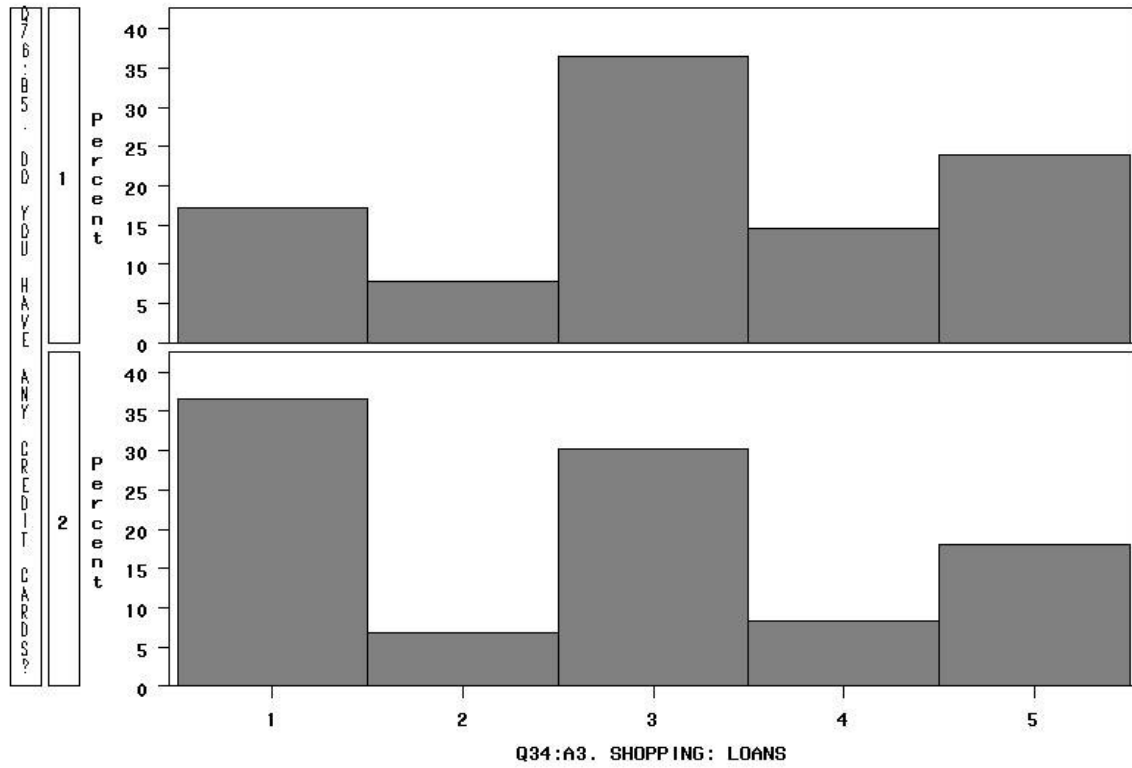
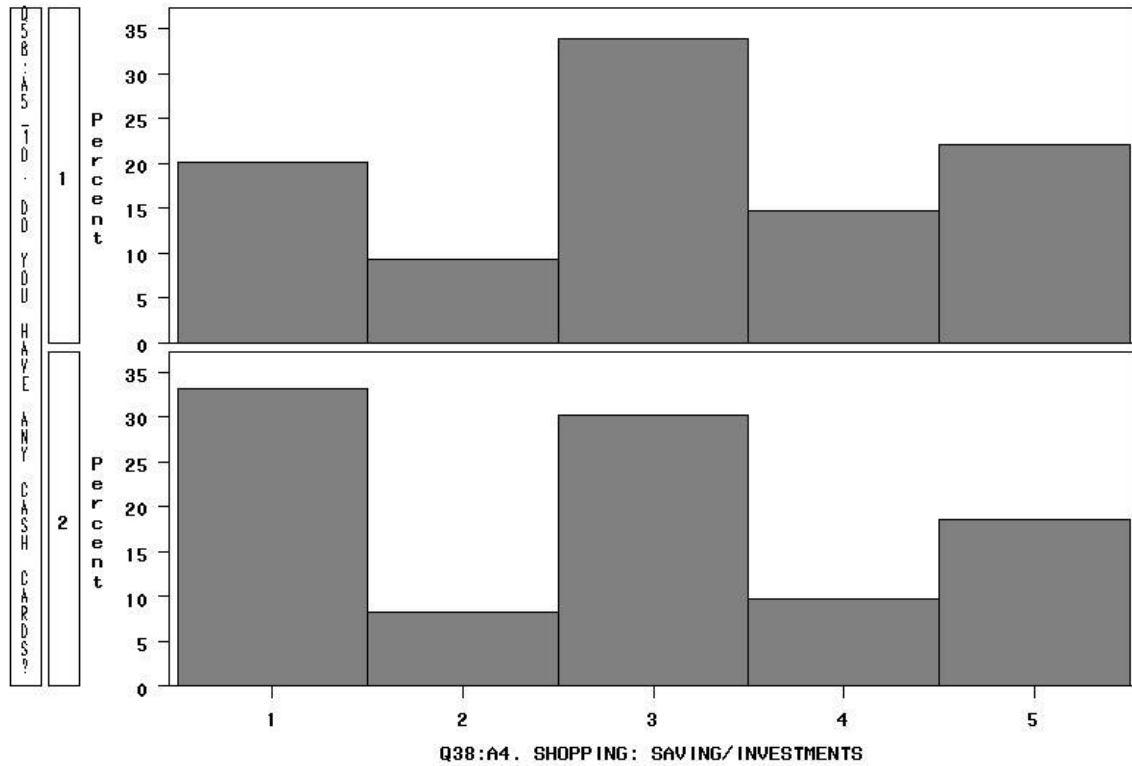


Figure B. 14. Proportion of ATM Card Users/Nonusers by Shopping for Saving
1 represents users, 2 represents nonusers.



APPENDIX C
PROC GENMOD TABLE: INTERACTION MODEL

Table C. 1 Relation of having smart card respect to predictors: Interaction model

LR Statistics For Type 3 Analysis			
Source	DF	Chi-Square	Pr > ChiSq
income	7	44.67	< .0001 ***
age	5	29.06	0.0004 ***
education	5	8.64	0.1016
attitude toward economy	2	19.57	< .0001 ***
attitude toward interest rate	2	2.93	0.3860
shopping behavior for loan	4	5.06	0.2595
shopping behavior for saving	4	23.68	0.0001 ***
use of financial software	1	9.12	< .0001 ***
income* econ-attitude	14	79.38	< .0001 ***
age*software-use	5	25.05	0.0001 ***

Table C. 2 Relation of having ATM card respect to predictors: Interaction model

LR Statistics For Type 3 Analysis			
Source	DF	Wald Chi-Square	Pr > ChiSq
income	7	68.96	< .0001 ***
age	5	565.74	< .0001 ***
education	5	63.40	< .0001 ***
attitude toward economy	2	2.80	.2364 ***
attitude toward interest rate	2	6.61	< .0368 ***
shopping behavior for loan	4	27.42	< .0001 ***
shopping behavior for saving	4	22.36	.0002 ***
use of financial software	1	0.19	< .6662 ***
age*software-use	5	128.93	< .0001 ***
attitude-econ*attitude-int	4	14.32	< .0063 ***
education*software-use	5	27.24	< .0001 ***

Table C. 3 Relation of having debit card respect to predictors: Interaction model

LR Statistics For Type 3 Analysis			
Source	DF	Chi-Square	Pr > ChiSq
income	7	190.73	< .0001 ***
age	5	1004.47	< .0001 ***
education	5	69.38	< .0001 ***
attitude toward economy	2	5.91	0.0100 ***
attitude toward interest rate	2	0.44	0.9272
shopping behavior for loan	4	38.18	< .0001 ***
shopping behavior for saving	4	15.24	0.0065 ***
use of financial software	1	4.15	< .0001 ***
income*attitude-econ	14	27.83	0.0150 ***
age * software use	5	26.16	< .0001 ***
attitude-econ*attitude-int	4	20.53	0.0004 ***
education*software use	5	24.82	0.0002 ***

Table C. 4 Relation of having credit card respect to predictors: Interaction model

LR Statistics For Type 3 Analysis

Source	DF	Chi-Square	Pr > ChiSq
income	7	1175.27	< .0001 ***
age	5	239.55	< .0001 ***
education	5	344.09	< .0001 ***
attitude toward economy	2	21.47	< .0001 ***
attitude toward interest rate	2	32.74	< .0001 ***
shopping behavior for loan	4	134.94	< .0001 ***
shopping behavior for saving	4	36.24	< .0001 ***
use of financial software	1	17.20	< .0001 ***
age*software-use	5	18.61	0.0023 ***
attitude-econ*attitude-int	4	49.81	< .0001 ***
education*software-use	5	38.15	< .0001 ***

APPENDIX D

PROBIT TABLE

Table D.1 Relation of having smart card respect to predictors: Interaction model

LR Statistics For Type 3 Analysis

Source	DF	Chi-Square	Pr > ChiSq
income	7	47.34	< .0001 ***
age	5	26.65	< .0001 ***
education	5	3.72	0.5898
attitude toward economy	2	26.63	< .0001 ***
attitude toward interest rate	2	10.97	0.0042
shopping behavior for saving	4	30.41	< .0001 ***
use of financial software	1	0.000	< .9974
income*attitude economy	14	70.29	< .0001 ***
age*software use	5	27.31	0.0001 ***
edu*software use	5	17.72	0.0033 ***
attitude economy*attitude interest	4	39.73	< .0001 ***

Table D.2 Relation of having debit card respect to predictors: Interaction model

LR Statistics For Type 3 Analysis			
Source	DF	Chi-Square	Pr > ChiSq
income	7	144.09	< .0001 ***
age	5	872.69	< .0001 ***
education	5	64.93	< .0001 ***
attitude toward economy	2	22.61	< .0001 ***
attitude toward interest rate	2	1.68	0.4320
shopping behavior for loan	4	34.03	< .0001 ***
shopping behavior for saving	4	10.34	0.0350 ***
use of financial software	1	4.70	0.0301 ***
income*shop for save	28	95.53	< .0001 ***
income*software use	7	88.81	< .0001 ***
income*shop for loan	28	72.72	< .0001 ***
age*software use	5	48.17	< .0001 ***
age*attitude economy	10	87.16	< .0001 ***
attitude economy*interest rate	4	23.31	0.0001 ***
education*software use	5	28.19	< .0001 ***