The Effect of Identity Theft on Consumer Demand for Electronic Banking

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Abstract

Identity theft affects millions of Americans each year, but costs individuals very little. News stories in the popular press have drawn the public's attention to this problem. But the real risk (probability) of identity theft, as well as the actual outcome, may differ from expectations. We assume that as consumers experience identity theft – either first-hand or second-hand – their subjective probability sets, utility function, and possibly even their expected cost functions will change. We explore how experiencing identity theft changes the behavior of consumer in their use of some transaction methods. In particular, we find that those with first-hand experience with identity theft require less security from accounts and are more likely to be early adopters of electronic transaction methods. While those with only second-hand experience with identity theft require more security and are less likely to be early adopters of electronic transaction methods.

Keywords: Heterogeneous Risk; Behavioral Banking; Identity Theft

JEL Codes: G210; G34

1.0 Introduction

Added technology has been a boon and a curse for financial intermediaries. It has been a boon because technology has reduced their costs and productivity. At the same time, technology has made it harder to verify whether the customer whose account is being credited with a transaction actually authorized that transaction. Of the billions of dollars lost in recent years to identity theft, most of the monetary loss was incurred by the financial institutions themselves.

Bank transaction methods and technologies have changed rapidly over the past fifty years, moving from labor and capital intensive paper, to less labor and capital intensive plastic, to the electronic forms of transactions. Over this time period, the technical efficiency of banks has improved. Researchers have consistently found that application of technology in banks has improved the efficiency of banks (see Daniel, Longbrake, and Murphy, 1973; Hunter and Timme, 1986, 1991; Hancock, Humphrey and Wilcox, 1999; Wheelock and Wilson, 1999). More recently, there has been some indication that online banking adoption has improved bank performance (Hernando & Nieto, 2007).

Because customers appreciate the convenience of many of these new methods and technologies (see Bauer and Hein, 2006), they have been employed to enhance the competitive strength of the bank or improve its market share. ATMs not only have been found to enhance efficiency of current banking operations, but have been found to be a cost effective way of geographically expanding a bank's market share (see Hannon and McDowell , 1984, 1987, 1990; Matutes and Padilla, 1994). Phonebanking technology was adopted by banks as a way of efficiently improving their market share (see Boukaert and Degryse, 1995; and Degryse, 1996). Even online banking has been found to be used to enhance the competition of banks (Hernandez-Murillo, Llobet, & Fuentes, 2010).

With banks benefiting from information, but not directly paying for breaches researchers (Roberds and Schreft, 2008; Shreft, 2007) have shown that in equilibrium, markets tend to support identity theft. Identity theft costs an estimated \$15.6 billion per year[1], and victimized an estimated 8.3 million Americans in 2005. The median value of goods and services obtained by identity thieves is \$500 per victim. The median amount that the theft costs the victim out-of-pocket is \$0, due in part to the legal indemnification for unauthorized uses of credit cards, debit cards and checks.

Despite the lack of monetary costs for most forms of identity theft, consumers have become increasingly aware of the risks of identity theft. Anderson, Durbin and Salinger (2008) report that newspaper articles using the term "identity theft" have increased from 30 in 1995 to 2,000 in 2000, and further increased to 250,000 in 2004.

Although the customer bears little direct monetary cost for most losses associated with their stolen identity, they may experience high levels of disutility. This disutility stems from two sources, the estimated hours needed to show the bank that those transactions were not yours. The second source of disutility stems from the perceived risk of loss. Much of the fear consumers have of identity theft is that they will lose large sums of money due to identity theft, or that their credit score will be ruined. They may, therefore, change their behavior to avoid that disutility. If consumers opt out of newer technology, the productivity gains enjoyed by financial institutions may be compromised.

In this paper we present a utility maximization model explaining why consumers choose the transaction methods they use. Based on this model, we identify three concepts important to consumers considering a transaction method: utility gained by using the method, expected costs associated with the method, and the subjective probability of disutility. In this paper we are particularly interested in how experience with identity theft affect the consumers perception of risk and usage of different transaction methods.

[1] This figure comes from (Synovate, 2007) Federal Trade Commission – 2006 Identity Theft Survey Report, page 9. This figure is far smaller than the amount reported in the 2003 report from the FTC (\$47.6 billion) as noted in the Federal Trade Commission report on the same page. It is also smaller than the amount reported in Cheney 2003 (\$32.9 billion).

We apply these concepts to data from the 2008 Survey of Consumer Payment Choice (SCPC), sponsored by the Federal Reserve Bank of Boston, and find that those experiencing identity theft are slightly more likely to use cash in transactions. This preference for cash can be seen in greater use of ATMs as well.

2.0 Theoretical Assumptions

We assume that the set of bank transactions methods used by consumers is that set which would maximize their expected utility. There are two ways to approach this utility maximization problem. First, we will assume that consumers select a bank, and then decide upon the set of transactions methods they will use to access their accounts. Second, we will assume that consumers can choose from all possible combinations of transaction methods at identical banks.

Single Account Static Model

We assume that bank customers adopt new transactions technologies because they perceive a higher expected utility. In particular, we assume that in a world without risk, the customer would know their utility from adopting a new technology, and it could be reasonably estimated with the following expression:

$$U(x) = f(x) + \sum_{i=1}^{n} \gamma_i g_i(x) + \sum_{i=1}^{n} \sum_{j=1}^{n} \gamma_i \gamma_j h_i(x) h_j(x) \quad [1]$$

The f(x) in the above expression is the utility function for the traditional bank account without any external access or payment options. The only way for the customer to withdraw funds is to physically go to the bank. The g(x) in the above expression is the marginal utility gained/lost by adding the *ith* transaction method (for instance debit card, check, online bill pay, etc.). The γ is an indicator variable, indicating whether or not the customer can access that transaction method, in essence turning each method on or off. The double summation is the marginal adjustment to the utility when both the *ith* and *jth* transactions methods are both included. This last expression is an attempt to better capture the marginal interactive utility when two transaction methods are substitutes of one another or when they are complimentary.

If we further assume that the above utility function were constrained by a budget constraint:

$$c(x, \gamma_i) = m \quad [2]$$

In this instance the cost is a function of the amount of money deposited and the ways in which the customer transacts with the institution. For instance, if the customer uses checks, the cost will increase to pay for the checks. In this simplified model, we are holding the costs to a fixed amount, *m*. As Bauer and Hein (2006) model the adoption of internet banking, they include human capital investment (learning to use the technology) as a possible cost of adopting a remote banking method.

Normally, utility maximization problems seek to find the optimal level of an input, for instance x. In this paper, we are interested in finding the optimal configuration of transaction methods, in other words which γ_i in the above formula are ones. Since the γ_i is just an indicator variable, the consumer would choose that set of γ_i that would maximize their utility give the budget constraint. The maximum utility for each configuration could be calculated; then all maxima could be compared to find the overall maximum. In this context, the consumer's use of transaction accounts is simply a function of added utility to the consumer, versus any added cost.

Single Account Stochastic Model

In this expansion, we assume that consumers perceive that risk is an important component in the decision to use remote transactions accounts. We further assume that the consumer seeks to maximize their expected utility subject to their expected budget constraint. If we further assume that there are k possible stochastic outcomes, each with a subjective probability of occurrence denoted as π, then *Equations 1 and 2* could be rewritten as:

$$E[U(x)] = \sum_{d=1}^{k} \pi_h \left[f_d(x) + \sum_{i=1}^{n} \gamma_{i_d} g_{i_d}(x) + \sum_{i=1}^{n} \sum_{j=1}^{n} \gamma_{i_d} \gamma_{j_d} h_{i_d}(x) h_{j_d}(x) \right] \quad [1a]$$

$\sum_{d=1}^{k} \pi_d c_d(x, \gamma_i) = m$ [2a]

As was true with the static model, the remote transactions used by consumers under this model will depend on the utility structure, as well as the cost structure. However, when we account for subjective risk, the remote access configuration of their account could now depend on the utility and costs of possible outcomes. The utility and costs of possible outcomes are now interacting with the subjective probability that those outcomes occur.

Multiple Account Static Model

Many households report having accounts with more than one depository institution. One possible explanation for more than one account is that consumers are better able to tailor their utility maximization of transactions accounts through the use of multiple providers. They may perceive that through restricting the use of some transaction methods to certain accounts, the security of the other accounts will be improved. In essence, consumers may see this as a way of limiting their exposure to the amount deposited in certain transaction accounts.

We assume that the consumer is faced with r possible combinations of transaction account. The utility that the consumer derives from their bank account can be denoted $U(x_1, x_2, \ldots, x_r)$. In contrast with the single account model, this model is continuous throughout. The marginal rate of substitution between account *i* and *j* would be $\frac{\partial U'_{x_i}}{\partial U'_{x_j}}$. The combination of accounts chosen by the consumer would be a function of the utility function, as well as the marginal cost of each additional transaction method.

Multiple Account Stochastic Model

Actual utility may differ from anticipated utility, and therefore we will explicitly model subjective probability in this model as well. This time we will let $\pi(x_1, x_2, \cdots, x_r)$ denote each consumer's subjective probability density function. We will further assume that consumers seek to maximize expected utility (they are risk neutral) as it pertains to their bank transaction accounts. Given the notation used thus far, the expected utility function and budget constraint could be rewritten:

$$E[U(x_1, x_2, \dots, x_r)] = \int \int \cdots \int \pi(x_1, x_2, \cdots, x_r)\, U(x_1, x_2, \cdots, x_r) dx_1 dx_2 \cdots dx_r \qquad [1b]$$

$$E[c(x_1, x_2, \dots, x_r)] = \int \int \cdots \int \pi(x_1, x_2, \cdots, x_r)\, U(x_1, x_2, \cdots, x_r) dx_1 dx_2 \cdots dx_r = m \qquad [2b]$$

In this stochastic model, the marginal rate of substitution[2] between account *i* and *j* would be $\frac{\int \partial \pi'_{x_i} \partial U'_{x_i} dx_i}{\int \partial \pi'_{x_j} \partial U'_{x_j} dx_j}$. The combination of accounts chosen by the consumer would be a function of the utility function, as well as the marginal cost of each additional transaction method. Again, the key concepts leading to a solution of the consumer problem are the shape of the utility function, the expected costs borne by the consumer, and the interaction between both utility and costs by the subjective probability function.

3.0 Data and Methodology

To examine these concepts empirically, we used data from the 2008 Survey of Consumer Payment Choice (SCPC), sponsored by the Federal Reserve Bank of Boston. The SCPC has been conducted every year starting in 2008. The only year subjects were asked about identity theft was the first year, 2008. The survey is conducted by the Rand Corporation, as part of their American Life Panel (ALP). The ALP is a group of around 5,000 people from throughout the United States, who have agreed to regularly participate in online surveys. The fact that all ALP subjects took the survey online may well mean that subjects were less technologically skeptical. Of 5,000 plus people participating in ALP, only 1,309 subjects participated in the 2008 SCPC.

We also wanted to control for the subjects risk aversion, but the SCPC did not ask about the subject's risk aversion. However, these subjects are taking several surveys over the course of a year.

[2] Since we are assuming that the consumer seeks to maximize their expected utility, the marginal rate of substitution should be made up of the marginal expected utilities, not the expected marginal utilities.

We found another survey (Well Being 48) that asked about risk aversion, and was being conducted simultaneously. Of the 1,309 participating in the SCPC, 1,164 also participated in the other survey and answered the risk aversion question. Subjects were asked: " How would you describe yourself: Are you generally willing to take risks or do you try to avoid taking risks?" They were then asked to respond on a Likert scale of 0 to 10. Smaller numbers denoted willingness to take on less risk, and larger numbers meant willingness to take on more risk. We use this variable in two ways. In some instances, we act as if the variable is approximately a continuous variable. In other applications (to be described later), we use three categories. We broke these proportions as evenly as the data would allow: 0-4 (36.60%), 5-6 (35.40%), 7-10 (28.00%).

The focus of this paper is to determine how experiencing identity theft affects the perception of the security of different transaction methods, and whether that shift in perception changes the behavior of the consumer in using them. Subjects were asked "Have you, or anyone you know well (family, friends, neighbors, coworkers, etc), ever been a victim of what you consider to be identity theft?" They were then given four possible responses: "1) Yes, myself and someone I know well", "2) Yes, someone I know well only", "3 Yes, myself only", or "4) No". For our purposes, we used three dummy variables. *Identity theft 1* is 1 if the subject has personally experienced identity theft (and is 0 otherwise). *Identity theft 2* is 1 if the subject knows someone who has experienced identity theft (and is 0 otherwise). *Identity theft* 3 is 1 if the either they or someone they know has experienced identity theft (and is 0 otherwise). It may look as if we just turned these backwards, but the first response in t he survey asked if they had experienced ***and*** someone they knew also had.

We wanted to see whether those with some personal experience with identity theft would perceive risks of financial transactions methods differently. To address this question, we used subjects' response to the following question: "Suppose a payment method has been stolen, misused, or accessed without the owner's permission. Rate the security of each method against permanent financial loss or unwanted disclosure of personal information." The respondent was asked to rate that risk using a Likert scale ranging from 1 (very risky) to 5 (very secure). Since this question aims primarily at risk, it probably does a fair job of measuring the probability of disutility.

Ordinal Logistic Regression:

To analyze this problem we use an ordinal logistic regression, where the Likert scaled response is the dependent variable. Anderson et al (2008) report that identity theft might be a function of age and income (the older and richer consumers are more likely to be targeted - and the longer one lives, the more likely one is to be a victim of anything). We use age and the log of the subject's net worth as proxy for income. We also controlled for demographic variables (race), and utility/cost variables. The utility/cost variables included education (proxy for any sunk human capital costs of using computerized systems – see Bauer and Hein [2006]), household size (number of people in the household), homeowner (indicator variable), and we also use the risk aversion variable (as a number between 0 and 10).

The above ordinal logistic regression was run on the following transactions methods: cash, checks, debit cards, credit cards, pre-paid card, and electronic bill pay. But this methodology only addresses the perceived risk of those transactions, and does not actually measure a change in behavior.

Bivariate Logistic Regression:

To test whether subjects changed their use of different transaction due to their experience with identity theft, we used the same inputs as described above, and used a bivariate dependent variable measuring whether or not the subject reported having adopted a transaction method or not. These methods were not the same set as before. We modeled the adoption of online banking, online bill pay services, debit card, and ATM card. These variables were those asked in the survey.

Modeling Risk Aversion (OLS and Multinomial Logistic Regression):

Up to this point we have used the risk aversion variable as an independent variable. It may depend on many of the other independent variables. In fact, it may be affected by the subject's experience with identity theft. To test those hypotheses, we run two tests. First, we run an OLS regression to see whether the Likert scaled risk aversion variable described earlier can be modeled by the other independent variables, and if so which of those variables best describe risk aversion. Second, we run a multinomial logistic regression model where we see if the three categories of risk aversion (high, moderate and low) are dependent on the same variables as in the OLS model.

The purpose of these tests is to test whether there is a substantial difference in modeling risk aversion as eleven Likert scaled responses, or collapsing them into three categories. We are also interested to see our variable sets operate differently under the three levels of risk aversion. In order to move to a conditional logistic regression analysis we will have to make a case that little is lost in restating risk aversion in far fewer outcomes.

Conditional Logistic Regression:

By "conditional logistic regression" we mean that we hold the risk aversion constant. If any of the independent variables also might affect the risk aversion, then we should hold the risk aversion constant to fully explore the effect of other independent variables. We use the method proposed by Bauer and Hein (2006) to estimate the parameters of a conditional logistic regression. These estimates begin with a multinomial logistic regression generated estimate of the following probability table:

Remote Access	*Risk Aversion*		
	High	***Moderate***	***Low***
No	P_{11}	P_{12}	P_{13}
Yes	P_{21}	P_{22}	P_{23}

As such, all general goodness of fit tests are derived from the multinomial logistic regression model.

4.0 Empirical Results

Table 1 presents the results from the ordinal logistic regression models run on the perception of risk from certain transactions. It should be remembered that all subjects take surveys regularly online, so they are likely not fearful of online transactions. However, it is interesting to note that those subjects who had personally experienced identity theft were more likely to use cash (seeing it as less risky), and also those who were more risk averse saw cash as less risky.

It is also interesting to note that those personally experiencing identity theft do not perceive more risk with any form of electronic transactions except for electronic bill pay. But just because they perceive more risk does not, by itself, lead to lowered use of it.

Table 2 presents the results of the bivariate logistic regression parameter estimates, modeling the adoption of four different transaction methods. It is important to note that risk aversion is significant in all models. All transactions are more likely to be adopted as the subject is less risk averse (the higher the risk aversion measure, the less risk averse one is), except the ATM card. It is also worth noting that if the subject has personally experienced identity theft, they are more likely to adopt an ATM card. This is likely the natural outcome of the preference for cash noted earlier for those with higher risk aversion and experience with identity theft. If they prefer cash, they will need to get cash from an ATM.

Since risk aversion is such an important variable in determining what transaction method is adopted, we now turn our attention to what variables determine a subject's risk aversion. Table 3 reports both the results of an ordinary least squares (OLS) regression model of the Likert scaled risk aversion variable, and a multinomial logistic regression model of a restatement of the that variable into three categories. It is important to note that the logistic regression results are stated in just the chi-square statistics, and therefore the sign is not relevant (since they can only be positive). It is noteworthy that the exact same variables are significant using either regression method – even though the comparable strength may not be maintained. It is also interesting to note that overall risk aversion is not affected by identity theft. However, those variables most likely to affect the adoption decision also tend to affect risk aversion.

Partly to control for the possible endogeneity of risk aversion in our model, we now run the adoption models as conditional logistic regression models. In these models we estimate the joint probabilities of risk aversion and adoption. Then we will hold the three categories of risk aversion constant and estimate the conditional probability of adopting the transaction methods.

In estimating these joint probabilities, two of the models (online bill pay and debit card) had problems estimating the multinomial logistic regression models. We had to drop some of the dummy independent variables in those cases. In tables 4 through 7 the comparable bivariate logistic regression is set next to the conditional regression results. Both the parameter estimates and the standard errors are reported.

With few exceptions, estimating the conditional logistic regression estimates did not change the importance of the variable in describing its relative importance in modeling the adoption decision.

5.0 Conclusions

Over the past several years, identity theft has become a popular topic in the press. It affects millions of Americans every year, and costs billions of dollars. The public has become more aware of the risks of identity theft. But do those who have experienced it behave differently than those who have not experienced it? In this paper, we present an expected utility maximization model to describe the behavior of consumers. Based on the model consumers should adopt transaction methods that added to their expected utility, and reduce expected cost. The shape of the utility function, the shape of the cost function and the subjective probability functions should all affect the transaction method chosen by consumers.

The data we used may not be the most unbiased when drawing conclusions about online methods, since it requires subjects to enter their answers to surveys (including income and age) into a computer online. And yet the data do add some understand of how identity theft victims adjust their perceptions and behaviors. Although there was no evidence of reduced usage of online bill pay from this tech-trusting sample, there is evidence that they perceive increased risk if they have experienced identity theft.

Consistent throughout the entire study is the theme that as subjects experience identity theft they perceive using cash as a safer alternative to electronic transactions. This preference for cash leads to an increase in the use of ATM machines. And although identity theft does not lead to increased risk aversion, it does lead in this regard to behavior that mimics risk aversion. The other group of people more likely to use cash (and by extension more likely to use ATM machines) is that group with higher levels of risk aversion.

Victims of identity theft in general might act much like very risk averse consumers when choosing transactions methods. It is unclear from this data set whether behaviors in general begin to mimic those of high risk aversion, since the survey is conducted via the internet.

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Table 1

Subjects were asked: "Suppose a payment method has been stolen, misused, or accessed without the owner's permission. Rate the security of each method against permanent financial loss or unwanted disclosure of personal information." The Likert scaled responses ranged from 1 (very risky) to 5 (very secure). In the table below are the ordinal regression results. The columns represent the different transaction methods. The figure on the same line as the variable name is the parameter estimate. The figure below the parameter estimate (in parentheses) is the estimate of the standard error.

	Cash	Checks	Debit Card	Credit Card	Pre-Paid Card	Electronic Bill Pay
Age	0.0022	0.0247 ***	-0.0136 ***	-0.0005	-0.0069	0.0046
	(0.0049)	(0.0048)	(0.0048)	(0.0048)	(0.0047)	(0.0048)
Higher Education	-0.0615	-0.1433	0.0574	0.1686	0.0120	0.0891
	(0.1226)	(0.1197)	(0.1209)	(0.1208)	(0.1190)	(0.1197)
Asian	-0.1139	-0.4795	0.2221	0.3494	0.3009	-0.2001
	(0.3976)	(0.3917)	(0.4031)	(0.4045)	(0.3917)	(0.3909)
African American	-0.1423	0.0045	0.2138	0.0055	-0.4561 *	0.0579
	(0.2425)	(0.2387)	(0.2439)	(0.2408)	(0.2376)	(0.2387)
Hispanic	0.3545	0.1930	-0.4210	-0.7125 **	0.1552	-0.2675
	(0.3116)	(0.2928)	(0.2931)	(0.2913)	(0.2946)	(0.2907)
Ln(Net Worth)	0.0430	0.0350	-0.0501	-0.0936 **	-0.0995 **	-0.0450
	(0.0489)	(0.0473)	(0.0479)	(0.0476)	(0.0471)	(0.0472)
Household Members	-0.0055	-0.0316	-0.0341 *	0.0058	-0.0268	0.0059
	(0.0207)	(0.0202)	(0.0204)	(0.0204)	(0.0201)	(0.0202)
Identity Theft 1	0.3814 *	-0.1819	-0.1889	-0.3052	-0.0180	-0.4277 **
	(0.2234)	(0.2146)	(0.2166)	(0.2159)	(0.2139)	(0.2143)
Identity Theft 2	0.1354	0.1113	-0.0503	-0.5243 *	0.3587	-0.4312
	(0.3111)	(0.2991)	(0.3033)	(0.3048)	(0.3000)	(0.2997)
Identity Theft 3	-0.3103	-0.2745	0.0779	0.5610 *	-0.1465	0.4433
	(0.3410)	(0.3290)	(0.3335)	(0.3347)	(0.3294)	(0.3296)
Risk Aversion	-0.0528 *	0.0433	-0.0186	0.0128	0.0105	0.0086
	(0.0283)	(0.0275)	(0.0278)	(0.0277)	(0.0274)	(0.0275)
χ^2	10.2117	43.5146	18.3217	19.2939	14.6466	11.5745
Significance	0.511452	0.0000	0.07441	0.0560	0.199254	0.3965
Pseudo r^2	0.0108	0.0450	0.0192	0.0202	0.0154	0.0122

***, **, * denote significance at the 1%, 5% and 10% level.

Table 2

Subjects were asked about what transaction methods they used. In the table below, the bivariate logistic regression parameters are listed on the same line as the name of the variable. The figure in parenthesis below the parameter estimate is the estimated standard error.

	Online Banking	Online Bill Pay	Debit Card	ATM Card
Intercept	1.8876 ***	0.0132	3.1321 ***	-1.6005 ***
	(0.5269)	(0.5115)	(0.6448)	(0.4861)
Age	-0.0311 ***	-0.0028	-0.0409 ***	0.0091
	(0.0069)	(0.0068)	(0.0082)	(0.0064)
Higher Education	0.6871 ***	0.0571	0.1409	0.2406
	(0.1705)	(0.1685)	(0.1967)	(0.1582)
Asian	-0.0813	0.6619	-0.0443	0.9242 *
	(0.6426)	(0.6447)	(0.7719)	(0.4720)
African American	-0.2534	-0.5663 *	0.2308	0.9483 ***
	(0.3542)	(0.3428)	(0.4933)	(0.3059)
Hispanic	-0.1242	0.3345	-0.2487	0.6276 *
	(0.4229)	(0.4461)	(0.5146)	(0.3497)
Ln(Net Worth)	-0.0047	0.0274	-0.0421	0.0280
	(0.0289)	(0.0295)	(0.0328)	(0.0262)
Household Members	0.0457	0.0759	0.1071	0.0791
	(0.0706)	(0.0679)	(0.0912)	(0.0618)
Identity Theft 1	0.3514	-0.1154	-0.4004	0.7496 ***
	(0.3263)	(0.3024)	(0.3630)	(0.2703)
Identity Theft 2	-0.0641	-0.5553	-0.9157	0.3347
	(0.4581)	(0.4527)	(0.5612)	(0.3686)
Identity Theft 3	-0.0348	0.7027	1.2551 **	-0.4992
	(0.4964)	(0.4940)	(0.6111)	(0.4142)
Risk Aversion	0.0925 **	0.0953 **	0.0912 **	-0.0682 *
	(0.0389)	(0.0395)	(0.0451)	(0.0365)
χ^2	64.0496	17.9276	64.0659	32.9892
Significance	< 0.001	0.0833	< 0.001	0.0005
Pseudo r^2	0.0670	0.0247	0.0670	0.0369
n	923	718	924	878

***, **, * denote significance at the 1%, 5% and 10% level.

Table 3

In this table we compare two models of risk aversion. In the OLS results below, the dependent variable is a Likert scaled risk aversion variable (0 to 10) where lower figures represent more risk aversion. The multinomial logistic regression categorizes the Likert scale into three categories: High risk aversion (0-4 on the Likert scale), moderate risk aversion (5-6 on the Likert scale), and low risk aversion (7-10 on the Likert scale). In the OLS column, figures on the line with the variable name are the parameter estimates. The figures below the parameter estimates, in parentheses are the standard errors.

In the multinomial logistic regression column, the figure on the same line as the variable name is the chi-square statistic measuring the overall significance of that variable to estimating the probability of falling in that risk aversion category. Because it is a chi-square statistic, the sign must be positive, and therefore no conclusions can be drawn regarding the correlation between the variable and risk aversion. In this instance the figure in the parentheses is the significance of chi-square statistic given the degrees of freedom.

Table 3 Continued

	OLS Regression	
Intercept	6.6326	***
	(0.3715)	
Age	-0.0231	***
	(0.0056)	
Higher Education	0.2637	*
	(0.1421)	
Asian	0.2280	
	(0.4676)	
African American	0.2448	
	(0.2841)	
Hispanic	-0.2735	
	(0.3482)	
Ln(Net Worth)	0.0870	***
	(0.0238)	
Household Members	-0.0219	
	(0.0563)	
Identity Theft 1	0.3635	
	(0.2557)	
Identity Theft 2	-0.0086	
	(0.3572)	
Identity Theft 3	-0.0534	
	(0.3926)	
F	4.1784	
Significance	< 0.001	
Pseudo r^2	0.0429	
n	943	

	Multinomial Logistic Regression	
Intercept	0.5873	
	(0.7455)	
Age	6.8764	**
	(0.0321)	
Higher Education	9.3627	***
	(0.0093)	
Asian	1.2292	
	(0.5409)	
African American	1.3621	
	(0.5061)	
Hispanic	0.3605	
	(0.8351)	
Ln(Net Worth)	9.3219	***
	(0.0095)	
Household Members	0.4487	
	(0.7991)	
Identity Theft 1	2.0607	
	(0.3569)	
Identity Theft 2	1.0035	
	(0.6055)	
Identity Theft 3	1.4808	
	(0.4769)	
χ^2	36.4292	
Significance	0.0137	
Pseudo r^2	0.0137	
n	943	

***, **, * denote significance at the 1%, 5% and 10% level.

Table 4 – Online Banking Adoption

In the table below is a comparison of the bivariate regression parameters estimates with a conditional logistic regression model. The bivariate regression model estimates the marginal probability of online banking adoption, and includes risk aversion as an independent variable. In the conditional logistic regression, the model estimates the conditional probability of adopting online banking given a certain level of risk aversion.

	Bivariate Logistic Regression	Conditional Logistic Regression Given the Following Levels of Risk Aversion		
		High	Moderate	Low
Intercept	1.8876 ***	1.4470 **	4.0271 ***	2.0282 **
	(0.5269)	-(0.7087)	-(0.8116)	-(0.9096)
Age	-0.0311 ***	-0.0263 **	-0.0463 ***	-0.0239 *
	(0.0069)	-(0.0103)	-(0.0117)	-(0.0134)
Higher Education	0.6871 ***	0.7886 ***	0.4886 *	0.8730 **
	(0.1705)	-(0.2609)	-(0.2896)	-(0.3417)
Asian	-0.0813	-0.2077	0.1836	-0.1683
	(0.6426)	-(1.1448)	-(1.0960)	-(1.1092)
African American	-0.2534	-0.3996	0.2586	-0.6306
	(0.3542)	-(0.5739)	-(0.6547)	-(0.6158)
Hispanic	-0.1242	0.1404	-0.1271	-0.4910
	(0.4229)	-(0.6755)	-(0.6910)	-(0.8268)
Ln(Net Worth)	-0.0047	0.0587	-0.0534	-0.0179
	(0.0289)	-(0.0468)	-(0.0478)	-(0.0542)
Household Members	0.0457	0.1498	-0.1263	0.1165
	(0.0706)	-(0.1157)	-(0.1102)	-(0.1456)
Identity Theft 1	0.3514	0.0590	0.0302	1.4480 *
	(0.3263)	-(0.5072)	-(0.5115)	-(0.7992)
Identity Theft 2	-0.0641	-0.1348	-0.2178	-0.0950
	(0.4581)	-(0.6861)	-(0.7184)	-(1.2725)
Identity Theft 3	-0.0348	0.0383	0.0806	-0.0033
	(0.4964)	-(0.7467)	-(0.7857)	-(1.3270)
Risk Aversion	0.0925 **			
	(0.0389)			
χ^2	64.0496	105.9714		
Significance	< 0.001	< 0.001		
Pseudo r^2	0.0670	0.1085		
n	923	923		

***, **, * denote significance at the 1%, 5% and 10% level.

Table 5 – Online Bill Pay

In the table below is a comparison of the bivariate regression parameters estimates with a conditional logistic regression model. The bivariate regression model estimates the marginal probability of online bill pay adoption, and includes risk aversion as an independent variable. In the conditional logistic regression, the model estimates the conditional probability of adopting online bill pay given a certain level of risk aversion.

	Bivariate Logistic Regression	Conditional Logistic Regression Given the Following Levels of Risk Aversion: High	Moderate	Low
Intercept	0.0971 (0.5269)	1.0325 (0.7356)	1.0395 (0.7177)	-0.2065 (0.8118)
Age	-0.0041 (0.0067)	-0.0058 (0.0110)	-0.0086 (0.0112)	0.0012 (0.0125)
Higher Education	0.0673 (0.1674)	-0.1222 (0.2743)	0.1263 (0.2827)	0.3362 (0.3204)
African American	-0.5778 * (0.3403)	-0.8111 (0.6528)	-0.4247 (0.5329)	-0.4825 (0.6010)
Ln(Net Worth)	0.0270 (0.0290)	-0.0465 (0.0475)	0.0428 (0.0514)	0.1163 ** (0.0543)
Household Members	0.0712 (0.0673)	0.0492 (0.1122)	0.0026 (0.1089)	0.1789 (0.1304)
Identity Theft 3	0.1962 (0.1698)	0.3281 (0.2815)	0.2348 (0.2869)	-0.0183 (0.3158)
Risk Aversion	0.0962 ** (0.0393)			
χ^2	14.4707		43.9817	
Significance	0.0434		0.047876	
Pseudo r^2	0.0200		0.0594	
n	718		718	

***, **, * denote significance at the 1%, 5% and 10% level.

Table 6 – Debit Card

In the table below is a comparison of the bivariate regression parameters estimates with a conditional logistic regression model. The bivariate regression model estimates the marginal probability of debit card adoption, and includes risk aversion as an independent variable. In the conditional logistic regression, the model estimates the conditional probability of adopting debit card given a certain level of risk aversion.

	Bivariate Logistic Regression	Conditional Logistic Regression Given the Following Levels of Risk Aversion: High	Moderate	Low
Intercept	3.1473 ***	2.7751 ***	5.3796 ***	3.4229 ***
	(0.6426)	(0.8184)	(1.0844)	(1.1864)
Age	-0.0408 ***	-0.0306 ***	-0.0608 ***	-0.0400 **
	(0.0082)	(0.0117)	(0.0149)	(0.0166)
Higher Education	0.1224	0.2950	0.1167	-0.1121
	(0.1950)	(0.2825)	(0.3402)	(0.4127)
African American	0.2505	0.4434	-0.0718	0.4936
	(0.4921)	(0.7754)	(0.7835)	(1.0614)
Hispanic	-0.2252	0.9857	-0.6468	-1.1181
	(0.5149)	(1.0560)	(0.8227)	(0.8402)
Ln(Net Worth)	-0.0420	-0.0174	-0.1179 **	0.0239
	(0.0326)	(0.0500)	(0.0543)	(0.0664)
Household Members	0.0979	0.0111	0.0640	0.3031
	(0.0912)	(0.1268)	(0.1629)	(0.2193)
Identity Theft 3	0.3046	0.2341	0.4858	0.1920
	(0.2025)	(0.2944)	(0.3611)	(0.4166)
Risk Aversion	0.0916 **			
	(0.0450)			
χ^2	61.0720	97.6683		
Significance	< 0.001	< 0.001		
Pseudo r^2	0.0640	0.1003		
n	924	924		

***, **, * denote significance at the 1%, 5% and 10% level.

Table 7 – ATM Card

In the table below is a comparison of the bivariate regression parameters estimates with a conditional logistic regression model. The bivariate regression model estimates the marginal probability of ATM card adoption, and includes risk aversion as an independent variable. In the conditional logistic regression, the model estimates the conditional probability of adopting ATM card given a certain level of risk aversion.

	Bivariate Logistic Regression	Conditional Logistic Regression Given the Following Levels of Risk Aversion		
		High	Moderate	Low
Intercept	-1.6005 ***	-2.0252 ***	-1.7361 ***	-2.5772 ***
	(0.4861)	(0.7140)	(0.6733)	(0.8296)
Age	0.0091	0.0068	0.0089	0.0168
	(0.0064)	(0.0105)	(0.0101)	(0.0123)
Higher Education	0.2406	0.3843	0.0414	0.3657
	(0.1582)	(0.2599)	(0.2538)	(0.3215)
Asian	0.9242 *	1.3677	0.5484	1.1049
	(0.4720)	(0.9410)	(0.7585)	(0.8073)
African American	0.9483 ***	0.5302	1.4361 ***	0.8634
	(0.3059)	(0.5430)	(0.5160)	(0.5566)
Hispanic	0.6276 *	0.0520	0.3003	1.7955 ***
	(0.3497)	(0.6336)	(0.5784)	(0.6734)
Ln(Net Worth)	0.0280	0.0275	0.0515	-0.0122
	(0.0262)	(0.0445)	(0.0423)	(0.0480)
Household Members	0.0791	0.1633	0.0040	0.0865
	(0.0618)	(0.1028)	(0.0985)	(0.1179)
Identity Theft 1	0.7496 ***	1.0436 **	0.0101	1.2341 **
	(0.2703)	(0.4790)	(0.4687)	(0.4810)
Identity Theft 2	0.3347	-0.0637	0.1893	0.9606
	(0.3686)	(0.6166)	(0.6418)	(0.6908)
Identity Theft 3	-0.4992	-0.3703	-0.1327	-1.1896
	(0.4142)	(0.6984)	(0.7026)	(0.7963)
Risk Aversion	-0.0682 *			
	(0.0365)			
χ^2	32.9892		81.3020	
Significance	0.0005		0.0034	
Pseudo r^2	0.0369		0.0884	
n	878		878	

***, **, * denote significance at the 1%, 5% and 10% level.