Three Essay on Risk and Financial Satisfaction

by

Patrick Payne, MBA

A Dissertation

In

Personal Financial Planning

Submitted to the Graduate Faculty
of Texas Tech University in
Partial Fulfillment of
the Requirements for
the Degree of

DOCTOR OF PHILOSOPHY

Approved

Dr. Charlene Kalenkoski
Co-Chair of Committee

Dr. Christopher Browning
Co-Chair of Committee

Dr. Russell James III

Dr. Michael Farmer

Dr. Michael Guillemette

Mark Sheridan
Dean of the Graduate School

August, 2015

Copyright 2015, Patrick Payne

ACKNOWLEDGMENTS

This dissertation would not have been possible without the support and instruction from many people. I would like to thank my dissertation chairs, Dr. Charlene Kalenkoski and Christopher Browning, for their many hours of reviewing, proofing, and commenting that have made this dissertation far better than I could have produced on my own. I would also like to thank the members of my committee for their helpful feedback. I owe a debt of gratitude to the faculty of Texas Tech, in particular Drs. Sandra Huston and Michael Finke, for more hours of advice, instruction, and mentoring than I can count.

I would, of course, be at a loss without the undying support of my wife and family. To them, and the many others who have sacrificed their time and wisdom to help me reach this point, I offer my most profound gratitude.

TABLE OF CONTENTS

ABSTRACT

Risk surrounds every aspect of our financial lives. Our investments may produce any of a range of possible returns. The price of our home may rise a great deal, or it may fall. We may die unexpectedly early. We may die unexpectedly late. Our income may be stable and consistent, it may be terminated abruptly, or it may rise suddenly. How we assess, manage, and react to risks such as these may have a dramatic effect on our ability to derive satisfaction from our finances.

In the first chapter of this dissertation, I examine the reaction of investors and non-investors to the volatility of the financial markets in the 2008 recession. I find that investors with medium or high levels of measured risk tolerance had significantly less financial satisfaction in 2008 than those of the lowest risk tolerance. This is likely due to the extreme volatility and large losses experienced by the market as a whole in 2008. This suggests that investors prioritize short-term volatility over long-term gains when assessing their satisfaction.

The second chapter of this dissertation examines how the general public reacts to volatility in the stock market. Using daily well-being data from the American Time Use Survey, I perform a Granger causality analysis to estimate that the general public does not begin to react to changes in the stock market until 30-100 days after the market movement occurs. This finding can help to explain a number of investor behaviors, including the tendency to mistime the market, and the disposition effect.

The third chapter explores the reaction to credit card risk. I find that risk tolerance does help mitigate the dissatisfaction that comes from mismanagement of credit cards. This suggests that more risk tolerant households who mismanage their credit cards are more satisfied that less risk tolerant households who use their cards in a similar manner. I also find evidence that the monetary costs may not be the primary driver of the dissatisfaction associated with credit card mismanagement.

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

RISK TOLERANCE AND FINANCIAL SATISFACTION IN RECESSIONS

Introduction

Risk tolerance is a cornerstone of modern portfolio theory. Investors with higher levels of risk tolerance are assumed to experience a smaller decline in utility as a result of a decline in their invested wealth. This premise is used by planners and researchers alike to make portfolio allocation recommendations. This paper tests this assumption by examining the financial satisfaction of individuals through the market declines of 2008-2009 as a function of their risk tolerance.

Theory: Risk tolerance

Risk tolerance is a measure of an individual's willingness to accept variation in outcomes. Because investment returns affect total lifetime household wealth, any volatility in those returns represents potential variation in future consumption levels. Financial planners and researchers alike attempt to measure an investor's risk tolerance in order to build a portfolio that is only as risky as the investor can tolerate, according to modern portfolio theory (Markowitz, 1952). The correct alignment of investor risk preferences with the risk profile of his/her portfolio increases his/her financial satisfaction by enabling the investor to achieve financial goals in his/her preferred manner.

Modern portfolio theory assumes that investors are rational. Rational investors incorporate the riskiness of the investment portfolio as well as their own risk tolerance into the investment decision process. Under a modern portfolio theory framework, a period of increased volatility in the market should be priced into the purchase decision of the investment. This implies that periods of market volatility should not affect investors' financial satisfaction, since market volatility was priced in to the original investment decision.

Empirical evidence suggests that measured risk tolerance can vary over time for individuals. Risk tolerance decreases with age and increases as macroeconomic conditions improve (Sahm, 2012). A significant portion of the shifts in risk tolerance, however, come from changes in market returns. (Yao & Curl, 2011) find that risk tolerance has a significant positive relationship with stock market returns.

Market volatility can change the way investors perceive the riskiness of their portfolios, and thus also change their satisfaction with their portfolios. Risk perception refers to the manner in which each individual processes, understands, and experiences uncertain events (Ricciardi, 2008). Unlike objective risk measures such as the beta of the portfolio or the variance of market returns overall, the perception of risk occurs after the fact. How an individual perceives risk may be based upon a wide variety of factors, many of which are unique to the individual. These factors have been found to include past experience with risk, instincts and preferences, and emotional reactions to the present situation (McDonald & Stehle, 1975). These factors vary significantly from individual to individual, which may cause a mismatch between individual risk perceptions and objective measures of risk (Ricciardi, 2004).

The literature suggests that risk perception is more predictive of behavior and preferences than is the objective riskiness (Weber, 2004). This suggests that individuals can perceive an increase in their investment risk exposure when no objective change has occurred (Loewenstein, Weber, Hsee, & Welch, 2001). For example, a period of highly volatile market returns such as the one experienced in 2008 might lead investors to believe to future returns will be more volatile than past returns have been. Investors who adopt this belief will therefore have a change in their perception of the systematic risk inherent in the market. Investors who experience a change in perception of the riskiness of their portfolio can cause them to feel that the portfolio may not be properly aligned with their own risk tolerance.

Risk perception involves processing information through the behavioral heuristics of the individual. Individuals also are susceptible to representativeness bias. The representativeness bias refers to the tendency for individuals to assume that their experience is representative of future events. Relatively naïve investors that experience substantial market declines such as those in 2008 are very likely to mistakenly assume that the losses they have experienced will be typical of future market returns, and thus become disillusioned with their investment prospects. Individuals also tend to overweight recent events and rely on the most easily processed information in their evaluation of risk, even when that information may not be particularly effective at estimating risk (Barberis & Thaler, 2003).

This concept of risk perception may be related to longitudinal variations in reported risk tolerances (Davies & Brooks, 2013). Gibson, Michayluk and Van de Venter (2013) find that those who perceived the risk of the market in 2008 to be higher than it was in 2006 were also those who changed their risk tolerance responses significantly. Another study found a strong negative correlation between investor expectations of stock market performance and actual recent market returns, suggesting that investors change their expectations of the reward for risk based on stock market movements (Greenwood & Shleifer, 2014).

Hoffman, Post, and Pennings (2013) examine the 2008-2009 financial crisis time period and measured risk tolerance, risk perception, and return expectations against actual market movements longitudinally. They find that investor risk tolerance tracks market returns, and that risk perception and risk tolerance are very strongly negatively correlated to each other. They also find that return expectations have no significant effect on risk-taking behaviors, but changes in risk perception and tolerance are significant predictors of risk taking behaviors in the crisis. This supports the hypothesis that risk perception is a useful tool for determining individual preferences.

A person's accumulated wealth, particularly when held in tax-advantaged retirement accounts, represents future spending power. This allows us reasonably to expect total wealth and relative wealth to have a similar effect on financial satisfaction as total income and relative income. Individuals who experience declines in wealth due to market volatility adjust their expectations of how much wealth they will have available to consume in the future. This change in expectations is a primary driver of the changes in risk perception that are created by market volatility and the accompanying changes in investor wealth.

The adjustment of risk perception induced by negative wealth shocks should theoretically be mitigated by the investor's level of risk tolerance. When market volatility makes the riskiness of the portfolio more salient to the investor, highly risk-averse investors are more likely to feel that the "new" riskiness of their portfolio exceeds the amount of risk they are willing to take. The result is investors who are dissatisfied with their portfolios. This change occurs despite the fact that the volatility experienced was always present in the portfolio. By the same logic, more risk-tolerant investors would be less likely to decide that the perceived increase in riskiness of their portfolio has exceeded the risk they are willing to accept.

The research question posed by this paper is whether or not higher levels of risk tolerance mitigated the loss of financial satisfaction expected from the market decline of 2008-2009. I use the respondent's self-reported financial satisfaction in the 2008 wave as the dependent variable. This wave is used because of the remarkable volatility the stock market experienced during this time period. The null hypothesis in the analysis is that risk tolerance has no relation to financial satisfaction. Rejection of the null hypothesis would indicate that investors' risk perceptions changed enough that the riskiness of the portfolio is no longer perceived to be consistent with their risk tolerance.

Data and Methodology

This study examines panel data from the 2004 and 2008 waves of the Health and Retirement study. This study is a national representative survey of Americans over the age of 50. It contains responses to questions about an array of life situations, health, cognitive ability, and socioeconomic status. The surveys in the 2004 and 2008 waves were administered between February 2004 and February 2005 and February 2008 and February 2009, respectively.

The financial satisfaction questions are included in the leave-behind questionnaire every wave. The leave-behind questionnaire is a series of questions that is left with the respondent at the end of the main body of the survey. It was created with the intention of collecting additional data from respondents without extending the length of the survey. This helps prevent respondent fatigue.

The leave-behind questionnaire is administered differently from the main study. The questions are divided into two groups. The first group is called the Participant Lifestyle Questionnaire and the second group is called the Participant Questionnaire on Work and Health. Respondents from the main body of the survey are divided randomly into two groups. At the end of the main survey, respondents assigned to group A are asked to complete the Lifestyle Questionnaire while group B respondents are asked to complete Work and Health Questionnaire. During the next survey wave, group A respondents are asked to complete Work and Health Questionnaire, and vice versa for group B respondents.

The outcome of this process is that any given question in the leave-behind questionnaire has data for only half of the main survey sample in each wave. This leaves a four-year interval between data points in the leave-behind questionnaire for each respondent. The most recent data from the group that responded to the financial satisfaction question in 2008 are available only in 2004, which is why the 2004 data are used as the control for initial financial satisfaction.

Financial satisfaction is interesting to study in the context of economics because it is a subcomponent of overall well-being, which is used routinely by many researchers as a proxy for utility (Clark, Frijters, & Shields, 2008). In this dataset, financial satisfaction responses are reported on a 5-point-ordinal scale, where 4 = "very satisfied" and 0 = "very dissatisfied". The result is a variable that is discrete, ordinal, and ordered. I use this as the dependent variable for this analysis. Table 1.1shows the distribution of financial satisfaction responses for both 2004 and 2008.

Table 1.1 Distribution of Financial Satisfaction Responses

	Financial Satisfaction in 2004		Financial Satisfaction in 2008	
0- Least Satisfied	53	8%	38	6%
1	90	14%	77	12%
2	297	46%	222	34%
3	175	27%	172	27%
4 - Most Satisfied	33	5%	139	21%
Total	648	100%	648	100%

Risk tolerance in the HRS is measured typically as an ordinal metric based upon the responses to questions regarding income risk. Respondents are told to imagine they have just moved to a new area and are trying to decide between two job opportunities. One job opportunity pays a fixed income, the other potentially pays more, but the income is uncertain. The respondent is asked which job they would take under various likelihoods of the risky job providing higher income.

The HRS has limitations on the availability of this variable. 2006 was the last year in which the risk tolerance question was asked. There are also non-response problems that make it difficult to use only the risk tolerance information from a single wave. In order to expand the sample, I take the 2006 risk tolerance response first if it is available. If the 2006 response is unavailable, then the 2004 is taken next, followed by the 2002 response. Respondents who do not have a risk tolerance measure in any of these three waves are excluded from the analysis.

The HRS records risk tolerance responses into six discrete categories. Higher survey responses indicate lower level of respondent risk tolerance. The distribution of risk tolerance responses is presented in Table 1.2.

Table 1.2 Distribution of Risk tolerance Responses

Risk tolerance Response	Number Observed	% of Total	Risk tolerance Category
1	30	4%	High
2	53	8%	High
3	61	9%	High
4	101	15%	Medium
5	141	21%	Medium
6	281	42%	Low

The distribution of risk tolerance responses makes it difficult to meaningfully divide the sample into traditional quintiles. I resolve this issue by categorizing respondents into three discrete risk tolerance groups. The high-risk tolerance group is represented by those in categories 1-3. The medium-risk tolerance group is made up of those with risk tolerance responses of 4 and 5, and the low-risk tolerance group is composed of those who reported the very lowest level of risk tolerance. Table 1.2 shows that approximately 42% of the sample of 648 respondents have low risk tolerance. The medium-risk tolerance group comprises some 36% of the sample, with the remaining 21% being classified in the highest risk tolerance group.

The total sample size of 648 individuals was reached based upon the availability of data. The first and most important criteria for inclusion in the sample is the availability of a financial satisfaction measure in both 2004 and 2008. The sample is next reduce by eliminating those who did not have a risk tolerance measure in 2006, 2004, or 2002. The final sample was reached by eliminating those that are missing basic demographic information. The sample mean was used as the response for those respondents missing income or asset information.

Controls are included for a number of variables based upon past empirical findings. The presence of companionship in the home has been shown to improve satisfaction in a variety of areas of one's life (Jakobsson, Hallberg, & Westergren, 2004), and also can decrease the impact of economic strain on the incidence of depression (Pearlin & Johnson, 1977). I control for marital status with a dummy variable set to a value of 1 if the respondent is married and/or partnered.

Controls for economic status also are included in the model. Specifically, I include the difference in logged total household income between the 2004 and 2008 waves. This income measure represents changes in comprehensive income; this includes wages and salaries, household business income, pension and annuity income, Social Security Disability and Supplemental and Retirement income, unemployment benefits and worker's compensation, alimony, and welfare income. Inclusion of his control is justified by evidence that income has a consistently strong, positive relation to well-being for young and middle-aged adults (Diener, Suh, Lucas, & Smith, 1999). The relation becomes less clear for older adults, such as those in our sample, but the data suggest that it probably does not change significantly (Pinquart & Sörensen, 2000).

The data do not permit us to directly measure the market experience of respondents. I estimate this effect using two variables. The first variable is equity participation. This variable is an indicator that is equal to 1 if a household owns stocks or has a personal retirement plan, and is equal to 0 if the household owns no stocks or retirement plan. This helps control for the household's exposure to risk in the financial markets.

The second variable is the relative percentage change in financial assets. This is measured as the z-score of the respondent's percentage change in financial assets between 2004 and 2008. The time gap and market performance between 2004 and 2008 was such that even after major market declines in 2008, most respondents still had higher levels of financial assets in 2008 than they did in 2004. This makes it so that using a simple percentage change in assets would not effectively capture the effects of market volatility. Standardizing the percentage change in financial assets zeroes out the overall average gains caused by time and leaves measurable values only for those who had substantially higher magnitude changes than the average.

These changes may reasonably be presumed to be caused by two forces. Either the respondent had an unusually high (or low) savings rate, or their portfolios were exposed to higher levels of market risk than average. The savings-rate explanation would have a significant effect only if the savings rate was extremely different than the average. Additional savings contributions also have a declining effect on the percentage change in assets, as the denominator in the percentage change formula increases. Thus, the z-score of percentage change in financial assets may be used as a reasonable estimate of exposure to market volatility.

Standardizing the percentage change in financial assets into a z-score creates a measure of how the individual did relative to the sample standard. If they had higher losses, this will be reflected as a negative value in the z-score, even if their overall change in assets from 2004 to 2008 is positive.

I also control separately for labor force status. The loss of labor income may influence risk perception because it increases the likelihood of the household suffering from consumption shortfalls. Accurately assessing changes in labor force status is made difficult in the diverse attitudes that respondents may have towards labor. For example, loss of full time employment may be viewed as a negative event for one respondent, perhaps due to the loss of income. The same even may be considered a positive event for another individual because they receive an increase in leisure time.

Likewise, entering retirement may be either a positive or a negative experience for the individual, depending on the circumstances under which they entered retirement.

The lack of a clear way to delineate positive labor force status changes from negative labor force status changes would cause any such variable to yield uninformative results. I therefore simply control for labor force status in 2008. Respondents are categorized as either employed, retired, or not working. Employed respondents can be either full- or part- time. Retired respondents may be either fully- or partially- retired. Not working respondents may be either unemployed, not in the labor force, or disabled. Each of these three categories are coded as separate indicator variables, with the variable being set to 1 if the respondent belongs to that category.

A number of socio-demographic characteristics have been identified in the literature as correlates of risk tolerance. These variables include age (Pålsson, 1996), gender (Bajtelsmit, Bernasek, & Jianakoplos, 1999), and educational attainment (Bertaut, 1998). I use these variables to more accurately control for the effect of risk attitudes in general.

Table 1.3 shows that the distribution of demographic characteristics within each risk tolerance group is approximately the same as the full sample in most cases. Some differences are worth noting, however. Women are overrepresented in the lowest-risk tolerance group relative to the full sample. They are also under-represented in the highest-risk tolerance group. College graduates are underrepresented in the lowest-risk tolerance group. Rates of equity ownership are lowest in the lowest-risk tolerance group but are similar between the medium- and high-risk groups. These data are all consistent with prior empirical evidence.

Results also show that the high-risk tolerance group had the largest positive change in financial assets between 2004 and 2008, but the lowest z-score. This result is informative to the circumstances of the high-risk tolerance group. The high average percentage change in financial assets indicates that the investment risks that the high-risk tolerance group take with their financial assets are producing good results for them in the long run. The low z-score indicates that their risky investments produced higher exposure to market volatility. This result indicates that the variable is successful in estimating exposure to market volatility.

Table 1.3 also shows that equity ownership rates are lowest in the lowest risk tolerance group. This indicates that the risk tolerance measure is estimating correctly the likelihood of stock ownership. Figure 1.1 plots the relation between financial satisfaction in 2008 to financial assets owned. The figure clearly shows that the relation between financial satisfaction and financial assets owned is almost perfectly exponential. A simple correlation analysis between these two variables indicates a 92.9% correlation between financial satisfaction and average level of financial assets.

Table 1.3 Descriptive Statistics by Risk tolerance Group

	Full Sample (n=648)	Low Risk Group (n=271)	Medium Risk Group (n=239)	High Risk Group (n=136)
Financial Satisfaction Variables				
Avg. Financial Satisfaction '04	2.03	2.00	2.06	2.05
Avg. Financial Satisfaction '08	2.36	2.36	2.45	2.19
Demographics Variables				
Age	62.37	62.70	61.49	63.34
Female	53.8%	58.4%	55.8%	41.7%
College Graduates	37.3%	28.7%	45.4%	39.0%
Risk Exposure Variables				
% Married	73.6%	77.2%	68.6%	75.5%
% Employed	47.4%	42.6%	51.6%	49.0%
% Not Working	3.2%	4.3%	2.3%	2.7%
% Retired	49.4%	53.2%	46.1%	48.3%
% Equity Owners in '08	26.5%	24.9%	29.0%	25.2%
% Δ Household Income	-14.3%	-17.0%	-5.6%	-24.5%
% Δ Financial Assets	26.2%	19.0%	21.4%	48.1%
Avg. Relative Change in Financial Assets (Z-Score)	0	0.05	0.001	-0.1722

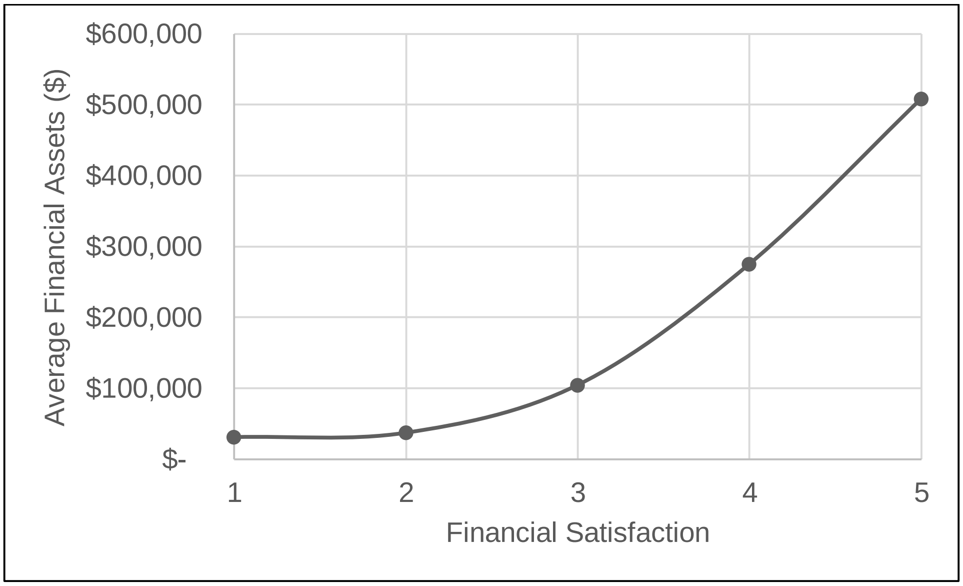

Figure 1.1 Average Financial Assets by Financial Satisfaction in 2008

Table 1.4 shows general economic conditions in the two waves. Of primary interest in this table is the standard deviation of the S&P 500 stock market index in the two periods. The table shows that the volatility of the S&P 500 during the 2008-2009 wave was substantially higher than it was during the 2004-2005 wave.

The lack of data on specific equity allocations within the HRS sample prevents this analysis from using these data directly. However, these data are useful to help visualize the volatility that respondents were subject to. News reports of market movements also tend to follow large cap indexes like the S&P 500, so the figures in the table may also be considered indicative of the most easily accessible public knowledge of general market movements. This suggests that respondents during the 2008 wave are subject to the potentially large shifts in risk perception and thus financial satisfaction discussed earlier.

Table 1.4 S&P 500 Close and Unemployment Rate by Wave

Feb 2004 to Feb 2005		
	Mean	Std Dev
S&P 500	1134	32
Unemployment Rate	5.55	0.13
Feb 2008 to Feb 2009		
	Mean	Std Dev
S&P 500	1215	188
Unemployment Rate	5.8	0.78

Model

I specify an ordered probit model for financial satisfaction (y_i^*) in 2008. An ordered probit model is appropriate for this analysis because of the nature of the dependent variable. The model is based on the assumption that latent financial satisfaction is a continuous variable. The financial satisfaction metric, however, is measured using a single Likert-scale response. The survey question therefore only permits us to view certain points along the unobserved continuous distribution of financial satisfaction. Likert-scale responses make it impossible to be certain where on the latent distribution the observed points are located relative to each other. We know only that a response of 1 is worse than a response of 2, but we do not know how much better 2 is than 1. This prohibits the use of an ordinary least squares model or any other model that assumes a continuous dependent variable.

The ordered probit model estimates the probability that respondent i will select alternative j. In this instance, the alternative j is the level of financial satisfaction reported, on a range of 0 to 4. The model works by estimating the probability that the latent continuous variable (y_i^*) is between alternative *j* and alternative *j*-1. The functional form of the model is specified as equation 1. μ_j is the intercept for alternative *j* and ε_i is the error term for respondent *i*. Equation 2 specifies the linear estimation of financial satisfaction (y_i^*) for the regression.

The primary independent variables of interest are indicators for the three risk tolerance categories. The medium-risk tolerance group is excluded because it is the reference group. $\lambda_1, \lambda_2, \gamma_i$, and ω_i are all variable parameters to be estimated. Z is the array of time-invariant independent variables. Time invariant variables include indicators for gender (female = 1), equity participation in 2008, retirement status in 2008, age in 2008 and its square, an indicator for education (college or higher = 1), and financial satisfaction in 2004. The time-dependent variables included in ΔK_i are relative change in financial assets and percentage change in household income.

$$
\begin{gathered}
prob(y_i^* = 0|\boldsymbol{x}) = \Phi(-\mathbf{x}'\beta), \\
prob(y_i^* = 1|\boldsymbol{x}) = \Phi(\mu_1 - \mathbf{x}'\beta) - \Phi(-\mathbf{x}'\beta), \\
prob(y_i^* = 2|\boldsymbol{x}) = \Phi(\mu_2 - \mathbf{x}'\beta) - \Phi(\mu_1 - \mathbf{x}'\beta), \\
prob(y_i^* = 3|\boldsymbol{x}) = \Phi(\mu_3 - \mathbf{x}'\beta) - \Phi(\mu_2 - \mathbf{x}'\beta), \\
prob(y_i^* = 4|\mathbf{x}) = \Phi(\mu_3 - \mathbf{x}'\beta) \\
Where\ 0 < \mu_1 < \mu_2 < \mu_3 < \mu_4
\end{gathered}
$$

$$
\begin{gathered}
y_i^* = \mathbf{x}'\beta + \varepsilon_i = \mu_j + \lambda_1 * HighRisk + \lambda_2 * LowRisk + \gamma_i \Delta K_i + \omega_i Z \\
+ \varepsilon_i \quad (Equation\ 1)
\end{gathered}
$$

Results

Table 1.5Table 1.5 Ordered Probit Parameter Estimates - Financial Satisfaction in 2008 presents regression results for the full sample.

Table 1.5 Ordered Probit Parameter Estimates - Financial Satisfaction in 2008

	Estimate	Standard Error
Financial Satisfaction in 2004	0.530 ***	0.050
High Risk tolerance	-0.257 **	0.118
Low Risk tolerance	-0.036	0.098
Married/Partnered	0.257 **	0.101
Employed	0.396	0.262
Retired	0.570 **	0.268
Change in Household Income	0.214 ***	0.065
Change in Financial Assets	-0.170 ***	0.044
Equity Ownership	0.458 ***	0.102
Female	0.096	0.090
Age	-0.010	0.060
Age Squared	0.0000	0.0001
College Graduates	0.112	0.096
Sample Size	648	
Pseudo R-Squared	0.1436	

(***, **, and * indicate statistical significance at the .01, .05, and .10 levels respectively)

Table 1.6 Marginal Effect of Significant Variables on the Probability of Reporting Each Level of Financial Satisfaction

	Financial Satisfaction Level	Mean	Std Error
High Risk Tolerance	0	0.026 **	0.013
	1	0.029 **	0.014
	2	0.026 **	0.011
	3	-0.024 **	0.012
	4	-0.056 **	0.025
Low Risk Tolerance	0	0.003	0.009
	1	0.004	0.011
	2	0.004	0.011
	3	-0.003	0.008
	4	-0.008	0.022
Financial Satisfaction in 2004	0	-0.049 ***	0.007
	1	-0.058 ***	0.007
	2	-0.060 ***	0.007
	3	0.044 ***	0.005
	4	0.122 ***	0.012
Equity Ownership	0	-0.035 ***	0.008
	1	-0.049 ***	0.012
	2	-0.065 ***	0.017
	3	0.034 ***	0.008
	4	0.115 ***	0.027
Change in Income	0	-0.012 *	0.007
	1	-0.017 *	0.009
	2	-0.051 **	0.022
	3	-0.014 *	0.008
	4	0.094 **	0.041
Relative Change in Assets	0	0.013 *	0.007
	1	0.017 *	0.009
	2	0.052 **	0.023
	3	0.014 *	0.008
	4	-0.095 **	0.042

Only the signs of estimates are interpretable from the aggregate results presented in Table 1.5. Significantly positive estimates indicate that the variable is associated with an increased probability of the respondent being in a higher level of financial satisfaction. The marginal effects in Table 1.6 can be interpreted by both their sign and relative magnitudes. Each significant result indicates a higher or lower probability of being in the corresponding level of financial satisfaction specified in the second to left column. Positive signs indicate a higher probability and negative signs indicate a lower probability.

Results show that high-risk tolerance is significantly negatively related to financial satisfaction for the general public. Those in the high-risk tolerance group are 5.6% less likely to be in the highest financial satisfaction level, and 2.3% more likely to be in the lowest financial satisfaction level. The results also indicate that investors in 2008 had an 11.5% increased probability of reporting the highest level of financial satisfaction. This suggests that the positive affect of owning equities on wealth levels provides positive satisfaction to individuals, but that those who are willing to take risks were significantly less satisfied in 2008 than were those who were more likely to have avoided risks.

I also find that those who were not working were significantly less satisfied with their financial situation than were those who were retired. Those with a partner in the home also were more satisfied with their finances than their counterparts.

Comparing Investors and Non-Investors

While the effect of market movements on the general population is interesting from a sociological, public policy, or economic perspective, financial planners are more likely to be interested in the effect that market movements will have on their clients. I test whether risk tolerance is related significantly to financial satisfaction for only those households that have holdings in the stock market.

Theory suggests that those with holdings in the stock market might reasonably be expected to have a different reaction to market volatility than those with no holdings in the market. The movements of the stock market have a direct effect on the lifetime consumption patterns of invested households. Individuals choose to invest in appreciating assets in order to prevent experiencing a reduction in consumption during retirement. The amount of future consumption that an investment will buy depends on its return. Therefore, excessive market volatility should rationally be perceived as a threat to the potential future consumption of invested households. No such relation exists for household that own no stocks.

Figure 1.2 shows that investors in 2008 had far greater levels of financial assets than did non-investors. Based on the original regression results and the correlation between financial assets and financial satisfaction illustrated in Figure 1.1 and Table 1.4, I would expect to find that investors have higher levels of financial satisfaction than non-investors in this time period.

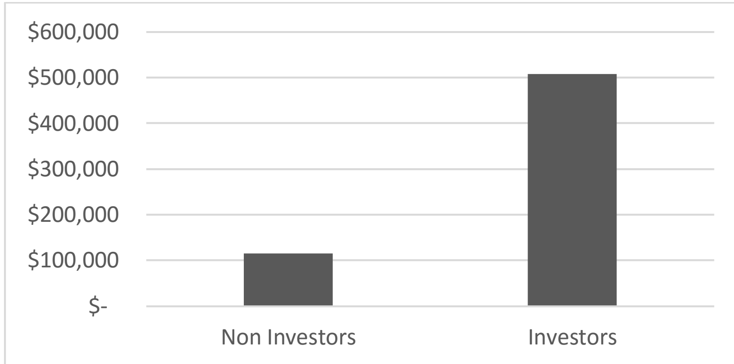

Figure 1.2 Average Financial Assets in 2008 by Investor Status

The model is specified the same as in the original regression, but with the sample divided by equity ownership. The restricted samples contain 182 investors and 466 non-investors respectively.

Table 1.7 and Table 1.8 present estimated regression results for parameter and estimated marginal effects for this analysis.

Table 1.7 Parameter Estimates – Financial Satisfaction in 2008 by Investor Status

	Investors		Non-Investors	
	Estimate	Standard Error	Estimate	Standard Error
Financial Satisfaction in 2004	0.776 ***	0.11	0.480 ***	0.06
High Risk tolerance	0.076	0.23	-0.385 ***	0.14
Low Risk tolerance	0.284	0.20	-0.130	0.11
Married/Partnered	0.352 *	0.20	0.265 **	0.12
Employed	-0.400	0.66	0.568 **	0.29
Retired	-0.240	0.67	0.726 **	0.30
Change in Household Income	0.339 **	0.15	0.171 **	0.07
Change in Financial Assets	-0.345 **	0.15	-0.156 ***	0.05
Female	0.212	0.19	0.074	0.10
Age (in 2008)	0.044	0.11	-0.019	0.07
Age Squared	<0.0001	0.0001	<0.0001	0.0001
College Graduates	0.195	0.19	0.091	0.11
Sample Size	182		466	
Pseudo R-Squared	0.2078		0.0985	

(***, **, and * indicate statistical significance at the .01, .05, and .10 levels respectively)

Table 1.8 Marginal Effects of Significant Variables on the Probability of Reporting Each Level of Financial Satisfaction by Investor Status

	Financial Satisfaction Level	Investors Mean	Investors Std Error	Non-Investors Mean	Non-Investors Std Error
High Risk Tolerance	1	-0.003	0.008	0.050 **	0.021
	2	-0.004	0.011	0.052 ***	0.019
	3	-0.011	0.034	0.020 ***	0.006
	4	-0.003	0.011	-0.051 **	0.020
	5	0.021	0.063	-0.071 ***	0.024
Low Risk Tolerance	1	-0.010	0.007	0.015	0.013
	2	-0.014	0.010	0.017	0.015
	3	-0.043	0.031	0.010	0.009
	4	-0.012	0.010	-0.016	0.014
	5	0.079	0.055	-0.026	0.023
Financial Satisfaction 2004	1	-0.028 **	0.011	-0.055 ***	0.009
	2	-0.039 ***	0.012	-0.064 ***	0.009
	3	-0.116 ***	0.019	-0.039 ***	0.008
	4	-0.031 **	0.013	0.059 ***	0.008
	5	0.215 ***	0.027	0.099 ***	0.013
Employed (vs unemployed)	1	0.015	0.026	-0.065 *	0.034
	2	0.021	0.036	-0.067 **	0.029
	3	0.065	0.114	-0.045 **	0.022
	4	0.011	0.012	0.054 ***	0.019
	5	-0.112	0.185	0.123 *	0.065
Retired (vs unemployed)	1	0.009	0.027	-0.091 **	0.043
	2	0.012	0.033	-0.096 ***	0.036
	3	0.033	0.085	-0.045 ***	0.014
	4	0.011	0.032	0.090 ***	0.033
	5	-0.065	0.176	0.141 **	0.055
Change in Income	1	-0.012 *	0.007	-0.020 **	0.009
	2	-0.017 *	0.009	-0.023 **	0.010
	3	-0.051 **	0.022	-0.014 **	0.006
	4	-0.014 *	0.008	0.021 **	0.009
	5	0.094 **	0.041	0.035 **	0.015
Relative Change in Assets	1	0.013 *	0.007	0.018 ***	0.006
	2	0.017 *	0.009	0.021 ***	0.006
	3	0.052 **	0.023	0.013 ***	0.004
	4	0.014 *	0.008	-0.019 ***	0.006
	5	-0.095 **	0.042	-0.032 ***	0.010

Of primary interest in this round of results is the lack of significance of risk tolerance for investors. This suggests that the risk tolerance of an investor did not significantly affect their reaction to the volatility of the market in 2008. This is the result predicted by the theory of risk perception.

The information presented in Figure 1.3 helps explain this result and its consistency with theory. This figure shows relative change in financial assets by risk tolerance and equity ownership. The differences across risk tolerance groups in this figure help to explain the regression results. The high-risk tolerance group were below average in asset growth regardless of whether they owned stocks or not. Investors in the low-risk tolerance group, however, had the best market results overall.

The returns data presented in Table 1.3 suggest that this group had relatively less risky portfolios than the other risk tolerance groups. This implies that the low-risk tolerance group had low-risk investment strategies that successfully mitigated losses in 2008. This indicates that the relatively positive short-term returns may contribute significantly to the financial satisfaction of the low-risk tolerance investors. Also note that non-investors had substantially lower asset growth rates regardless of their risk tolerance. This is consistent with the returns data in Table 1.3 that suggests that the returns earned in the market by investors from 2004 to 2008 exceeded the short-term market losses in 2008.

The overall conclusion drawn from the regression results and Figure 1.3 and Table 1.3 suggests that short-term volatility has a significantly negative impact on investors, and that risk tolerance is more predictive of the investor's exposure to market risk than it is of their capacity to endure risk without experiencing dissatisfaction. Long-term gains are also not sufficient to offset the loss of financial satisfaction induced by short-term market losses.

Risk perception may be the cause of the dissatisfaction of investors. Note that it is rational for investors to update their beliefs about the risks of their portfolio across time. However, if investors are updating their risk expectations rationally according to the objective data available to them, then the most risk tolerant investors should have had the highest level of financial satisfaction.

It is a fundamental principle of investing that low asset prices imply high expected future returns. Thus, the recessionary conditions of the market in 2008 represented a prime portfolio rebalancing opportunity for the rational investor. For those who were willing to take the risk, additional allocations to equities in 2008 were the rational choice. Indeed, retrospective analysis of market performance shows that the S&P 500 gave about a 120% return in 2009. This remarkable gain was only given to those who were willing to accept the perceived high-risk opportunity presented by the recession. Thus, we should expect that investors with rational perceptions of risk and high degree of risk tolerance should have been very satisfied by the wealth building opportunity presented by the crash of 2008.

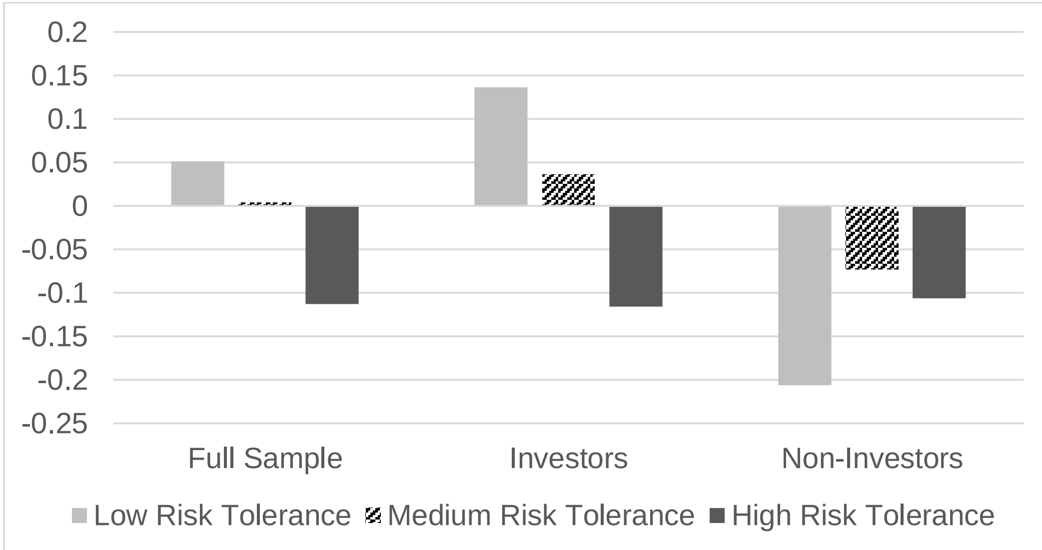

Figure 1.3 Relative Change in Financial Assets by Risk tolerance and Equity Ownership

Limitations and Future Research

Note that the results from investors-only is a small sample only 182 respondents. This small sample size may have caused some type II errors in the regression results, and some of the insignificant variables may in fact be significant. Future research could expand on the current analysis with a larger dataset of investors.

I also note that the risk tolerance question in the HRS is a measure of income risk only. It is feasible that respondents may have different attitudes towards the risk in their portfolios than they do in their income stream. This should not rationally be the case (Milevsky & Huang, 2011). Nevertheless, future research could expand on this study by utilizing a more direct measure of investment risk tolerance.

Summary

Financial planners rely on measures of risk tolerance to build portfolios for their clients on the assumption that more risk-tolerant clients will experience less disutility from a market decline. My results indicate that investors with medium or high levels of measured risk tolerance had significantly less financial satisfaction in 2008 than those of the lowest risk tolerance. This is likely due to the extreme volatility and large losses experienced by the market as a whole in 2008. This suggests that investors prioritize short-term volatility over long-term gains when assessing their satisfaction.

This is informative to how financial planners build portfolios and manage client expectations. The results illustrate that even investors who report having a high level of risk tolerance would not be expected to be happier in a market decline than those reporting high levels of risk tolerance. The implication for planners is that risk and client expectations must still be managed for every client, regardless of their expressed level of risk tolerance.

Planners and individual investors can also use these findings to mitigate the reaction to market losses. The significance of the relation between financial assets and financial satisfaction suggests that refocusing an investors on long-term gains can help to offset the pains of short-term losses. The average percentage change in financial assets from 2004 to 2008 was positive in this sample, even after the substantial market losses in 2008. This suggests that changing the investor's focus to the long-term gains and the long-term investment plan should be at least somewhat effective in helping to mitigate the loss of satisfaction caused by market losses.

I also find evidence that investors may not be fully rational when updating their beliefs about the riskiness of their portfolios. Investors should update their expectations about the riskiness of their portfolio over time. This is both rational and optimal. However, a rational investor should have had an increase in satisfaction because of the opportunity for high future returns presented by declining asset prices. The lack of any indication of this occurring in my results suggests that the perceptions of risk that were formed in 2008 were not fully rational.

CHAPTER 2

PUBLIC REACTION TO STOCK MARKET VOLATILITY: EVIDENCE FROM THE ATUS

Introduction

How does the public react to changes in the stock market? We know from a substantial body of research that sentiment can affect the stock market (Baker & Wurgler, 2007), and even that sentiment can predict future stock market movements (Bollen, Mao, & Zeng, 2011). Public interest in the market also is evident from the considerable resources that news outlets expend on reporting on market movements multiple times throughout each day. But does the affect work in both directions? Do market movements affect sentiment? This paper addresses these questions by testing whether market movements are correlated with changes in the well-being of the general public.

Modern portfolio theory describes the relationship between asset selection and investor risk tolerance (Markowitz, 1952). Risk tolerance is defined as how much variation in outcomes an individual is willing to accept. Assets with higher levels of volatility in returns are inherently less desirable than assets with more stable returns because higher levels of volatility ultimately create higher uncertainty in future consumption for the investor.

Modern portfolio theory assumes that investors are economically rational. Under this assumption, investors should experience no change in their well-being when the market experiences high periods of volatility. This is because a rational investor considers the volatility of their investment at the time of purchase. To the rational investor, short term fluctuations in the market are simply a part of the investing process that they understood when they made their investment decision. If this assumption proves valid, we would expect to find no relationship between market movements and well-being.

The rules of economic rationality are not always followed by individuals in practice. A wide array of cognitive biases and errors have been identified that cause individuals to make sub-optimal conditions, or to make choices that are otherwise not rational. Examples of such biases include an excessive desire to avoid losses (Kahneman & Tversky, 1979), the overreliance on easily available data (Tversky & Kahneman, 1973), overconfidence (Fischhoff, Slovic, & Lichtenstein, 1981), the tendency to mentally view fungible assets as belonging to distinctly different accounts (R.H. Thaler, 2004), the tendency to compare results to a self-defined anchor point (Tversky & Kahneman, 1974), and the effect of emotion of cognitive processes (Loewenstein et al., 2001).

Stock market research has indicated that these and other biases can interact to create a market effect known as investor sentiment. Investor sentiment is defined as the beliefs that investors hold about the future prospects of their investments. These beliefs are, by definition, not justified by the objective facts of the investment environment.

The effects of investor sentiment have been tied empirically to a number of market phenomenon, such as excessive volatility (Shiller, 1980), mean reversion (Fama & French, 1988; Poterba & Summers, 1988), overreaction to news (Hersh Shefrin, 2000), and even the overall value of (Campbell & Shiller, 1988; Fama & French, 1989). Many modern investment researchers accept the existence of investor sentiment and focus their collective efforts on the task of quantifying the magnitude of impact that investor sentiment has on investment markets (Baker & Wurgler, 2007).

Theory: Risk Perception

A fundamental driver of investor sentiment is the perception of risk (De Long, Shleifer, Summers, & Waldmann, 1990). Risk perception is the subjective assessment risk made by an individual. This assessment depends on the individual's comprehension of the situation and their previous experience with risky events (Ricciardi, 2008). It is important to note the extremely subjective nature of an individual's perception of risk. This inherent subjectivity is sufficient that risk perceptions frequently fail to align with objective risk measures (Ricciardi, 2004).

The misperception of market risk can affect all members of society, not just investors. This is because general information about market movements are published in general, not only to investors. Volatility in the market may be perceived as increasing general risk for households because of the risk-as-feeling hypothesis.

The risk-as-feelings hypothesis is an addition to the cognitive approach that traditional economic theory uses to describe how individuals assess risk. The hypothesis suggests that the perception of risk is affected by emotional reactions as well as objective risk assessments. It posits that instinctive reactions often override more logical decision making processes and cause individuals to perceive and react to risk in ways that are at odds with the objective assessments of the risk. This hypothesis has found empirical support in a wide variety of applications and tests (Loewenstein et al., 2001). One study finds that the weather (as a proxy for mood and emotional balance) can affect both future market movements and the reaction to market news, suggesting that the risk people perceive is being affected by their emotional state (Hirshleifer & Shumway, 2003).

Consider a person watching the evening news when the news anchors report the closing value of the Dow Jones Industrial Average market index. The anchors are careful to point out that the market is down off its high of the prior week. The viewer at this point may feel negative emotions, even though he owns no stocks. The fact that other people's money may be in jeopardy increases the viewer's sense that his own money may also be at risk. The viewer may also feel that there is has been an increase of risk in many other areas of his life. For example, the viewer' may fear that the probability of a general economic downturn has increased, even if the market movement was not substantial enough to warrant any such concern.

Perceived risk is generally the most salient information about risk that individuals have. It therefore is not surprising to find that the perception of risk drives risk taking behaviors and preferences more strongly than do objective risk measures (Weber, 2004). This leads us to hypothesize that changes in the stock market will be associated with emotional well-being for the general public, even if they do not own any stocks.

Data

This analysis uses data from the American Time Use Survey (ATUS). The ATUS is a nationally representative survey administered by the U.S. Bureau of Labor Statistics. It collects a 24 hour time diary for nearly every day of the calendar year. This on-going household survey samples approximately 1,200 Americans each month from respondents who participated in the Current Population Survey. Surveys are weighted to give equal representation to each every day of the week so that results may be generalized to any given day.

The 2010 and 2012 survey waves are used here because they contain well-being measure in addition to the time diary data. The Day Reconstruction Method (DRM) is applied to these measures to assess the daily well-being of individuals from time diary data. Three of the respondent’s reported activities from the day are randomly selected for assessment. For each activity, the respondent is asked to report, on a seven point Likert scale, their level of stress, sadness, tiredness, happiness, and sense of the meaningfulness of their activities.

The survey provides weights that permit the calculation of average levels of each of these emotion states of the total sample for each day. The first step in calculating the average level of well-being in a day is to calculate the average level of each emotion state experienced by the survey respondents. Equation 1 provides the formula for estimating the average level of emotion E during a day, where *i* denotes the respondent, and *k* denotes the sampled activity. Variable *w* is the activity level weight, and *E* is the level of emotion reported by respondent *i* during activity *k*.

$$\bar{E} = \frac{\sum_i \sum_k w_{ik} E_{ik}}{\sum_i \sum_k w_{ik}} \qquad (Equation\ 1)$$

After using Equation 1 to estimate the average level of each emotion during a day, we use Equation 2 to estimate the average balance of emotions experienced during a day. The estimate of average well-being on day *t*, defined as W_t, is the sum of the averages of the positive emotions (happiness and sense of meaning) minus the sum of the averages of the negative emotions (stress, sadness, tiredness).

$$W_t = \left(\bar{E}_{Happy} + \bar{E}_{Meaning}\right) - (\bar{E}_{Sad} + \bar{E}_{Stress} + \bar{E}_{Tired}) \qquad (Equation\ 2$$

Model

We apply a Granger causality analysis to determine whether the public mood responds to stock market movements. This procedure tests if changes in two time series are Granger causal to each other. Granger causality implies that stock market movements provide predictive information about public well-being in the near future. It does not imply causation.

This approach is suitable for this analysis because it rests on the logic that if X is predictive of Y, then changes in X should occur systematically before changes occur in Y. In the present analysis, this approach will test to see if stock market movements systematically occur before changes in average public well-being. If such a relation is found, then stock market movements will be said to be Granger causal

In a similar study, a Granger causality analysis was employed to determine that the emotional content of tweets from the micro-blogging website Twitter provided predicative information about future stock market movements (Bollen et al., 2011). The present analysis performs a similar analysis, but in the opposite direction.

The Granger causality is modeled as M_1 and M_2 in equations 3 and 4.

$$M_1\!: \; W_t = \alpha + \sum_{i=1}^{n} \beta_i W_{t-i} + \varepsilon_t \qquad (Equation\; 3)$$

$$M_2\!: \; W_t = \alpha + \sum_{i=1}^{n} \beta_i W_{t-i} + \sum_{i=1}^{n} \gamma_i X_{t-i} + \varepsilon_t \qquad (Equation\; 4)$$

Where X_t is defined as the average return of the S&P 500 index between day *t* and day $t - m$. W_t is the average level of well-being on day *t* as previously defined in Equation 2. α is the intercept of the regression. β_i and γ_i are the correlations between lagged well-being and lagged stock market returns. Estimates of γ_i that are significant provide evidence of Granger causality. M_1 is the reduced form model, and specifies past well-being as the only predictor of future well-being. Model M_2 specifies that lagged market returns contain predicative information about future well-being. The null hypothesis is that lagged stock market movements do not predict public well-being (ie $\gamma_i = 0$).

Results

Results for lagged 1-day, 7-day, 3-day, and 30-day average returns are presented in Tables 2.1 through 2.4 (see appendix) and in graphical form in Figures 2.1 through 2.4. These figures show the magnitude and statistical significance of lagged market returns against changes in public well-being. So, for example, the furthest right data point in **Error! Reference source not found.** shows that 1-day arket returns from 120 days earlier are estimated to have a correlation of about 0.06 with changes in public well-being, and that this result is significant at less than 1%. This also implies that changes in 1-day market returns can predict approximately 6% of the changes in public well-being 120 days after the movement.

Results for the 1-, 3-, and 7-day return periods show a high degree of noise and generally low levels of significance relative to the results for the 30-day return period. This may be a statistical artifact caused exhibit higher relative volatility exhibited by the shorter-term average returns data. This subjects the short term analyses to increased noise and thus makes significance more difficult to detect. However, each of these figures show consistent level of significance after a 100 day lag.

Error! Reference source not found. presents the results for lagged 30-day verage market returns. This figure indicates that public reaction to market movements may begin as early as 30-days after the movement. The magnitude of the parameter estimates suggest that lagged 30-day market returns can explain between 5% and 10% of the total changes in public well-being. This magnitude of the effect begins to decline about 110 days after the market movement occurs.

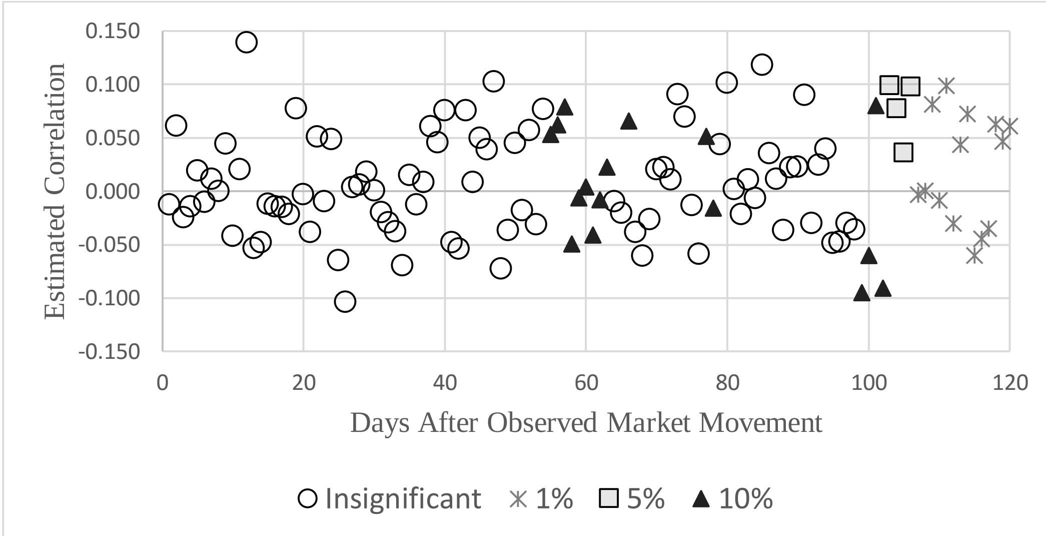

Figure 1.4 Correlations between Well-being and Lagged 1-day S&P 500 Returns

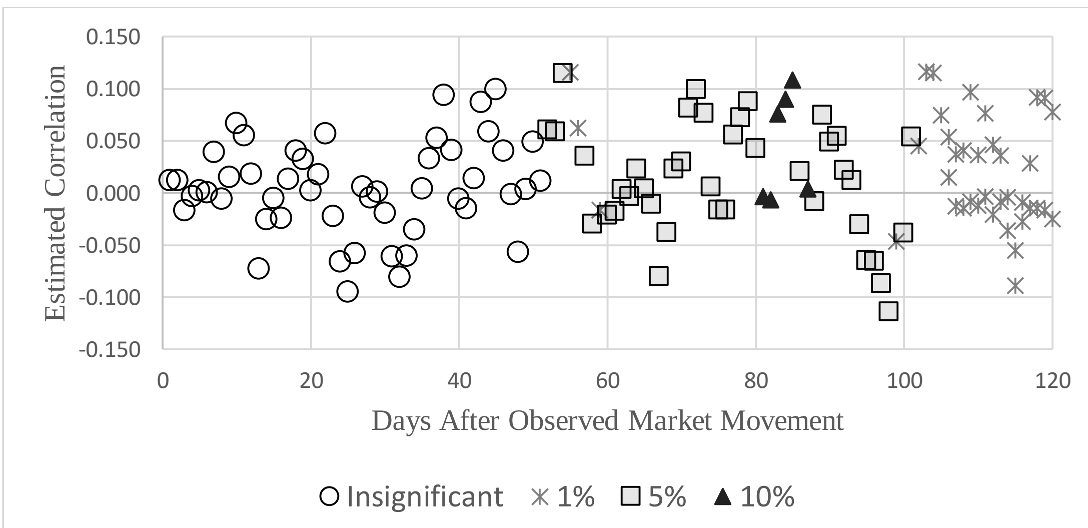

Figure 1.5 Correlations between Well-being and Lagged 3-day S&P 500 Returns

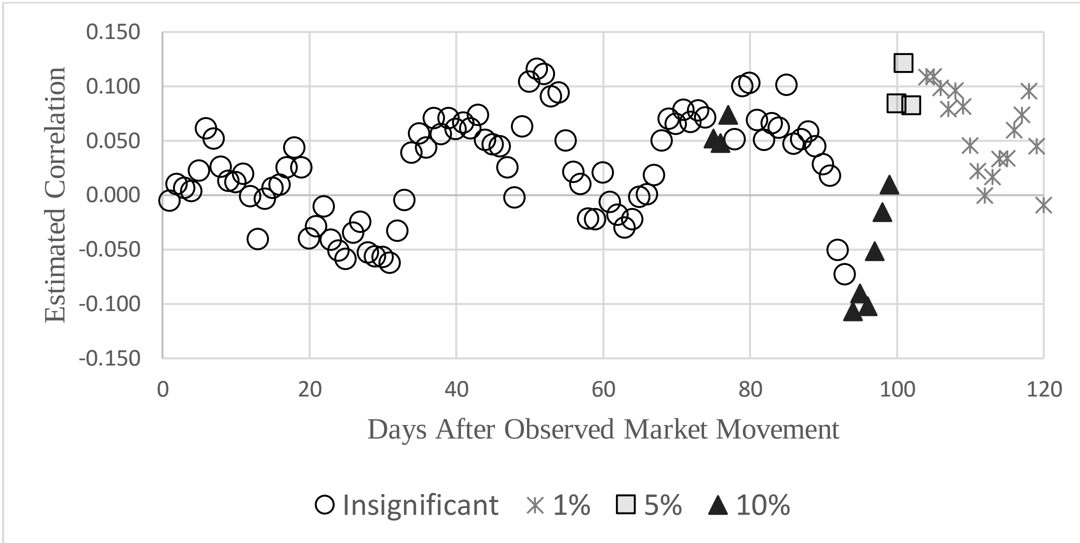

Figure 1.6 Correlations between Well-being and Lagged 7-day S&P 500 Returns

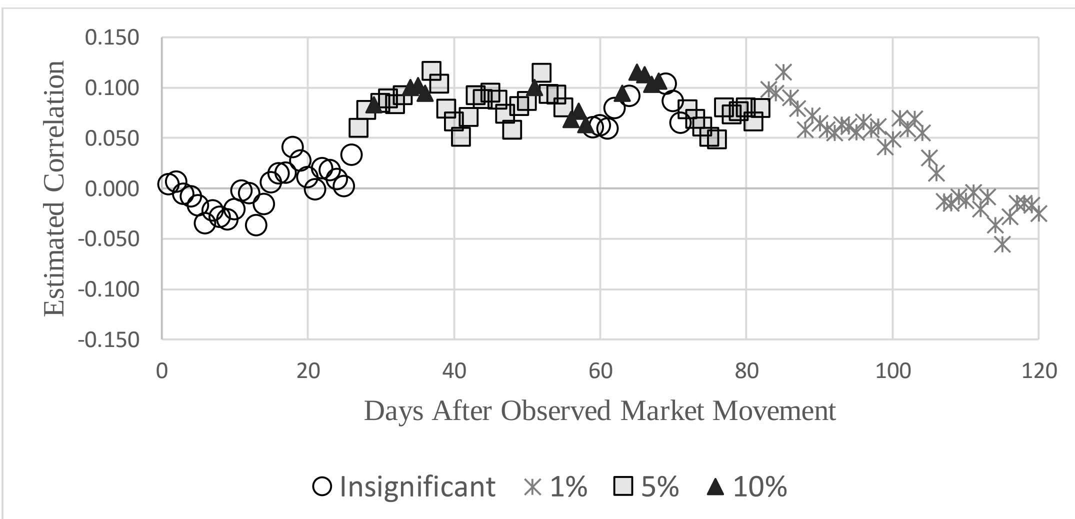

Figure 1.7 Correlations between Well-being and Lagged 30-day S&P 500 Returns

Discussion

One possible interpretation of these results could be that public receives only delayed information about market movements. However, with many local and national news outlets publishing market movements multiple times per day, it seems unlikely that a substantial portion of the public would be unaware of the movements in the market. It seems more likely that the public does not acknowledge or otherwise accept that the recent market movements will persist until substantially after the fact. In other words, the public delays its reaction to market movements until it is certain that the movements represent persistent changes and not just short term volatility. The general public also may use the stock market as a signal for economic conditions, with sustained movements predicting future swings in the broader economy.

The sample did not distinguish between those who are financially exposed to market volatility and those who are not. It is likely that the investors and non-investors would have different reactions to market movements. The prevalence of overconfidence among investors also may help to explain the results (Griffin & Tversky, 1992). Investors often overestimate their own ability to select successful investments. Armed with this confidence, they reassure themselves that, although recent performance has been poor, their investment is sure to turn around soon. Eventually, the investor must admit that the investment is a failure, and experience the negative emotions associated with investment losses. My results indicate that this realization comes upon the investor about 30-110 days after the initial loss.

This consumption-based explanation for wealth effects, while theoretically sound, has only weak empirical support. This is due primarily to the distribution of equity holdings in the United States. Poterba (2000) reports that stocks represent only 4.1% of total net worth of the bottom 80% of stock owners by wealth. A recent PEW study found that only 55% of households even own stocks at all. The relatively small proportion of wealth held by most households in equities suggests that changes in equity values may not have a substantial impact on consumption by the general public.

There are other indications that equity losses have only a minimal effect on household consumption levels. Thaler (1990) argues that households categorize their assets into various mental accounts based on the purpose for which the assets will be used. This mental accounting phenomenon causes households to not consume the assets in their investment accounts because most of those funds have been earmarked for retirement. Retirement plans with tax-favored status also have tax penalties for early withdrawal. This further dis-incentivizes households from consuming retirement assets.

A number of studies have empirically confirmed that there is a low average marginal propensity to consume out of equity holdings. One study estimates the wealth effect of equities is about 0.02 in the short run and 0.042 in the long run. They compare this finding to an analogous wealth effect for other forms of wealth of 0.014 and 0.061, respectively (Meyer, 1994). Another study estimates that the wealth effect for changes in equity values is about 0.03 and for all other forms of wealth is about 0.075 (Brayton & Tinsley, 1996). More recent evidence has confirmed that this trend continues into the 21st century (Case, Quigley, & Shiller, 2005). This lack of propensity to consume equity holdings implies that market volatility will change actual consumption by only a small amount. The theorized change in public satisfaction and well-being caused by market volatility would therefore be expected to be relatively small under a consumption-based theory.

This finding might help to explain a number of investor behaviors. Consider the disposition effect. The disposition effect describes the reluctance of investors to sell their losing stocks, and their tendency to sell their winning stocks prematurely (H. Shefrin & Statman, 1985). While the loss aversion described by prospect theory (Kahneman & Tversky, 1979) has typically viewed as the predominant driver of this effect, recent empirical tests have found that loss aversion is less able to explain this phenomenon than had been theorized (Barberis & Xiong, 2009). The delayed reactions found here may be able to provide insight into this phenomenon.

Consider an investor who has just learned that a stock he/she purchased has fallen in value. These results suggest that the investor would not be expected to experience a significant emotional response until at least 30 days after the stock price falls. Why might this occur? It is possible that in the first days following the loss, the investor will console himself/herself that the stock price may yet recover, and that there is no need to worry. After 30 or 60 days, however, hope begins to fade and the investor must acknowledge the loss to themselves.

This may also help to explain the tendency for investors to mistime the market. Friesen and Sapp (2007) find that the tendency for investors to mistime cash flows into and out of mutual funds causes substantial losses. For example, consider the market rebound out of the recession in March 2009. The ideal time to buy back in to the market would have been during the first week of March. If an investor waited 30 days after market returns to be convinced that the positive returns of March would hold, he/she would have missed the approximately 17% monthly (200% annualized) return that the S&P 500 returned during that month. Thus the delay in reaction would have proven costly to the investor. Such a market mistiming could be at least partially explained by the delayed emotional reactions we have shown here.

This information could be useful to financial planners as well. The delayed and, perhaps more importantly to the planner, extended emotional reaction to market movements can inform the planner's approach to managing client reactions. Many planners make a habit of contacting their clients on particularly bad market days to provide reassurance. The evidence presented here suggests that a client's adverse reaction to negative market movements is likely to extend far longer than the initial shock. We can conclude that follow up communications between planner and clients could reasonably be expected to improve client satisfaction and well-being.

Data Appendix:

This appendix contains the full detailed results of the granger causality model presented in Chapter 2.

Table 1.9 Correlations between Well-being and Lagged 1-day S&P 500 Returns

Days Lagged	Pearson Correlation	F-Stat	F-Stat P-Value	Chi-Squared Stat	Chi-squared P-Value
1	-0.013	0.066	0.797	0.067	0.796
2	0.061	1.032	0.357	2.085	0.353
3	-0.025	0.861	0.461	2.619	0.454
4	-0.014	0.666	0.616	2.715	0.607
5	0.019	0.587	0.710	3.001	0.700
6	-0.010	0.474	0.828	2.918	0.819
7	0.012	0.409	0.897	2.952	0.889

8	0.000	0.361	0.940	2.994	0.935
9	0.045	0.364	0.952	3.406	0.946
10	-0.042	0.411	0.942	4.288	0.933
11	0.020	0.391	0.960	4.510	0.953
12	0.139	1.108	0.351	14.005	0.300
13	-0.053	1.153	0.312	15.860	0.257
14	-0.048	1.153	0.309	17.152	0.248
15	-0.012	1.053	0.399	16.849	0.328
16	-0.014	0.970	0.489	16.634	0.410
17	-0.015	0.958	0.506	17.527	0.419
18	-0.022	0.916	0.559	17.826	0.467
19	0.078	1.014	0.442	20.932	0.341
20	-0.003	0.958	0.513	20.898	0.403
21	-0.038	0.953	0.522	21.935	0.403
22	0.051	0.918	0.571	22.228	0.446
23	-0.009	0.871	0.639	22.138	0.512
24	0.049	0.878	0.633	23.398	0.496
25	-0.065	0.910	0.592	25.369	0.442
26	-0.104	1.181	0.248	34.422	0.125
27	0.004	1.153	0.274	35.050	0.138
28	0.006	1.133	0.295	35.869	0.146
29	0.018	1.089	0.346	35.889	0.177
30	0.001	1.048	0.400	35.872	0.212
31	-0.020	1.034	0.420	36.744	0.220
32	-0.029	1.040	0.410	38.357	0.203
33	-0.038	1.035	0.418	39.537	0.201
34	-0.070	0.994	0.482	39.292	0.245
35	0.015	0.945	0.561	38.667	0.308
36	-0.012	0.940	0.571	39.744	0.307
37	0.008	0.923	0.603	40.272	0.328
38	0.060	0.973	0.518	43.851	0.237
39	0.046	0.953	0.555	44.265	0.259
40	0.076	0.984	0.503	47.095	0.205
41	-0.048	1.000	0.475	49.301	0.175
42	-0.054	1.013	0.453	51.441	0.151
43	0.076	1.069	0.361	55.829	0.091
44	0.008	1.034	0.417	55.560	0.114
45	0.050	1.046	0.396	57.762	0.096
46	0.039	1.046	0.396	59.344	0.090
47	0.103	1.112	0.292	64.752	0.044

48	-0.073	1.181	0.200	70.630	0.018	
49	-0.036	1.138	0.252	69.830	0.027	
50	0.045	1.140	0.249	71.695	0.024	
51	-0.018	1.123	0.270	72.430	0.026	
52	0.057	1.142	0.242	75.506	0.018	
53	-0.031	1.194	0.177	80.880	0.008	
54	0.077	1.260	0.114	87.367	0.003	
55	0.053	1.300	0.084	92.329	0.001	*
56	0.063	1.318	0.072	95.821	0.001	*
57	0.079	1.314	0.073	97.741	0.001	*
58	-0.049	1.301	0.080	98.988	0.001	*
59	-0.006	1.314	0.071	102.225	0.000	*
60	0.004	1.346	0.054	107.108	0.000	*
61	-0.041	1.320	0.065	107.396	0.000	*
62	-0.008	1.294	0.079	107.544	0.000	*
63	0.023	1.265	0.097	107.453	0.000	*
64	-0.010	1.251	0.107	108.495	0.000	
65	-0.021	1.239	0.116	109.762	0.000	
66	0.066	1.264	0.095	114.347	0.000	*
67	-0.038	1.239	0.114	114.403	0.000	
68	-0.061	1.215	0.135	114.489	0.000	
69	-0.026	1.181	0.171	113.561	0.001	
70	0.020	1.152	0.207	113.052	0.001	
71	0.022	1.135	0.230	113.642	0.001	
72	0.011	1.148	0.211	117.196	0.001	
73	0.090	1.181	0.167	122.903	0.000	
74	0.069	1.162	0.190	123.342	0.000	
75	-0.013	1.206	0.136	130.542	0.000	
76	-0.059	1.214	0.127	133.909	0.000	
77	0.052	1.277	0.075	143.560	0.000	*
78	-0.015	1.253	0.091	143.581	0.000	*
79	0.044	1.220	0.119	142.421	0.000	
80	0.101	1.203	0.135	143.046	0.000	
81	0.002	1.137	0.220	137.674	0.000	
82	-0.021	1.089	0.300	134.300	0.000	
83	0.011	1.072	0.331	134.711	0.000	
84	-0.007	1.060	0.354	135.684	0.000	
85	0.118	1.111	0.258	144.795	0.000	
86	0.035	1.114	0.252	147.762	0.000	
87	0.012	1.113	0.254	150.234	0.000	

88	-0.036	1.119	0.243	153.768	0.000	
89	0.022	1.140	0.208	159.546	0.000	
90	0.023	1.130	0.223	160.898	0.000	
91	0.090	1.176	0.158	170.384	0.000	
92	-0.030	1.161	0.177	171.111	0.000	
93	0.025	1.164	0.172	174.641	0.000	
94	0.039	1.189	0.140	181.424	0.000	
95	-0.049	1.198	0.129	186.018	0.000	
96	-0.047	1.204	0.122	190.237	0.000	
97	-0.030	1.202	0.124	193.101	0.000	
98	-0.036	1.218	0.107	199.120	0.000	
99	-0.095	1.269	0.066	210.991	0.000	*
100	-0.060	1.246	0.082	210.708	0.000	*
101	0.081	1.260	0.072	216.616	0.000	*
102	-0.090	1.291	0.052	225.767	0.000	*
103	0.099	1.344	0.030	238.895	0.000	**
104	0.077	1.401	0.016	253.343	0.000	**
105	0.036	1.376	0.021	253.004	0.000	**
106	0.098	1.435	0.010	268.255	0.000	**
107	-0.003	1.537	0.003	292.004	0.000	***
108	0.001	1.532	0.003	295.947	0.000	***
109	0.082	1.633	0.001	320.784	0.000	***
110	-0.009	1.613	0.001	322.022	0.000	***
111	0.099	1.874	0.000	380.348	0.000	***
112	-0.030	1.830	0.000	377.771	0.000	***
113	0.044	1.884	0.000	395.183	0.000	***
114	0.073	1.866	0.000	397.869	0.000	***
115	-0.060	1.908	0.000	413.691	0.000	***
116	-0.044	1.926	0.000	424.426	0.000	***
117	-0.034	1.887	0.000	422.759	0.000	***
118	0.063	1.875	0.000	426.800	0.000	***
119	0.047	1.856	0.000	429.577	0.000	***
120	0.061	1.866	0.000	438.941	0.000	***

Table 1.10 Correlations between Well-being and Lagged 3-day S&P 500 Returns

Days Lagged	Pearson Correlation	F-Stat	F-Stat P-Value	Chi-Squared Stat	Chi-squared P-Value
1	0.012	0.073	0.787	0.073	0.786
2	0.012	0.065	0.937	0.131	0.937
3	-0.017	0.286	0.836	0.869	0.833
4	-0.003	0.281	0.890	1.146	0.887
5	0.002	0.230	0.949	1.179	0.947
6	0.000	0.240	0.963	1.482	0.961
7	0.039	0.470	0.857	3.391	0.847
8	-0.006	0.605	0.774	5.011	0.756
9	0.015	0.525	0.856	4.917	0.842
10	0.066	1.134	0.335	11.841	0.296
11	0.055	1.044	0.406	12.043	0.361
12	0.018	1.008	0.440	12.743	0.388
13	-0.073	1.085	0.370	14.923	0.312
14	-0.026	1.062	0.390	15.805	0.325
15	-0.005	0.984	0.471	15.752	0.399
16	-0.024	1.023	0.430	17.545	0.351
17	0.013	1.106	0.345	20.234	0.262
18	0.040	1.122	0.327	21.834	0.239
19	0.032	1.142	0.305	23.569	0.213
20	0.002	1.090	0.357	23.774	0.252
21	0.018	1.121	0.321	25.805	0.214
22	0.057	1.107	0.334	26.813	0.218
23	-0.022	1.310	0.154	33.304	0.076
24	-0.066	1.272	0.176	33.915	0.086
25	-0.095	1.216	0.218	33.918	0.110
26	-0.058	1.171	0.258	34.113	0.132
27	0.006	1.217	0.211	36.998	0.095
28	-0.005	1.209	0.216	38.278	0.093
29	0.001	1.181	0.241	38.902	0.104
30	-0.019	1.126	0.299	38.546	0.136
31	-0.061	1.229	0.189	43.692	0.065
32	-0.081	1.242	0.175	45.774	0.054
33	-0.061	1.210	0.201	46.240	0.063
34	-0.036	1.153	0.259	45.599	0.088
35	0.004	1.093	0.333	44.694	0.126
36	0.033	1.138	0.273	48.116	0.085

37	0.052	1.137	0.272	49.642	0.080	
38	0.094	1.130	0.280	50.892	0.079	
39	0.041	1.111	0.303	51.630	0.085	
40	-0.006	1.138	0.266	54.487	0.063	
41	-0.015	1.129	0.275	55.704	0.063	
42	0.014	1.108	0.303	56.275	0.069	
43	0.087	1.257	0.136	65.683	0.015	
44	0.059	1.208	0.178	64.885	0.022	
45	0.099	1.212	0.173	66.894	0.019	
46	0.040	1.173	0.213	66.546	0.025	
47	-0.001	1.165	0.221	67.846	0.025	
48	-0.057	1.162	0.223	69.465	0.023	
49	0.004	1.158	0.226	71.035	0.022	
50	0.049	1.195	0.181	75.178	0.012	
51	0.011	1.283	0.101	82.787	0.003	
52	0.060	1.482	0.021	97.945	0.000	**
53	0.059	1.533	0.013	103.854	0.000	**
54	0.115	1.549	0.011	107.423	0.000	**
55	0.116	1.597	0.007	113.425	0.000	***
56	0.062	1.563	0.009	113.595	0.000	***
57	0.035	1.532	0.011	113.922	0.000	**
58	-0.030	1.511	0.013	115.001	0.000	**
59	-0.016	1.541	0.010	119.933	0.000	***
60	-0.021	1.532	0.010	121.860	0.000	**
61	-0.018	1.496	0.014	121.639	0.000	**
62	0.003	1.470	0.017	122.204	0.000	**
63	-0.004	1.432	0.024	121.589	0.000	**
64	0.023	1.392	0.033	120.747	0.000	**
65	0.004	1.377	0.037	122.016	0.000	**
66	-0.011	1.383	0.035	125.121	0.000	**
67	-0.080	1.412	0.026	130.332	0.000	**
68	-0.038	1.392	0.031	131.156	0.000	**
69	0.023	1.391	0.030	133.816	0.000	**
70	0.030	1.357	0.041	133.181	0.000	**
71	0.081	1.423	0.021	142.443	0.000	**
72	0.099	1.413	0.023	144.239	0.000	**
73	0.077	1.421	0.021	147.955	0.000	**
74	0.006	1.391	0.027	147.681	0.000	**
75	-0.016	1.475	0.011	159.592	0.000	**
76	-0.016	1.451	0.014	160.058	0.000	**

77	0.055	1.439	0.016	161.806	0.000	**
78	0.072	1.410	0.021	161.504	0.000	**
79	0.087	1.377	0.029	160.701	0.000	**
80	0.043	1.358	0.034	161.512	0.000	**
81	-0.003	1.300	0.059	157.449	0.000	*
82	-0.007	1.253	0.088	154.525	0.000	*
83	0.076	1.287	0.065	161.675	0.000	*
84	0.090	1.277	0.070	163.383	0.000	*
85	0.109	1.288	0.063	167.770	0.000	*
86	0.020	1.312	0.049	174.067	0.000	**
87	0.004	1.300	0.055	175.561	0.000	*
88	-0.008	1.318	0.045	181.180	0.000	**
89	0.074	1.362	0.029	190.496	0.000	**
90	0.049	1.343	0.035	191.161	0.000	**
91	0.054	1.382	0.023	200.286	0.000	**
92	0.022	1.379	0.023	203.280	0.000	**
93	0.012	1.349	0.032	202.295	0.000	**
94	-0.031	1.340	0.034	204.509	0.000	**
95	-0.065	1.364	0.026	211.873	0.000	**
96	-0.066	1.378	0.022	217.727	0.000	**
97	-0.087	1.392	0.019	223.704	0.000	**
98	-0.114	1.387	0.020	226.758	0.000	**
99	-0.047	1.445	0.010	240.209	0.000	***
100	-0.038	1.411	0.015	238.609	0.000	**
101	0.054	1.430	0.012	245.854	0.000	**
102	0.045	1.456	0.008	254.645	0.000	***
103	0.117	1.457	0.008	259.113	0.000	***
104	0.115	1.569	0.002	283.657	0.000	***
105	0.075	1.538	0.003	282.780	0.000	***
106	0.054	1.540	0.003	287.897	0.000	***
107	0.037	1.661	0.001	315.738	0.000	***
108	0.041	1.658	0.001	320.319	0.000	***
109	0.097	1.908	0.000	374.819	0.000	***
110	0.036	1.948	0.000	388.947	0.000	***
111	0.076	1.987	0.000	403.395	0.000	***
112	0.047	1.944	0.000	401.209	0.000	***
113	0.036	2.098	0.000	440.223	0.000	***
114	-0.004	2.101	0.000	448.070	0.000	***
115	-0.089	2.086	0.000	452.251	0.000	***
116	-0.009	2.080	0.000	458.315	0.000	***

117	0.029	2.009	0.000	450.000	0.000	***
118	0.092	1.983	0.000	451.410	0.000	***
119	0.091	1.946	0.000	450.428	0.000	***
120	0.077	1.928	0.000	453.567	0.000	***

Table 1.11 Correlations between Well-being and Lagged 7-day S&P 500 Returns

Days Lagged	Pearson Correlation	F-Stat	F-Stat P-Value	Chi-Squared Stat	Chi-squared P-Value
1	-0.006	0.013	0.911	0.013	0.911
2	0.010	0.168	0.846	0.339	0.844
3	0.006	0.120	0.949	0.364	0.948
4	0.004	0.098	0.983	0.398	0.983
5	0.022	0.214	0.956	1.096	0.954
6	0.061	0.687	0.660	4.236	0.645
7	0.052	0.586	0.768	4.231	0.753
8	0.026	0.653	0.733	5.414	0.713
9	0.013	0.589	0.807	5.513	0.788
10	0.012	0.536	0.865	5.599	0.848
11	0.019	0.514	0.894	5.931	0.878
12	-0.001	0.496	0.917	6.265	0.902
13	-0.041	0.572	0.877	7.865	0.852
14	-0.003	0.634	0.837	9.434	0.802
15	0.007	0.560	0.905	8.971	0.879
16	0.010	0.528	0.933	9.056	0.911
17	0.025	0.518	0.944	9.488	0.924
18	0.043	0.557	0.929	10.839	0.901
19	0.025	0.579	0.922	11.943	0.888
20	-0.040	1.193	0.255	26.030	0.165
21	-0.029	1.175	0.268	27.043	0.169
22	-0.011	1.202	0.240	29.110	0.142
23	-0.041	1.182	0.256	30.051	0.148
24	-0.051	1.155	0.279	30.798	0.160
25	-0.059	1.093	0.346	30.491	0.206
26	-0.035	1.041	0.411	30.322	0.255
27	-0.025	1.053	0.394	32.020	0.231
28	-0.053	1.047	0.401	33.169	0.230
29	-0.057	1.005	0.461	33.121	0.273
30	-0.057	0.954	0.538	32.682	0.337
31	-0.062	0.933	0.574	33.156	0.362
32	-0.033	0.959	0.535	35.343	0.313
33	-0.005	0.980	0.503	37.426	0.273
34	0.039	0.931	0.582	36.831	0.339
35	0.057	0.915	0.611	37.423	0.359
36	0.044	0.888	0.657	37.546	0.398

37	0.070	0.897	0.645	39.177	0.372	
38	0.056	0.860	0.708	38.761	0.435	
39	0.070	0.948	0.563	44.041	0.267	
40	0.060	0.958	0.547	45.876	0.242	
41	0.067	0.955	0.553	47.120	0.237	
42	0.061	0.900	0.652	45.695	0.321	
43	0.074	0.928	0.605	48.452	0.262	
44	0.051	0.878	0.695	47.138	0.346	
45	0.046	0.868	0.714	47.917	0.355	
46	0.044	0.908	0.646	51.479	0.268	
47	0.025	0.964	0.544	56.153	0.169	
48	-0.003	0.978	0.519	58.464	0.143	
49	0.063	1.112	0.288	68.241	0.036	
50	0.104	1.281	0.105	80.580	0.004	
51	0.116	1.225	0.149	78.983	0.007	
52	0.111	1.221	0.151	80.692	0.007	
53	0.091	1.187	0.185	80.395	0.009	
54	0.094	1.220	0.149	84.639	0.005	
55	0.050	1.204	0.163	85.544	0.005	
56	0.021	1.150	0.226	83.607	0.010	
57	0.010	1.148	0.228	85.399	0.009	
58	-0.022	1.154	0.218	87.831	0.007	
59	-0.023	1.167	0.201	90.792	0.005	
60	0.021	1.250	0.113	99.489	0.001	
61	-0.007	1.226	0.133	99.715	0.001	
62	-0.019	1.229	0.129	102.151	0.001	
63	-0.030	1.249	0.110	106.022	0.001	
64	-0.023	1.246	0.111	108.108	0.001	
65	-0.002	1.239	0.117	109.711	0.000	
66	0.000	1.216	0.137	109.940	0.001	
67	0.018	1.196	0.156	110.451	0.001	
68	0.050	1.172	0.183	110.427	0.001	
69	0.070	1.167	0.188	112.217	0.001	
70	0.065	1.143	0.220	112.158	0.001	
71	0.078	1.238	0.110	123.904	0.000	
72	0.067	1.230	0.116	125.599	0.000	
73	0.078	1.211	0.133	126.117	0.000	
74	0.071	1.189	0.156	126.236	0.000	
75	0.052	1.264	0.086	136.810	0.000	*
76	0.048	1.256	0.091	138.489	0.000	*

77	0.074	1.244	0.099	139.837	0.000	*
78	0.051	1.220	0.120	139.710	0.000	
79	0.100	1.220	0.119	142.403	0.000	
80	0.103	1.209	0.129	143.773	0.000	
81	0.069	1.154	0.195	139.738	0.000	
82	0.050	1.106	0.269	136.433	0.000	
83	0.066	1.104	0.271	138.748	0.000	
84	0.062	1.085	0.306	138.811	0.000	
85	0.101	1.123	0.238	146.334	0.000	
86	0.047	1.125	0.234	149.242	0.000	
87	0.051	1.149	0.196	155.191	0.000	
88	0.058	1.153	0.190	158.469	0.000	
89	0.045	1.163	0.176	162.678	0.000	
90	0.028	1.157	0.184	164.706	0.000	
91	0.018	1.174	0.160	170.140	0.000	
92	-0.051	1.176	0.157	173.426	0.000	
93	-0.073	1.218	0.110	182.743	0.000	
94	-0.107	1.232	0.097	187.964	0.000	*
95	-0.090	1.257	0.077	195.125	0.000	*
96	-0.102	1.261	0.073	199.241	0.000	*
97	-0.051	1.249	0.081	200.732	0.000	*
98	-0.016	1.298	0.051	212.087	0.000	*
99	0.010	1.296	0.051	215.406	0.000	*
100	0.084	1.317	0.041	222.662	0.000	**
101	0.121	1.322	0.039	227.239	0.000	**
102	0.082	1.413	0.014	246.982	0.000	**
103	0.151	1.491	0.005	265.162	0.000	***
104	0.109	1.504	0.005	271.901	0.000	***
105	0.109	1.573	0.002	289.261	0.000	***
106	0.099	1.585	0.002	296.225	0.000	***
107	0.079	1.591	0.001	302.311	0.000	***
108	0.096	1.593	0.001	307.784	0.000	***
109	0.082	1.603	0.001	314.850	0.000	***
110	0.046	1.584	0.001	316.348	0.000	***
111	0.022	1.690	0.000	343.086	0.000	***
112	0.000	1.636	0.001	337.592	0.000	***
113	0.017	1.654	0.001	347.040	0.000	***
114	0.033	1.738	0.000	370.734	0.000	***
115	0.034	1.713	0.000	371.245	0.000	***
116	0.060	1.805	0.000	397.813	0.000	***

117	0.074	1.756	0.000	393.310	0.000	***
118	0.096	1.757	0.000	399.949	0.000	***
119	0.045	1.793	0.000	414.966	0.000	***
120	-0.009	1.781	0.000	418.896	0.000	***

Table 1.12 Correlations between Well-being and Lagged 30-day S&P 500 Returns

Days Lagged	Pearson Correlation	F-Stat	F-Stat P-Value	Chi-Squared Stat	Chi-Squared P-Value	
1	0.004	0.007	0.933	0.007	0.932	
2	0.006	0.014	0.986	0.029	0.986	
3	-0.006	0.333	0.802	1.013	0.798	
4	-0.008	0.317	0.867	1.292	0.863	
5	-0.017	0.302	0.912	1.544	0.908	
6	-0.035	0.525	0.789	3.237	0.779	
7	-0.022	0.524	0.817	3.782	0.805	
8	-0.028	0.467	0.880	3.867	0.869	
9	-0.031	0.449	0.908	4.207	0.897	
10	-0.021	0.419	0.937	4.378	0.929	
11	-0.002	0.530	0.883	6.115	0.866	
12	-0.005	0.493	0.919	6.230	0.904	
13	-0.037	0.906	0.547	12.455	0.491	
14	-0.016	1.017	0.434	15.132	0.369	
15	0.006	1.212	0.258	19.407	0.196	
16	0.015	1.149	0.306	19.713	0.233	
17	0.015	1.043	0.409	19.097	0.323	
18	0.041	1.203	0.254	23.418	0.175	
19	0.027	1.237	0.223	25.524	0.144	
20	0.011	1.214	0.237	26.487	0.150	
21	-0.001	1.183	0.261	27.229	0.163	
22	0.020	1.283	0.176	31.075	0.095	
23	0.018	1.210	0.230	30.780	0.128	
24	0.009	1.125	0.312	29.979	0.186	
25	0.002	1.160	0.272	32.353	0.148	
26	0.033	1.333	0.128	38.851	0.050	
27	0.060	1.526	0.046	46.387	0.012	**
28	0.077	1.510	0.048	47.830	0.011	**
29	0.084	1.452	0.063	47.847	0.015	*
30	0.084	1.523	0.040	52.165	0.007	**
31	0.089	1.511	0.041	53.705	0.007	**
32	0.083	1.472	0.050	54.257	0.008	**
33	0.092	1.470	0.048	56.144	0.007	**
34	0.100	1.423	0.062	56.265	0.010	*
35	0.102	1.343	0.096	54.933	0.017	*
36	0.095	1.361	0.084	57.548	0.013	*

37	0.116	1.556	0.023	67.929	0.001	**
38	0.104	1.520	0.028	68.457	0.002	**
39	0.079	1.548	0.022	71.926	0.001	**
40	0.066	1.611	0.013	77.128	0.000	**
41	0.051	1.571	0.016	77.499	0.001	**
42	0.070	1.512	0.025	76.786	0.001	**
43	0.092	1.514	0.023	79.085	0.001	**
44	0.088	1.445	0.038	77.639	0.001	**
45	0.095	1.434	0.039	79.175	0.001	**
46	0.088	1.448	0.034	82.152	0.001	**
47	0.074	1.418	0.042	82.566	0.001	**
48	0.058	1.418	0.041	84.757	0.001	**
49	0.081	1.432	0.035	87.832	0.001	**
50	0.086	1.395	0.046	87.791	0.001	**
51	0.100	1.344	0.066	86.711	0.001	*
52	0.114	1.379	0.049	91.166	0.001	**
53	0.093	1.410	0.038	95.479	0.000	**
54	0.093	1.383	0.046	95.914	0.000	**
55	0.080	1.368	0.050	97.165	0.000	**
56	0.069	1.341	0.060	97.517	0.001	*
57	0.077	1.313	0.074	97.704	0.001	*
58	0.063	1.285	0.090	97.797	0.001	*
59	0.060	1.243	0.121	96.702	0.001	
60	0.062	1.236	0.126	98.306	0.001	
61	0.059	1.223	0.136	99.447	0.001	
62	0.079	1.210	0.147	100.607	0.001	
63	0.095	1.264	0.098	107.368	0.000	*
64	0.092	1.260	0.100	109.312	0.000	
65	0.115	1.335	0.054	118.222	0.000	*
66	0.113	1.316	0.062	119.030	0.000	*
67	0.104	1.294	0.073	119.512	0.000	*
68	0.107	1.272	0.087	119.892	0.000	*
69	0.104	1.235	0.115	118.720	0.000	
70	0.087	1.233	0.116	120.984	0.000	
71	0.065	1.229	0.118	122.995	0.000	
72	0.078	1.341	0.045	136.940	0.000	**
73	0.068	1.410	0.023	146.794	0.000	**
74	0.061	1.361	0.037	144.452	0.000	**
75	0.051	1.354	0.038	146.486	0.000	**
76	0.048	1.339	0.043	147.702	0.000	**

77	0.080	1.384	0.028	155.524	0.000	**
78	0.073	1.408	0.021	161.287	0.000	**
79	0.076	1.383	0.027	161.390	0.000	**
80	0.080	1.456	0.012	173.096	0.000	**
81	0.066	1.439	0.015	174.345	0.000	**
82	0.079	1.444	0.014	178.144	0.000	**
83	0.099	1.508	0.006	189.481	0.000	***
84	0.095	1.489	0.008	190.523	0.000	***
85	0.116	1.537	0.004	200.189	0.000	***
86	0.091	1.525	0.005	202.217	0.000	***
87	0.079	1.507	0.006	203.511	0.000	***
88	0.059	1.490	0.007	204.793	0.000	***
89	0.073	1.475	0.008	206.396	0.000	***
90	0.065	1.472	0.008	209.562	0.000	***
91	0.059	1.502	0.006	217.657	0.000	***
92	0.055	1.515	0.005	223.351	0.000	***
93	0.064	1.558	0.003	233.757	0.000	***
94	0.061	1.527	0.004	233.138	0.000	***
95	0.056	1.527	0.004	237.099	0.000	***
96	0.066	1.548	0.003	244.568	0.000	***
97	0.058	1.544	0.003	248.042	0.000	***
98	0.062	1.567	0.002	256.040	0.000	***
99	0.042	1.579	0.002	262.499	0.000	***
100	0.049	1.542	0.003	260.640	0.000	***
101	0.070	1.582	0.002	271.932	0.000	***
102	0.059	1.663	0.001	290.795	0.000	***
103	0.070	1.645	0.001	292.498	0.000	***
104	0.055	1.759	0.000	318.038	0.000	***
105	0.030	1.728	0.000	317.763	0.000	***
106	0.015	1.699	0.000	317.531	0.000	***
107	-0.013	1.748	0.000	332.285	0.000	***
108	-0.015	1.767	0.000	341.336	0.000	***
109	-0.008	1.771	0.000	347.796	0.000	***
110	-0.012	1.764	0.000	352.311	0.000	***
111	-0.004	1.784	0.000	362.272	0.000	***
112	-0.021	1.787	0.000	368.696	0.000	***
113	-0.009	1.845	0.000	387.126	0.000	***
114	-0.036	1.842	0.000	392.861	0.000	***
115	-0.055	1.811	0.000	392.653	0.000	***
116	-0.028	1.823	0.000	401.699	0.000	***

117	-0.015	1.785	0.000	399.819	0.000	***
118	-0.015	1.823	0.000	415.066	0.000	***
119	-0.017	1.832	0.000	423.855	0.000	***
120	-0.025	1.832	0.000	430.810	0.000	***

CHAPTER 3

CREDIT RISK AND FINANCIAL SATISFACTION

Introduction

Credit cards can be a useful tool for individual economic management, but their use does not come without risk. We are indebted to the traditional finance literature for a substantial body of work studying risk and our reaction to it. Surprisingly, the inherent riskiness of credit card use has not received direct empirical attention yet. This paper begins to fill this gap by assessing how an individual's level of risk tolerance influences his/her financial satisfaction in the presence of credit card use and management.

THE ECONOMICS OF CREDIT CARDS

Credit use increases satisfaction by allowing an individual to maintain a consistent level of consumption across time. This process maximizes the individual's marginal utility of consumption in each period because it permits his/her to transfer resources from time periods of low marginal utility of consumption to time periods of high marginal utility of consumption.

Different forms of credit are suited to smoothing consumption across different time frames. Mortgages and student loans, for example, smooth consumption over long periods of time. Vehicle loans and service credits smooth over shorter timer periods. Although the different forms of credit can have wide-varying characteristics, terms, and costs, each type performs the same basic function of consumption smoothing.

Credit cards are best suited for smoothing across months, weeks, or even days but are fundamentally no different from any other form of credit. Credit cards are optimal to use in the short-term but not in the long term because of their high interest rates. Their ability to carry a revolving balance makes them particularly useful for individuals that wish to manage relatively small, variable consumption shocks. Thus credit cards are theorized to increase financial satisfaction because they allow convenient consumption smoothing over the short-term.

Studies have shown that effective resource management is an important contributor to financial satisfaction, and that credit cards are an important component of effective financial management (Godwin & Carroll, 1986; Hira & Mueller, 1987; Hira, 1987; Garman, 2006). Titus, Fanslow, & Hira (1989) have found that financial satisfaction declines in the presence of rising levels of wealth. This decrease in satisfaction was believed to have been caused partly by the lack of adequate financial emergency preparedness. This suggests that credit availability might be associated positively with financial satisfaction because credit may be used to fund short-term emergency needs.

Credit Risk

The risk of credit-card use comes from the demands it places upon future income. Every use of credit necessarily places an obligation on future income. Any failure to meet that obligation is met with a penalty of some kind. This is a risk to the individual because future income is inherently uncertain.

The use of credit cards does not directly affect the uncertainty of future income. Instead, the use of credit cards imposes additional costs to the individual if a negative income shock should occur. These costs can be either monetary or non-monetary. For example, falling behind on debt service payments is likely to generate direct monetary costs in the form of fees and penalty charges. It also could create indirect penalties such as increased interest rates on credit cards or credit score damage. Finally, a default caused by a negative income shock could induce non-monetary costs such as the irritation of dealing with collection agencies or the fear of repossession.

The way a individual uses and manages his/her credit cards will affect the magnitude of effect of credit cards on the individual's the risk associated with credit cards. Individuals that mismanage their credit cards may be subject to substantial penalties and fees. Individuals that use their cards to carry large balances are subject to high interest rate charges. Empirical evidence consistent with this idea suggests that individuals with a high debt-to-income ratio have been found to have significantly lower levels of financial satisfaction (T. K. Hira, 1987). Poor management of credit cards and other debts has been found to increase stress among college students as well (Hayhoe, Leach, Turner, Bruin, & Lawrence, 2000).

The Role of Risk tolerance

Standard economic theory allows for models to be built that specify optimal levels of credit use in the presence of uncertain future income. These models have been used extensively to refine our understanding of optimal borrowing activities under a variety of circumstances (see, for example, Leland, 1968; Sandmo, 1970; and Sibley, 1975).

Fan, Chang, and Hanna (1994) extended these models by building an economic model of optimal credit use under uncertain future income and various levels of risk tolerance. Their two-period model attempted to maximize the sum of utility from present consumption and utility from discounted uncertain future consumption. Their model predicts that credit use should increase with increasing certainty of future income, and that risk tolerance is positively associated with utility as the amount borrowed and uncertainty of future income increases. This theoretical premise has yet to be tested empirically.

There is also empirical evidence that suggests that a relationship between risk tolerance and financial satisfaction exists. Studies have shown that the subjective assessment of credit obligations is more important in explaining financial satisfaction than the objective measurement of family debt burden such as the debt repayment-to-income ratio (Lown & Ju, 1992). This subjective assessment comes from the person's own tolerance and attitude towards risk, as well as his ability to accurately perceive the risk he faces (Ricciardi, 2008).

The perceptions that an individual has about credit cards also may affect his/her ability to derive satisfaction from their use. In 2000, 33% of individuals reported that they believe that “credit cards are good” while 51% report that “credit cards are bad” (Durkin, 2000). This negative opinion of credit cards may be preventing some individuals from realizing the maximum satisfaction they might from credit cards.

Individuals often have misperceptions about the nature of the risks that they face (Ricciardi, 2008). These misperceptions often stem from a combination of emotional reactions, past experiences with uncertain situations, instincts, and preferences that are unique to the individual (McDonald & Stehle, 1975; Ricciardi, 2004). It also has been found that risk perceptions can be more predictive of behavior and preferences than the objective riskiness of the situation (Weber, 2004).

The most similar analysis to the analysis in this paper is Lown and Ju (1992). This paper developed a model of credit use and financial satisfaction that factored in both actual credit use activities and attitudes toward credit use. Their results showed that feelings of concern about individual credit use was the strongest predictor of financial satisfaction. The second- and third- strongest predictors were individual income and individual wealth, respectively. These three variables are indicators either of risk tolerance or the capacity to absorb risk. Income and accumulated individual wealth both permit the individual to absorb a negative income shock without incurring additional costs associated with defaulting on credit.

This paper extends the work of Lown and Ju (1992) by incorporating a direct measure of risk tolerance as an independent variable in an ordered probit model. It will test the relations between financial satisfaction, risk tolerance, and credit use and management. I propose to test two hypotheses in this paper. The first hypothesis is that the financial satisfaction of those with higher risk tolerance will be less likely to be affected negatively by their credit card use. The second proposes that the financial satisfaction of those with higher risk tolerance will be less likely to be affected negatively by their credit-management behaviors.

DATA AND METHODOLOGY

This analysis uses data from the 2010 wave of the Health and Retirement Study (HRS). The focus of this study is Americans over the age of 50, and it is designed to be nationally representative of this group. The study contains questions about a wide array of topics, including cognitive ability, life circumstances, health, and socioeconomic status. The 2010 survey wave was administered between February 2010 and February 2011.

The financial satisfaction of the respondent is the dependent variable in this model. This data come from the leave-behind questionnaire portion of the study. This questionnaire was left with the respondent to complete at their leisure after the main body of the survey was completed. Its purpose was to allow expanded collection of data at a minimal risk of respondent fatigue.

The leave-behind questionnaire was different from the main survey. The questionnaire is divided into two subsets of questions. These w\ere called the Participant Lifestyle Questionnaire and the Participant Questionnaire on Work and Health. Survey respondents are divided randomly into two groups upon completion of the main survey. Respondents assigned to Group A were given the Lifestyle Questionnaire subset of questions to complete and Group B respondents were given the Work and Health Questionnaire subset of questions. The groups then switched questions at the next wave; Group A respondents were given the Work and Health Questionnaire, and vice versa for Group B respondents. This results in only half of the full respondent group providing data for each subset of questions in the leave-behind questionnaire.

Questions on credit card use and management were included in the modules section of the survey. The modules were a section of the main survey body that contain new questions every wave. This means that there was one data point for credit card use and attitudes for each respondent in the HRS. These data are found in the 2010 wave of the survey.

The primary independent variable of interest in this analysis is risk tolerance. Risk tolerance in the HRS was reported as an ordinal metric. Responses were evaluated using responses to questions regarding income-risk preferences. The questions asked respondents to imagine they must move to a new area and decide between two available job opportunities. One job opportunity pays a certain income, the other has an uncertain, but potentially larger, level of income. The respondent was asked which job they would take under various probabilities of the risky job providing higher income.

There were limits on the availability of this variable within the survey. This question was terminated in 2006. There were also some non-response problems that make it difficult to rely upon a single survey wave to produce observations for every respondent in the survey. These gaps in the data make it necessary to use observations from multiple waves of the survey in order to obtain as many useful observations as possible. I take the 2006 risk tolerance response first if it is available. If the 2006 response is unavailable, then the 2004 response is used. Finally, I use the 2002 response is used if no response is available for either 2004 or 2006. Any respondent lacking a risk tolerance response in at least one of these three waves was excluded from the sample. The distribution of available risk tolerance responses is presented in

Table 1.13 Distribution of Risk Tolerance Responses

Risk Tolerance Response	% Income Willing to Risk	Number Observed	% of Total	Risk Tolerance Category
1	75%	16	5%	High
2	50%	20	7%	High
3	33%	29	10%	High
4	20%	40	13%	High
5	10%	65	21%	High
6	0%	135	44%	Low

The distribution of risk tolerance responses in this sample does not separate itself naturally into traditional quintiles. I address this issue by specifying only two distinct risk tolerance categories. The high-risk tolerance group is represented by those in highest 5 levels of risk tolerance responses. The low-risk tolerance group is composed of those who reported the very lowest level of risk tolerance. This categorization is reasonable because it identifies those who were unwilling to accept any level of risk from those who were willing to take even a small risk for a chance at a large gain. This categorization also provides an adequate sample size for both categories.

Table 1.13 shows that approximately 44% of the sample of 305 respondents have low risk tolerance. The remaining 56% are classified as having high risk tolerance. The model therefore measures risk tolerance by using an indicator variable that is equal to 1 for high-risk tolerance respondents.

I separate the effects of credit cards on financial satisfaction into two broad categories for this model. The first category is credit use. Credit use variables include the number of cards owned and the logged balance of all credit card debt. These variables indicate the manner in which credit cards are used by the individual. The second category of credit card effect variables is called credit-management. This category includes the number of negative credit-management behaviors reported by the individual and whether or not the individual considers himself/herself a convenience or installment user.

The data permit me to identify eight different credit-management behaviors. The questions that identify these behaviors are provided in Table 1.14. The number of negative credit card behaviors indicated by response to the first seven questions is used as a measure of credit card mismanagement. This variable is interacted with respondent risk tolerance to assess the degree to which risk tolerance mitigates the impact of the individual's management of his/her credit cards. The eighth question is used to identify the individual as either an installment or revolving credit card user. Figure 1.8 presents the distribution of the number of credit mismanagement behaviors for each individual.

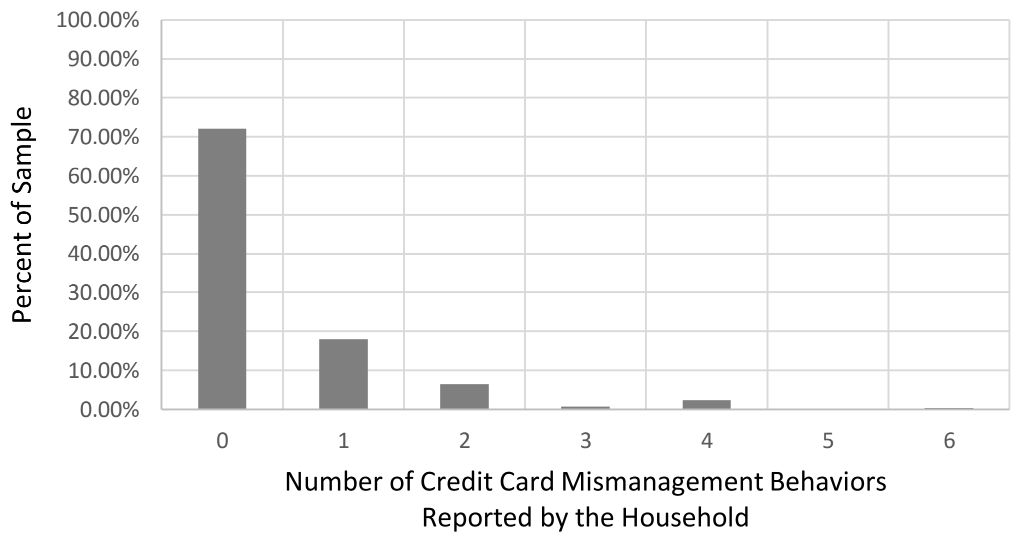

Figure 1.8 Distribution of Number of Credit Card Mismanagement Behaviors

Table 1.14 Credit Management Questions

Question Text	Response Indicating Mismanagement of Credit Cards
Introduction: Which of the following describes your experience with credit cards in the past twelve months? For each statement, please indicate whether it is true for you or not.	
1. In the past twelve months you have been two or more payments behind on your credit cards.	TRUE
2. In the past twelve months you always paid your credit card bills on time.	FALSE
3. In some months you paid only the minimum credit card payment.	TRUE
4. In some months you were charged a fee for a late credit card payment.	TRUE
5. In some months you borrowed over the limit and had to pay an over the limit credit card fee.	TRUE
6. In some months you used a credit card for a cash advance.	TRUE
7. In some months you borrowed on your credit cards even when you had money in a bank account.	TRUE
8. In some months you carried over a credit card balance and got charged interest.	TRUE

Control Variables

Financial satisfaction is interesting to study in the context of economics because it is a subcomponent of overall well-being, a measure which is used routinely by many researchers as a proxy for utility (Clark et al., 2008). Standard economic theory predicts that objective measures of financial well-being, such as income and accumulated wealth, should be significant contributors to utility and financial satisfaction. Empirical evidence has given substantial support to this premise. Income is consistently strongly positively related to well-being for young and middle-aged adults (Diener et al., 1999). The relation becomes less clear for older adults, such as those in our sample, but it does seem to continue (Pinquart & Sörensen, 2000).

Other research has found that, while financial satisfaction does indeed depend in great part upon objective measures, subjective comparisons to a relevant reference point are also important (Ackerman & Paolucci, 1983; E. P. Davis & Helmick, 1985; Hafstrom, 1983). In fact, empirical evidence has suggested repeatedly that subjective measures contribute substantially to the predictive value of objective measures (Ackerman & Paolucci, 1983; E. Davis & Helmick, 1983; George, 2010).

Demographic characteristics also contribute to overall levels of satisfaction. Married couples report higher levels of well-being than the unmarried at all ages (Pinquart & Sörensen, 2000). For persons over the age of 65, the impact of marital status on well-being declines (George, Okun, & Landerman, 1985). Further research has indicated that living alone may have a more powerful effect on well-being than being married, indicating that companionship of any form can have similar psychological benefits as marriage (Jakobsson et al., 2004).

Older people tend to have higher levels of happiness than young and middle-aged people (Pinquart & Sörensen, 2000; Yang, 2008). Even when samples consider only the middle-aged and older, the positive relation between age and happiness remains strong (Steverink, Westerhof, Bode, & Dittmann-Kohli, 2001; Tran, Wright, & Chatters, 1991). Longitudinal evidence provides deeper insight into this trend; happiness peaks around age 65 and then begins to decline, but remains high (Mroczek

& Spiro III, 2005). Another study finds that happiness is u-shaped with respect to age, and that happiness reaches its minimum near age 50 (Blanchflower & Oswald, 2008).

These findings suggest several useful control variables that are related either to risk tolerance or financial satisfaction. I control for gender (female = 1), age, marital status (married/partnered = 1), and education (college graduate = 1). I also control for the number of earners in the household because having multiple sources of income provides a cushion against individual income shocks. This would affect the amount of risk the individual faces, or perceives that he/she faces. Table 1.15 and Table 1.16 show descriptive statistics for the entire sample by risk tolerance and financial satisfaction responses.

Table 1.15 Descriptive Statistics by Risk Tolerance

	Total Sample	High Risk Tolerance	Low Risk Tolerance
	Mean	Mean	Mean
Primary Variables			
Financial Satisfaction	3.38	3.5	3.36
% with High Risk Tolerance	56%	-	-
Credit Use Variables			
Number of Cards	3.56	4.11	3.49
Amount Owed on Cards	$2,430	$4,747	$2,058
Credit Management Variables			
Credit Mismanagement Count	0.75	1.03	0.71
% Installment Users	30.80%	36.11%	30.11%
Control Variables			
Financial Assets	$213,155	$235,445	$210,173
Household Income	$55,915	$54,057	$56,165
% Female	64.30%	41.67%	67.29%
Age	66.00	65.27	66.09
% Married/Partnered	67.50%	66.67%	67.66%
% College Graduates	30.80%	36.11%	30.11%
Number of Earners	0.84	0.94	0.83
Number of Observations	305		

Table 1.16 Descriptive Statistics by Financial Satisfaction

	Total Sample	Financial Satisfaction Level				
		(Low)	< < - - - - - - - - - - - - - - - - - > >			(High)
	Mean	Mean	Mean	Mean	Mean	Mean
Primary Variables						
Financial Satisfaction	3.38	-	-	-	-	-
% Reporting High Risk Tolerance	56%	67%	51%	64%	46%	52%
Credit Use Variables						
Number of Cards	3.56	2.06	3.35	3.72	3.65	3.74
Amount Owed on Cards	$2,430	$7,365	$3,997	$1,747	$1,698	$1,999
Credit Management Variables						
Credit Mismanagement	0.75	1.72	1.19	0.70	0.58	0.48
% Installment Users	30.80%	50.00%	37.84%	33.04%	30.86%	14.81%
Control Variables						
Financial Assets	$213,155	$35,367	$76,005	$147,337	$309,192	$362,505
Household Income	$55,915	$29,996	$30,234	$55,781	$73,670	$55,808
% Female	64.30%	61.11%	54.05%	63.48%	66.67%	70.37%
Age	66.00	63.28	63.92	66.00	65.99	68.35
% Married/Partnered	67.50%	55.56%	56.76%	70.43%	71.60%	66.67%
% College Graduates	30.80%	33.33%	18.92%	28.70%	35.80%	35.19%
Number of Earners	0.84	1.06	0.92	0.78	0.94	0.70
Observations	305	18	37	115	81	54

The descriptive statistics show that more risk tolerant respondents have more credit cards, higher card balances, are more likely to be installment users, have about the same wealth and income levels, and have more negative credit management practices on average than those who are less risk tolerant. It is interesting to note, then, that the high risk tolerance group also has higher average levels of financial satisfaction.

Table 1.16 shows that there is no obvious relation between risk tolerance and financial satisfaction levels. Interesting trends do appear when the lowest financial satisfaction group is compared to the other groups. Respondents with the lowest financial satisfaction had the lowest number of credit cards, but the highest balances. This group of respondents also had a higher percentage of installment users and engage in more credit card mismanagement behaviors on average than the other groups. Unsurprisingly, total financial assets and income are monotonically positively related with financial satisfaction.

Model

I estimate an ordered probit model in order to examine the effects of risk tolerance and credit card use on financial satisfaction (y_i) in 2010. The ordered probit model is appropriate because the financial satisfaction variable is ordered, nominal, and discrete, and there is an underlying or latent continuous measure of satisfaction that is behind what is reported.

The limitations of the measurement of financial satisfaction permitted by the survey makes it impossible to determine exactly where on the unobserved distribution of the latent variable the observation points occur. Because the data are ordered, we know that 2 is better than 1 and that 3 is better than 2, but we do not know how much better than each other each response is. This condition prevents the use of an ordinary least squares model or any other model that assumes a continuous dependent variable.

The ordered probit model estimates the probability that respondent i will select alternative j. In the current model, the various alternatives (j) are the reported levels of financial satisfaction.

An ordered probit model can be written as:

$$prob(y_i = 0|\boldsymbol{x}) = \Phi(-\mathbf{x}'\beta),$$

$$prob(y_i = 1|\boldsymbol{x}) = \Phi(\mu_1 - \mathbf{x}'\beta) - \Phi(-\mathbf{x}'\beta),$$
$$prob(y_i = 2|\boldsymbol{x}) = \Phi(\mu_2 - \mathbf{x}'\beta) - \Phi(\mu_1 - \mathbf{x}'\beta),$$
$$prob(y_i = 3|\boldsymbol{x}) = \Phi(\mu_3 - \mathbf{x}'\beta) - \Phi(\mu_2 - \mathbf{x}'\beta),$$
$$prob(y_i = 4|\boldsymbol{x}) = 1 - \Phi(\mu_3 - \mathbf{x}'\beta)$$
$$where\ 0 < \mu_1 < \mu_2 < \mu_3 < \mu_4$$

$$\begin{gathered}\mathbf{x}'\beta = \mu_j + \lambda_1 * HighRisk \\ +\lambda_2 * CreditUse \\ +\lambda_3 * CreditMismanagement \\ +\lambda_4 * (HighRisk\ \ x\ \ CreditUse) \\ +\lambda_5 * (HighRisk\ \ x\ \ CreditMismanagement) + \gamma_i X_i\end{gathered}$$

$\boldsymbol{x}$ is the array of independent variables and β is a vector of parameter estimates. μ_j is the intercept for each alternative j. Φ is the cumulative density function of the standard normal distribution.

This model is similar to that used in Lown and Ju (1992) because both models separate the effects of credit card use from the effects of credit card management in their analysis of financial satisfaction. My model extends the model in Lown and Ju (1992) by testing for mitigating effects from the risk tolerance of the respondent.

RESULTS

Table 1.17 reports the marginal effects of every statistically significant variable on the probability of reporting each level of financial satisfaction. These marginal effects indicate the change in the probability of a respondent reporting the indicated level of financial satisfaction for a change in the variable listed. For example, the table indicates that having a high risk tolerance leads to a respondent have a 4.3% increased probability of reporting a financial satisfaction level of 1, and a 3.9% decreased probability of the respondent reporting a financial satisfaction level of 3. Marginal effects that are not statistically significant are omitted from Table 1.17.

The results indicate that engaging in credit mismanagement behaviors increased the probability of respondents 13.7% and 9.8% reporting a financial satisfaction of 1 or 2, respectively, and 13.5% and 23.6% reduced probability of reporting a financial satisfaction of 3 and 4 as compared to those with no credit mismanagement behaviors reported. The high risk tolerance-x credit mismanagement behaviors interaction term shows the opposite pattern; highly risk tolerant respondents who also mismanage their credit cards have an increased probability of reporting higher levels of financial satisfaction than other users.

The net marginal effect of credit mismanagement on financial satisfaction for highly risk tolerant individuals is obtained by adding the marginal effects from credit mismanagement and the marginal effects from the high risk tolerance x credit mismanagement term. The results indicate that each additional credit mismanagement behavior engaged in reduces the probability of financial satisfaction of 4 by 1.3% for high risk tolerance individuals, and 8.7% for low risk tolerance individuals. For a financial satisfaction level of 3, the marginal effect of each additional credit mismanagement behavior are 4.6% and .6% for high- and low- risk tolerance individuals respectively. The difference in these two sets of marginal effect suggests that high risk tolerance individuals have a higher probability of reporting high levels of financial satisfaction than those with lower risk tolerance when the individual is mismanaging his/her credit card. The fact that the marginal effects are still negative even after accounting for risk tolerance is evidence that the mismanagement of credit cards is associated with financial dissatisfaction for all borrowers. Regardless of their risk tolerance, but that the magnitude of the effect is smaller for those with high risk tolerance. Thus, I fail to reject my second hypothesis.

Table 1.17 Estimated Marginal Effects of Significant Variables on the Probability of Reporting Each Level of Financial Satisfaction

	Variable	Marginal Effect	Std Error
Financial Satisfaction = 0	High Risk Tolerance	0.029	0.019
	Credit Mismanagement Behaviors	0.035 ***	0.012
	High Risk Tolerance x Credit Mismanagement Behaviors	-0.038 **	0.017
	Installment User	0.049	0.030
	Log Household Income	-0.038 ***	0.014
Financial Satisfaction = 1	High Risk Tolerance	0.043 *	0.025
	Credit Mismanagement Behaviors	0.049 ***	0.017
	High Risk Tolerance x Credit Mismanagement Behaviors	-0.054 **	0.025
	Installment User	0.066 *	0.034
	Log Household Income	-0.053 ***	0.016
Financial Satisfaction = 2	High Risk Tolerance	0.045	0.028
	Credit Mismanagement Behaviors	0.048 ***	0.018
	High Risk Tolerance x Credit Mismanagement Behaviors	-0.053 **	0.026
	Installment User	0.052 **	0.024
	Log Household Income	-0.052 ***	0.015
Financial Satisfaction = 3	High Risk Tolerance	-0.039 *	0.023
	Credit Mismanagement Behaviors	-0.046 ***	0.016
	High Risk Tolerance x Credit Mismanagement Behaviors	0.051 **	0.023
	Installment User	-0.066 *	0.035
	Log Household Income	0.050 ***	0.015
Financial Satisfaction = 4	High Risk Tolerance	-0.078	0.048
	Credit Mismanagement Behaviors	-0.087 ***	0.028
	High Risk Tolerance x Credit Mismanagement Behaviors	0.094 **	0.042
	Installment User	-0.101 **	0.050
	Log Household Income	0.093 ***	0.027

(, **, and *** indicate significance at the .10, .05, and .01 levels)*

Discussion

The mitigating effect of risk tolerance on financial satisfaction is only significant on the effect of credit mismanagement practices. This effect is not strong enough to reverse the overall negative effect of credit mismanagement practices. For both high- and low- risk tolerance groups, the marginal effects of credit card mismanagement are negative on the probabilities of reporting high levels of financial satisfaction. This is consistent with theory and my second hypothesis; more risk tolerant individuals derive more satisfaction from their credit cards than less risk tolerant individuals in the presence of credit mismanagement behaviors.

No credit use variables were significant. This result, in connection with the credit management results, suggests that any dissatisfaction produced by the use of credit cards comes from the problems associated with mismanagement and not from the total amount owed or number of cards owned. The results suggest that being an installment user has a detrimental effect on the probability of having a high level of financial satisfaction, but that the amount that is being carried has no significant effect. Since the monetary cost of being an installment user is a function of the amount owed, it is reasonable to conclude that it is not the monetary costs of installment use that drives the dissatisfaction this behavior produces.

This may be evidence that the monetary costs of borrowing are not the primary drivers of dissatisfaction from credit card use. Rather, it may be non-monetary costs that cause dissatisfaction to individuals. These non-monetary costs could be emotional, such as the stress of carrying a balance or fear of bankruptcy. They also may be situational due to the hassle of tracking the card balance or of dealing with collection letters and calls, for example.

It is also interesting to note that logged financial income is significantly positively related to financial satisfaction levels, but logged wealth is insignificant. This is informative to the way in which individuals perceive the role of credit card debt and financial variables. This suggests that individuals consider their income as a more useful hedge against the risks of credit use than they do their accumulated wealth.

This result may have several possible explanations. Most financial assets are held in retirement accounts, which have sizeable penalties for premature withdrawals. These penalties reduce the desirability of using retirement assets to service or repay debts. There may be tax consequences, potential investment losses, and illiquidity issues even for assets not held in retirement accounts. Restrictions like these would further reduce the usefulness of financial assets as a tool for managing credit use. Income, by contrast, is highly liquid and readily available for the maintenance of credit obligations.

Despite the drawbacks of liquidating many types of financial assets, individuals with adequate assets should still consider using some of them to pay down their credit card balances. The high interest rates charged by credit cards are very likely to exceed the potential returns on many types of financial assets. Therefore, individuals with both large amounts of financial assets and high credit card debt are making a suboptimal choice.

Table 1.18 shows the availability of assets within households that could be used to repay or otherwise manage credit card debt. For the purposes of this table, I define liquid assets as the sum of checking account balances and the value of any certificates of deposit owned by the individual. The table shows that the majority of individuals are revolving users who have adequate liquid assets to pay off their credit cards. This group also has the highest level of total financial assets. And has the highest average level of financial satisfaction. Those who do not have the means to pay off their cards were the least satisfied groups.

Table 1.18 Availability of Financial Assets for Credit Management

	Obs.	Average Financial Assets	Average Liquid Assets	Average Credit Card Balance	Average Financial Satisfaction
Installment Users					
Inadequate liquid assets to pay off credit cards	40	$72,307	$2,130	$9,691	2.9
Adequate liquid assets to pay off credit cards	54	$176,403	$44,408	$2,606	3.24
Revolving Users					
Inadequate liquid assets to pay off credit cards	38	$36,458	$984	$3,166	2.97
Adequate liquid assets to pay off credit cards	173	$296,006	$56,584	$536	3.62

The behavioral heuristic known as mental accounting also may help to explain this behavior. Mental accounting is the process whereby individuals mentally assign their assets into separate, non-transferable accounts (R. Thaler, 1985). Individuals engaging in mental accounting do not see their financial assets as being available to use to manage and potentially eliminate credit card debt. This is because they mentally assign financial assets to a certain task, such as growth, and therefore do not permit themselves to use those assets for credit management.

Unfortunately, my data do not have information regarding respondent credit card risk perceptions. The inability to control for risk perceptions may reduce the impact of risk tolerance on financial satisfaction estimated in this analysis. Future research that measures of risk perception should be able to extend this analysis profitably.

Summary

This paper seeks to determine the relations between risk tolerance, credit use, and credit management behaviors and satisfaction with credit card use. I find evidence that having a high risk tolerance can increase the satisfaction of credit card users, even when those users engage in unwise credit behaviors. I also find that risk tolerance cannot completely offset the dissatisfaction associated with the mismanagement of credit. This suggests that highly-risk-tolerant borrowers can be more satisfied with their credit use than their less risk tolerant counterparts.

There is also evidence that any dissatisfaction derived from credit cards comes from their mismanagement, and not their use. Owing more money or having multiple credit cards had no effect on the financial satisfaction of the borrower. This suggests also that the costs that individuals are most dissatisfied with are not monetary in nature. Instead, it may be the non-monetary costs of credit card mismanagement, such as stress or anxiety, which drive an individual to be dissatisfied with his/her financial situation.

I also find evidence that credit card users may engage in mental accounting practices in the management of their finances. My results indicate that ownership of large amounts of financial assets does not affect their satisfaction when controlling for credit use and management behaviors. High income, by contrast, has a strong positive effect on financial satisfaction. While this finding is mostly consistent with rational credit and investing behaviors, the tendency for many individuals to carry both high levels of financial assets as well as high levels of credit card debt suggests that they may engage in mental accounting practices in the assessment and use of their financial assets.

CONCLUSION

This dissertation addresses questions regarding how risk tolerance affects how we respond to risk. Specifically, I test how risk tolerant individuals react to stock market risk and credit card risk. I find that risk tolerance is generally not helpful for predicting an investors response to market volatility in the short-run, but that in the long run more risk tolerant investors are likely to have higher levels of financial satisfaction. In chapter two, I find that the general public does not react to market movements until 30-100 days after the market movement has occurred. In chapter three, I find that more risk tolerant individuals are more satisfied with their credit card management behaviors than their less risk tolerant counterparts.

Financial planners and advisors rely on measures of risk tolerance to help manage their client's wealth and to maximize their client's satisfaction. My results suggest that this information may not always be reliable as a predictor of the client's response to the financial risks they face. Planners should expect to manage client expectations and reactions to negative events, even for clients who report high levels of risk tolerance.

BIBLIOGRAPHY

Ackerman, N., & Paolucci, B. (1983). Objective and subjective income adequacy: Their relationship to perceived life quality measures. Social Indicators Research, 12(1), 25-48.

Bajtelsmit, V. L., Bernasek, A., & Jianakoplos, N. A. (1999). Gender differences in defined contribution pension decisions. Financial Services Review, 8(1), 1-10.

Baker, M., & Wurgler, J. (2007). Investor sentiment in the stock market: National Bureau of Economic Research Cambridge, Mass., USA.

Barberis, N., & Thaler, R. (2003). A survey of behavioral finance. Handbook of the Economics of Finance, 1, 1053-1128.

Barberis, N., & Xiong, W. (2009). What Drives the Disposition Effect? An Analysis of a Long-Standing Preference-Based Explanation. The Journal of Finance, 64(2), 751-784.

Bertaut, C. C. (1998). Stockholding behavior of US households: evidence from the 1983–1989 survey of consumer finances. Review of Economics and Statistics, 80(2), 263-275.

Blanchflower, D. G., & Oswald, A. J. (2008). Is well-being U-shaped over the life cycle? Social Science & Medicine, 66(8), 1733-1749.

Bollen, J., Mao, H., & Zeng, X. (2011). Twitter mood predicts the stock market. Journal of Computational Science, 2(1), 1-8.

Brayton, F., & Tinsley, P. (1996). A guide to FRB/US: a macroeconomic model of the United States: Board of Governors of the Federal Reserve System (US).

Campbell, J. Y., & Shiller, R. J. (1988). The dividend-price ratio and expectations of future dividends and discount factors. Review of Financial Studies, 1(3), 195-228.

Case, K. E., Quigley, J. M., & Shiller, R. J. (2005). Comparing wealth effects: the stock market versus the housing market. Advances in macroeconomics, 5(1).

Clark, A. E., Frijters, P., & Shields, M. A. (2008). Relative income, happiness, and utility: An explanation for the Easterlin paradox and other puzzles. Journal of Economic Literature, 95-144.

Consedine, N. S., Magai, C., & King, A. R. (2004). Deconstructing positive affect in later life: A differential functionalist analysis of joy and interest. The International Journal of Aging and Human Development, 58(1), 49-68.

Davies, G. B., & Brooks, O. P. (2013). Risk Tolerance.

Davis, E., & Helmick, S. (1983). Composite measures of financial satisfaction: An analysis of two indices. Paper presented at the Proceedings of the Symposium on Perceived Economic Well-Being.

Davis, E. P., & Helmick, S. A. (1985). Family financial satisfaction: The impact of reference points. Home Economics Research Journal, 14(1), 123-131.

De Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990). Noise trader risk in financial markets. Journal of political Economy, 703-738.

Diener, E., Suh, E. M., Lucas, R. E., & Smith, H. L. (1999). Subjective well-being: Three decades of progress. Psychological bulletin, 125(2), 276.

Durkin, T. A. (2000). Credit cards: Use and consumer attitudes, 1970-2000. Fed. Res. Bull., 86, 623.

Fama, E. F., & French, K. R. (1988). Permanent and temporary components of stock prices. The journal of political economy, 246-273.

Fama, E. F., & French, K. R. (1989). Business conditions and expected returns on stocks and bonds. Journal of Financial Economics, 25(1), 23-49.

Fan, J. X., Chang, Y. R., & Hanna, S. (1994). Real income growth and optimal credit use. Financial Services Review, 3(1), 45-58.

Fischhoff, B., Slovic, P., & Lichtenstein, S. (1981). Lay foibles and expert fables in judgements about risk. Progress in resource management and environmental planning, 3, 161-202.

Friesen, G. C., & Sapp, T. R. (2007). Mutual fund flows and investor returns: An empirical examination of fund investor timing ability. Journal of Banking & Finance, 31(9), 2796-2816.

George, L. K. (2010). Still happy after all these years: Research frontiers on subjective well-being in later life. The Journals of Gerontology Series B: Psychological Sciences and Social Sciences, 65(3), 331-339.

George, L. K., Okun, M. A., & Landerman, R. (1985). Age as a moderator of the determinants of life satisfaction. Research on Aging, 7(2), 209-233.

Godwin, D. D., & Carroll, D. D. (1986). Financial management attitudes and behaviour of husbands and wives. Journal of Consumer Studies & Home Economics, 10(1), 77-96.

Greenwood, R., & Shleifer, A. (2014). Expectations of returns and expected returns. Review of Financial Studies, hht082.

Griffin, D., & Tversky, A. (1992). The weighing of evidence and the determinants of confidence. Cognitive psychology, 24(3), 411-435.

Hafstrom, J. (1983). Satisfaction with present standard of living: Predictions using various statistical techniques. Paper presented at the Proceedings of the Midwest Symposium on Perceived Economic Well-Being.

Hayhoe, C. R., Leach, L. J., Turner, P. R., Bruin, M. J., & Lawrence, F. C. (2000). Differences in spending habits and credit use of college students. Journal of Consumer Affairs, 34(1), 113-133.

Hira, T., & Mueller, M. (1987). THE APPLICATION OF A MANAGERIAL SYSTEM TO MONEY MANAGEMENT-PRACTICES. Iowa State Journal of Research, 62(2), 219-233.

Hira, T. K. (1987). Factors affecting satisfaction with various aspects of households' finances. Paper presented at the The Destiny of Families: How Their Futures Are Chosen, Indianapolis, IN.

Hirshleifer, D., & Shumway, T. (2003). Good day sunshine: Stock returns and the weather. The Journal of Finance, 58(3), 1009-1032.

Hoffmann, A. O., Post, T., & Pennings, J. M. (2013). Individual investor perceptions and behavior during the financial crisis. Journal of Banking & Finance, 37(1), 60-74.

Jakobsson, U., Hallberg, I. R., & Westergren, A. (2004). Overall and health related quality of life among the oldest old in pain. Quality of Life Research, 13(1), 125-136.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. Econometrica: Journal of the Econometric Society, 263-291.

Leland, H. E. (1968). Saving and uncertainty: The precautionary demand for saving. The quarterly journal of economics, 465-473.

Loewenstein, G. F., Weber, E. U., Hsee, C. K., & Welch, N. (2001). Risk as feelings. Psychological bulletin, 127(2), 267.

Lown, J. M., & Ju, I.-S. (1992). A model of credit use and financial satisfaction. Financial Counseling and Planning, 3(1), 105-124.

Markowitz, H. (1952). Portfolio selection. The Journal of Finance, 7(1), 77-91.

McDonald, J. G., & Stehle, R. E. (1975). How do institutional investors perceive risk? The Journal of Portfolio Management, 2(1), 11-16.

Meyer, L. H. (1994). The WUMM Model Book. St. Louis: LH Meyer and Associates.

Milevsky, M. A., & Huang, H. (2011). Spending Retirement on Planet Vulcan: The Impact of Longevity Risk Aversion on Optimal Withdrawal Rates (corrected July 2011). Financial Analysts Journal, 67(2), 45-58.

Mroczek, D. K., & Spiro III, A. (2005). Change in life satisfaction during adulthood: findings from the veterans affairs normative aging study. Journal of personality and social psychology, 88(1), 189.

Pålsson, A.-M. (1996). Does the degree of relative risk aversion vary with household characteristics? Journal of Economic Psychology, 17(6), 771-787.

Pearlin, L. I., & Johnson, J. S. (1977). Marital status, life-strains and depression. American Sociological Review, 704-715.

Pinquart, M., & Sörensen, S. (2000). Influences of socioeconomic status, social network, and competence on subjective well-being in later life: a meta-analysis. Psychology and aging, 15(2), 187.

Poterba, J. M., & Summers, L. H. (1988). Mean reversion in stock prices: Evidence and implications. Journal of Financial Economics, 22(1), 27-59.

Ricciardi, V. (2004). A risk perception primer: a narrative research review of the risk perception literature in behavioral accounting and behavioral finance. Available at SSRN 566802.

Ricciardi, V. (2008). The psychology of risk: The behavioral finance perspective. Handbook of finance.

Sahm, C. R. (2012). How much does risk tolerance change? The Quarterly Journal of Finance, 2(04).

Sandmo, A. (1970). The effect of uncertainty on saving decisions. The Review of Economic Studies, 353-360.

Shefrin, H. (2000). Beyond greed and fear: Understanding behavioral finance and the psychology of investing: Oxford University Press.

Shefrin, H., & Statman, M. (1985). The disposition to ride winners too long and sell losers too soon: Theory and evidence. Journal of Finance, 41, 774-790.

Shiller, R. J. (1980). Do stock prices move too much to be justified by subsequent changes in dividends? : National Bureau of Economic Research Cambridge, Mass., USA.

Sibley, D. S. (1975). Permanent and transitory income effects in a model of optimal consumption with wage income uncertainty. Journal of Economic Theory, 11(1), 68-82.

Steverink, N., Westerhof, G. J., Bode, C., & Dittmann-Kohli, F. (2001). The personal experience of aging, individual resources, and subjective well-being. The Journals of Gerontology Series B: Psychological Sciences and Social Sciences, 56(6), P364-P373.

Thaler, R. (1985). Mental accounting and consumer choice. Marketing science, 4(3), 199-214.

Thaler, R. H. (1990). Anomalies: Saving, fungibility, and mental accounts. The Journal of Economic Perspectives, 193-205.

Thaler, R. H. (2004). Mental accounting matters: Russell Sage Foundation. Princeton, NJ: Princeton University Press.

Titus, P. M., Fanslow, A. M., & Hira, T. K. (1989). Net worth and financial satisfaction as a function of household money managers' competencies. Home Economics Research Journal, 17(4), 309-318.

Tran, T. V., Wright, R., & Chatters, L. (1991). Health, stress, psychological resources, and subjective well-being among older Blacks. Psychology and aging, 6(1), 100.

Tversky, A., & Kahneman, D. (1973). Availability: A heuristic for judging frequency and probability. Cognitive psychology, 5(2), 207-232.

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. Science, 185(4157), 1124-1131.

Weber, E. U. (2004). Perception matters: Psychophysics for economists. The psychology of economic decisions, 2, 163-176.

Yang, Y. (2008). Social inequalities in happiness in the United States, 1972 to 2004: An age-period-cohort analysis. American Sociological Review, 73(2), 204-226.

Yao, R., & Curl, A. L. (2011). Do market returns influence risk tolerance? Evidence from panel data. Journal of family and economic issues, 32(3), 532-544.