The psychology of investor behavior: Stock market expectations and portfolio decisions during market volatility

by

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B.S., Embry-Riddle Aeronautical University, 2004
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AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Personal Financial Planning
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Abstract

This dissertation aims to understand the psychological aspects of investor behavior, exploring the pivotal role of stock market expectations in the context of market volatility. Financial decision-making during times of heightened market volatility demands a delicate balance between potential gains and risks. The study seeks to gain a deeper understanding of how personality traits and emotional disposition influence stock market expectations and subsequently affect investment decisions, with a focus on an older population aged 50 and above. This demographic, approaching or entering retirement, faces unique challenges in making investment choices, where investor mistakes could have significant implications for funding retirement.

Drawing on the theoretical foundations of behavioral finance and psychology, the research employs hierarchical and structural equation modeling to analyze data from the 2018 and 2020 waves of the Health and Retirement Study (HRS), a nationally representative sample of those aged 50 and older. The exploration begins by conceptualizing stock market outlook as an indicator of respondents' anticipations regarding future stock values. By evaluating individuals' stock market expectations, the study provides insights into their subjective assessments of potential risks and rewards associated with stock investments. Stock market outlook is posited as a situational trait, acting as a primary predictor of stock reallocation behavior.

The study delves into the Big Five elemental traits, recognizing their significant roles in shaping financial decision-making. These elemental traits influence compound traits, specifically positive and negative affect, which in turn shape the situational trait of stock market expectations. The research focuses on stock market expectations as a core construct, representing individuals' anticipations about future stock market performance. This approach provides a

comprehensive understanding of how individuals perceive and respond to uncertainty in the financial market. By exploring stock market expectations through the lens of personality and affect, this research illuminates the intricate relationships between psychological traits and investment decisions during times of market volatility.

The study offers insights into the relationship between personality traits, emotions, and stock market expectations and how they collectively shape investment portfolio changes. Financial practitioners and firms can harness these insights to better understand investors' stock market expectations, thereby providing tailored guidance during market volatility. Such informed support can lead to more rational financial decisions, advising investors on the potential negative consequences of reacting to short-term market fluctuations. Additionally, the study contributes to the literature on the relationship between psychology and financial markets, deepening the understanding of how individuals navigate investment decisions amidst economic turbulence. Focusing on the unique challenges faced by the older demographic underscores the importance of targeted support to mitigate the impact of investor mistakes and protect the financial well-being of this population.

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Dedication

I dedicate this dissertation to my family. To my wife, Karen, who as always allowed me to pursue my goals, no matter how ambitious, while continuing to make sure our household runs smoothly. I could not have done this without your encouragement, love, and support. To my daughter, Alexandra, for the needed breaks we spent at the playground, riding bikes, or coaching your sports. Your patience when I was busy was also a gift. Alex, you are full of incredible amounts of potential, and my favorite job in life is helping you realize all that you can do, and then watching you do it. To my parents, who did the same for me.

Chapter 1 - Introduction

Introduction

Volatility in the stock market often instills fear in investors. A common reaction to market volatility among individuals is to reduce their allocation to risky investments and increase their allocation to less risky investments such as bonds and cash (Escobari & Jafarinejad, 2019; Naseem et al., 2021). This is often referred to as a "flight to safety" or risk aversion and can be seen as a natural response to market uncertainty and the desire to protect one's portfolio from potential losses. However, evidence indicates consistently maintaining one's strategic asset allocation over full market cycles generally outperforms reactive short-term decisions (Greenwood & Shleifer, 2014).

According to classical economic theory, the rational approach during volatility is retaining one's desired risk level by staying committed to a diversified portfolio aligned with goals and tolerance (Fama, 1965; Markowitz, 1952). By sticking to their investment plan, investors avoid emotional decisions that could negatively impact their returns. The purpose of this research is to investigate the personality traits, dispositional affect, and stock market outlook factors related to portfolio changes among investors aged 50 and older during a time of market volatility. That is, to see how personality provides an enduring affective disposition which influences how individuals form stock market expectations. This understanding contributes to the literature by offering insights into the type of person that is more likely to exhibit this behavior, offering key stakeholders the opportunity to provide help to those who need it most, for example, by providing them with education about market cycles, especially during turbulent economic conditions. Additionally, focusing on an older demographic's unique challenges in managing investment choices during market uncertainty will shed light on the importance of tailored support for this vulnerable population approaching or living in retirement.

Statement of the Problem

During times of market volatility, some investors will reduce the risk level of their portfolio after the market value has gone down. They do this because they have a fear of losing money and they feel the best action is to protect their portfolio from further losses (Tversky & Kahneman, 1991). However, older investors who reduce their risk level significantly after a market decline may miss out on the long-term growth potential of their investments. Improperly timed portfolio decisions near retirement, for example, reducing risk in response to a market downturn, can negatively impact an investor's retirement plan, counteracting the effects of their previous beneficial financial decisions. For those that have not yet retired, this can result in requiring an individual to delay their retirement age. For those that have retired, reducing risk during a downturn may require reducing their withdrawal amount thereby causing a reduction to their retirement income stream (Forsyth et al., 2021; MacDonald et al., 2013; Pfau, 2015). Therefore, it is critical for investors to understand their risk tolerance and have a well-diversified portfolio that aligns with their investment goals, time horizon, and risk tolerance, that they can stick with when the market gets volatile.

Individual investors, especially those near retirement or that have recently retired, face unique challenges when it comes to managing their portfolios during times of market volatility. As investors near retirement, they often shift their investment objectives from capital appreciation to capital preservation (Rabbani et al., 2021). This means that they may seek to reduce the risk level of their portfolios to minimize the impact of market downturns and protect their assets from significant losses. However, reducing risk too much may also limit their ability to generate the returns necessary to fund their retirement expenses.

Moreover, research has shown that as individuals age, they become more sensitive to the negative effects of financial losses (Brooks et al., 2018). This phenomenon, known as loss aversion, can lead to emotional decision-making during times of market volatility, causing investors to make decisions based on fear and panic rather than logic and rational thinking (Boyce et al., 2016). Loss aversion can be particularly pronounced in older investors who have accumulated significant wealth over their lifetime, as they may be more reluctant to take risks with their hard-earned assets (Mrkva et al., 2020).

Purpose and justification of study

Investors, especially those near retirement or recently retired, should remain disciplined and avoid making reactive decisions during times of market turbulence. Investors who stick to their long-term investment strategies and maintain their investment portfolio allocation during market downturns tend to achieve better investment outcomes over the long run (Browning & Finke, 2015). In contrast, investors who reduce the risk level of their portfolio during market turbulence may miss out on potential gains when the market recovers. It is important for investors to maintain a long-term perspective and avoid reacting to short-term market fluctuations. By remaining disciplined and avoiding impulsive decisions, investors can achieve their long-term investment goals and avoid the negative consequences of market volatility.

While investors should act in a certain way to, their actual behavior might differ. The purpose of this study is to examine the role of personality traits, dispositional affect, and stock market outlook on the extent to which individual investors, particularly those aged 50 and older, make allocation changes in response to market volatility. Specifically, this dissertation seeks to investigate whether these factors are associated with a greater likelihood of reducing risk in response to market downturns.

Rationale

The rationale for this study is based on the importance of understanding how individual investors react to market volatility, especially as they approach retirement. While previous research has examined the effects of market volatility on stock market outlook, few studies have examined the impact of how that outlook manifests in actual investor behavior. This study aims to fill this gap in the literature by examining these factors and their potential role in investment decisions.

Significance

The significance of this research is evident in the potential impact on financial planners and their ability to help older investors navigate the markets during times of volatility, or provide them additional education and resources necessary to aid their decision making process. Researchers will have a better understanding of the decision-making process. Findings would also allow software developers the ability to create assessments that financial planners can use with their clients in addition to current risk profiling assessments. To the extent that a financial planner has information regarding which clients are more prone to reducing the risk level of their portfolio during times of uncertainty, they will able better positioned to positively influence their client's decisions and financial outcomes.

Need for the study

The need for this study arises from the lack of research that specifically focuses on the role of personality traits, dispositional affect, and stock market expectations in the investment decision-making of older investors during market volatility. By investigating this relationship, this study will provide valuable insights for financial advisors, researchers, and investors themselves on how to better manage investment decisions during periods of market volatility. Moreover, this study has practical implications for the development of financial education and investment programs tailored to the specific needs and characteristics of older investors.

The goal is to have a deeper understanding of the characteristics and mechanisms of older investors that are more likely to display loss-averse behavior during volatile markets. The potential negative impact of improperly timed portfolio decisions near retirement, such as reducing risk in response to a market downturn, underscores the importance of understanding the investor decision-making process during times of uncertainty. Therefore, this dissertation aims to address these gaps in the literature and contribute to a better understanding of the investor decision-making process during times of market volatility among older investors.

Introduction to the Theoretical Framework

The Meta-theoretic Model of Motivation (3M) developed by Mowen (2000) serves as the foundational theoretical framework for understanding consumer behavior and psychological characteristics underlying financial decision-making. The 3M model proposes a hierarchical structure of traits, ranging from broad personality characteristics to specific behavioral dispositions. At the broadest level are elemental traits, which encompass well-established "Big Five" personality traits, such as Openness to experience, Conscientiousness, Extroversion, Agreeableness, and Neuroticism (Costa & McCrae, 1992). Moving to narrower scopes, compound traits are applicable across various situational contexts, while situational traits represent dispositions to behave within specific life domains, including financial decision-making. At the narrowest level are surface traits, reflecting observable and actual behavioral tendencies. This theoretical framework will be applied in this dissertation to explore the relationship between personality traits, dispositional affect (positive and negative), stock market expectations, and their influence on investing behavior.

The key constructs in this study come from the Health and Retirement Study Psychosocial and Lifestyle Questionnaire and are grounded in validated measures. The Big Five personality traits are assessed using items designed for survey research drawn from MIDUS and IPIP, showing good internal reliability (Lachman & Weaver, 1997; IPIP, 2023). Positive and negative affect are measured using items from PANAS-X, also demonstrating high reliability (Watson & Clark, 1994). The stock market expectations response asks about expectations for market performance has been used in prior research on investor sentiment using HRS data (Hudomiet et al., 2011). Finally, the stock allocation change operationalizes investor behavior based on an established approach (Browning & Finke, 2015). This measure provides a tangible, observable behavior that reflects an investor's response to their stock market expectations.

By utilizing the 3M model, this dissertation endeavors to analyze investor behavior comprehensively. The hierarchical structure of the 3M model allows for the examination of elemental traits, which contribute to compound traits like positive and negative affect—an essential aspect of financial decision-making. Situational traits, including stock market expectations, play a central role in shaping investment behavior during uncertain market conditions. That is, personality provides an enduring affective disposition which influences how individuals form stock market expectations. Through this integrated approach, the research seeks to shed light on how personality traits, dispositional affect, and stock market expectations collectively influence investment decisions, empowering financial advisors and practitioners to provide tailored guidance and support to their clients during times of market volatility.

Understanding the intricate interplay of these psychological factors can ultimately lead to better-informed investment choices and improved financial outcomes for investors.

Hypotheses

H1: Elemental traits (i.e., Big 5 personality traits) add explanatory power to the model investigating stock reallocation behavior.

H2: Positive and negative affect adds explanatory power to the model investigating stock reallocation behavior.

H3: Stock market expectations add explanatory power to the model investigating stock reallocation behavior.

Elemental Traits

H4: Openness to experience is positively associated with an increase in stock allocation.

H5: Conscientiousness is positively associated with an increase in stock allocation.

H6: Extraversion is positively associated with an increase in stock allocation.

H7: Agreeableness is positively associated with an increase in stock allocation.

H8: Neuroticism is negatively associated with an increase in stock allocation.

Compound Traits

H9: Positive affect is positively associated with an increase in stock allocation.

H10: Negative affect is negatively associated with an increase in stock allocation.

Situational Traits

H11: Stock market outlook is positively associated with an increase in stock allocation.

Potential Implications

The findings of this study have implications for various stakeholders in the field of financial planning, including researchers, financial planning practitioners, and financial technology providers. By examining the relationship between personality traits, affect, stock market expectations and portfolio behavior among older investors during market downturns, this dissertation aims to add to the body of knowledge on the integrated psychological factors that influence investor decision-making. These insights can be leveraged to improve the delivery of financial planning services. Furthermore, the implications of this study extend to the broader academic community, as researchers can build upon these findings to further test models of investor decision-making and explore the long-term financial outcomes associated with different investment behaviors. Overall, the implications of this study have implications for improving the financial outcome of investors, particularly those who are approaching or are in retirement.

Researchers

The implications of this research offer insights for researchers exploring the intersection of behavioral finance, psychology, and investment decision-making. By delving into the factors that shape investors' behavior during market uncertainty, this study contributes to an understanding of the psychological mechanisms associated with investment behavior during market volatility. Future research can expand on these findings to refine and adapt theoretical frameworks, aiming to better explain investor behavior across various economic conditions.

Financial Planning Practitioners

Financial planners often encounter older clients seeking to reduce their portfolio's risk during market downturns. The results of this dissertation highlight the role of personality traits, affect, and stock market expectations in influencing risk aversion tendencies among older investors. The findings of this dissertation suggest a relationship among personality traits, affect, and stock market expectations with risk aversion tendencies in older investors. It reveals that stock market expectations can change based on market conditions, and such shifts in outlook might lead to suboptimal investment decisions. By understanding that personality traits may impact a client's affect, which in turn impacts their stock market expectation and subsequent behavior, financial planners can take a proactive approach in guiding their clients through market uncertainty. Aligning investment strategies with clients' overall risk profiles and retirement goals ensures a well-balanced approach that accounts for both short-term market fluctuations and long-term financial objectives. Moreover, emphasizing the importance of staying committed to their investment plans and providing ongoing education on the potential consequences of short-term decisions can empower clients to maintain a disciplined approach, minimizing the impact of emotional reactions during turbulent economic landscapes. Integrating regular assessments of stock market expectations into the client-advisor relationship helps identify those clients who may be more susceptible to emotional decision-making during market volatility, allowing for targeted support and guidance to prevent potentially detrimental choices and foster a more informed and rational investment behavior.

Financial Technology Providers

The findings of this study have potential implications for financial technology providers. Financial technology providers, such as robo-advisors, offer investment advice and management to investors through automated processes. As the use of these platforms becomes more widespread, understanding how investors make allocation decisions during periods of market volatility becomes crucial. The results of this study can help these providers to develop algorithms that account for the individual's personality traits, affect, and stock market expectations when providing investment advice. This can help investors make better-informed investment decisions, which may lead to improved investment outcomes. Furthermore, the insights gained from this study can also help financial technology providers improve their customer retention rates by providing customized recommendations that align with the investors' individual preferences and risk tolerance. Overall, the implications for financial technology providers are significant, as they can leverage these insights to enhance their products and services, leading to greater investor outcomes.

Summary

The focus of this dissertation is on the portfolio behavior of individual investors aged 50 and older during a period of market volatility. The purpose of this study is to investigate the role of personality traits, positive and negative affect, and stock market expectations in the allocation decisions of older investors during market downturns. The study will test the importance of stock market expectations on investor behavior as well as its antecedents of personality traits and affect. The rationale for this study is that older investors face a unique challenge during periods of market volatility, as their portfolio decisions may impact the sustainability of their subsequent retirement income. The significance of this study lies in the fact that it can provide valuable insights for researchers, financial planning practitioners, and financial technology providers on how to better support older investors during times of market turbulence. The potential implications of this research may help older investors to make more informed portfolio decisions that align with their long-term financial goals and can potentially improve their financial outcomes during retirement.

Chapter 2 - Review of Literature

The purpose of this dissertation is to explore the factors that influence investment portfolio behavior during times of increased uncertainty, with a specific focus on the role of stock market expectations and its determinants. Investment decisions become increasingly complex as individuals approach or enter retirement, requiring a delicate balance between potential financial gains and associated risks. The COVID-19 pandemic has highlighted the significance of understanding how cognitive and personality traits shape investment portfolio changes.

This chapter begins by examining the behavior of individuals with their investment portfolios during times of greater uncertainty and highlights the potential negative consequences of such behavior on future financial outcomes. It then delves into the Meta-Theoretic Model of Motivation and Personality (3M) (Mowen, 2000) as one of two guiding frameworks for this study. The 3M theory offers a hierarchical understanding of personality traits, emphasizing the interplay between elemental traits, compound traits, situational traits, and surface traits. Within this context, the subsequent sections review previous research on personality traits and investment decision-making, with a specific focus on the influential "Big Five" personality traits (Costa & McCrae, 1992) and their associations with investment behavior.

Stock market expectations play a pivotal role in shaping investor behavior, particularly during periods of heightened uncertainty. An individual's subjective outlook on future market performance reflects their risk perceptions, optimism or pessimism, and willingness to invest in equities versus safer assets (Dominitz & Manski, 2007; Hurd, 2009). More positive stock market expectations are associated with a higher likelihood of stock ownership and growth-oriented investment strategies (Hudomiet et al., 2011; Puri & Robinson, 2007). Conversely, negative expectations tend to drive more conservative asset allocations and risk aversion (Dominitz & Manski, 2007). As market volatility increases, expectations become accentuated and can precipitate reactive investment decisions (Deaves et al., 2010). Therefore, understanding the determinants of stock market expectations and their influence on portfolio changes is crucial during times of economic turbulence. This chapter will explore this relationship to gain insights into the mechanisms shaping investment choices.

Investor Behavior During Times of Market Volatility

During times when the market is volatile, individual investors can react in different ways. Each investor may have their own unique response to market volatility. Some may become more cautious and withdraw their investments, while others might see it as an opportunity to make strategic moves. This section aims to provide insights into investor behavior when faced with market uncertainty and increased volatility. The examination of rational models, such as the Efficient Market Hypothesis (Fama, 1970), allows us exploration of expected investor behavior based on the assumption of rationality and optimal decision-making. However, empirical evidence reveals deviations from these rational expectations in actual investor behavior. Known relationships, including age, gender, risk tolerance, and financial knowledge, provide valuable insights into the factors that influence investor behavior during market volatility. Additionally, the influence of personality traits and risk perception on investor behavior is a crucial aspect to consider. By exploring these psychological aspects, we can gain a deeper understanding of the complexities underlying investor decision-making in the face of market turbulence.

Rational Models and Expected Investor Behavior

Rational models play a role in understanding expected investor behavior during times of market volatility. The models, including the Modern Portfolio Theory (MPT), Efficient Market Hypothesis (EMH), Capital Asset Pricing Model (CAPM), Arbitrage Pricing Theory (APT), and Rational Expectations Theory, provide comprehensive insights for understanding how investors should ideally respond to these situations (Fama, 1970; Markowitz, 1952; Muth, 1961; Ross, 1976; Sharpe, 1964). Grounded in the assumption of rationality, these theories suggest that investors, armed with all available information, make decisions that maximize their utility. This rationality is expected to guide their actions during market downturns, influencing whether they choose to hold, sell, or buy more assets.

One such theory, the Modern Portfolio Theory (MPT), posits that investors, cognizant of their risk tolerance and required rate of return, construct an optimal portfolio (Markowitz, 1952). This portfolio is carefully crafted to balance the potential for growth with the investor's ability to withstand losses. In the face of a market drawdown, the rational response, according to MPT, is to hold or even rebalance the portfolio. This rebalancing often involves seizing the opportunity to purchase depreciated assets, thereby maintaining the desired asset allocation in their portfolio. This behavior is driven by the desire to maintain an optimal balance of risk and return, even during periods of market volatility. The theory suggests that a rational investor views a market downturn not as a threat, but as a potential opportunity for portfolio optimization.

Similarly, the Efficient Market Hypothesis (EMH) suggests that asset prices reflect all available information (Fama, 1970). In the context of a market drawdown, the rational investor, guided by EMH, would perceive the new prices as fair. This perception could lead them to hold their portfolio, under the belief that the market will correct itself, or even buy more assets if they anticipate a market rebound. This behavior is predicated on the belief in market efficiency and the idea that prices will eventually reflect their true value.

The Capital Asset Pricing Model (CAPM) and the Arbitrage Pricing Theory (APT) further elaborate on the rational investor's response. CAPM suggests that investors might increase their risk level during a drawdown, expecting higher returns due to the increased systematic risk (Sharpe, 1964). This behavior is driven by the understanding that higher risk can potentially lead to higher returns. APT, on the other hand, posits that rational investors might hold their diversified portfolio or increase their holdings in depreciated assets if the expected return, given the macroeconomic factors, remains attractive (Ross, 1976). This behavior is based on the belief in arbitrage opportunities and the power of diversification.

Lastly, the Rational Expectations Theory posits that investors make decisions based on their rational outlook, available information, and past experiences (Muth, 1961). This theory suggests that rational investors would have anticipated a market drawdown and adjusted their portfolio accordingly, potentially holding or buying more assets at lower prices. This behavior is driven by the belief that their expectations and predictions, based on available information, are generally accurate.

In summary, theories of rational behavior provide a comprehensive framework for understanding how investors should ideally behave during market downturns. However, it is important to note that these theories are based on the assumption of rationality, an ideal that may not always hold in practice. Empirical research often finds that actual investor behavior deviates from these rational predictions, a topic that will be explored in the following sections. This divergence between theory and practice underscores the complexity of investor behavior and the influence of factors beyond rationality.

Age and Investor Behavior

Age remains a predominant determinant in investor behavior. During times of market volatility, older investors, who are usually closer to retirement and have a more pressing need to protect their wealth, typically exhibit greater risk aversion. This pattern was particularly evident during the Great Financial Crisis, when older investors disproportionately shifted their portfolios towards safer assets (Gerrans et al., 2015).

Dohmen et al. (2018) explored this link between age and risk-taking further by examining life-cycle patterns of risk-taking. They found a decline in willingness to take risks with increasing age, suggesting that age is inversely proportional to risk appetite. This is consistent with the life-cycle hypothesis, which posits that individuals increase their savings during their working years to sustain consumption during retirement, implying a decline in risk tolerance as one ages.

Furthermore, age-related heterogeneity in investor behavior is not solely a product of individual-level characteristics. Korniotis and Kumar (2011) propose that cognitive abilities, which tend to decline with age, significantly impact investment decisions. As investors age, they may struggle to process complex financial information, leading them to be more risk-averse.

Gender also shapes investor behavior significantly, particularly during volatile markets. Empirically, men tend to demonstrate higher risk tolerance than women, who are typically more conservative investors. This dichotomy was apparent during the COVID-19 market turmoil, where women displayed a greater tendency to shift towards less risky assets, aligning with earlier findings by Barber and Odean (2001).

Financial Assets and Investor Behavior

The influence of financial resources on investment behavior during periods of market volatility highlights the impact of individual economic circumstances on financial decision-making processes. For example, investors with higher income or greater net worth tend to display resilience and often maintain, or even increase, their positions in riskier assets during turbulent times. This is because such investors are often better positioned to weather investment losses without significantly compromising their overall financial health (Grable & Carr, 2014). Greater financial resources, in this case, often equate to a higher risk capacity, allowing these individuals to pursue potentially higher returns despite market volatility.

In contrast, those with lower income or net worth are more likely to scale back their investment in riskier assets when markets become volatile. Due to their tighter financial constraints, these investors are less capable of absorbing significant losses and therefore exhibit more pronounced risk aversion. This tendency was evident during the Great Financial Crisis, as lower-income investors significantly reduced their equity investments in response to escalating market turmoil (Malmendier & Nagel, 2016; Nagel & Xu, 2022). Furthermore, the COVID-19 pandemic provided further evidence of the role of financial resources in investor behavior during market volatility. High net worth individuals were found to have increased their risk exposure, seeking opportunities amid the chaos, while those with less financial flexibility adopted a more cautious approach, prioritizing the preservation of their wealth (Menkhoff & Schröder, 2022).

Education and Investor Behavior

The role of education in shaping investor behavior, especially during periods of market volatility, is substantial and multilayered. Investors with higher educational levels are more likely to have better access to and understanding of complex financial information, thereby positioning them to make more informed investment decisions (Van Rooij et al., 2012). Their educational background also tends to equip them with the necessary tools to decipher economic indicators, understand market trends, and analyze financial news, resulting in a well-rounded comprehension of market dynamics. In fact, during the Great Financial Crisis, investors with higher educational attainment were less likely to panic sell, indicating their nuanced understanding of the market and its fluctuations (Bodnaruk & Simonov, 2015).

A second perspective on the influence of education on investor behavior revolves around the investor's approach to financial decision-making. Higher educated investors generally exhibit a propensity for adopting a long-term perspective, remaining less susceptible to impulsive decision-making driven by short-term market movements. This trait was particularly evident during the market volatility prompted by the COVID-19 pandemic. Investors with a higher level of education demonstrated adaptive investment behavior, strategically adjusting their portfolios to the shifting market conditions rather than reacting impulsively to market turmoil (Ortmann et al., 2020). Hence, education confers not only the analytical tools for understanding markets but also instills an investor discipline that encourages consistent, strategic decision-making in the face of market volatility.

Risk tolerance and Investor Behavior

Risk tolerance stands as a critical determinant in the sphere of investor behavior. At its core, risk tolerance is an individual's willingness to endure uncertainty and potential losses in the pursuit of higher returns (Grable, 2017). Notably, those with a higher risk tolerance are more inclined to maintain or even augment their investment in risky assets during periods of market volatility, driven by the prospect of substantial returns (Guiso et al., 2018). The link between risk tolerance and investor behavior was markedly apparent during the Great Financial Crisis.

Investors with higher risk tolerance demonstrated remarkable resilience, continuing to engage in the stock market despite the uncertainty and potential for loss (Hoffmann et al., 2013).

A further dimension of risk tolerance relates to the individual's past experiences with financial losses. Empirical evidence indicates that investors who have previously encountered substantial market downturns are generally more cautious during periods of market volatility (Nagel & Xu, 2022). For instance, during the COVID-19 pandemic, these investors, having learned from their past experiences, exhibited heightened risk aversion by reducing their exposure to risky assets. This cautious approach serves as a protective mechanism against the repeat of past financial disappointments, further illustrating the profound influence of risk tolerance on investor behavior in volatile markets.

In summary, this section has sought to highlight the influence of various socio-demographic and economic factors on investor behavior, particularly during periods of market volatility. Age, gender, financial resources, education, and risk tolerance have all emerged as critical determinants that shape an individual's propensity to invest in risky assets. Interestingly, the nature of these influences reflects the intricacies of human behavior, underscoring the departure of actual investor behavior from the predictions of classical financial theory. Moving forward, examining the underlying psychological aspects that shape these tendencies and responses emerges as a crucial step. These psychological components, ranging from personality traits, to how risk is perceived by an individual, can potentially unveil deeper layers of understanding into the complex mosaic of investor behavior.

Psychological Aspects of Investor Behavior

Investor behavior, particularly during periods of heightened market volatility, extends beyond the scope of traditional economic theories, which assume a rational, utility-maximizing individual. Instead, a more realistic portrayal of investor behavior also factors in a variety of psychological aspects, such as personality traits, and how the riskiness of the financial markets are perceived. These psychological determinants can reveal the complex, often non-rational, patterns of investor behavior during times of economic stress, like the during the Great Financial Crisis and the COVID-19 pandemic.

Personality traits and investor behavior

Investor behavior is multifaceted and influenced significantly by individual personality traits. The Big Five personality framework, encompassing traits such as openness, conscientiousness, extraversion, agreeableness, and neuroticism, offers a robust model to understand this relationship (Costa & McCrae, 1992). Each of these traits characterizes distinct patterns of thought, emotion, and behavior, providing a psychological lens through which to understand variations in investor behavior during periods of market volatility.

Empirical Evidence on Actual Investor Behavior

Investor behavior, particularly during periods of market turbulence, does not always align with traditional rational theories. Notably, it exhibits considerable heterogeneity that is significantly shaped by various sociodemographic factors. This divergence from rational theories becomes pronounced when observing the reactions of U.S. investors during pivotal periods of market volatility, such as the Great Financial Crisis and the COVID-19 pandemic.

Conscientiousness and financial decision-making

Conscientiousness, a trait within the Big Five, has been a focus of investigation in relation to investor behavior. Conscientiousness reflects individuals' tendency to be organized, responsible, and diligent in their endeavors (John & Srivastava, 1999). Research has shown that individuals high in conscientiousness exhibit more disciplined and prudent investment behaviors.

They are more likely to engage in long-term financial planning, follow investment strategies more consistently, and adopt a cautious approach to risk (Ahmad & Shah, 2020; Ganzach & Wohl, 2018; Hill & Jackson, 2016; Kaur & Goel, 2022; Lauter et al., 2023; Letkiewicz & Fox, 2014).

Similarly, Lauter et al. (2023) found that more conscientious traders outperform their peers on a risk-adjusted basis. Furthermore, conscientiousness has been found to be positively correlated with diligent financial planning and long-term investment strategies (Asebedo, 2018). Conscientious individuals tend to prioritize financial stability and exhibit greater self-control, which may result in more prudent decision-making and reduced susceptibility to impulsive investment choices during times of market uncertainty.

Emphasizing this disciplined investment behavior, investors high in conscientiousness typically focus on long-term financial planning and careful risk management. This often translates to a lower trading frequency and a long-term investment strategy (Ishfaq et al., 2020). Even in the face of significant market turbulence, such as the COVID-19 pandemic, these investors showed resilience by adhering to their investment strategies and refraining from impulsive selloffs. This behavior illustrates a commitment to their financial goals and highlights the stability conscientiousness brings to investment decisions (Oehler & Wedlich, 2018).

Neuroticism and financial decision-making

Neuroticism, or emotional instability, has been associated with various aspects of investor behavior, further elucidating its impact on financial decision-making. Individuals high in neuroticism tend to demonstrate risk-averse tendencies (Liu et al., 2021) and heightened sensitivity to market fluctuations (Oehler & Wedlich, 2018). Individuals who score high on neuroticism have a propensity to experience negative emotions, such as anxiety and fear, which may lead to a heightened sense of uncertainty and an aversion to financial losses (Grable & Roszkowski, 2008).

Research has shown that individuals with high levels of neuroticism are more likely to engage in frequent trading and exhibit a greater tendency for market timing (Cheng et al., 2019; Tauni et al., 2015). This behavior can stem from their emotional volatility and heightened responsiveness to short-term market movements. However, excessive trading and market timing have been associated with suboptimal investment performance and increased transaction costs (Barber & Odean, 2001; Foltice & Langer, 2015).

Moreover, neuroticism has been linked to heightened financial worry and a tendency to focus on potential losses rather than potential gains (Brown & Taylor, 2014; McCleskey & Gruda, 2021; Sachdeva & Lehal, 2023). This cognitive bias, known as loss aversion, may lead individuals high in neuroticism to avoid or divest from risky investments, seeking greater stability and security in their portfolios (Aren & Hamamci, 2020; Mayfield et al., 2008). As a result, they may exhibit a more conservative investment approach, favoring low-risk assets or fixed-income securities over higher-risk equity investments.

In addition, neuroticism has been found to influence individuals' response to financial information and advice. High levels of neuroticism have been associated with a greater susceptibility to negative financial news and a tendency to overreact to market downturns (Lerner et al., 2015; Xu et al., 2015). This heightened emotional reactivity may lead to impulsive decision-making, such as panic selling during market declines, which can have detrimental effects on investment outcomes.

Adding further to this understanding, neuroticism, characterized by the intensity of negative emotions such as depression and anxiety, often correlates with conservative investment behavior. During the 2008 financial crisis, investors high in neuroticism were more likely to shift their portfolios towards less risky assets, demonstrating their heightened sensitivity to market fluctuations and risk aversion (R. Durand et al., 2013). This tendency to favor safer investments underlines the potential influence of neuroticism on individuals' investment behaviors and choices.

Openness to experience and financial decision-making

Moreover, the Big Five trait of openness to experience has been linked to investor behavior. Openness to experience encompasses individuals' curiosity, imagination, and receptiveness to novel ideas and experiences (John & Srivastava, 1999). Research has shown that individuals high in openness tend to exhibit a greater willingness to explore new investment opportunities, embrace innovative financial products, and engage in alternative investment strategies (Kaplan & Klebanov, 2011; Fisher et al., 2019). Their inclination towards new experiences and information-seeking behavior may drive them to consider a wider range of investment options and adapt more flexibly to changing market conditions.

Further expanding on this understanding, openness to experience, which captures the breadth, depth, originality, and complexity of an individual's mental and experiential life, often leads to more adventurous investment behavior. Individuals high in openness are often attracted to novel and complex investment opportunities such as alternative assets, which may include cryptocurrencies (Dakroub et al., 2021). Their propensity for exploration and novelty may make them more comfortable with taking calculated investment risks. This tendency could potentially lead to a diversified and dynamic portfolio, reflecting their adaptive and explorative nature.

Agreeableness and financial decision-making

Lastly, the trait of agreeableness within the Big 5 has also been examined in relation to investor behavior. Agreeableness reflects individuals' tendencies to be cooperative, considerate, and empathetic towards others (John & Srivastava, 1999). During volatile markets of the Great Financial Crisis of 2007-2009, researchers found those with higher levels of agreeableness associated with lower allocations to stocks in their IRAs and 401k accounts (Ameriks et al., 2009). Studies have found that individuals high in agreeableness may exhibit a more cautious approach to investment decision-making, valuing stable and socially responsible investment options (Nga & Ken Yien, 2013; Sekścińska & Markiewicz, 2020). Yadav and Narayanan (2021) posit that personality trait agreeableness relates to herding behavior which may impact their investment decision-making to sell stocks when the market is trending downward. These findings underscore the relevance of agreeableness in shaping the investment choices and risk preferences of individuals.

Extraversion and financial decision-making

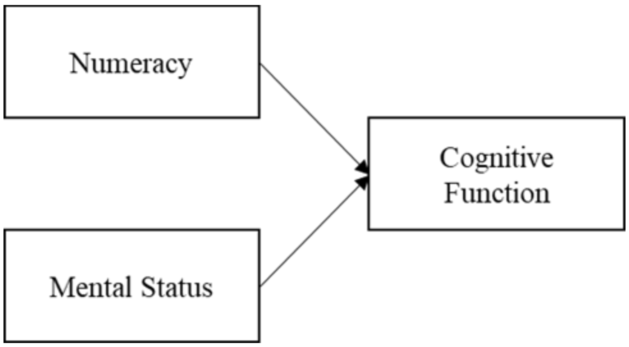
One of the key traits examined is extraversion, which refers to individuals' level of sociability, assertiveness, and tendency to seek excitement and stimulation (John & Srivastava, 1999). Studies have found that extraversion is positively associated with a preference for risky investments (Palomäki et al., 2021), a propensity for investment risk-taking (Durand et al., 2013), and a greater willingness to engage in speculative trading (Oehler & Wedlich, 2018). Moreover, Cicerale et al., (2022) found that extraversion is linked with less risk aversion during times of market volatility. Individuals high in extraversion may be more inclined to take risks and actively seek investment opportunities, driven by their desire for excitement and potential rewards. Individuals high in extraversion may be more inclined to take risks and actively seek investment opportunities, driven by their desire for excitement and potential rewards. This enthusiasm extends to periods of uncertainty, such as the COVID-19 pandemic, where extraverted investors demonstrated a propensity to retain or even increase their risky investments, showcasing their capacity to embrace uncertainty in anticipation of potential gains (Ishfaq et al., 2020).

The findings collectively illustrate a complex relationship between the Big Five personality traits and investor behavior. The multifaceted nature of personality, from risk-taking tendencies influenced by extraversion and openness, to the disciplined strategies of conscientious individuals, the cautious approach of agreeable investors, and the stress-reactive decisions of those high in neuroticism, profoundly shapes financial decision-making. While personality traits offer a valuable lens to understand investor behavior, other psychological influences are equally significant. Human decision-making in the financial context is influenced by a multitude of factors, with cognitive ability being a crucial aspect. Acknowledging this, the subsequent section will focus on cognitive ability and its role in investor behavior, exploring how individuals' cognitive capabilities play a critical role in shaping their investment decisions.

Cognitive Ability and Investor Behavior

Cognitive ability, encompassing a range of mental processes such as attention, memory, reasoning, and problem-solving, plays a pivotal role in investor behavior. These cognitive abilities, which can vary across individuals and change over time, significantly influence the way investors process information, perceive risk, and make financial decisions. Notably, cognitive abilities often decline with age, which can have profound implications for financial decision-making processes (Peng & Kievit, 2020). This section delves into the intricate relationship between cognitive ability and investor behavior, exploring how factors such as numeracy and mental status shape financial decisions (see Figure 2.2), and how cognitive decline can impact investment strategies, particularly among older adults.

Figure 2.1. Hierarchical Structure of Cognitive Function



Cognitive decline and investor behavior

Research conducted by Browning and Finke (2015) sheds light on the relationship between cognitive ability and investor behavior, emphasizing the impact of cognitive factors on allocation changes during the Great Financial Crisis of 2008-2009. The authors found that individuals with lower cognitive ability exhibited a tendency to allocate away from stocks during market volatility. They found that compared to those with the lowest levels of cognitive ability, respondents with higher cognitive ability are less likely to reduce their stock allocation by 50% or more, suggesting that the quality of investment decisions in old age may be compromised by cognitive decline.

Cognitive decline, often associated with aging, can have implications for investor behavior. As individuals age, there is evidence to suggest that cognitive abilities may decline, including memory, processing speed, and executive functions (Salthouse, 2019). These cognitive changes can affect an individual's ability to comprehend complex financial information, make rational investment decisions, and adapt to market conditions.

Furthermore, cognitive decline may also influence individuals' subjective probability judgements such as stock market expectations. As cognitive abilities decline, individuals may become more risk-averse and prefer safer investment options to protect their financial well-being (Mata et al., 2018). They may exhibit a heightened sensitivity to potential losses and may be more inclined to prioritize capital preservation over potential gains. Cognitive decline can impact the ability to process complex financial information, evaluate risks accurately, and assess the long-term consequences of investment decisions (Hershey et al., 2015). These cognitive limitations may lead to more conservative investment strategies and a reluctance to engage in riskier financial activities (Hershey & Mowen, 2000).

Building on the understanding of how cognitive ability and its decline with age can influence investor behavior, it is essential to delve deeper into the specific cognitive dimensions that play a significant role in financial decision-making. Two such dimensions, numeracy and mental status, have been identified as key factors that shape investor behavior. The following sections will explore these dimensions in detail, shedding light on their influence on investor behavior and the implications for financial decision-making, particularly in the context of aging and cognitive decline.

Numeracy and Investor Behavior

Numeracy, defined as the ability to accurately calculate mathematical problems, plays a role in shaping investor behavior and financial decision-making. Consumers with greater numeracy skills exhibit several positive financial behaviors and outcomes. For instance, individuals with higher numeracy skills tend to be better prepared for retirement, as they can estimate the amount of savings needed for future financial security (Banks et al., 2010; Estrada-Mejia et al., 2016). They are also more likely to invest in higher quality portfolios, making informed investment decisions (Gaudecker, 2015). Furthermore, individuals with greater numeracy skills demonstrate a better understanding of credit card terms and are more capable of comparing credit values over time (Soll et al., 2013).

The relationship between numeracy and investor behavior has been examined in various studies. In the context of stock ownership, research suggests a positive association between cognitive ability, including numeracy, and the propensity to hold stocks in an aged population (Christelis et al., 2010). It has been found that individuals with higher cognitive abilities are more likely to engage in stock ownership, favoring information-intensive financial instruments like stocks versus bonds (Christelis et al., 2010; Finke et al., 2017). The positive association of numeracy and stock ownership was found to exist during market volatility during the Spring of 2020 (Binder, 2020). The ability to comprehend complex financial information and assess the risks associated with stock ownership plays a significant role in the decision-making process, however, the relationship between numeracy and decision-making quality is complex and not yet fully understood (Estrada-Mejia et al., 2016).

Mental Status and Investor Behavior

Mental status, as a dimension of cognitive ability, plays a role in shaping investor behavior. Basic cognitive functions such as memory, attention, and language abilities are essential for comprehending financial information and making sound investment decisions. Individuals with intact mental status are better equipped to process and retain financial knowledge, evaluate investment risks accurately, and adapt to changing market conditions (Kiso & Hershey, 2017). On the other hand, cognitive impairments, such as difficulties in memory or attention, can hinder an individual's financial decision-making abilities and lead to suboptimal choices (Agarwal & Mazumder, 2013). Therefore, accounting for the influence of mental status on investor behavior is crucial for researching its impact on the financial decision-making process.

Assessment of basic mental status is commonly used in the clinical context of admitting patients to skilled nursing facilities and long-term care facilities (Li et al., 2022). Surveys of mental status help medical professionals document the health, function and care processes for incoming patients. They are not commonly used in the context of financial behavior research, however a few studies have explored the association of mental status and financial behavior.

Mental status, encompassing basic cognitive functioning, plays a crucial role in shaping financial behavior among individuals. Gerstenecker et al. (2018) explored the factor structure of financial capacity using the Financial Capacity Instrument (FCI) as a proxy measure, revealing four key factors: Basic Monetary Knowledge and Calculation Skills, Financial Judgment, Financial Conceptual Knowledge, and Financial Procedural Knowledge. The study emphasized the importance of considering cognitive abilities when examining financial behavior, particularly in individuals with cognitive impairments. Further supporting this association, Niccolai et al. (2017) identified cognitive predictors of declining financial capacity in persons with mild cognitive impairment (MCI). Their findings highlighted the significance of semantic arithmetic knowledge, visual memory, and attention as longitudinal cognitive predictors of financial skill decline in individuals with MCI. These studies underscore the need to consider mental status and specific cognitive abilities when assessing and supporting portfolio allocation changes in older adults, particularly those with cognitive impairments.

While cognitive abilities, including numeracy and mental status, play a foundational role in shaping investor behavior, they also intersect with individuals' expectations about the stock market's future performance. Stock market expectations, which encapsulate an investor's subjective outlook on potential market movements, are pivotal in guiding financial decisions. The interplay between cognitive abilities and these expectations creates a nuanced landscape that significantly influences investment choices. Delving deeper into this relationship will illuminate the intricacies of stock market expectations and their impact on investor behavior.

Stock Market Expectations and Investor Behavior

An individual's subjective expectations regarding future stock market performance play a pivotal role in investment decisions, especially during periods of volatility (Hurd, 2009). More positive expectations reflect greater optimism and confidence, which encourage stock ownership and growth-oriented investments (Dominitz & Manski, 2007; Puri & Robinson, 2007). For instance, Hudomiet et al. (2011) found that higher expectations preceding the 2008 financial crisis predicted a lower likelihood of selling equities during the downturn. In contrast, negative expectations are associated with pessimism, risk aversion, and a preference for conservative investments (Deaves et al., 2009; Hurd, 2009).

Expectations also interact with age, as some research indicates older investors tend to have more pessimistic market outlooks (Dominitz & Manski, 2007). Negative expectations were found to be associated with a lower probability of stock ownership among older respondents (Hurd et al., 2010). This suggests expectations may partially mediate age differences in investment behaviors. Additionally, expectations can reflect experiences, as investors who have lived through market declines may form more negative outlooks (Malmendier & Nagel, 2016). However, other studies propose Expectations can also evolve independently from past experiences (Greenwood & Shleifer, 2014).

The relationship between expectations and behavior is complex. While negative expectations are associated with "flight to safety", some highly pessimistic investors still participate in equities, likely for expected returns (Hurd et al., 2012). Also, over-optimism can lead to excessively risky investments (Puri & Robinson, 2007). Mediators like personality likely play a role in how expectations translate to behavior. Nonetheless, expectations are a critical factor in investment choices during volatility.

In summary, subjective stock market expectations substantially influence investor behavior (Deaves et al., 2009; Hurd, 2009). While negative expectations encourage conservatism, positive outlooks support risk-taking. Gaining clarity on the origins and impacts of market expectations is integral to understanding investment decision-making, especially amidst volatile conditions.

Impact of Reducing Risk

Reducing risk during a time of market volatility is a common strategy used by older investors to protect their portfolios from future potential losses. However, this strategy can have significant implications for retirement wealth adequacy and retirement income. Research has shown that such risk reduction can lead to lower retirement income levels, potentially jeopardizing an individual's retirement security (Munnell & Rutledge, 2013). This finding emphasizes the importance of considering the impact of reducing risk on retirement outcomes.

A study conducted by Blanchett et al. (2018) further explore the potential consequences of reducing equity exposure during market downturns. Their research reveals that even a minor reduction in equity exposure can significantly increase the likelihood of portfolio failure, particularly for retirees with a longer time horizon. The find this to effect to magnified during periods of low return, and during times of low bond yields (Blanchett, 2014). This suggests that the strategy of reducing risk during market volatility should be carefully evaluated to avoid compromising the long-term financial security of retirees.

In addition to the direct impact on retirement income, the concept of sequence of return risk plays a crucial role in understanding the consequences of risk reduction. Sequence of return risk refers to the order in which investment returns occur and can have a negative effect on portfolio outcomes, particularly during the transition from accumulation to decumulation phases of retirement. Poor returns early in retirement, combined with a reduced exposure to equities, can diminish the overall portfolio value and potentially jeopardize the sustainability of retirement income (Clare et al., 2020). This highlights the need to manage both risk reduction and the sequence of returns to ensure a secure retirement.

Moreover, the decision to reduce portfolio risk often involves shifting investments from higher-risk, higher-return assets (e.g., stocks) to lower-risk, lower-return assets (e.g., bonds or cash equivalents). While this can protect the investor's wealth from short-term market volatility, it can also limit the growth potential of their portfolio. According to a study by Qi et al. (2022), safer portfolio allocations, while providing stability, may not significantly improve retirement adequacy compared to riskier portfolios. This suggests that reducing portfolio risk could potentially lead to lower retirement wealth, especially if the shift is made too early or too drastically.

Furthermore, reducing risk during market volatility can have practical implications for retirees' financial planning and lifestyle. Retirees may be required to adjust their retirement budget, limit their expenses, and potentially compromise their quality of life in order to accommodate the lower retirement income resulting from risk reduction (Blanchett, 2023). Moreover, reducing risk may also restrict spending flexibility, limiting retirees' ability to maintain their desired lifestyle throughout retirement (Blanchett et al., 2017; Finke et al., 2013). These considerations emphasize the need for retirees to carefully assess the potential consequences of risk reduction on their retirement income and make informed decisions to preserve their long-term financial security.

Lastly, the decision to reduce portfolio risk must also take into consideration the individual's risk tolerance and financial goals. Waring and Siegel (2015) propose a spending rule for retirees that balances the need for a stable income with the risk of running out of money. This approach requires an understanding of the individual's risk tolerance and the ability to adjust spending based on the current value of the portfolio. A drastic reduction in portfolio risk might not be suitable for individuals with a higher risk tolerance and a desire for a higher retirement income.

In summary, reducing risk during market volatility can have significant ramifications for retirement income and the sustainability of funds. It is important to recognize that risk reduction may increase the likelihood of portfolio failure. Therefore, retirees must carefully evaluate the impact of risk reduction on their retirement outcomes, including potential adjustments to their budget and lifestyle. While reducing portfolio risk can provide stability, it can also limit the growth potential of their portfolio and lead to lower retirement wealth and income. These decisions should be made carefully, taking into consideration the individual's risk tolerance, financial goals, and retirement plans.

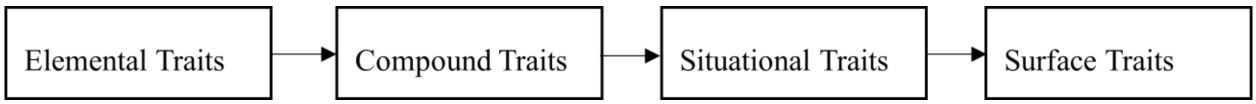
Transitioning to the next section, exploration will be made into how these decisions and behaviors can be further understood through the Meta-theoretic Model of Motivation and Personality Theory, and how stock market expectations overlap. The theory provide an understanding of the psychological and perceptual factors that influence investor behavior.

Meta-theoretic Model of Motivation and Personality Theory

This study will employ the Meta-theoretic model of Motivation and Personality (3M) to investigate the psychological characteristics associated with older investors allocation changes during market volatility, given the empirical evidence supporting the ability of the 3M to explain a variety of traits and consumer behaviors within the financial domain (Mowen, 2000). The 3M is a comprehensive theoretical framework that integrates approaches from control theory (Carver & Scheier, 1998), evolutionary psychology (Buss, 1999), trait theory (Costa & McCrae, 1992), and hierarchical models of personality (Goldberg, 1993). Developed by Mowen (2000), the model aims to provide a comprehensive account of how personality interacts with situations to influence feelings, thoughts, and behavior. By integrating principles from multiple domains, the 3M provides a more comprehensive and nuanced understanding of the complex interactions between personality, cognitive ability, and subsequent behavior. The model has been successfully applied to various fields, including personal financial planning (Asebedo et al., 2019), consumer behavior (Flynn et al., 2016), and personality psychology (Schneider & Coulter, 2015). The 3M model has been applied in various contexts to understand motivation and personality, making it a useful theoretical framework for studying financial behavior.

The 3M model's unique contribution to understanding financial behavior lies in its comprehensive approach to personality traits. The model delineates four types of traits: Elemental Traits, Compound Traits, Situational Traits, and Surface Traits (see Figure 2.1). Each of these traits plays a distinct role in shaping an individual's behavior and responses to different situations. By focusing on these four types of traits, the 3M model provides a nuanced understanding of how personality influences financial behavior. This focus on personality traits offers a framework for exploring the relationship between personality and financial decision-making.

Figure 2.2. Hierarchy of Personality traits within the 3M Model, adapted from Mowen (2000).



Hierarchy of Personality Traits

Elemental traits

The 3M model incorporates a hierarchical organization of traits, categorizing them into four distinct levels: elemental, compound, situational, and surface (Mowen, 2000). This hierarchical structure provides a framework for understanding the multidimensional nature of personality and its influence on behavior across different levels of analysis. At the elemental level, traits are considered the basic building blocks of personality within the 3M model, and they are often measured using established personality inventories such as the Big Five personality traits, which include openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism (Costa & McCrae, 1992). These elemental traits capture broad dimensions of personality that are believed to underlie individual differences in behavior and motivation (Mowen, 2000).

The Big Five traits have been extensively researched and have demonstrated robust associations with various aspects of behavior and life outcomes. Openness to experience reflects an individual's inclination towards curiosity, imagination, and intellectual pursuits. Conscientiousness pertains to traits such as organization, responsibility, and self-discipline. Extraversion captures an individual's tendency to seek social interactions, assertiveness, and positive affect. Agreeableness is characterized by traits related to empathy, cooperation, and altruism. Neuroticism represents emotional instability and tendencies towards negative affect and anxiety. The 3M model suggests that elemental traits add explanatory power to the investigation of investment allocation changes, beyond basic individual characteristics and economic factors, highlighting the importance of considering these traits in understanding investment behavior (Mowen, 2000). These elemental traits, representing the fundamental dimensions of personality, combine to form compound traits at the next level of the hierarchy within the 3M model.

Compound traits

According to the 3M model, compound traits play a crucial role in predicting situational and surface traits, complementing the elemental traits, and providing a more comprehensive understanding of personality's influence on behavior (Mowen, 2000). Compound traits are specific dispositions that arise from the interplay of elemental traits, guiding patterns of behavior. By incorporating compound traits into the predictive model, a greater amount of variance in behavior can be accounted for compared to relying solely on elemental traits. This hierarchical approach acknowledges the incremental explanatory power of compound traits, capturing nuances and complexities in behavior beyond the broad dimensions of personality traits.

Relevant to financial contexts, positive and negative affect represent significant compound traits within the 3M framework. Positive affect encompasses emotions like happiness, joy, and enthusiasm, while negative affect reflects distressing states such as fear, nervousness, and irritability (Watson et al., 1988). Asebedo et al. (2019) incorporated positive and negative affect as compound traits in a study of older pre-retirees' savings behaviors using the Health and Retirement Study. The results revealed affect as a significant predictor, supporting their status as relevant compound traits in financial models. By acknowledging the role of affective dispositions, the 3M model provides a more comprehensive understanding of how personality shapes financial behaviors like portfolio allocation decisions.

Situational traits

Situational traits within the 3M model are unidimensional dispositions that guide behavior in specific contexts (Mowen, 2000). These traits emerge from the interplay between elemental traits, compound traits, and situational influences. In financial contexts, an individual's subjective expectations regarding future stock market performance represents a highly relevant situational trait. Positioned within the hierarchical structure, situational traits provide a comprehensive explanation for the variance observed in surface-level traits.

Stock market expectations encompass individuals' perceptions of the potential gains or losses in the equities market over a given timeframe (Hurd, 2009). These expectations arise from the combination of personality tendencies, emotional dispositions, cognitive capacities, and the situational factors unique to the market context (Asebedo et al., 2019). During periods of volatility, expectations become accentuated and can precipitate different investor behaviors based on whether outlooks are positive or negative (Deaves et al., 2009).

Therefore, this study focuses on stock market expectations as the key situational trait, aiming to understand its determinants and relationship with portfolio allocation decisions. The investigation of expectations as a situational trait aligns with empirical evidence showing its significant role in investment choices, especially during market uncertainty (Dominitz & Manski, 2007; Greenwood & Shleifer, 2014). By exploring the origins and outcomes of this situational trait, insights can be gained into the mechanisms underlying investor behavior.

Surface traits

Surface traits, within the 3M, are observable behaviors that result from the interplay of elemental traits, compound traits, and situational traits (Mowen, 2000). These traits manifest as specific behaviors, attitudes, and preferences. In the context of this study, portfolio allocation change is considered a surface trait. This refers to the asset allocation risk level change across the individual's investment portfolio, as measured by the percentage held in stocks versus less risky assets, such as amounts invested in bonds, cash, and cash equivalents. As a surface trait, this change of asset allocation risk level is an observable behavior that reflects the relationship of underlying personality traits and specific situational factors, such as one's stock market expectations. This approach provides an understanding of the factors shaping investment decisions and behaviors.

Cognitive Appraisal

Cognitive Appraisal, as a construct within the 3M model, refers to the information processing that occurs after an individual experiences an unexpected event. This cognitive appraisal process operates independently of the hierarchy of traits, representing an additional possible path in the decision-making process. During cognitive appraisal, individuals engage in thinking, planning, and analytical processes to understand the causes and implications of the event. While cognitive appraisal interacts with hierarchical traits, it is conceptually distinct from them. If the cognitive appraisal occurs, the individual steps back to ask "why" and assess the situation considering their goals and objectives. Cognitive appraisal is a cognitive mechanism that contributes to behavior and informs the subsequent actions individuals undertake in response to changing circumstances (Mowen, 2000).

A noteworthy aspect of the 3M model is its acknowledgment of the primacy of affect over cognitive appraisal, which is consistent with the view of Zajonc and Markus (1982). In other words, emotional responses are generated before the conscious recognition of information coming from the environment. The 3M model adopts this perspective, viewing cognitive appraisal as the information process bypassing the emotional response and leading directly to the decision-making process at the situational trait level. This aligns with risk perception theory, discussed next, as the risk as analysis construct, as shown in figure 2.4.

By incorporating Cognitive Appraisal in accordance with the 3M model, this study aims to achieve a more comprehensive understanding of the interplay between psychological traits, cognitive abilities, and risk perception during investment decision-making. Through exploring this integration, valuable insights can be gained into the mechanisms through which individual differences and cognitive processing influence the formation of risk perception and subsequent investment behaviors amidst uncertain market conditions. This analytical approach provides a robust foundation for investigating the complex dynamics underlying investor behavior, facilitating the identification of key factors that contribute to the decision-making process in times of market volatility.

Stock Market Expectations and Investor Behavior

Decision-making under uncertainty is significantly influenced by individuals' subjective judgments about the likelihood of future events. In the realm of financial decision-making, these judgments often revolve around forecasting future market outcomes. Rather than relying solely on data-driven analysis, individuals often lean on intuitive heuristics to form these predictions (Kahneman & Tversky, 1973). Such subjective judgments play a pivotal role in shaping decisions across various sectors, including health and finance (Slovic et al., 2004).

Research on investor’s expectations of market movements commonly asks about an individuals' expectations about short-term stock market trends, for example whether they are bullish, bearish, or neutral over the next six months. For example, the American Institute of Individual Investors Sentiment Survey has been asking its members this question on a weekly basis since 1987 (AAII Investor Sentiment Survey, n.d.). An individual's response can directly influence their investment strategy: a pessimistic outlook might lead to reduced equity holdings, while optimism could encourage greater market risk. These judgments also influence decisions related to other financial instruments, such as income annuities (*LIMRA*, n.d.).

For retirees or those nearing retirement, these judgments become even more critical. A sudden shift to a more conservative outlook after a market downturn, driven by heightened loss aversion, can lead to premature portfolio adjustments (Weber et al., 2002). Loss aversion, the tendency to prioritize avoiding losses over acquiring equivalent gains (Tversky & Kahneman, 1991), can result in overly cautious decisions. For retirees relying on investment returns, such decisions can jeopardize their financial stability. In contrast, maintaining a consistent investment strategy, aligned with long-term goals, tends to yield better results than reactive shifts.

Grasping the psychological underpinnings of these market expectations is crucial for financial professionals advising clients through market fluctuations. Such understanding can inform educational initiatives, promoting more realistic and data-informed market expectations. By fostering well-informed judgments, investors can make decisions that align with their long-term financial goals, rather than being swayed by short-term emotions. This research seeks to delve deeper into the factors influencing these judgments, aiming to provide insights that can enhance financial advice and outcomes.

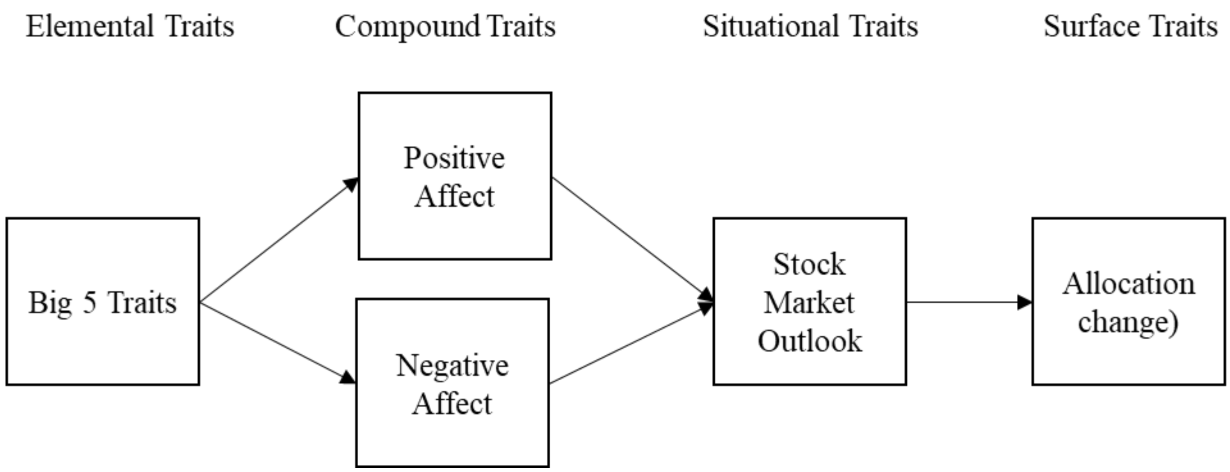
Integration of Stock Market Expectations and 3M Theory

The role of stock market expectations and the 3M model of personality and motivation offers a holistic theoretical framework to analyze the associations of personality traits and stock market expectations in shaping investor behavior. This combined approach facilitates an exploration of the underlying mechanisms prompting individuals' market expectations and subsequent investment decisions. By integrating the individual differences in personality from the 3M model with the subjective judgments about future market outcomes, results in a more comprehensive understanding of how individuals perceive and respond to market expectations.

Previous literature highlights how stock market expectations, which capture individuals' subjective judgments about the likelihood of future market outcomes, play a role in investment decisions. These judgments often revolve around predicting market trends and are influenced by individual differences in personality traits. The 3M model, with its hierarchical structure, provides a framework to understand how these individual differences influence stock market expectations and subsequent investment behaviors. By conceptualizing positive and negative affect as compound traits within the 3M model, and deriving them from the elemental traits represented by the Big Five traits, the model captures the nuanced influences of personality on stock market expectations.

The 3M model's situational trait, stock market expectations, is influenced by both elemental traits (Big Five personality traits) and compound traits (positive and negative affect). This situational trait is hypothesized to be directly associated with the surface trait, which in this study is the stock reallocation behavior. This hierarchical structure provides an understanding of how personality traits and stock market expectations shape investment decisions. Figure 2.4 offers a visual representation of this integrated theoretical framework, illustrating the interplay between the constructs of stock market expectations and the 3M model in shaping investment behavior.

Figure 2.3 Empirical Model of 3M Theory, adapted from Mowen (2000).



This integrated theoretical framework lays the groundwork for the empirical investigation of the relationships between the Big Five personality traits, positive and negative affect, stock market expectations, and investment behavior. By examining these relationships, insights into the personality and cognitive factors that drive investment decisions, especially during market volatility, can be examined. This approach, therefore, offers an opportunity for enhancing the understanding of investor behavior and guiding interventions to foster effective investment decision-making.

Socio-Demographic and Financial Correlates of Investor Behavior

In addition to psychological characteristics, a relationship between investor behavior and socio-demographic and financial factors has been established within the literature. Evidence suggests that investors rebalance their portfolio away from stocks as they approach and after retirement (Fagereng et al., 2017). Gender has been found to account for differences in allocation to stocks with men reporting higher allocation to stocks then women, however, women who self-select into stock market participation invest the same portfolio share in stocks as do their male peers, independent of the society's degree of gender role differences (Barasinska & Schäfer, 2018). In a study of the stock allocation in defined contribution plans, married individuals were more likely to take on less risk than single households (Yilmazer & Lyons, 2010). Researchers have found a higher percentage of White households to own high return investments such as stocks, real estate, or private business assets as compared to Black and Hispanic households (Shin & Hanna, 2017). During the Great Financial Crisis of 2008, White households made smaller reductions to risky assets than Black and Hispanic households (Browning & Finke, 2015). In terms of education levels, higher education levels were negatively associated with allocating away from stocks during market volatility (Browning & Finke, 2015). In a study examining the impact of perceived health status on investment portfolio behavior, Bressan et al. (2014) found that only poor self-reported health as compared to objective health measures, had a negative effect on portfolio choice. Similarly, Atella et al. (2012) provided robust empirical evidence supporting the importance of perceived health status over objective health status in investment portfolio decisions. Their findings indicated that poor perceived health was associated with a decrease in equity allocations.

In terms of financial planning characteristics, those with higher liquid net worth were more likely to make no portfolio changes during the market volatility of COVID-19 (Menkhoff & Schröder, 2022). The authors also found young, educated, high income, risk tolerant investors to be net buyers during the pandemic. How closely someone follows the stock market was found to be positively associated with trading frequency during the pandemic (*How Memestocks Affected Investors' Actions And Emotions*, 2021). In a study of investor behavior as predicted by cognitive decline in older investors, Browning and Finke (2015) found that a higher proportion of liquid net worth allocated to stocks prior to market volatility was associated with a higher likelihood to allocate away from stocks during market volatility. These make important control variables in the proposed study of investor behavior during the pandemic.

Summary of Literature

This chapter provides a comprehensive overview of investor behavior during times of market volatility. It began with a discussion of rational models of expected investor behavior, followed by an examination of empirical evidence on actual investor behavior. This review emphasized the deviations from rationality observed in real-world behavior and shed light on the significant role played by psychological and cognitive factors in shaping investment decisions. The chapter then introduced the 3M Model (Mowen, 2000), which presents a hierarchical framework for understanding personality traits and their influence on behavior. It discussed elemental traits, compound traits, situational traits, and surface traits, emphasizing their relevance to investor behavior. Furthermore, the chapter explored subjective probability judgements such as stock market expectations, and highlighted the integration of this theory with the 3M Model to gain a comprehensive understanding of risk perception and its impact on investor behavior. Additionally, the chapter discussed the role of socio-demographic variables in influencing investor behavior.

While the existing literature has provided valuable insights into investor behavior during market volatility, there are gaps that this study aims to address. First, there is a need for further exploring the combined effect of the hierarchy of personality traits in comparison to the impact of cognitive ability on the perception of risk during times of market volatility, particularly in relation to rational models of expected behavior. Additionally, the structure of the relationship between personality traits, affect, and stock market expectations benefits from a more in-depth examination to better understand how these factors collectively influence investor behavior. By addressing these gaps, this study aims to contribute to a more comprehensive understanding of investor behavior.

Chapter 3 - Methodology

The primary objective of this dissertation is to investigate the factors that are associated with investment portfolio behavior during market volatility. Specifically, this research aims to gain an understanding of how stock market expectations and its determinants, with a particular emphasis on emotion and personality traits, influence individuals' investment decisions. By analyzing the structure between personality traits, mood, and stock market expectations, this study aims to provide an understanding of the factors that shape investor decision-making during market volatility.

To accomplish this goal, the study adopts a statistical method known as structural equation modeling (SEM), which allows for the simultaneous testing of multiple relationships and provides a comprehensive framework to analyze the proposed theoretical model, incorporating both latent and observed variables. The research is conceptualized by the structure of the 3M model of personality and motivation (Mowen, 2000), which provides a framework to analyze how personality traits influence investment behavior. By integrating these theories and leveraging SEM, this research seeks to understand the associations of personality traits, affect, and stock market outlook on investment behavior during a time of heightened uncertainty.

Dataset and Sample Selection

Data for this study were derived from the 2018 and 2020 waves of the Health and Retirement Study (HRS), a nationally representative data set sponsored by the National Institute on Aging (grant number NIA U01AG009740) and conducted by the University of Michigan. The RAND data file is a user-friendly longitudinal data set based on the Health and Retirement Study data and was developed at RAND with funding from the National Institute on Aging and the Social Security Administration. The HRS dataset offers comprehensive information on various aspects of individuals' health, retirement, and financial behavior, making it an ideal resource for investigating factors influencing investment decisions. The respondents of the survey are drawn from an older population, specifically those aged 50 and older.

To construct the variables of interest, responses from the 2020 RAND HRS Longitudinal data file was paired with investment portfolio data from the 2018 and 2020 HRS survey waves to calculate investment portfolio behavior (RAND HRS 2020 Longitudinal File 2020 (V1), 2023). Moreover, data on personality, cognition, and psychological responses were extracted from the 2018 and 2020 Leave-Behind Psychosocial and Lifestyle Questionnaire (LB), which is administered on a rotating basis to a subset of the HRS sample during each biennial cycle (Smith et al., 2017). The LB responses are used for constructing the latent variables representing key measures, such as Neuroticism, Conscientiousness, Numeracy, and Mental Status. The analytic sample was restricted to financial respondents for households with liquid financial assets greater than $0 in 2018 and 2020. Liquid financial assets encompass cash, cash equivalents, bonds, stocks, and mutual funds. The final analytic sample for the hierarchical regression comprised of 3,077 respondents aged 50 and older who met the liquid net worth criteria. The sample size of the structural model consisted of 4,329 respondents aged 50 and older.

The discrepancy in sample sizes between the hierarchical regression and the structural model can be attributed to the different data handling techniques employed in each analysis. For the hierarchical regression, listwise deletion was utilized in Stata. This method involves excluding any observation or participant with missing data on any of the variables included in the analysis. While this approach ensures that the analysis is based on complete cases, it can lead to a substantial reduction in sample size, especially if there's a considerable amount of missing data across different variables. As a result, the hierarchical regression had a reduced sample size of N = 3,077.

Conversely, the structural model employed Maximum Likelihood (ML) estimation to handle missing data. ML is a more flexible approach that uses all available data to estimate model parameters, even when some data points are missing. It does so by estimating the likelihood of observing the available data given the parameters and maximizes this likelihood to find the best-fitting model. This method allows for the inclusion of participants with partial data, leading to a larger sample size. Consequently, the structural model had a larger sample size of N = 4,329.

Variable Measurement

Outcome Variable: Stock Reallocation

The main investor behavior outcome of interest is stock reallocation (SR), serving as the surface trait. It is measured as the change of share of equity holdings, as a percentage of total liquid financial assets, between the respondent's 2018 and 2020 survey dates (see Table 3.1). For the purposes of this analysis, it does not differentiate between investments held in qualified and non-qualified accounts, but rather aggregates all liquid financial assets into the household's total investment portfolio. Investments held in stocks individually, in mutual funds, and in individual retirement accounts (IRAs) are aggregated as investments in stocks. The HRS collectively refers to investments in IRAs and Keogh accounts as IRAs.

The sample used in the analysis includes both the financial respondent and non-respondent individuals within the household. Since some households in the HRS have both partners participate in the survey, an adjustment was made to account for the non-independence of observations to prevent underestimation of variance estimates. Respondents who were unable to provide information on the percentage of their IRA invested in stocks were excluded from the stock reallocation sample, as the calculation of market adjustment could not be performed for these cases. Additionally, respondents without any financial assets were excluded from the model.

This study utilizes non-restricted data from the HRS, which provides information on the month and year of the survey completion rather than the specific date. The HRS 2018 wave was conducted between April 2018 and June 2019, with 70% of the surveys completed by October 2018. Similarly, a special COVID-19 HRS 2020 survey was conducted from February 2020 to May 2021, with 77% of surveys completed by October 2020. These time frames encompass two volatile periods in the U.S. stock market, including a significant decline of 13.5% in the S&P 500® during the fourth quarter of 2018 and a peak-to-trough decrease of 33.7% in the spring of 2020 upon the initial news of the COVID-19 pandemic (S&P Dow Jones Indices LLC, 2023). These market fluctuations highlight the relevance and timeliness of the dataset for examining investor behavior in the context of market volatility.

To account for the heterogeneous investment returns experienced by each household, between their specific survey dates, a three-step calculation was implemented. The three-step calculation process outlined here is essential for isolating allocation changes driven by individual choices, separate from asset class performance during the specific survey dates. Initially, by summing the stock values and calculating the nominal percent change, it establishes a basic understanding of allocation shifts. However, this initial step alone does not account for variations in asset class performance. The subsequent steps consider the specific performance of stocks, bonds, cash and cash equivalents during the survey period, ensuring that allocation changes accurately reflect both investor decisions and market dynamics. This approach enhances the precision of findings, allowing for a clear separation of changes influenced by individual choices from those due to asset class performance.

First the total value of stocks held by each respondent was summed for each survey date. The stock percentage is calculated by dividing the stock value by the sum of the respondent's total liquid assets, including cash, cash equivalents, and bonds. The nominal percent change in stock allocation was obtained by subtracting the stock percentage in 2018 from the stock percentage in 2020. This calculation enabled the assessment of the absolute change in stock allocation between the respondent's 2018 and 2020 survey dates.

In the second step of the calculation, an expected change in stock allocation is determined. The performance adjustment is implemented to account for allocation changes due to the performance of the underlying asset classes. Stocks, bonds, and cash do not generate the same annual return, and failing to account for this discrepancy would inaccurately attribute allocation changes solely to the investor rather than the investments themselves.

This step involves multiplying the value of the respondent's stocks in 2018 by the returns of the S&P 500 during the respondent's survey period. Similarly, the expected change calculation is done for the respondent's bond holdings using the returns of the Barclay's Aggregate Bond Index, and three-month CD rates for cash and cash equivalents. The analysis takes into consideration the specific survey dates. This is crucial because asset prices can exhibit significant fluctuations within a given year, as observed in 2018 and 2020. By accounting for the asset class performance during the respondent's survey dates, the analysis avoids assuming that all respondents earned identical asset returns during this period, thereby enhancing the precision of the findings. The 2020 expected stock percent is calculated by dividing the performance-adjusted value of stocks by the performance-adjusted bond and cash values. The expected percent change in stocks is the 2020 expected stock percent minus the 2018 stock percent.

In the final step, the stock reallocation variable is the nominal percent change in stocks minus the expected percent change. Reducing one's allocation in stocks is represented by a negative value and positive values indicate an increase in the percentage allocated to stocks. S&P 500 index performance was used as the proxy for stocks because is regarded as a gauge of the large cap U.S. equities market, including the 500 leading companies in leading industries of the U.S. economy, which are publicly held on either the NYSE or NASDAQ, and covers approximately 80% of the total US equity valuation (Standard and Poors, 2022). Movement in the S&P 500 is also used to predict shareholder sentiment in the market ("2021 Investment Company Fact Book", 2021). To estimate bond returns the Barclays Aggregate Bond Index was chosen because it includes most of the investment-grade bonds traded in the United States, including treasury securities, mortgage-backed bonds, and corporate bonds. Three-month CD rates were chosen because they represent a high return option on cash, while still providing liquidity. Savings rates between 2018 and 2020 were very similar to three-month CD rates; however, CD rates for the period were far more accessible and therefore used in this analysis.

Approximately two years passed between the 2018 and 2020 survey wave interview dates. Prior research nor empirical findings find justification for making allocation changes in a two-year time frame based purely on the passage of time. Allocation changes make sense for older investors that have had a change to their goals, objectives, risk profile, or life change, such as retirement. Those factors were accounted for in this analysis.

Table 3.1. Measurement of Stock Reallocation Investor Behavior (outcome variable)

Variable	Measurement

Stock Reallocation	Asset-class performance-adjusted change in stock allocation share from 2018 to 2020.

Elemental Traits: Big 5 Personality Traits

Elemental traits, which represent the fundamental components of personality, are operationalized using the Big Five personality traits (Costa & McRae, 1992): (a) Openness to experience, (b) Conscientiousness, (c) Extroversion, (d) Agreeableness, and (e) Neuroticism. To measure the Big Five traits, latent variables were constructed using indicators derived from a combination of data from the 2018 and 2020 Psychosocial and Lifestyle Questionnaire (Smith et al., 2017). The indicators for the Big Five traits were developed based on data from the Midlife in the United States (MIDUS) national survey and the International Personality Item Pool (IPIP) (*IPIP*, n.d.; Lachman & Weaver, 1997; Smith et al., 2017). Respondents rated 31 adjectives on a four-point Likert-type scale, ranging from 1 (a lot) to 4 (not at all), indicating the extent to which they felt each adjective described them. The original 26 items were drawn from MIDUS (Lachman & Weaver, 1997). In 2010, 5 items from IPIP were added to expand coverage of sub-facets of conscientiousness. Higher scores on the adjective ratings generally indicated stronger identification with each adjective, except for the specific items that were not reverse coded, where higher scores meant less identification with those adjectives. Measurement of the elemental traits used in this study is summarized in Table 3.2 below.

Table 3.2. Measurement of Elemental Traits

Variables	Measurement
Openness	Latent variable with 7 ordinal Likert-type indicators measured separately on a 4-point scale with higher scores representing stronger presence of the openness to experience trait.
Conscientiousness	

	Latent variable with 10 ordinal Likert-type indicators measured separately on a 4-point scale, with higher scores representing a stronger presence of the conscientiousness trait.
Extraversion	Latent variable with 5 ordinal Likert-type indicators measured separately on a 4-point scale with higher scores representing stronger presence of the extroversion trait.
Agreeableness	Latent variable with 5 ordinal Likert-type indicators measured separately on a 4-point scale with higher scores representing stronger presence of the agreeableness trait.
Neuroticism	Latent variable with 4 ordinal Likert-type indicators measured separately on a 4-point scale with higher scores representing stronger presence of the neuroticism trait.

Openness to experience was measured as a latent variable with the following seven adjectives: creative, imaginative, intelligent, curious, broad-minded, sophisticated, and adventurous. Conscientiousness was measured as a latent variable with the following ten adjectives serving as indicators: reckless, careless, impulsive, organized, responsible, hardworking, self-disciplined, cautious, thorough, and thrifty. Reponses to reckless, careless, and impulsive were reverse-coded their original coding, while the other seven indicators retained their original scale so that all sub-facets oriented towards low conscientiousness. Extroversion was measured as a latent variable with the following five adjectives serving as indicators: outgoing, friendly, lively, active, and talkative. Agreeableness was measured as a latent variable with the following five adjectives serving as indicators: helpful, warm, caring, softhearted, and sympathetic. Neuroticism was measured as a latent variable consisting of four sub-facet indicators: moody, worrying, nervous, and calm. Calm was reverse coded so that scores indicated greater identification with a greater presence of the neuroticism trait. Each indicator is measured on a 4-point Likert-type scale based upon the extent to which the respondents felt the adjectives described them; higher scores reflected greater identification with the sub-facet.

Responses for each adjective were included within the model as ordinal indicator variables estimating each separate personality trait construct. Within the current sample, each elemental personality trait demonstrated adequate internal reliability, illustrated in Table 3.3, with Cronbach's Alpha scores ranging from 0.70 for neuroticism to 0.80 for openness to experience (Taber, 2018).

Table 3.3 Cronbach's Alphas for Big 5 Personality Trait Scales

Big 5 Personality Trait	Items	Cronbach's α	*M*	*S.D.*	Min.	Max.
Openness to Exp.	7	0.80	2.93	0.58	1	4
Conscientiousness	10	0.72	3.26	0.41	1	4
Extraversion	5	0.76	3.23	.54	1	4
Agreeableness	5	0.79	3.49	.51	1	4
Neuroticism	4	.70	1.98	0.61	1	4

Compound Trait: Positive and Negative Affect

Informed by prior literature and the 3M model, this study focused on the compound traits positive affect and negative affect. To capture this compound trait, indicators were derived from the 2018 and 2020 Psychosocial and Lifestyle Questionnaire (Smith et al., 2017) and used to construct the latent variable representing positive and negative affect. These scales assess positive and negative dimensions of emotional (hedonic) well-being. The 2006 HRS questionnaire used a measure of positive and negative affect derived from MIDUS (Mroczek & Kolarz, 1998). Beginning in 2008, most of the 25 items to assess positive and negative affect were chosen from the Positive and negative Affect Schedule – Expanded Form (PANAS-X) (Watson & Clark, 1994). Some items were obtained from the work of other researchers in this area of study (Carstensen et al., 2000; Ong et al., 2006).

Table 3.4 Measurement of Compound Trait

Variable	Measurement
Positive affect	Latent variable with 13 Likert-type indicators measured separately on a 5-point scale with higher scores representing higher levels of positive affect.
Negative affect	Latent variable with 12 Likert-type indicators measured separately on a 5-point scale with higher scores representing higher levels of negative affect.

In this study, participants used a five-point Likert scale to indicate how strongly they felt specific emotions in the past 30 days. The scale ranged from 1 (very much) to 5 (not at all). For positive affect, respondents reported the extent to which they felt determined, enthusiastic, active, proud, interested, happy, attentive, content, inspired, hopeful, alert, calm, and excited. For negative affect, respondents reported the extent to which they felt afraid, upset, guilty, scared, frustrated, bored, hostile, jittery, ashamed, nervous, sad, and distressed. All responses were reverse coded, with higher scores indicating more intense levels of affect. If more than six items were missing for each affect construct, those observations were list-wise deleted. Each emotion's responses were incorporated into the model as ordinal indicators, estimating the distinct positive and negative affect constructs. In this sample, both positive and negative affect constructs exhibited strong internal reliability as illustrated in Table 3.5, with Cronbach's Alpha scores of .93 and .90, respectively (Carmines, 1979).

Table 3.5 Cronbach's Alpha for Positive Affect and Negative Affect

Scale	Items	Cronbach's α	*M*	*S.D.*	Min.	Max.
Positive Affect	13	0.93	3.02	0.61	1	5
Negative Affect	12	0.90	3.27	0.49	1	5

Situational Trait: Stock Market Expectations

Stock market expectation is operationalized in this study using a subjective probability judgment question that asks respondents to estimate the percent chance that mutual fund shares invested in blue-chip stocks will increase in value over the next year, as detailed in Table 3.4. Specifically, respondents provide a percentage ranging from 0 to 100 reflecting their perceived likelihood that stock values will rise over the following 12 months. Higher values indicate greater optimism and positive expectations regarding future stock market performance. This aligns with the conceptualization of subjective probability judgments as reflecting individuals' perceptions of the likelihood of uncertain outcomes (Tversky & Fox, 1995; Tversky & Kahneman, 1974). By eliciting respondents' percent chance judgments about market performance, this measure provides insights into subjective outlooks and expectations that shape investment behaviors, following the approach taken by Hudomiet et al. (2011).

Table 3.6. Measurement of Stock Market Expectation

Variable	Measurement
Market Expectation	Observed continuous variable ranging from 0 – 100. Higher values indicate more optimism in the stock market in the following year.

Confirmatory Factor Analysis

Confirmatory factor analyses (CFA) were performed on latent variables representing seven constructs in the model: each of the Big 5 traits, positive affect, and negative affect. In the process of evaluating the confirmatory factor analyses (CFAs), several steps were undertaken to ensure the best model fit. Initially, the measurement models were tested based on the theoretical underpinnings, without allowing any factors to covary. The fit of these models was assessed using a combination of fit indices, including chi-square, RMSEA, SRMR, CFI, and TLI. If the initial model did not demonstrate an acceptable fit, modifications were considered. One common approach to improve model fit was to allow factors to covary, especially if there was a theoretical justification or if modification indices suggested a significant improvement in fit by doing so. However, any modifications made to the model were done judiciously, ensuring that they were not only statistically justified but also theoretically meaningful. After each modification, the model was re-evaluated to determine if the fit had improved. The final models were those that provided the best balance between statistical fit, theoretical coherence, and parsimony.

Confirmatory factor analysis of Big Five traits

The Big Five personality traits, often referred to as the 'Five Factor Model,' represent broad domains of personality that have been extensively researched and validated in various populations. Each trait is believed to encompass a range of related but distinct facets or sub-traits. In this study, CFAs were conducted for each of the Big Five traits to validate their structure in the context of the current sample and to ensure that the indicators used for each trait provided a coherent and reliable measure of the underlying construct. Table 3.7 illustrates the model fit statistics for each of the personality trait CFAs.

Openness to experience. The seven indicators for openness were chosen *a priori* using the following adjectives: creative, imaginative, intelligent, curious, broad-minded, sophisticated, and adventurous. The covariance of *creative* and *imaginative* were allowed to covary, as well as the covariance of *sophisticated* and *adventurous* indicating interrelatedness. Factor loadings ranged from .47 to .79 and all were significant with $p < 0.001$. The modified CFA had a good fit ($\chi 2$ [12] = 355.10, $p < .001$; *RMSEA* = .07; *SRMR* = .03; *CFI* = 0.97; *TLI* = 0.95) and were within the ranges suggested by Kline (2016).

Conscientiousness. The factors of conscientiousness were chosen *a priori* using ten adjectives: not reckless, not careless, not impulsive, organized, responsible, hardworking, self-disciplined, cautious, thorough, and thrifty. During the CFA process, the indicators of not reckless, not careless, and not impulsive, were eliminated from this construct due to low factor loadings. Factor loadings for the remaining indicators ranged from 0.33 to 0.64. The variances of two pairs of variables were allowed to covary with each other, which indicates a strong interrelationship between being thrifty and thorough and being thrifty and cautious. All loadings were significant with $p < .001$. The CFA model fit was good ($\chi 2$ [12] = 128.043, $p < .001$; *RMSEA* = .04; *SRMR* = .02; *CFI* = 0.98; *TLI* = 0.97). All fit statistics are within the ranges suggested by Kline (2016).

Extraversion. Extroversion was measured as a latent variable with the following five adjectives serving as indicators: outgoing, friendly, lively, active, and talkative. The variance of being active was allowed to covary with being outgoing and also talkative, and the variance of being outgoing was allowed to covary with being talkative. This indicates an interrelatedness of the subfactors of extraversion. Factor loadings ranged from 0.47 to 0.68 and all were significant at $p < 0.001$. CFA model fit was good ($\chi 2$ [2] = 17.901, $p < 0.001$; *RMSEA* = .037; *SRMR* = .008; *CFI* = 0.998; *TLI* = 0.988). All fit statistics were within ranges suggested by Kline (2016).

Agreeableness. Agreeableness was measured as a latent variable with the following five adjectives serving as indicators: helpful, warm, caring, softhearted, and sympathetic. The variance of being softhearted was allowed to covary with being sympathetic, indicating an interrelated relationship of subfactors. Factor loadings ranged from .55 to .77. All factor loadings were significant at $p <0.001$. CFA model fit was good ($\chi 2$ [4] = 4.339, $p < 0.001$; *RMSEA* = .004; *SRMR* = .004; *CFI* = 0.999; *TLI* = 0.999). All fit statistics were within ranges suggested by Kline (2016).

Neuroticism. Neuroticism consists of four sub-facets: moody, worrying, nervous, and calm. Calm was reverse coded so that scores indicated greater identification with high neuroticism. The variance of worrying was allowed to vary with the covariance of being nervous. Factor loadings ranged from .33 for worrying to .85 for not calm and were significant with $p <$ .001. The CFA model fit was good ($\chi 2$ [1] = 7.442, p = .006; *RMSEA* = .03; *SRMR* = .01; *CFI* = 0.99; *TLI* = 0.99). All fit statistics are within the ranges suggested by Kline (2016).

Table 3.7 CFA Model Fit Statistics of Big Five Personality Traits

Big Five CFAs	$\chi 2$ [df]	*p*	RMSEA	CFI	TLI	SRMR
Openness	355.10 [12]	<0.001	0.069	0.970	0.948	0.028
Conscientiousness	128.13 [12]	<0.001	0.041	0.984	0.972	0.017
Extraversion	17.90 [2]	<0.001	0.037	0.990	0.988	0.008
Agreeableness	4.34 [4]	<0.001	0.004	0.990	0.990	0.004
Neuroticism	7.37 [1]	<0.001	0.034	0.990	0.991	0.005

Confirmatory factor analysis of positive and negative affect

Positive and Negative Affect represent two fundamental dimensions of emotional experience that capture an individual's propensity to experience positive or negative emotions, respectively. Often conceptualized within the framework of the Positive and Negative Affect Schedule (PANAS), with the subfactors chosen *a priori* based on validated instruments in the HRS, these dimensions have been rigorously examined across diverse populations and settings. In the present study, CFAs were executed for both Positive and Negative Affect to validate their structure within the context of the sampled population. This was essential to ensure that the indicators chosen for each dimension offered a consistent and reliable reflection of the underlying emotional construct. Table 3.8 illustrates model fit statistics for each of the CFAs.

Positive Affect. The thirteen subfactors of positive affect were determined, enthusiastic, active, proud, interested, happy, attentive, content, inspired, hopeful, alert, calm, and excited. The variances of several pairs of variables were allowed to covary with each other, which indicates a strong interrelationship between the subfactors of feeling positive emotion. This variance indicates the nuance in what each sub-emotion is attempting to measure, as the instrument approaches positive emotions from multiple angles. Factor loadings ranged from 0.61 to 0.78 and were all significant at p <0.001. CFA model fit was good ($\chi 2$ [31] = 80.428, p < .001; *RMSEA* = .017; *SRMR* = .007; *CFI* = 0.999; *TLI* = 0.997). All fit statistics were within the ranges suggested by Kline (2016).

Negative Affect. The twelve subfactors of negative affect were feeling afraid, upset, guilty, scared, frustrated, bored, hostile, jittery, ashamed, nervous, sad, and distressed. The variances of several pairs of variables were allowed to covary with each other, which indicates a strong interrelationship among the subfactors feeling negative emotion. This variance indicates the nuance in what each sub-emotion is attempting to measure, as the instrument approaches negative emotions from multiple angles. Factor loadings ranged from 0.52 to 0.73, and were all significant at p <0.001. CFA model fit was good ($\chi 2$ [28] = 67.536, p < .001; *RMSEA* = .016; *SRMR* = .007; *CFI* = 0.990; *TLI* = 0.997). All fit statistics were within the ranges suggested by Kline (2016).

Table 3.8 CFA Model Fit Statistics of Positive and Negative Affect

Affect CFAs	$\chi 2$ [df]	*p*	RMSEA	CFI	TLI	SRMR
Positive Affect	80.428 [31]	<0.001	0.017	0.999	0.997	0.007
Negative Affect	67.536 [28]	<0.001	0.016	0.990	0.997	0.007

Socio-Demographic, Cognitive, and Financial Control Variables

The socio-demographic, cognitive, and financial characteristics included in this study were derived from relevant literature on investor behavior. These variables were incorporated into the model as control variables, allowing for the examination of their potential influence on the relationships under investigation. To provide a comprehensive overview of the measurement of these variables, a detailed summary is presented in Table 3.5.

Table 3.9. Measurement of Control Variables

Variable	Measurement
Age	Continuous variable ranging from age 50 to 104 in 2018.
Gender	0 for female; 1 for male.
Marital Status	1 for coupled household; otherwise, 0 in 2018.
Race	0 if respondent reported being White; 1 for Black, 2 for other.
Education	1 if respondent reported some college level education or beyond; otherwise, 0 in 2018.
Employment Status	1 if respondent is working for pay; 0 if not in 2018.
Health Status	Continuous variable ranging from 1 to 5; self-rated in 2018.
Numeracy Scale	Continuous variable ranging from 0 to 3; count of correct responses.
Mental Status Scale	Continuous variable ranging from 0 to 8; count of correct responses.
Net Worth	Inverse hyperbolic sine transformation liquid net worth in 2018.
Time Horizon	0 if financial planning time horizon is less a few months to less than 5 years. 1 if the financial planning time horizon is 5 years or greater in 2018.
Follow Market	1 if respondent follows the stock market not at all; 2 for somewhat closely; 3 for very closely in 2018.
Risk Share	Percent of liquid financial assets allocated to stocks in 2018.
Sentiment	1 if 2020 wave response date was March or April 2020, else 0.

Socio-Demographic. The controls were included to capture lifecycle and demographic effects on stock holdings. Control variables used in the structural equation model include age, gender (male/female), household marital status (coupled/not coupled), race (White/Black/Other), education (less than college/college and higher), employment status (working for pay/not), and self-assessed health status (1 = poor to 5 = excellent). All socio-demographic variables were obtained from the 2020 RAND HRS longitudinal data file (RAND HRS Longitudinal File 2020 (V1), 2023).

Cognitive Ability. Two scales were used, one for numeracy and one for mental status. The selection of these indicators is guided by the literature on intelligence and cognition in aging, as well as the understanding that cognitive impairment often manifests initially through difficulties in learning and memory (Ashford et al., 1989; Masur et al., 1994; Welsh et al., 1992). These measures were adapted for use in the HRS from the TICS (Brandt et al., 1988) which was modeled after the Mini-Mental State Exam (Folstein et al., 1983) for use over the telephone. The eight subfactors were rescaled to put the items on a 0 to 1 scale.

Numeracy measures an individual's ability to understand and apply numerical skills in everyday life. Since investing requires mathematical skills, this study of older investors retains this important control variable. The three questions require the respond to apply math skills of probability ("If the chance of getting a disease is 10 percent, how many people out of 1,000 would be expected to get the disease?") and division ("If 5 people all have the winning numbers in the lottery and the prize is two million dollars, how much will each of them get?"). The third numeracy question asked respondents to apply compound interest on a savings account. The mental status scale consists of eight subscale items: immediate recall, delayed recall, one question each for the day, month, year, and day of the week, and a question asking the name of the vice president and president of the United States. If the subscale item is responded to correctly, it is coded as 1, otherwise 0. Since the immediate and delayed recall questions are the number of correct responses from a list of ten words, the number is divided by 10 to put it on a 0 to 1 scale, giving it an equal weighting in the scale as the other six items. The variables were coded 1 if respondent provided the correct answer, 0 if incorrect or "don't know." Respondents who refused to answer any given item were assigned a missing value. Table 3.8 illustrates the internal consistency of the two cognitive scales.

Table 3.10 Cronbach's Alpha for Positive Affect and Negative Affect

Scale	Items	Cronbach's α	*M*	*S.D.*	Min.	Max.
Mental Status	8	0.76	.75	0.16	0	1
Numeracy	3	0.68	1.40	1.11	0	3

Financial Planning. Financial planning specific characteristics were included to control for stock reallocation behavior. For liquid net worth, the inverse hyperbolic sine transformation of net worth was used to address issues related to the distributional properties of the net worth variable. Net worth data often exhibit skewness, potentially violating the assumption of normality required by the statistical model (Burbidge et al., 1988). A measure of financial planning time horizon is employed to account for variations in individuals' perspectives on their financial goals and planning horizons. A measure of stock market monitoring is used to capture the extent to which respondents track and follow the stock market. To account for variations in stock allocation, the percentage of liquid net worth allocated to stocks was included as a control variable. This approach aligns with previous research methods that have examined changes in allocation based on a predetermined starting equity percentage (Browning & Finke, 2015). A dummy variable was created where respondents interviewed in March and April 2020 were coded as 1 and those interviewed before March or after April 2020 were coded 0. This is done to capture the effect of the highly publicized market volatility of March and April 2020 on the stock reallocation decisions of older investors. The expected relationship between all model variables and investor behavior is provided in Table 3.11. A positive effect means that it would be positively associated with increasing allocation to stocks from 2018 to 2020.

Table 3.11. Expected Relationship between Model Variables and Investor Behavior (outcome variable)

Variable	Expected Effect
Elemental Traits	
Openness to Experience	+
Conscientiousness	+
Extraversion	+
Agreeableness	+
Neuroticism	–
Compound Trait	
Positive Affect	+
Negative Affect	–
Situational Trait	
Stock Market Outlook	+
Control Variables	
Age	–
Male Gender (females)	+
Married (unmarried)	+
White Race (Black or Other)	+
College education (less than college)	+
Employed (not employed)	+

Self-reported health status	+
Numeracy scale	+
Mental status scale	+
Inv. Hyp. Sine Transform Net Worth	+
Time Horizon	+
Follow Market	–
Risk Share	+
Market Sentiment	–

Data Analysis

In figure 3.1 the theoretical model is shown representing the key constructs of the 3M Model (Mowen, 200). The key constructs of the hierarchy of personality traits are elemental traits, compound traits, situational traits, and surface traits. Elemental traits serve as the foundational building blocks of personality, capturing broad dimensions that underlie individual differences in behavior and motivation. Compound traits are derived from these elemental traits, representing more complex combinations of personality characteristics. Situational traits emerge from the interplay between elemental and compound traits, reflecting behavioral predispositions in specific contexts. Lastly, surface traits are observable behaviors or tendencies that result from the interactions of the other three levels of traits.

In analyzing the Health and Retirement Study (HRS) data in Stata, the vce (cluster hhid) command was utilized to account for intra-household correlations. The HRS often includes multiple respondents from the same household, leading to potential similarities in their responses due to shared environments or experiences. By employing *vce (cluster hhid)*, the analysis adjusts for these correlations, providing cluster-robust standard errors. This adjustment helps to ensure that the standard errors are more accurate, recognizing the potential non-independence of observations within households, and thereby yielding more reliable regression results.

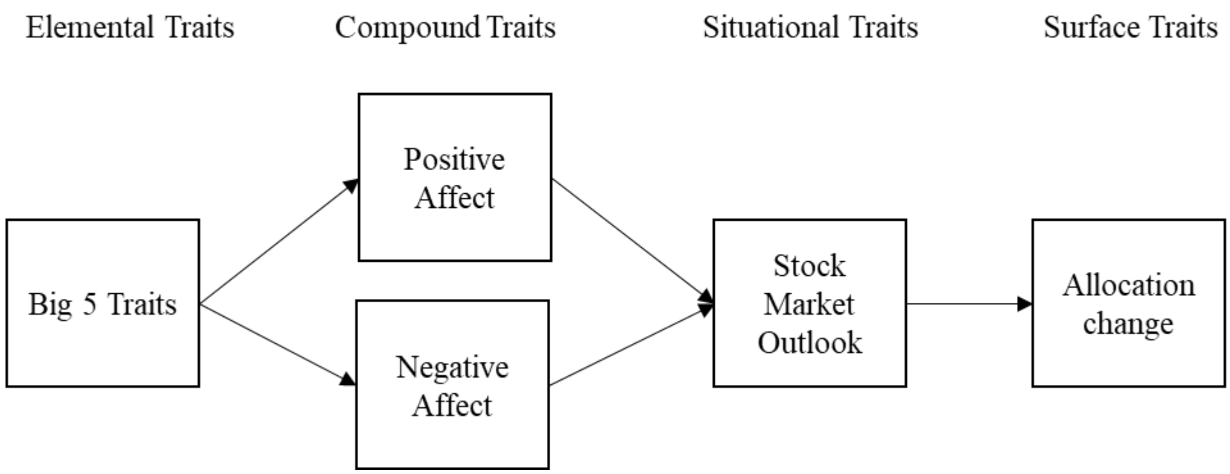
Analysis Structure

Initial variable coding was completed using Stata 17. The comparison of the hierarchical blocks was tested using OLS regression in Stata 17. Since this study uses structural equation modeling, Mplus 8.9 (Muthén & Muthén, 2017) was used to conduct the path analysis for the structural model. Confirmatory Factor Analysis (CFA) was first completed to analyze the factor structure of each latent variable. Each latent variable of the Big 5 as well as positive affect and negative affect were analyzed. Next, the structural model was analyzed that contained each of the Big Five personality traits, serving as elemental traits, and positive affect and negative affect serving as compound traits. Last, the full structural model as analyzed.

During the data analysis phase, the measurement model was assessed using confirmatory factor analysis (CFA) to ensure the constructs' validity and reliability. The fit of the model to the data was evaluated using several fit indices. According to Kline (2016), the chi-square statistic ideally should be non-significant, indicating a good model fit. However, due to its sensitivity to sample size, it often results in model rejection in large samples. Therefore, other fit indices were weighed more heavily. The Root Mean Square Error of Approximation (RMSEA) was expected to be less than 0.08 for an acceptable fit and ideally less than 0.05 for a good fit. The Standardized Root Mean Square Residual (SRMR) was anticipated to be less than 0.08. The Comparative Fit Index (CFI) and the Tucker-Lewis Index (TLI) were both expected to be greater than 0.90 for an acceptable fit, with values greater than 0.95 indicating a good fit. After a wellfitting measurement model was established, the structural model was tested to examine the relationships between the constructs as hypothesized.

Missing data was addressed using Maximum Likelihood (FIML) estimation in Mplus. This analytical method treats all the variables, including latent variables, as continuous (Muthén and Muthén, 2017). Under ML, missing data is handled using listwise deletion for any cases with missing observations. This resulted in not including 14,067 cases in the analysis from an initial data set of 17,144 survey respondents, largely due to the limited respondents with financial assets that also answered the Leave-Behind Psychosocial survey, which was expected. This left a sample size of 3,044. The covariance coverage of the data ranged from 0.20 to 1.0.

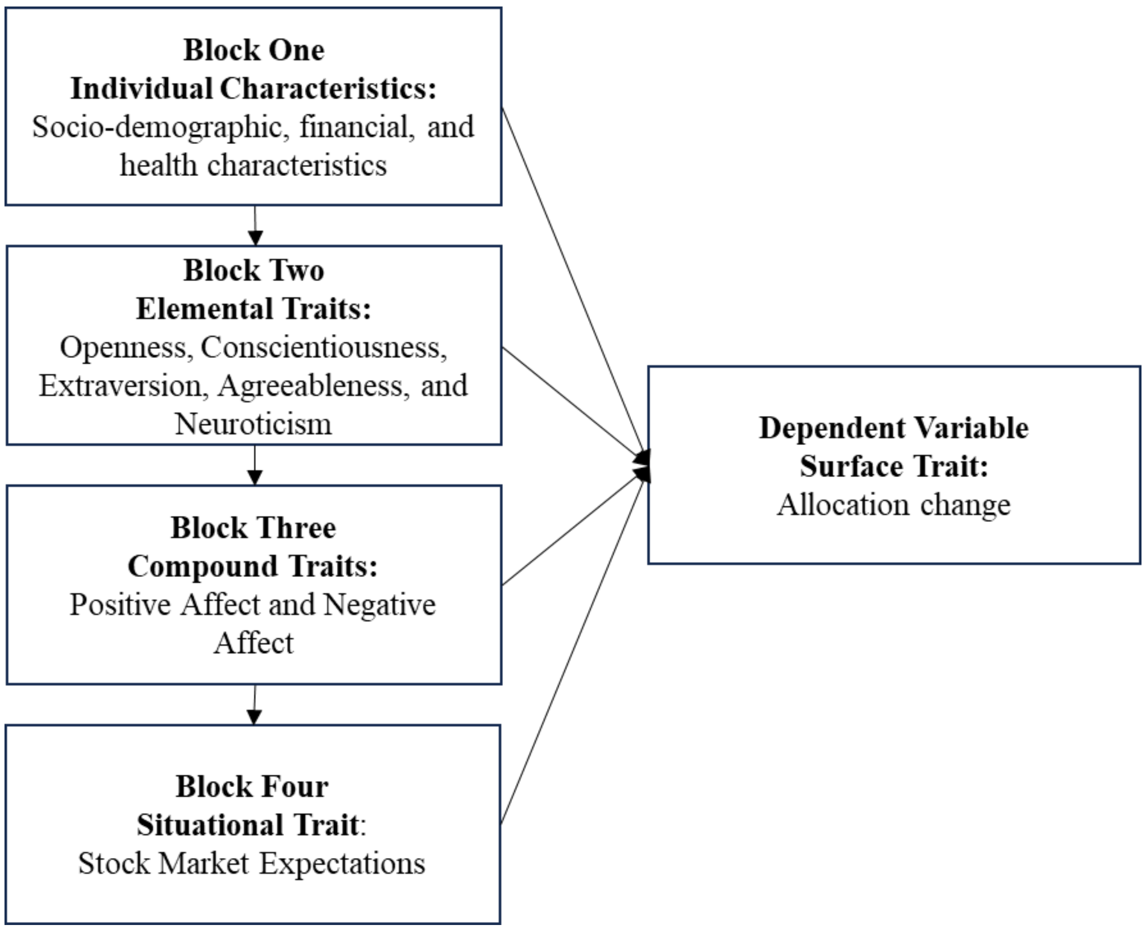
Figure 3.1 Theoretical model based on adaption of Mowen's 3M model (2000)



Hypotheses

The hierarchical structure of the 3M provides an integrated framework for investing stock reallocation behavior during market volatility. According to the 3M, stock reallocation is a surface trait, serving as the dependent variable. Block one represents control variables informed by existing literature to provide a foundation for the hierarchical model, which includes basic socio-demographic, physical and cognitive health, and financial characteristics. Block two variables adds the elemental traits of openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism from the Big Five personality traits (Costa & McCrae, 1992). Block three adds positive affect and negative affect to model. Lastly, block four adds the situational trait of stock market expectations to the model.

Figure 3.2 Empirical Model of Stock Reallocation, according to the 3M (Mowen, 2000)



According to 3M, each block should increase the explanatory power of the model above and beyond that of the previous blocks. The analysis involved assessing the incremental variance explained by each model by examining the changes in R-square values. Therefore, the following hypotheses are explored:

H1: Elemental traits (i.e., Big 5 personality traits) add explanatory power to the model investigating stock reallocation behavior.

H2: Positive and negative affect adds explanatory power to the model investigating stock reallocation behavior.

H3: Stock market expectations add explanatory power to the model investigating stock reallocation behavior.

In accordance with the 3M, psychological characteristics at each level of the hierarchy combine to influence behavior. Also, the 3M posits that each of the main constructs may exhibit a significant direct effect with investor behavior. Prior literature indicated that personality traits, such as the Big 5 are associated with investment risk-taking behavior. Moreover, emotions (i.e., positive affect, and negative affect) have been found to be associated with financial behavior. Lastly, a more bullish market outlook has been found to be positively associated with increasing risk. Therefore, the following additional hypotheses representing the main constructs of 3M are explored:

Elemental Traits

H4: Openness to experience is positively associated with an increase in stock allocation.

H5: Conscientiousness is positively associated with an increase in stock allocation.

H6: Extraversion is positively associated with an increase in stock allocation.

H7: Agreeableness is positively associated with an increase in stock allocation.

H8: Neuroticism is negatively associated with an increase in stock allocation.

Compound Traits

H9: Positive affect is positively associated with an increase in stock allocation.

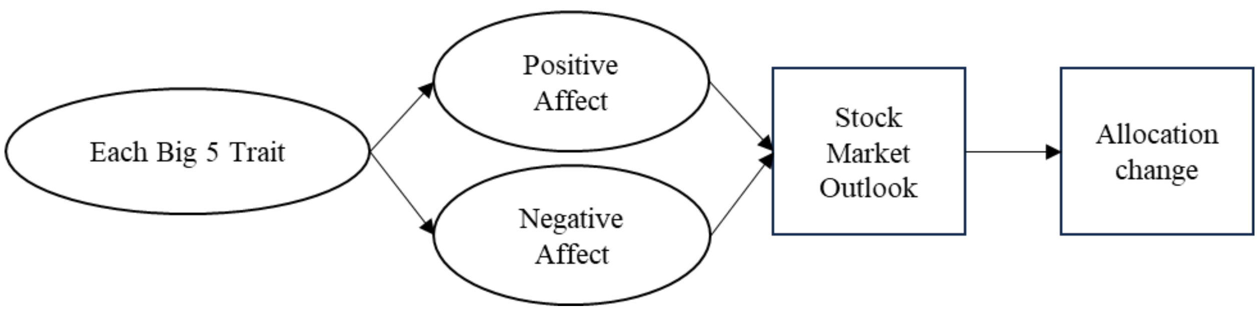
H10: Negative affect is negatively associated with an increase in stock allocation.

Situational Traits

H11: Stock market outlook is positively associated with an increase in stock allocation.

The purpose of this study is to investigate the relationship between older investor's psychological characteristics and investing behavior during a time of market volatility, according to the 3M (Mowen, 2000). Structural equation model will be used to constrain direct paths and direct effects. The theory posits a direct effect from one trait level to the next, such that elemental traits have a direct effect on compound traits, compound traits and cognitive ability have a direct effect on situational traits, and situational traits have a direct effect on the surface trait. The analytical structural model is shown in Figure 3.3. Elemental traits will be represented by the Big 5 personality traits; positive affect and negative affect are the compound trait; stock market expectation represents the situational trait; and the outcome variable of interest is the surface trait allocation change.

Figure 3.3 Structural Model for Stock Reallocation, according to the 3M (Mowen, 2000)



The data analysis process followed a structured approach to enhance the robustness and validity of the findings. The theoretical underpinnings of the 3M Model provided a comprehensive framework to understand the hierarchical structure of personality traits and their influence on investment behavior. By employing advanced statistical techniques, such as structural equation modeling in Mplus, the study aimed to capture the intricate relationships between the constructs. The use of confirmatory factor analysis aimed to measure the latent variables accurately and reliably. Furthermore, the handling of missing data using Maximum Likelihood (ML) aimed to reduce potential biases and maintain the power of the analyses. The subsequent sections will review the findings and results in the context of the stated hypotheses, with the goal of offering insights into the relationship of psychological characteristics and investment behaviors during market volatility.

Chapter 4 - Findings and Results

The core objective of this dissertation was to understand the relationship between older investors' psychological characteristics and their investment behaviors during periods of market volatility. Drawing from the foundational principles of the 3M Model (Mowen, 2000), this research aimed to understand how varying levels of personality traits, from elemental to situational, influence investment decisions, particularly in the context of stock allocation. By employing a combination of statistical techniques, including hierarchical regression and structural equation modeling, this study sought to provide an understanding of the psychological factors associated with portfolio risk adjustments during market volatility. This chapter presents the findings and results derived from the analyses, addressing the hypotheses posited in the previous chapters.

This chapter outlines the results of the analyses. It starts by reviewing the demographic characteristics of the analytic group. Following this, the outcomes of the hierarchical regression are discussed, highlighting the role each block plays in explaining investor behavior. The chapter then examines the measurement model fit before moving on to the structural model. The results of the structural model are then provided, offering insights into the associations between psychological traits and investment decisions. The chapter concludes with a summary of the analyses, relating them to the hypotheses and expectations.

Demographic characteristics of the sample

An overview of the sample characteristics is presented in Tables 4.1 and 4.2. The analytic sample for the hierarchical regressions comprised of 3,077 observations, which, when weighted according to the guidelines provided in the Health and Retirement Study (HRS) documentation, correspond to an estimated 6.4 million U.S. households with individuals aged 50 and older. Given the oversampling techniques utilized in the HRS, weighted percentages are reported to ensure accurate representation.

The gender distribution is 59.88% females (n= 1,844) and 40.12% males (n= 1,233). In terms of household marital status, 53.07% (n= 1,633) were in a coupled relationship, while 46.93% (n= 1,444) were single. Most of the sample identified as White (87.99%, n= 2,707), followed by Black (8.09%, n= 249), and other racial categories (3.92%, n= 121). When considering educational attainment, 64.14% (n= 1,973) of the participants had achieved a college degree or higher, while 35.86% (n= 1,104) had less than a college education. The employment status revealed that a significant portion of the sample, 80.32% (n= 2,470), were retired, while 19.68% (n= 607) were actively employed, which is consistent with expectations of this age group. In terms of financial planning, 53.15% (n= 1,636) had a time horizon of less than 5 years, and 46.85% (n= 1,441) planned for 5 years or longer. Regarding engagement with the stock market, 41.99% (n= 1,292) of the participants did not follow it at all, 47.20% (n= 1,452) followed it somewhat closely, and a smaller segment, 10.82% (n= 333), followed it very closely.

Table 4.1 Sample Characteristics of Categorical Variables (*N*= 3,077)

Variable	n	% (weighted)
Gender		
Female	1,844	59.88%
Male	1,233	40.12%

Household marital status		
Couple	1,633	53.07%
Single	1,444	46.93%
Race		
White	2,707	87.99%
Black	249	8.09%
Other	121	3.92%
Education		
Less than college	1,104	35.86%
College or higher	1,973	64.14%
Employment status		
Working for payment	607	19.68%
Not working for payment	2,470	80.32%
Financial planning time horizon		
Less than 5 years	1,636	53.15%
5 years or longer	1,441	46.85%
Follow stock market		
Not at all	1,292	41.99%
Somewhat closely	1,452	47.20%
Very closely	333	10.82%

Table 4.2 Sample Characteristics of Scales and Continuous Variables (*N* = 3,077)

Variable	*M*	*SD*	Min	Max	Cronbach's Alpha
Dependent Variable					
Stock allocation change	-9.30%	0.35	-1	1	-
Control Variables					
Age	74.74	7.02	50	97	-
Numeracy Scale	1.8	1.03	0	3	0.67
Self-report of health	3.39	0.93	1	5	-
Mental status scale	0.83	0.09	0	1	0.76
Liquid net worth*	542,217	1,990,018	0	117,652,000	-
Stock allocation (2018)	32.69%	36.00%	0	1	-
Elemental Traits					
Openness	2.97	0.53	1	4	0.8
Conscientiousness	3.32	0.38	1	4	0.72
Extroversion	3.22	0.54	1	4	0.76
Agreeableness	3.52	0.48	1	4	0.79
Neuroticism	1.88	0.58	1	4	0.7

Compound Traits					
Positive affect	3.64	0.02	1	5	0.93
Negative affect	1.79	0.02	1	5	0.90
Situational Traits					
Stock market expectation	49.68	25.26	0	100	-

*Inverse hyperbolic sine transformation of liquid net worth includes stocks, bonds, cash in qualified and non-qualified accounts was used in the regression. Liquid net worth reported in this table.

Further examination of the continuous variables revealed that the average age of participants was 74.74 years, with a range from 50 to 97 years. Their numeracy skills, gauged on a scale from 0 to 3, had a mean score of 1.8, with Cronbach's alpha of 0.67. Participants' self-reported health, assessed on a scale from 1 to 5, averaged at 3.39. The mental status scale, which spanned from 0 to 1, had a mean of 0.83 and Cronbach's alpha of 0.76. The liquid net worth of participants averaged $542,217, with values ranging from 0 to $117M. In 2018, participants' mean stock allocation stood at 32.69%, with allocations spanning from 0% to 100%.

The elemental and compound trait scales indicated a stronger presence of psychological attributes across the sample, shown in Table 4.2. On a one to four scale, respondents generally felt that the elemental personality characteristics of openness to experience (M= 2.97), conscientiousness (M = 3.32), extroversion (M = 3.22), and agreeableness (M = 3.52) described them. Compound traits showed an average score of 3.64 for positive affect and 1.79 for negative affect, both on a scale from 1 to 5. The situational trait, stock market expectation, had an average score of 49.68, with values ranging from 0 to 100, indicating a neutral market outlook.

Hierarchical Regression Results

The findings from the four-block hierarchical regression model are shown in Table 4.3. The results provide significant evidence of an association of elemental, compound, and situational psychological traits to stock reallocation behavior during market volatility, as conceptualized within the framework of the 3M Model (Mowen, 2000).

Table 4.3 Hierarchical Regression of Stock Allocation Changes of Older US Adults (*N* = 3,077)

	Block 1		Block 2		Block 3		Block 4	
Variable	*b*	*SE*	*b*	*SE*	*b*	*SE*	*b*	*SE*
Socio-demographics								
Age (2018)	.002***	-0.002	.002***	-0.002	.002***	-0.002	.002***	-0.001
Gender (Female)	-0.002	0.012	-0.015	0.013	-0.011	0.013	-0.017	0.013
Marital Status (Not coupled)	-0.005	0.017	-0.001	-0.022	-0.007	-0.022	-0.005	-0.012
Race (White)								
Black	-0.024	0.177	-0.022	0.018	-0.021	0.018	-0.013	0.018
Other	-0.032	.0215	-0.033	0.022	-0.033	0.022	-0.026	0.022
Education (Less than HS)	0.021	0.012	0.020	0.012	0.020	0.013	0.018	0.012
Employed	0.019	0.014	0.019	0.014	0.020	0.014	0.018	0.014
Liquid net worth	.002***	0.001	.003***	0.001	.003***	0.001	.002***	0.001
Self-reported health	0.003	0.006	0.006	-0.011	0.007	-0.011	0.006	-0.001
Mental status scale	0.157	-0.105	0.167	-0.107	0.167	-0.107	0.167	-0.107
Numeracy scale	0.010	0.006	0.010	0.006	0.007	0.011	0.009	0.001
Financial time horizon	0.006	0.011	0.006	0.011	0.006	0.011	0.007	0.011
Sentiment	0.008	-0.02	-0.001	0.012	-0.002	0.012	-0.002	0.012
Follow market (Not at all)								
Somewhat closely	0.011	0.013	0.012	0.013	0.012	0.013	0.012	0.013
Very closely	.085***	0.023	.085***	0.023	.089***	0.023	.084***	0.023
Stock Allocation (2018)	-.497***	0.018	-.497***	0.019	-.498***	0.019	-.505***	0.019
Elemental Traits								
Openness			.046*	-0.024	.047*	-0.024	.047*	-0.024
Conscientiousness			-.069**	-0.029	-.068**	-0.029	-.068**	-0.029
Extraversion			-0.034	-0.029	-0.034	-0.029	-0.034	-0.029
Agreeableness			0.02	-0.032	0.02	-0.032	0.02	-0.032
Neuroticism			0.021	-0.019	0.021	-0.019	0.021	-0.019
Compound Traits								
Positive Affect					-0.010	0.010	-0.010	0.010
Negative Affect					.073***	-0.027	.075***	-0.027
Situational Traits								
Stock Market Expectation							.001***	0.001
Constant	-.123***	0.054	0.029**	-0.195	0.044***	-0.208	-0.01***	-0.207
R-squared	.239		0.240		0.241		0.248	

Note: Data from 2018 and 2020 waves of HRS. N= 3,077. Standard errors adjusted on household id.
*** *p<.01, *** ** *p<.05, * p<.1*

The hierarchical regression was conducted to examine the predictors of stock reallocation, defined as the percent change in stock allocation from 2018 to 2020. The analysis was structured in four blocks, with each block introducing a new set of predictors that align with the personality trait levels of the 3M Model. Model one incorporated the block one socio-demographic variables of age, gender, marital status, education level, and employment status. It also included financial, cognition, and health variables such as liquid net worth, self-reported health status, mental status, numeracy, how closely they follow the market, the percent allocated to stocks before the crisis, and the market sentiment.

In the first block, socio-demographic variables were entered. Age in 2018 was a significant predictor and positively associated with stock reallocation (b = .002, SE = 0.002, p < .01), indicating that for every one-year increase in age, there was a 0.2% increase in stock reallocation. Gender, marital status, race, education level, employment status, self-reported health, mental status scale, numeracy scale, financial time horizon, and sentiment were also entered into the model, but they were not significant predictors of stock reallocation. Liquid net worth was a significant predictor, with every unit increase in liquid net worth being associated with a 0.2% increase in stock reallocation (b = .002, SE = 0.001, p < .01). Those who followed the market very closely in 2018 were significantly more likely to reallocate their stocks during the market volatility of COVID-19 (b = .085, SE = 0.023, p < .01). The percent allocated to stocks in 2018 was also a significant and negative predictor of stock reallocation (b = -.497, SE = 0.018, p < .01). This suggests that for every one percentage point increase in the stock allocation in 2018, there is an expected decrease of 0.497 percentage points in the change of stock allocation from 2018 to 2020, holding all other variables constant. In other words, individuals who had a higher percentage of their portfolio allocated to stocks in 2018 were associated with decreasing their stock allocation during the market volatility of COVID-19.

In the second block, elemental traits were introduced to the model. Openness to experience was found to be positively associated with stock reallocation (b = .046, SE = 0.024, p < .1). This indicates that for every unit increase in the openness to experience personality trait, there was a corresponding 4.6 percentage points increase in allocation to stocks. On the other hand, conscientiousness was negatively related to stock reallocation (b = -.069, SE = 0.029, p < .05). Specifically, for every unit increase in conscientiousness, there was a decrease of 6.9 percentage points in allocation to stocks during market volatility. The other elemental traits—extraversion, agreeableness, and neuroticism—were also included in the model, but they did not demonstrate significant relationships with stock reallocation. The socio-demographic variables, such as age and stock allocation in 2018, retained their significance and direction of association with stock reallocation from the first block. This consistency underscores the robustness of these relationships even when accounting for personality traits.

In the third block, model three introduced the compound traits of positive and negative affect scales. Negative affect emerged as a significant predictor (b = .073 (SE = 0.027, $p < .01$). For each unit increase in negative affect, there was a corresponding increase of 7.3 percentage points allocated to stocks from 2018 to 2020. The relationship of age and stock allocation maintained their significance and direction with stock reallocation.

In the final block, situational traits were incorporated into the model. Notably, stock market expectation was a significant predictor (b = .001, SE = 0.001, $p < .01$). This suggests that for one percent increase in the expectation of stock market returns, there was a corresponding increase of 0.1 percentage points in stock allocation from 2018 to 2020. This finding underscores the importance of individuals' expectations about the stock market in influencing their decisions to adjust their stock allocations.

Incremental Variance Explained by Successive Regression Blocks

In the hierarchical regression analysis, Block 1, which included sociodemographic variables, accounted for 23.9% of the variance in the dependent variable, $F(3042) = 57.79$, $p < .001$. With the addition of the Big 5 personality traits in Block 2, an additional 0.1% of the variance was explained, resulting in a total of 24.0% variance explained, $F(3042) = 43.86$, $p = .028$. Introducing positive affect and negative affect in Block 3 further explained an additional 0.1% of the variance, cumulatively accounting for 24.1% of the variance, $F(3042) = 39.87$, $p = .017$. Lastly, by adding stock market expectations in Block 4, an additional 0.7% of the variance was explained, bringing the total variance explained to 24.8%, $F(3042) = 38.82$, $p = .005$.

The hierarchical regression analysis provided evidence in support of the hypotheses derived from the 3M model. Specifically, the inclusion of each successive block added to the explanatory power of the model, as evidenced by the significant incremental increases in R-square values. For Hypothesis 1, the addition of the Big 5 personality traits in Block 2, representing the elemental traits, provided a significant increase in the variance explained, underscoring their role in understanding stock reallocation behavior. Hypothesis 2 was supported as the introduction of positive and negative affect in Block 3, representing the compound traits, led to a further significant increase in the explained variance. Lastly, Hypothesis 3 was supported with the addition of stock market expectations in Block 4, representing the situational trait, which also resulted in a significant increase in the model's explanatory power. The specific changes in R-square and their significance levels for each block are detailed in Table 4.4. Collectively, these findings illustrate the significance of the hierarchical structure of personality traits and psychological factors in the context of stock reallocation behavior. It can be seen that while the differences in R-square are statistically significant, they may not be practically significant, as each successive block's explanatory measure increases 0.01% to 0.07%.

Table 4.4 Incremental Variance Explained in Hierarchical Regression Analysis

Block	*F*	Block df	Residual df	*p*	R^2	Δ in R^2
1	57.79	16	3042	<0.001	0.239	
2	43.86	21	3042	0.028	0.240	0.001
3	39.87	23	3042	0.017	0.241	0.001
4	38.82	24	3042	0.005	0.248	0.007

Multicollinearity Assessment

Before proceeding with the main analyses, the predictors in the model were analyzed to test that they did not exhibit high multicollinearity, which could distort the structural equation results. Multicollinearity refers to the situation in which two or more predictors in a regression model are highly correlated, meaning that one can be linearly predicted from the others with a substantial degree of accuracy. First, a correlation matrix of the elemental and compound traits was analyzed, shown in Table 4.5. The correlations were all statistically significant at p <0.001, and ranged from -.17 to .24. The strongest correlation was between Extraversion and Positive Affect at 0.24.

Table 4.5 Correlation Matrix of Elemental and Compound Trait Latent Variables

	Openness	Consc.	Extrav.	Agree.	Neurot.	Pos. Affect	Neg. Affect
Openness	1.00	0.19^{***}	0.21^{***}	0.14^{***}	-0.07^{***}	0.24^{***}	-0.05^{***}
Consc.		1.00	0.18^{***}	0.15^{***}	-0.08^{***}	0.23^{***}	-0.08^{***}
Extrav.			1.00	0.18^{***}	-0.09^{***}	0.27^{***}	-0.10^{***}
Agree.				1.00	-0.04^{***}	0.17^{***}	-0.04^{***}
Neurot.					1.00	-0.17^{***}	0.21^{***}

Pos. Affect	1.00	-0.18***
Neg. Affect		1.00

Variance Inflation Factor (VIF) was employed to assess multicollinearity among the predictors. Typically, a VIF value above 10 is indicative of high multicollinearity (Kutner, Nachtsheim, & Neter, 2004). In this study, none of the predictors exceeded this threshold. Given that all VIF values were well below the commonly used threshold of 10, it can be concluded that multicollinearity should not present an issue in this model.

Measurement Model Results

The measurement component of the structural model underwent evaluation using a Confirmatory Factor Analysis (CFA), as discussed in Chapter 3. Modification indices of each CFA were consulted and implemented based on the theoretical constructs. All fit statistics are within the ranges suggested by Kline (2016), as illustrated in Table 4.6.

Table 4.6 Confirmatory Factor Analysis of Elemental and Compound Traits

Factor	$\chi 2$ [df]	*p*	RMSEA	CFI	TLI	SRMR
Big Five CFAs						
Openness	355.10 [12]	<0.001	0.069	0.970	0.948	0.028
Conscientiousness	128.13 [12]	<0.001	0.041	0.984	0.972	0.017
Extraversion	17.90 [2]	<0.001	0.037	0.990	0.988	0.008
Agreeableness	4.34 [4]	<0.001	0.004	0.990	0.990	0.004
Neuroticism	7.37 [1]	<0.001	0.034	0.990	0.991	0.005
Affect CFAs						
Positive Affect	718.472 [50]	<0.001	0.049	0.983	0.973	0.021
Negative Affect	718.472 [50]	<0.001	0.045	0.982	0.974	0.021

Before integrating the CFA from each of the Big Five personality traits, positive affect, and negative affect into the full structural model, a measurement model was conducted and analyzed, that does not yet add relationships between the constructs in accordance with the 3M

Theory. Modification indices were consulted and considered based on theory. The variance of the latent variable factors was allowed to covary only at the elemental trait level. Some pairs of the elemental traits factors were allowed to covary based on modification indices, for example E4_active and C6_hardworking, which are theoretically similar. None of the factors of personal affect were allowed to covary with the variance of the factors of negative affect since each of these latent variables are distinct measures.

A suite of fit indices was employed to gauge the model's congruence with the data as shown in Table 4.7. While the chi-square statistic was significant ($\chi2(1211) = 13{,}214.987$, $p < .001$), the measure is sensitive to large samples, often leading to minor deviations from a perfect fit. Given the substantial sample size in this study, the chi-square's sensitivity might be the primary reason for its significance. Kline (2016) recommends utilizing other fit indices such as RMSEA, CFI, TLI, and SRMR for a more nuanced evaluation of model fit.

Table 4.7 Goodness of Fit Measures of the Measurement Model

Fit Measure	Value	Indication of Fit	Suggested Cut-off Values	Reference
Chi-Square ($\chi2$)	13214.987 df: 1211 *p* <0.001	Significant	Sensitive to sample size. Models with N>400 typically results in significant model chi-square test	Kline, 2016
RMSEA	0.042	Good	Excellent < .01, good < .05, acceptable < .08	Browne & Cudeck, 1993
90% CI of RMSEA	(0.041, 0.042)	Good	Upper bound < .05 to pass not-close-fit test. Upper bound < .10 to pass poor-fit test	Kline, 2016
CFI	0.912	Acceptable	<.90 poor fit, .90 - .95 acceptable, <.95 great	Kenny, 2015

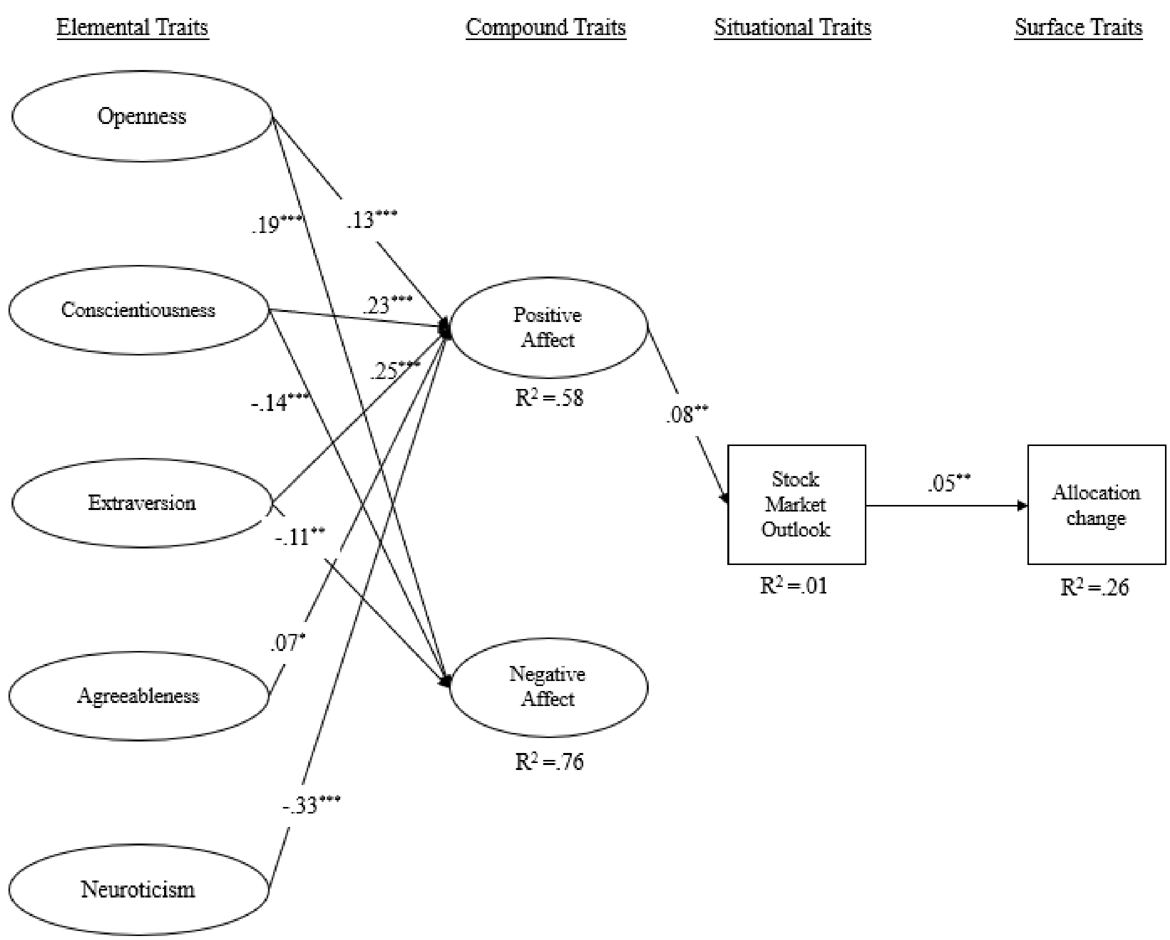
TLI	0.900	Acceptable	<.90 poor fit, .90 - .95 acceptable, <.95 great	Kenny, 2015
SRMR	0.051	Acceptable	≤ 0.08	Hu & Bentler, 1999

The results indicate significant loadings of all factors and standardized factors ranged from 0.382 for C10_thrifty to 0.770 for PA2_enthusiastic. The Root Mean Square Error of Approximation (RMSEA) is 0.042 and suggesting an acceptable error of approximation. Browne and Cudeck (1993) suggest values below 0.05 denote a close fit, while those up to 0.08 are deemed acceptable. The Comparative Fit Index (CFI) and the Tucker-Lewis Index (TLI) were 0.912 and 0.900, respectively, both exceeding the recommended threshold of 0.90, which indicates an acceptable fit (Kline, 2016). The Standardized Root Mean Square Residual (SRMR) was measured at 0.051, below the recommended threshold of 0.08, reinforcing the model's good fit (Hu & Bentler, 1999). The measurement model will be integrated within the structural model.

Structural Model Results

A structural diagram in Figure 4.1 illustrates the statistically significant relationships between the elemental, compound, situational, and surface traits, with standardized parameter estimates. The structural model incorporated the measurement model variables, placing them in the appropriate level within the 3M Theory, as well as added stock market expectations as the situational trait, stock reallocation as the surface trait, as well as regressing on the control variables. The results underscore the 3M Model of Motivation and Personality's ability to explaining the association between older investor’s psychological attributes and their portfolio behavior during market volatility. Model Fit Indices indicate an acceptable fit for RMSEA and SRMR ($\chi^2(2{,}092) = 9{,}029.19$, $p < .001$; RMSEA = .028, 90% CI [.027, .029], CFI = .881, TLI = .870, SRMR = .061) according to Kline (2016). The chi-square fit is significant and expected for sample sizes greater than 400 (Kline, 2016). CFI and TLI do not meet the acceptable standard of >0.90, but model fit indices indicated a good fit during the measurement model analyses. The model accounted for 26% of the variance in stock reallocation behavior (R^2 = .258). Additionally, compound traits accounted for 1% of the variance in stock market expectations (R^2 = .01). Consistent with the 3M framework, the elemental traits—openness, conscientiousness, extroversion, agreeableness, and neuroticism—significantly influenced the compound traits, yielding r-squared values of .58 for positive affect, and .76 for negative affect.

Figure 4.1 Structural Model Predicting Stock Reallocation (*N* = 4,329)



Note: Model Fit Indices: χ_2(2,092) = 9,029.19, p = <.001; RMSEA = .028, 90% CI [.027, .029], CFI = .881, TLI = .870.All model results were computed with Mplus with STDYX standardization and maximum likelihood (ML) estimator to facilitate testing of the direct effects with 5,000 bootstrap draws (Muthen & Muthen, 2017). * *p < .05*. ***p < .01*. ****p < .001*.

Direct Effects with Stock Reallocation Behavior

Results for the direct effects of stock reallocation behavior are provided in Table 4.8. In the examination of the direct effects of stock reallocation behavior on various traits, the results provided insights into the proposed hypotheses. Hypotheses four through ten, which postulated associations between stock allocation and the elemental and compound traits, were not supported by the data. Specifically, openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism—all elemental traits—did not exhibit statistically significant associations with stock reallocation behavior. Similarly, the compound traits, positive and negative affect, were not directly associated with stock reallocation behavior. However, results provided support for hypothesis eleven, which proposed a positive association between stock market outlook (a situational trait) and stock reallocation. The data revealed a significant positive association between stock market outlook and stock reallocation behavior during market volatility (β = 0.054, p = 0.003), underscoring the influence of individuals' perceptions of the stock market on their allocation decisions. A one standard deviation increase in stock market outlook, was associated with a 0.054 standard deviation increase in stock reallocation, holding all else equal.

Turning to the sociodemographic variables, age in 2018 had a notable positive association with the percent change in stocks held from 2018 to 2020 (β = 0.101, p < 0.001). This means that for every standard deviation increase in age, there was a 0.101 standard deviation increase in the percent change of stocks reallocated, suggesting older individuals were more inclined to adjust their stock holdings, contrary to expectations. Similarly, attentiveness to the market was positively linked with stock reallocation (β = 0.058, p = 0.003). A one standard deviation increase in following the market closely corresponded to a 0.058 standard deviation increase in the percent change of stocks reallocated. In contrast, having a higher stock allocation before the 2020 market volatility was significantly associated with a decrease in stock reallocation during COVID-19 ($\beta = -0.525$, $p < 0.001$). Specifically, a one standard deviation increase in stock allocation prior to the volatility led to a 0.525 standard deviation decrease in the percent change of stocks reallocated. This indicates that those who held riskier positions before the market downturn were more likely to reduce their stock exposure in response to the market's uncertainty. Other sociodemographic variables, such as gender, marital status, race, and education, among others, did not show statistically significant associations with stock reallocation.

Table 4.8 Direct Effects with Stock Reallocation Behavior (N = 4,329)

Parameter	Unstandardized b	Unstandardized SE	Standardized β	Standardized SE	p-value
Elemental Traits (Big Five)					
Openness	0.027	0.036	0.041	0.06	0.456
Conscientiousness	-0.002	0.035	-0.002	0.05	0.962
Extraversion	0.001	0.028	0.001	0.05	0.998
Agreeableness	-0.023	0.037	-0.029	0.05	0.533
Neuroticism	-0.062	0.069	-0.079	0.09	0.369
Compound Traits (Affect)					
Positive Affect	-0.007	0.021	-0.015	0.04	0.729
Negative Affect	0.104	0.062	0.138	0.08	0.093
Situational Trait					
Stock market outlook	0.001	0.001	0.054	0.02	0.003**
Socio-demographics					
Age (2018)	0.004	0.001	0.101	0.02	<.001***
Gender (Female)	0.019	0.013	0.028	0.02	0.151
Marital Status (Not coupled)	-0.008	0.012	-0.011	0.02	0.535
Race (White)	-0.014	0.012	-0.022	0.01	0.229
Education (Less than HS)	0.019	0.12	0.028	0.02	0.13
Employed	0.015	0.015	0.018	0.02	0.328
Liquid net worth	0.002	0.001	0.028	0.02	0.132
Self-reported health	0.002	0.006	0.006	0.02	0.754
Mental status scale	0.029	0.049	0.011	0.02	0.564
Numeracy scale	0.001	0.006	0.002	0.02	0.901
Financial time horizon	0.008	0.011	0.013	0.02	0.46
Sentiment	-0.002	0.012	-0.003	0.02	0.867
Follow market (Not at all)	0.03	0.01	0.058	0.02	0.003**
Stock Allocation (2018)	-0.483	0.017	-0.525	0.02	<.001***
R^2	0.26				

Note: Model Fit Indices: χ 2(2,092) = 9,029.19, p = <.001; RMSEA = .028, 90% CI [.027, .029], CFI = .881, TLI = .870.All model results were computed with Mplus with STDYX standardization and maximum likelihood (ML) estimator to facilitate testing of the direct effects with 5,000 bootstrap draws (Muthen & Muthen, 2017).
** p < .05. **p < .01. ***p < .001.*

Direct Effects Across Hierarchical Trait Levels in the 3M Model

In accordance with the 3M Model, each trait level is expected to have a direct effect on the previous level (Mowen, 2000). Results are shown in Table 4.9. For the direct effect of stock market outlook on affect, a significant positive relationship was observed with positive affect and outlook ($\beta = 0.082$, $p = 0.003$). This suggests that for each one standard deviation increase in stock market experience, there is an associated 0.082 standard deviation increase in positive affect. No significant relationship was found between stock market outlook and negative affect.

Turning to the influence of positive affect on the Big Five personality traits, significant relationships were observed with neuroticism ($\beta = -0.332$, $p < 0.001$), agreeableness ($\beta = 0.072$, $p = 0.041$), extraversion ($\beta = 0.254$, $p < 0.001$), conscientiousness ($\beta = 0.229$, $p < 0.001$), and openness ($\beta = 0.134$, $p < 0.001$). Specifically, a one standard deviation increase in positive affect was associated with a 0.332 standard deviation decrease in neuroticism, and increases of 0.072, 0.254, 0.229, and 0.134 standard deviations in agreeableness, extraversion, conscientiousness, and openness, respectively.

Regarding the impact of negative affect on the Big Five, significant associations were found with neuroticism ($\beta = 0.842$, p < 0.001), extraversion ($\beta = -0.109$, $p = 0.004$), conscientiousness ($\beta = -0.141$, p < 0.001), and openness ($\beta = 0.193$, $p < 0.001$). A one standard deviation increase in negative affect corresponded to an 0.842 standard deviation increase in neuroticism, and decreases of 0.109 and 0.141 standard deviations in extraversion and conscientiousness, respectively. Conversely, the same increase in negative affect was linked to a 0.193 standard deviation increase in openness. No significant relationship was observed between negative affect and agreeableness.

Table 4.9 Direct Effects Across Hierarchical Trait Levels in the 3M Model (*N* = 4,329)

	Unstandardized		Standardized		
	b	SE	β	SE	p-value
Stock Market Exp. on Affect					
Positive Affect	0.014	1.078	0.082	0.03	0.003**
Negative Affect	-0.995	1.745	-0.017	0.03	0.568
Positive Affect on Big Five					
Neuroticism	-0.546	0.042	-0.332	0.02	<.001***
Agreeableness	0.119	0.058	0.072	0.04	0.041*
Extraversion	0.315	0.045	0.254	0.04	<.001***
Conscientiousness	0.316	0.053	0.229	0.04	<.001***
Openness	0.182	0.052	0.134	0.04	<.001***
Negative Affect on Big Five					
Neuroticism	0.88	0.047	0.842	0.02	<.001***
Agreeableness	-0.029	0.041	-0.028	0.04	0.477
Extraversion	-0.086	0.03	-0.109	0.04	0.004**
Conscientiousness	-0.124	0.037	-0.141	0.04	<.001***
Openness	0.166	0.037	0.193	0.04	<.001***

Note: Model Fit Indices: χ 2(2,092) = 9,029.19, p = <.001; RMSEA = .028, 90% CI [.027, .029], CFI = .881, TLI = .870.All model results were computed with Mplus with STDYX standardization and maximum likelihood (ML) estimator to facilitate testing of the direct effects with 5,000 bootstrap draws (Muthen & Muthen, 2017).
** p < .05. **p < .01. ***p < .001.*

Indirect Effects: Mediation Across the Trait Levels in the 3M Model

In line with the 3M Model's hierarchical structure, indirect effects through mediating variables provide insights into the pathways through which traits influence stock reallocation decisions. The indirect effects are presented in Table 4.10.

Starting with the indirect effects of Openness on stock reallocation, two significant paths were observed. The path from Openness through Positive Affect to Market Expectations and then to Stock Reallocation was significant ($\beta = 0.001$, $p = 0.073$). This indicates that for every standard deviation increase in Openness, there's an associated 0.001 standard deviation increase in stock reallocation, mediated by Positive Affect and Market Expectations. However, the other paths involving Openness, including those mediated by Negative Affect, were not statistically significant.

For Conscientiousness, the indirect effect through Positive Affect to Market Expectations and then to Stock Reallocation was significant ($\beta = 0.001$, $p = 0.049$). This suggests that a one standard deviation increase in Conscientiousness results in a 0.001 standard deviation increase in stock reallocation, mediated by Positive Affect and Market Expectations. The other paths involving Conscientiousness did not reach statistical significance.

Extraversion's indirect effect on stock reallocation through Positive Affect to Market Expectations was significant ($\beta = 0.001$, $p = 0.045$). This means that for every standard deviation increase in Extraversion, there's a corresponding 0.001 standard deviation increase in stock reallocation, mediated by Positive Affect and Market Expectations. The other pathways involving Extraversion were not significant.

Neuroticism exhibited a significant indirect effect on stock reallocation through Positive Affect to Market Expectations ($\beta = -0.001$, $p = 0.039$). Specifically, a one standard deviation increase in Neuroticism is associated with a 0.001 standard deviation decrease in stock reallocation, mediated by Positive Affect and Market Expectations. The other indirect paths involving Neuroticism, especially those mediated by Negative Affect, were not statistically significant.

Lastly, while Positive and Negative Affect are primarily mediators in this model, their indirect effects on stock reallocation through Market Expectations were examined. Neither Positive nor Negative Affect showed significant indirect effects on stock reallocation through Market Expectations.

In summary, the indirect effects illustrate how personality traits influence stock reallocation decisions. Affective states are associated with financial behaviors. Additionally, market expectations serve as key mediators, linking inherent personality traits to investment choices.

Table 4.10 Indirect Effects Mediated Across Trait Levels (*N* = 4,329)

Exogenous Variable Path	Unstandardized		Standardized	
	b	SE	β	SE
Openness → Pos. Aff. → SR	-0.001	0.004	-0.002	0.006
Openness → Neg. Aff. → SR	0.017	0.011	0.027	0.017
Openness → Pos. Aff. → Mark. Exp. → SR	0.000	0.000	0.001	0.001
Openness → Neg. Aff. → Mark. Exp. → SR	0.000	0.000	0.000	0.000
Conscientiousness → Pos. Aff. → SR	-0.002	0.007	-0.003	0.010
Conscientiousness → Neg. Aff. → SR	-0.013	0.009	-0.019	0.013
Conscientiousness → Pos. Aff. → Mark. Exp. → SR	0.001*	0.000	0.001*	0.001
Conscientiousness → Neg. Aff. → Mark. Exp. → SR	0.000	0.000	0.000	0.000
Extraversion → Pos. Aff. → SR	-0.002	0.007	-0.004	0.011
Extraversion → Neg. Aff. → SR	-0.009	0.006	-0.015	0.01
Extraversion → Pos. Aff. → Mark. Exp. → SR	0.001*	0.000	0.001*	0.001
Extraversion → Neg. Aff. → Mark. Exp. → SR	0.000	0.000	0.000	0.000
Agreeableness → Pos. Aff. → SR	-0.001	0.003	-0.001	0.003
Agreeableness → Neg. Aff. → SR	-0.003	0.005	-0.004	0.006
Agreeableness → Pos. Aff. → Mark. Exp. → SR	0.000	0.000	0.000	0.000
Agreeableness → Neg. Aff. → Mark. Exp. → SR	0.000	0.000	0.000	0.000
Neuroticism → Pos. Aff. → SR	0.004	0.011	0.005	0.014

Neuroticism → Neg. Aff. → SR	0.092	0.055	0.116	0.069
Neuroticism → Pos. Aff. → Mark. Exp. → SR	-0.001*	0.001	-0.001*	0.000
Neuroticism → Neg. Aff. → Mark. Exp. → SR	-0.001	0.001	-0.001	0.000
Positive Affect → Mark. Exp. → SR	0.000	0.000	0.000	0.000
Negative Affect → Mark. Exp. → SR	0.000	0.000	0.000	0.000

Note: Model Fit Indices: χ 2(2,092) = 9,029.19, p = <.001; RMSEA = .028, 90% CI [.027, .029], CFI = .881, TLI = .870.All model results were computed with Mplus with STDYX standardization and maximum likelihood (ML) estimator to facilitate testing of the direct effects with 5,000 bootstrap draws (Muthen & Muthen, 2017).
* p < .05. **p < .01. ***p < .001

Summary of Analyses

Hierarchical Regression Analysis: Testing Hypotheses 1 to 3

The hierarchical regression analysis was structured to systematically examine the predictors of stock reallocation, defined as the percent change in stock allocation from 2018 to 2020. This approach was designed to align with the hierarchical nature of the 3M Model, introducing predictors in successive blocks. The first block incorporated socio-demographic and financial variables, revealing age in 2018 and the percent allocated to stocks in 2018 as significant predictors. Specifically, older individuals and those with a higher stock allocation in 2018 were more likely to adjust their stock holdings during the market volatility of COVID-19.

The second block introduced the elemental traits, with openness and conscientiousness emerging as significant predictors of stock reallocation. The third block, which incorporated the compound traits, highlighted negative affect as a significant predictor. Finally, the fourth block introduced situational traits, with stock market expectations emerging as a significant predictor. The incremental variance explained by each block in the hierarchical regression analysis provided empirical support for the hypotheses derived from the 3M model. It should be noted that while the results were statistically significant, they may not be practically significant, which is discussed more in the next chapter.

Structural Model Findings: Testing Hypotheses 4 to 11

In the examination of the direct effects of stock reallocation behavior on various traits, the results provided insights into the proposed hypotheses. Hypotheses four through ten, which postulated associations between stock reallocation and the elemental and compound traits, were not supported by the data. However, results provided support for hypothesis eleven, which proposed a positive association between stock market outlook (a situational trait) and stock reallocation. The data revealed a significant positive association between stock market outlook and stock reallocation behavior during market volatility, where bearish outlooks predicted moving away from stocks, and vice versa.

Relationships Across the 3M Structure

In accordance with the 3M Model, each trait level is expected to have a direct effect on the previous level. For the direct effect of stock market outlook on affect, a significant positive relationship was observed with positive affect and outlook. Turning to the influence of positive affect on the Big Five personality traits, significant relationships were observed with neuroticism, agreeableness, extraversion, conscientiousness, and openness. Regarding the impact of negative affect on the Big Five, significant associations were found with neuroticism, extraversion, conscientiousness, and openness. These findings illustrate the importance of considering the hierarchical structure of personality traits and psychological factors when examining stock reallocation behavior.

The indirect effects further show the pathways through which personality traits influence stock reallocation decisions. While some traits might not directly impact investment choices, their effects become evident when channeled through affective states and market expectations. For example, traits like openness and conscientiousness, though not directly associated with stock reallocation, have an indirect influence via their relationships with positive and negative affect. This emphasizes the path-dependent nature of decision-making in financial contexts, where both inherent personality traits and current psychological states intersect.

Chapter 5 - Discussion, Implications, and Conclusions

Stock market volatility presents challenges for investors, particularly those in the older age demographic. Given their often shorter investment horizons and a propensity for risk aversion, older investors are faced with critical decisions during market downturns. They must consider whether to adjust their portfolio's risk profile to potentially mitigate further losses or to maintain their current allocation in anticipation of a market recovery. The market turbulence experienced in spring 2020, due to the emergence of the COVID-19 pandemic, exemplified such periods of decision-making uncertainty for these investors.

During market volatility, a natural reaction is to adjust a portfolio with the intention of safeguarding against potential losses (Escobari & Jafarinejad, 2019; Naseem et al., 2021). However, evidence suggests that consistently maintaining one's asset allocation throughout market cycles tends to yield better results than attempting to time the market (Giglio et al., 2020; Greenwood & Shleifer, 2014). Financial planners and asset management firms have an opportunity to educate investors about these findings and the nature of business and market cycles. By understanding the characteristics of investors who may be more reactive to market changes, professionals can offer targeted educational resources and guidance. This approach ensures that investors make informed decisions that align with their unique goals, time-horizon, risk profile, and objectives.

Despite the extensive body of literature on investor behavior, there remain unresolved questions regarding the determinants of such behavior (Bihari et al., 2022). The complexity of this research domain arises from several factors. For instance, the same individual might react differently to stock market volatility events based on the underlying event. For example, while the Great Financial Crisis of 2008-2009 primarily stemmed from a breakdown of the financial system, the market turbulence during COVID-19 was rooted in economic uncertainties due to a health pandemic. The nature of the stock market volatility can influence investors' responses, potentially constraining the generalizability of findings. Another challenge in this research area is the selection of pertinent drivers of investor behavior. Browning and Finke (2015) identified a association of cognitive function and stock reallocation during the Great Financial Crisis, yet they did not incorporate individual differences in personality. In contrast, Jiang, Peng, and Yan (2023) emphasized the significant roles of Big Five personality traits in equity investment decisions.

This study sought to explore the portfolio behavior of older adults during the market volatility induced by the COVID-19 pandemic, using the 3M Model of Motivation and Personality as its foundational framework (Mowen, 2000). By analyzing sociodemographic factors, personality traits, and both positive and negative affect, the research aimed to offer a holistic understanding of the complexities inherent in financial decision-making. The overarching objective was to add to the existing body of literature on financial behavior while providing actionable insights for financial practitioners and institutions. This chapter delves into the research findings, linking them to their theoretical foundations, and discusses broader implications, study limitations, and avenues for future research.

Discussion of research findings

The study investigated the association between personality traits, as conceptualized within the 3M Model of Motivation and Personality (3M), and stock reallocation behavior during periods of market volatility. Specifically, the research aimed to understand how elemental, compound, and situational traits influenced individuals' decisions to adjust their stock allocations in response to the market volatility brought about by the uncertainty during the COVID-19 pandemic. The 3M Model posits a hierarchical structure of personality traits, where elemental traits influence compound traits, and compound traits, in turn, influence situational traits (Mowen, 2000). This hierarchical nature was central to the study's analytical approach, which used both hierarchical regression and structural equation modeling. Hierarchical regression was employed to sequentially introduce predictors, allowing for the examination of the incremental variance explained by each set of traits. The structural model, on the other hand, was utilized to understand the direct effects and path analysis of these traits on stock reallocation behavior. Overall, results support the ability of the 3M to explain the psychological aspects associated with investor behavior of older adults during market volatility. Furthermore, results of this study illustrate the important role that stock market outlook has in connecting broader personality dispositions to investor behavior.

Direct Effects

Psychological relationships

The study aimed to explore the association of various psychological traits on stock reallocation behavior. The hypotheses tested are shown in table 5.1 below, and whether or not they were supported. Hypotheses 4 through 10 were rooted in the premise that elemental and compound traits would exhibit significant associations with stock reallocation behavior. Specifically, hypotheses posited that openness to experience (H4), conscientiousness (H5), extraversion (H6), and agreeableness (H7) would be positively associated with an increase in allocation to stocks, while neuroticism (H8) was hypothesized to be negatively associated. Additionally, positive affect (H9) was expected to show a positive relationship with an increase of allocation to stocks, whereas negative affect (H10) was anticipated to exhibit a negative relationship. However, the results did not support these hypotheses, suggesting that these elemental and compound traits did not have a direct significant association with stock reallocation behavior. This contrasts with some previous research that has found personality traits, especially from the Big Five, to influence financial behaviors (Brown & Taylor, 2014).

Hypothesis 11, on the other hand, focused on the situational trait of stock market outlook. It was posited that an individual's stock market outlook would be positively associated with an increase in allocation to stocks. In other words, the hypothesis was that those who had optimistic expectations of future stock market returns would be positively associated with an increase to stock allocation. The findings provided support for this hypothesis, indicating a significant positive association between stock market outlook and stock reallocation behavior during market volatility. This aligns with prior research that emphasizes the role of situational factors, such as future market returns, in shaping investment decisions (Dominitz & Manski, 2007; Hudomiet et al., 2011). The influence of individuals' perceptions of the stock market on their allocation decisions underscores the importance of situational traits in the investment decision-making process. For example, results support the notion that situational traits (i.e., market expectations) hold the strongest relationship with portfolio behavior (i.e., the surface trait) give their adjacent location with the 3M model (Mowen, 2000).

Table 5.1 Hypotheses That Were Supported

H #	**Hypothesis**	**Supported?**
	Does the addition of the 3M Block add explanatory power?	
1	Big 5 traits add explanatory power	Yes
2	Positive and Negative Affect add explanatory power	Yes
3	Market expectations add explanatory power	Yes
	There is a (+/-) significant association with (variable) and increasing allocation to stocks.	
	Elemental Traits	
4	Openness is positively associated	No

5	Conscientiousness is positively associated	No
6	Extraversion is positively associated	No
7	Agreeableness positively associated	No
8	Neuroticism is negatively associated	No
	Compound Traits	
9	Positive affect is positively associated	No
10	Negative affect is negatively associated	No
	Situational Traits	
11	Stock market outlook is positively associated	Yes

The direct effect results align with Mowen's (2000) assertion that research often emphasizes more tangible and narrowly defined traits, such as stock market outlook, when examining consumer behavior. These specific traits tend to have stronger associations with behavior than broader traits, such as elemental and compound traits. The current findings expand upon existing literature by establishing a link between stock market outlook as a situational trait and the stock reallocation behavior of individuals during market volatility.

Previous research primarily examined financial self-efficacy, mastery scales, and task orientation when studying the saving behaviors of older adults (Asebedo et al., 2019, 2022). Notably, these studies overlooked the influence of market performance during their respective measurement periods. In contrast, the present study underscores the significance of stock market expectations in shaping stock reallocation decisions, while also considering asset class performance between survey intervals. By centering on stock market expectations as a situational trait, this research aimed to enrich the understanding of how individuals modify their portfolios amid market fluctuations, thereby adding depth to the prevailing literature.

Sociodemographic relationships

Previous research has found associations of sociodemographic factors with investment behaviors. Although this study did not formulate explicit hypotheses regarding these relationships, it drew upon expectations grounded in prior literature and established theories of financial behavior. Factors such as age, income, and education, among others, have been associated with investment decisions.

Age emerged as a significant variable associated with stock reallocation behavior. Contrary to expectations, older individuals in the sample were associated with increasing their allocation to stock holdings. The study expected to find age associated with decreasing stock allocation, aligning with the life-cycle hypothesis, which posits that as individuals approach retirement, they may become more conservative in their investment choices to preserve capital (Modigliani & Brumberg, 1954). Empirical findings have further supported this notion, suggesting that age is often inversely related to risk-taking, with older individuals typically prioritizing capital preservation (Blake et al., 2014). However, the observed behavior in this study suggests that older individuals were not necessarily more conservative but were instead, increasing their allocation stocks during the period of market volatility. This could be attributed to their lived experiences of past market downturns, prompting them to be more proactive in response to market valuations. Additionally, older investors might have perceived the market downturn as an opportunity to buy undervalued stocks, leveraging their experience and long-term perspective on market recoveries (Dohmen et al., 2018).

Another significant sociodemographic variable was a person’s self-reported attentiveness to the stock market. Those who reported closely following the market was associated with a significant positive relationship to increasing allocation to stocks. However, it was anticipated that individuals who closely follow the market would be more inclined to reduce their allocation. The underlying assumption was that individuals who monitor the market more frequently might exhibit greater sensitivity to its fluctuations, especially when comparing, for example, daily price movements, as opposed to less frequent intervals, such as weekly or monthly returns. This phenomenon, where investors react more strongly to short-term market variations, has been discussed in behavioral finance literature, suggesting that more frequent observations can lead to myopic loss aversion (Barberis, 2018; R. B. Durand et al., 2019; Sicherman et al., 2016). The distinction should be noted between closely tracking one's own account values and monitoring the broader stock market, with this study focusing on the latter. In essence, results of this study suggest a positive association between those who closely track the stock market and increasing allocation to stocks during market volatility, all else being equal.

Lastly, the proportion an investor allocated to stocks prior to the market volatility of 2020 was significantly associated with portfolio decisions during COVID. Individuals with a higher stock allocation before the market downturn were associated with reducing their stock exposure during the COVID-19 market volatility. This observation contrasts with previous literature in financial research, where the percentage allocated to stocks has often been used as a proxy for an individual's risk tolerance (Ameriks et al., 2020; Hvide & Panos, 2014; Kuzniak et al., 2015)). Researchers refer to this as revealed preference, suggesting that a higher stock allocation reveals an investor's greater willingness to take on risk (Berk & Van Binsbergen, 2016). The findings from this study indicate that the revealed preference was not supported in the context of the COVID-19 market volatility. For example, those with apparent higher risk tolerances, as indicated by their stock allocations, exhibited risk-averse behaviors during periods of heightened market uncertainty. This observation aligns with Browning and Finke (2015), who documented similar behavior during the volatile markets of 2008. These combined results suggest that using stock allocation as a proxy for risk preference may not properly reflect an investor's risk tolerance.

Hierarchy of Traits

The hierarchical regression analysis provided insights into the hierarchical relationships between personality traits and stock reallocation behavior. The analysis was designed to progressively introduce variables that correspond with the personality trait levels of the 3M Model. The results highlighted the role of the hierarchical structure of personality traits in the context of stock reallocation behavior. Each successive block in the regression enhanced the explanatory power of the model, with situational traits, such as stock market outlook, showing a strong association with stock reallocation decisions, consistent with hypotheses one through three.

In examining the associations across trait levels, the hierarchical structure of the 3M Model became evident. Elemental traits, which form the foundational layer of personality, showed significant relationships with compound traits. For instance, positive affect, a compound trait, was significantly associated with several elemental traits, including neuroticism, agreeableness, extraversion, conscientiousness, and openness. This suggests that broader emotional states, like positive affect, can be influenced by more narrowed personality characteristics.

Additionally, the study found an association between compound traits and situational traits. Positive affect, a compound trait, demonstrated a significant relationship with the situational trait of stock market outlook. This suggests that emotional states, such as positive affect, can influence perceptions related to specific situations, like the stock market outlook. This observation is consistent with the 3M Model's proposition, where compound traits influence situational traits, which in turn are associated with elemental traits. The results offer empirical results for the hierarchical structure and relationships among personality traits in the realm of financial decision-making.

Implications of findings

The study provides insights into the personality attributes associated with investment decisions, especially during market volatility. These insights add to the academic field of behavioral finance and have practical relevance for stakeholders in the financial planning domain. For researchers, this study highlights areas for further exploration into the psychological aspects of financial behavior. Financial planning practitioners can draw upon these insights to refine their client advisory methods. As the financial sector continues to evolve with technological advancements, the findings also have relevance for financial technology providers. Moreover, the study highlights the importance of consumer policies that prioritize the financial well-being of investors.

Researcher Implications

The findings of this study provide insights into the relationships between personality traits, affect, stock market expectations, and portfolio behavior among older investors during market downturns. This research emphasizes the role of hierarchical personality traits in financial decision-making, adding depth to the existing literature. The focus on the hierarchical nature of personality traits can lead researchers to reconsider existing behavioral finance models. By integrating these findings, more comprehensive models that account for the multi-dimensional nature of personality traits can be developed and tested.

The versatility of the study's framework presents a unique opportunity for researchers to test research questions in related contexts. One implication for researchers is the potential to apply the study's framework to different market conditions. While the current study analyzed a period of market volatility, the same model could be examined during times of low volatility and a rising market. This would provide empirical support as to whether the observed associations between personality attributes and investment decisions are robust across varying economic scenarios. Furthermore, while this study centered on older investors, similar methodologies could be applied to different demographic groups, offering insights into whether the observed behaviors are consistent across age groups or unique to older investors. With the increasing integration of artificial intelligence in financial decision-making, understanding how the identified psychological factors influence investor behavior in these tech-driven environments becomes relevant. By exploring these avenues, researchers can contribute to the field of behavioral finance, making it adaptive to the evolving financial landscape.

Financial Planning Practitioner Implications

The findings of this study provide insights for financial planning practitioners, especially when advising older clients during market downturns. Recognizing the associations between personality traits, affect, and stock market expectations on investment decisions can help practitioners tailor their advice to align with clients' psychological profiles. One implication for financial planners is regarding the importance of checking in with clients during market volatility. This study highlights the value of regularly assessing a client's stock market expectations. Such assessments can complement risk tolerance questionnaires, which, when used alone, have shown limited utility. By understanding the potential influence of these factors on a client's decision-making process, financial planners can guide their clients through market uncertainties. Integrating these assessments into the advisory process can help identify clients more prone to emotional decision-making during volatile periods, allowing for advice that emphasizes long-term strategies over short-term market reactions.

Financial planning practitioners would benefit by incorporating the study's findings regarding clients who frequently monitor the market. The results indicate that individuals who track the market were associated with increasing their allocation to stocks during market volatility. This behavior might indicate a more informed or engaged investor. Those consistently exposed to market information often view market downturns not as threats, but as opportunities to buy stocks at lower prices. With this understanding, providing more frequent market updates to these clients could further enhance their informed perspective, potentially fostering more strategic investment behaviors that align with their unique goals and objectives.

Financial planning practitioners can benefit from the insights provided by the hierarchical structure of personality traits as presented by the 3M Model (Mowen, 2000). By being aware of the relationships between different traits, practitioners can better tailor their advisory methods. For instance, understanding that a client's stock market expectations might be influenced by broader emotional states can help in framing discussions and advice. Financial planners could consider incorporating questions related to the Big Five personality traits or affect into their initial client assessments. For example, if a client scores high on extraversion and positive affect, they might be more optimistic about the stock market's future performance. This type of client would likely require less communication during market volatility.

Similarly, understanding a client's level of neuroticism can offer insights into their potential responses to market volatility. The study indicated that individuals with higher neuroticism levels tended to have stronger reactions to market downturns, such as selling off stock. Financial planners could consider providing more frequent communication with high-neuroticism clients during turbulent market periods. These clients could also benefit from clear explanations of market movements and the reasoning behind their investment strategy to increase their financial knowledge. By recognizing these personality traits, practitioners can better tailor their communication strategies, prioritizing clients who may need more guidance.

Financial Technology Provider Implications

The increasing integration of financial technology in the financial planning process adds considerations for providers. As robo-advisors and software that integrates artificial intelligence gain traction, these platforms could benefit by considering the psychological attributes that play a role in investor behavior, as identified in this study. Financial technology providers can incorporate insights from the hierarchical structure of personality traits to enhance their algorithms. This means that investment advice can be data-driven while also being sensitive to an individual's psychological profile.

For instance, platforms might consider incorporating periodic assessments of stock market expectations alongside traditional risk assessment tools. If these assessments indicate the investor starts to have a more bearish outlook on the stock market, it could serve as a signal for the platform to initiate a more detailed check-in with the investor. This proactive approach provides an opportunity to offer market education, with the goal of informing investors so they can make decisions in line with their broader financial plan. By recognizing and responding to shifts in investor sentiment, fintech platforms can enhance their value proposition, potentially keeping investors engaged and aligned with their long-term investment strategies if their outlook turns negative during market volatility.

In summary, integrating psychological theory into investment advice offers financial professionals and fintech software a more informed approach. By recognizing and addressing behavioral tendencies that stem from psychological traits of clients, professionals can tailor advice to align with individual client profiles. This tailored approach strengthens the relationship between client and advisor and increases the likelihood of successful implementation and adherence to investment strategies.

Limitations of current study

The current study had some limitations. Although the research provided insights into the association between personality traits and stock reallocation behavior, it is important to acknowledge these constraints to understand the research findings and their implications. Recognizing these limitations also offers direction for subsequent research.

One potential limitation of this study pertains to the classification of Positive and Negative Affect as a compound trait within the 3M framework. The nature of affect—whether it's a stable dispositional trait or a transient state—can vary based on the measurement approach. In the Health and Retirement Study (HRS), participants were queried about emotions experienced over the preceding weeks, which might capture more transient feelings rather than stable dispositions. While this could be seen as a limitation, it also serves as a strength of the research. It offers insights into how short-term emotions might influence stock market expectations. It is worth noting that Asebedo (2018) employed Positive and Negative Affect as a compound trait in a study involving a similar population. However, future research might consider exploring other measures, such as optimism and pessimism, to determine if they offer a more distinct representation of compound traits, especially if there is a concern that affect, as measured in the HRS, might not fully encapsulate a trait-like quality.

One limitation of the study is the level of detail provided by the timing of the data. The public HRS dataset provides information on the month when the survey was taken, but not the exact day. This lack of day-level precision could introduce measurement error when calculating the dependent variable. The computation of the allocation change requires performance adjustments based on the underlying asset classes between the two survey dates. Without the exact day, this calculation might be less accurate, potentially affecting the precision of the results and the subsequent interpretations.

Another limitation is the level of detail in the portfolio data. The study provides information about the investment holdings at the asset class level. While the survey captures the dollar amount invested in stocks, stock-based mutual funds, bonds, cash, and cash equivalents, it doesn't specify the individual ticker symbols of the holdings. Consequently, performance adjustments for computing allocation changes are based on general asset class performance assumptions, not specific funds. Additionally, the study infers behavior from reported allocation changes and assumed asset class returns, rather than from direct transactional data. Although this approach likely approximates actual portfolio behavior, direct transactional data would offer greater precision and could impact the findings.

One limitation of the study is that it did not capture the sources of information used to make investment choices. While the research indicates how individuals adjusted their portfolios during market volatility, it is not clear if these adjustments were made independently or based on recommendations from others. These recommendations could come from a variety of sources, including financial planners, friends, family, co-workers, or the media or internet. Having such information would offer a more detailed understanding of the investment decision-making process during market volatility.

Recommendations for future studies

The limitations identified in the current study offer opportunities for refining and expanding future research. One suggestion is to refine the measurement of changes in stock allocation. Accessing data that specifies the exact day of the survey, rather than the month, would enhance the accuracy when calculating allocation changes. This is because the method used to calculate the stock allocation change is based on price changes between the respondent's survey months. Specifically, day-level data would improve the accuracy of the allocation change calculation, especially when the intra-month volatility is high, which would lead to more accurate measurement.

To achieve a more accurate understanding of portfolio behavior, future research would benefit from accessing data on the specific holdings within respondents' portfolios instead of at the asset class level of detail as provided in the HRS. By having this detailed information, researchers would not need to adjust the account balances between survey dates based on asset class performance. Additionally, having access to actual transaction records between survey dates would offer insights into the specific investment decisions made during volatile market periods, and when they were made. This level of detail would not only strengthen the validity of the findings but also provide a clearer perspective on individual investment decisions made during volatile markets.

Another opportunity for future research is to incorporate information on the external sources of information used to make investment decisions. This would provide insights into the impact of advice from financial planners, friends, family, or other sources on investment choices. For instance, the relationship between an investor's negative market outlook and their stock reallocation decisions might be influenced by the advice of a financial professional. In statistical terms, the financial professional's advice could mediate the relationship between market outlook and stock reallocation. Understanding this relationship would help distinguish the role of individual judgment and personality traits from the influence of external recommendations in investment decisions.

Exploring portfolio decision-making based on tax treatment offers another area for research. By examining decisions related to qualified versus non-qualified assets, researchers can understand how decision-making might vary based on the tax treatment of the account type. Drawing from concepts in mental accounting, it is possible that employer-sponsored qualified plans are treated differently than taxable investment accounts (Zhang & Sussman, 2017). This examination can provide insights into investment strategies designed for different financial goals and constraints.

A longitudinal study examining portfolio behavior over multiple market cycles could provide insights into how investors adapt based on past experiences and the nature of market downturns. This research could assess whether individuals adjust their strategies based on past investment outcomes, such as decisions made during the 2008-2009 Great Financial Crisis, and how they respond to different types of market challenges, like the economic effects of the Covid pandemic. Investigating these patterns would offer a clearer understanding of whether the specific context of market volatility influence investor behavior.

Similarly, in addition to downturns, it would be insightful to study investor behavior in periods characterized by low volatility and positive returns. Investigating how the 3M framework applies in these more stable, upward-trending market conditions could reveal whether investors exhibit different behavioral tendencies when markets are favorable. Such research could help determine if the psychological attributes identified in the 3M model are consistent across varying market scenarios or if they manifest differently when the investment landscape is perceived as less risky.

Conclusions

The primary goal of this research was to explore the relationships between personality traits, affect, stock market expectations, and portfolio behavior among older investors during market volatility periods. The findings highlighted the role of stock market outlook in stock reallocation decisions. Understanding the psychological factors influencing investor decision-making, especially in volatile market conditions, is crucial. The 3M Model (Mowen, 2000) served as a foundational framework, outlining the hierarchical structure of personality traits and their impact on financial behaviors. This study contributes to the existing literature by integrating insights from both psychology and finance, offering an additional perspective on investor behavior.

This research offers insights that are relevant for a diverse group of stakeholders in the financial planning arena. For academic researchers, the study found an association between psychological traits and investment behaviors by using the 3M Model. These findings can serve as a foundation for further exploration into the psychological factors of financial decisions. Financial planning practitioners can use these insights to tailor their advisory methods, recognizing the influence of personality traits and stock market expectations on investment choices. Fintech providers can consider integrating psychological insights into their platforms, with the goal of providing financial planning advice that is both data-driven and attuned to individual psychological profiles. By addressing these factors, the financial industry may be better positioned to serve investors, especially during periods of market volatility, leading to more informed and strategic investment decisions.

The study was not without its limitations. Addressing these constraints in subsequent research would be helpful to add to the field's body of knowledge of investor behavior during times of market volatility. One limitation was the level of detail on the survey date, which was limited to the month level instead of the exact date, which could impact the accuracy of the stock allocation calculations. The research also depended on general asset class data, lacking detailed insights into specific portfolio holdings. This meant making assumptions about asset class performance between survey dates, which could influence the study's precision. These issues could be resolved if the researcher had access to the specific underlying holdings and trade confirmations over time. Moreover, the study did not capture the potential influences from sources of advice on investment decisions. For example, previous research found that those who had more optimistic economic outlooks were more likely to use a professional financial planner (Ludwig et al., 2023). This leaves questions about the role of sources of advice on investment behaviors. Recognizing these limitations provides a clearer context for the findings and offers direction for future research.

The results of this dissertation suggest that stock market outlook provides a key connecting personality traits to investor behavior. Market expectations appear to be associated with investor portfolio decisions during volatile markets. This points to an opportunity for further research on how these expectations fit into the financial planning process. Further exploration is warranted on the various factors associated with market expectations and the mediators that play a role between these expectations and portfolio decisions. As the financial landscape continues to evolve, insights from such research will be helpful to guide more informed and effective decision-making for investors, aiming for a better alignment between psychological predispositions and financial strategies.

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Appendix A - Statistical Programming

The following is code I created in Stata 17 for this project.

Statistical programming (Stata)

```
/*************************************************************************
	*Title: Dissertation
	*Created by: Eric
	*Created on: 11/14/2022
	*Last modified on: 11/2/2023
	*Last modified by: Eric
	*Purpose: Imports and cleans variables from HRS (2018-2020)
*************************************************************************
*********/

	clear all

	*File path for .dta
	*use "C:\Users\[YOUR.INFO.HERE]\Dropbox\RC808 Ludwig Lim\Reallocation
paper\data\edited\cfp_with_income2.dta"

	*use "C:\Users\erict\Dropbox\RC808 Ludwig Lim\Reallocation
paper\data\edited\cfp_with_income2.dta"

	*=====================================================================
========
	*Set directories
	*=====================================================================
========

	global projdir "C:\Users\erict\OneDrive\K-State PhD\Dissertation\Data"
	cd "$projdir"
	global data_ed "${projdir}\edited"
	global data_raw "${projdir}\raw"
	global data_covid "${projdir}\2020_HRS_COVID"

	*=====================================================================
========
	*Import RAND HRS data
	*=====================================================================
========

	/*
	page 41 has table of contents for these vars

	h14atotb = net worth

	HwATOTB = Sum (HwAHOUS, HwAHOUB, HwARLES, HwATRAN, HwABSNS, HwAIRA,
HwASTCK, HwACHCK,
	HwACD, HwABOND, HwAOTHR) - Sum (HwAMORT, HwAHMLN, HwADEBT, HwAMRTB)
	*/
```

```
      use hhid pn hhidp raracem ragender raeduc r14mstat h14itot r14work
r14shlt h14atotb /*word recall combo is r14tr20*/ r14imrc r14dlrc /*mental
status | r14mstot is total*/ r14ser7 r14bwc20 r14mo r14dy r14yr r14dw r14scis
r14cact r14pres r14vp r14mstot r14tr20 /* combo of 2 scales cogtot*/
r14cogtot using "${data_raw}\fat\randhrs1992_2018v2.dta", clear

      *gender = ragender.
      gen gender = .
      replace gender = 0 if ragender == 2 /*female*/
      replace gender = 1 if ragender ==1 /*male*/

      *race is raracem (3 categories: white, black, other, 1,2,3)
      gen race3 =.
      replace race3 = 0 if raracem == 1 /*white*/
      replace race3 = 1 if raracem == 2 /*black*/
      replace race3 = 2 if raracem == 3 /*other*/

      ***********************************************************************
*****
      *Marital status
            gen marstat2018 =.
            replace marstat2018 = 0 if r14mstat == 1 | r14mstat ==3
            replace marstat2018 = 1 if r14mstat == 2 | r14mstat ==4 |
r14mstat ==5| r14mstat ==6 | r14mstat ==7 | r14mstat ==8  | r14mstat ==.m |
r14mstat ==.j
            * 0 = couple ; 1= single
      *need to drop the missing here so I end up with only the 17k
            drop if marstat2018 ==.
            drop r14mstat
      ***********************************************************************
****
      *Education
      *less than college = 0, college or higher =1
                  gen educ2018=.
                  replace educ2018 = 0 if raeduc==1 | raeduc==2 |raeduc==3
                  replace educ2018 = 1 if raeduc==4 | raeduc==5
                  drop raeduc
      ***********************************************************************
****
      *Work status
      *0= not working for pay, 1=working for payment
      gen workstat2018 =.
      replace workstat2018 = 0 if r14work ==0
      replace workstat2018 = 1 if r14work ==1

      ***********************************************************************
***
      *Perceived health status= healthstat2018
      *reverse code so higher value = better health
      revrs r14shlt
      gen healthstat2018 = revr14shlt
      drop revr14shlt
      drop r14shlt
      ***********************************************************************
**
      *inverse hyperbolic sine transformation of Net Worth
```

```
gen ihst_nw18 = .
replace ihst_nw18 = asinh(h14atotb)
rename h14atotb networth2018
**********************************************************************
*
*inverse hyperbolic sine transformation of Income
gen ihst_inc18 =.
replace ihst_inc18 = asinh(h14itot)
rename h14itot totinc_2018
**********************************************************************
*                              Cognitive Variables
* only asked to those age 65+
*  r14imrc r14dlrc = "word recall"
* r14ser7 r14bwc20 r14mo r14dy r14yr r14dw r14scis r14cact r14pres
r14vp = "mental status"
*these had responses as 1.xxx, so cleaning that up for Mplus
gen countbwd18 =.
replace countbwd18 = 0 if r14bwc20 == 0
replace countbwd18 = 1 if r14bwc20 == 1
replace countbwd18 = 2 if r14bwc20 == 2

gen identmo18 =.
replace identmo18 = 0 if r14mo == 0
replace identmo18 = 1 if r14mo == 1

gen identdy18 = .
replace identdy18 = 0 if r14dy == 0
replace identdy18 = 1 if r14dy == 1

gen identyr18 = .
replace identyr18 = 0 if r14yr == 0
replace identyr18 = 1 if r14yr == 1

gen identdw18 = .
replace identdw18 = 0 if r14dw == 0
replace identdw18 = 1 if r14dw == 1

gen identscis18 = .
replace identscis18 = 0 if r14scis == 0
replace identscis18 = 1 if r14scis == 1

gen identcact18 = .
replace identcact18 = 0 if r14cact == 0
replace identcact18 = 1 if r14cact == 1

gen identpres18 = .
replace identpres18 = 0 if r14pres == 0
replace identpres18 = 1 if r14pres == 1

gen identvp18 = .
replace identvp18 = 0 if r14vp == 0
replace identvp18 = 1 if r14vp == 1

*need to rescale the word recall vars to put them on a 0 to 1 scales
*this puts the cog vars all on a 0 to 1 weighting
*then, bring these into a scale as control variables
gen imrc18 =.
```

```
	replace imrc18 = r14imrc/10

	gen dlrc18 =.
	replace dlrc18 = r14dlrc/10

	*scale for control variable (without cact and scis
	gen mentstatscale =.
	replace mentstatscale = (identmo18 + identdy18 + identyr18 + identdw18
+ identpres18 + identvp18 + imrc18 + dlrc18)/8


	drop hhidpn
	gen hhidpn = hhid + pn
	save "${data_ed}\randetl.dta", replace
	clear
	*============================================================================
========
	*============================================================================
========
	*How to get monthly asset prices: for 2018 and 2020 survey dates
	*============================================================================
========
	*2/17/2022 etl
	*last edited 2/23/2021 by etl
	***************

	*from video: https://www.youtube.com/watch?v=Ro161kajKWc
	*if havent done so alrady: ssc install getsymbols, replace
	*if need help on options, help getsymbols

	*=====================================================
	* Steps for getting asset prices and merging with HRS
	*=====================================================
	*(1) Generate asset prices for each survey year and save separatly; ex.
SPY18, SPY20.
		*survey dates for 2018: 04/2018 to 06/2019
	*(2) Create a survey date var in each fat file  ex. moyr18, moyr20,
then
	*(3) Merge asset price data with appropriate year's fat file
	*(4) Merge the fat files
	*(5) merge fats with RAND
	*...then onto creating a variable to calculate the performance

	*(1) Generate asset prices for each survey year; ex. SPY18, SPY20.
	*asset prices for 2018
	clear
	getsymbols SPY AGG BIL, ya fy(2018) fm(4) fr(m)
	drop open_SPY high_SPY low_SPY close_SPY volume_SPY daten open_AGG
high_AGG low_AGG close_AGG volume_AGG  open_BIL high_BIL low_BIL close_BIL
volume_BIL
	format %tmCCYY-NN period

	*survey dates are:
	*2018: 4/2018 to 6/2019
	*2020: 2/2020 to 5/2021
	rename period moyr18
	*2018 asset price data set
```

```
	gen obs= _n
	gen spy18 = adjclose_SPY if inrange(obs,1,15)
	gen agg18 = adjclose_AGG if inrange(obs,1,15)
	gen bil18 = adjclose_BIL if inrange(obs,1,15)
	keep if spy18 !=.
	drop adjclose_AGG
	drop adjclose_BIL
	drop adjclose_SPY
	drop obs
	save "${data_ed}\asset prices\2018.dta", replace
	clear
	*asset prices for 2020

	getsymbols SPY AGG BIL ^VIX, ya fy(2018) fm(4) fr(m)
	drop open_SPY high_SPY low_SPY close_SPY volume_SPY daten open_AGG
high_AGG low_AGG close_AGG volume_AGG  open_BIL high_BIL low_BIL close_BIL
volume_BIL open__VIX high__VIX low__VIX adjclose__VIX volume__VIX
	format %tmCCYY-NN period
	rename period moyr20
	gen obs= _n
	gen spy20 = adjclose_SPY if inrange(obs,24,38)
	gen agg20 = adjclose_AGG if inrange(obs,24,38)
	gen bil20 = adjclose_BIL if inrange(obs,24,38)
	gen vix20 = close__VIX if inrange(obs,24,38)
	keep if spy20 !=.
	drop adjclose_AGG
	drop adjclose_BIL
	drop adjclose_SPY
	drop close__VIX
	drop obs


		*sentiment variable based on volatility
		*do it based on highest vol months: March, April June, October,
and Jan 2021
		*VIX >30 in those months
		gen sentiment = 0
		replace sentiment = 1 if vix20 > 30
		*label define sentiment 0 "Low vol" 1 "High vol"
		*label values sentiment sentiment

		*this is for March and April 2020
		gen sentv2 = 0
		replace sentv2 = 1 if vix20 >30 & vix20 <31 | vix20 >50
		*label define sentv2 0 "post-Covid" 1 "Early Covid Hvol"
		*label values sentv2 sentv2
	save "${data_ed}\asset prices\2020.dta", replace
	clear

	*======================================================================
========
	**#                        Import fat file data
	*======================================================================
========
	*adding 2016 variables, then merge 2016 w/ 2018 w/ 2020

	*                              ***********
```

```
      *                                    2016 (p)
      *                                ***********
      use hhid hhidpn pn plb025 pb132 plb032_2 using
"${data_raw}\fat\h16f2b.dta" , clear


      ***********************************************
      ** Financial self efficacy **
      **    fse_2016
      ***********************************************
       *FSE 0-10 scale How much control do you have over your fin sit these
days?
       *N=6,192, Mean=7.48
       rename plb025 fse2016
      *********************************************************************
*

      *General risk tolerance 2016
      *N=20,912, M=5.47

            gen genrisk2016 = .
            replace genrisk2016 = pb132
            replace genrisk2016 = . if pb132 == -8 | pb132 ==98 | pb132 ==99

      *Financial Risk tolerance 2016
      *0-10, Mean 3.25, N=6,235
            rename plb032_2 finrisk_2016

      *********************************************************************
*
            drop hhidpn
      gen hhidpn = hhid + pn
            save "${data_ed}\fat16.dta", replace
            clear

      *                                ***********
      **#                                2018 (q)
      *                                ***********
      *alternatively for the IRA and stock/bond/cash data, I could pull the
values from the longitudinal file and get a MUCH higher N...but still need to
get the IRA stock %s from the 2018 fat file and would be back to a lower N
again


      use hhid hhidpn pn  qa019 qa501 qa500 qb014 qb132 qlb032_2 qp047
qq166_1 qq167_1 qq168_1 qq169_1 qq166_2 qq167_2 qq168_2 qq169_2 qq166_3
qq167_3 qq168_3 qq169_3 qq514_1 qq514_2 qq514_3 qq515_1 qq515_2 qq515_3 qq317
qq318 qq319 qq320 qq331 qq332 qq333 qq334 qq345 qq346 qq347 qq357 qq358 qq359
qq359 qq360 qp041 qp097 /*lb vars*/  /*PANA*/ qlb026a qlb026b qlb026c qlb026d
qlb026e qlb026f qlb026g qlb026h qlb026i qlb026j qlb026k qlb026l qlb026m
qlb026n qlb026o qlb026p qlb026q qlb026r qlb026s qlb026t qlb026u qlb026v
qlb026w qlb026x qlb026y /*Big 5*/ qlb031a qlb031b qlb031c qlb031d qlb031e
qlb031f qlb031g qlb031h qlb031i qlb031j qlb031k qlb031l qlb031m qlb031n
qlb031o qlb031p qlb031q qlb031r qlb031s qlb031t qlb031u qlb031v qlb031w
qlb031x qlb031y qlb031z_1 qlb031z_2 qlb031z_3 qlb031z_4 qlb031z_5 qlb031z_6
/*Cognitive ability*/ qd174 qd178 qd179 qd180 using
"${data_raw}\fat\h18f2a.dta", clear
```

```
		gen moyr18 = ym(qa501,qa500)
		format %tmCCYY-NN moyr18

		rename qa019 age_2018

		gen genrisk2018 = .
		replace genrisk2018 = qb132
		replace genrisk2018 = . if qb132 == -8 | qb132 ==98 | qb132 ==99


	*How willing are you to take risks in financial matters. 0-10 scale

		rename qlb032_2 finrisk2018


	*stock market outlook (not risk perception) (higher value = more
bullish)

	*			///  marketxp18   \\\

	gen marketexp18 =.
		replace marketexp18 = qp047
		replace marketexp18 = . if qp047 ==-8 | qp047 ==998 | qp047 ==999

	*financial planning periods time horizon 0: <5 years; 1 = 5yrs+
		gen fpperiods2018=.
			replace fpperiods2018= qp041
			replace fpperiods2018 = . if qp041 ==-8
			replace fpperiods2018 = 0 if qp041 == 1 | qp041 == 2 |
qp041 == 3
			replace fpperiods2018 = 1 if qp041 == 4 | qp041 == 5 |
qp041 == 8 | qp041 == 9
	drop qp041


	* how closely do you follow the market? 0: not at all, 1: somehwhat, 2:
very closely
		gen fmkt18 =.
		replace fmkt18= qp097
		replace fmkt18 = . if qp097 == -8 | qp097==8 | qp097==9
		revrs fmkt18
		gen followmkt2018=revfmkt18
		drop qp097
		drop fmkt18
		drop revfmkt18
	/*
			label define followmkt2018 1 "Not at all" 2 "Somewhat
closely" 3"Very Closely"
			label values followmkt2018 followmkt2018
	*/


				*******************************
				**    Cognitive ability     **
```

```
                  *   fluid recall and numeracy
                  ********************************


      ********************************
      * numeracy (math ability 3 Qs)
      * numeracy
      ********************************
      *numeracy scale from num1 num2 num3; 0-3 scale.
      *make categorical. 0=belowavg 1or 2= average, 3=above avg

      *num1 100==1, else=0
      *qd178 "Next I would like to ask you some questions which assess how
people use numbers in everyday life.  If the chance of getting a disease is
10 percent, how many people out of 1,000 would be expected to get the
disease?"? (should be 10,228 =1)
            gen num1 = qd178
            replace num1 = 1 if qd178== 100
            replace num1 = 0 if qd178 > 100 | qd178 <100
            drop qd178

      *num2 400,000 ==1, else=0
      *qd179 If 5 people all have the winning numbers in the lottery and the
prize is two million dollars, how much will each of them get? (should be
6,219 =1)
            gen num2 = qd179
            replace num2 = 1 if qd179== 400000
            replace num2 = 0 if qd179 > 400000 | qd179 <400000
            drop qd179

      *num3 240 or 242 ==1, else 0
      *Let's say you have $200 in a savings account. The account earns 10
percent interest per year. How much would you have in the account at the end
of two years? (i'm coding both 240 and 242 as correct bc didn't specify
compound); should be 5,259=1
            gen num3 = qd180
            replace num3 = 1 if qd180== 240 | qd180== 242
            replace num3 = 0 if qd180 ==241 | qd180 <240 | qd180>242
            drop qd180

      *numeracy scale, continuous
            gen numeracy = num1 + num2 + num3

      ***********************************************************************
*****

      *
      **********************************************
      **#                          Psychological Variables 2018
      *
      *
      **********************************************
      *LB section coding

      ***********************************************
      ** Positive / Negative Affect **
      **      pa_2018   na_2018
```

```
*******************************************
*PANA 26a....y
*During the last 30 days, to what degree did you feel....?
      *1 = Very much, 2 = Quite a bit, 3 = Moderately, 4 = A little, 5
= Not at all
      *Create an index of positive affect by reverse-coding items Q27c,
d, f, g, h, k, p, q, t, u, v, x, and y and averaging the scores across all 13
items. Set the final score to missing if there are more than six items with
missing values.
      *Create an index of negative affect by reverse-coding items Q27
a, b, e, i, j, l, m, n, o, r, s, and w and averaging the scores across all 12
items. Set the final score to missing if there are more than six items with
missing values

            revrs qlb026c qlb026d qlb026f qlb026g qlb026h qlb026k
qlb026p qlb026q qlb026t qlb026u qlb026v qlb026x qlb026y
*drop if there are more than 6 items with missing values. I checked and
there are no Obs were this is true
*egen mpa_2018 = rowmiss(revqlb026c revqlb026d revqlb026f revqlb026g
revqlb026h revqlb026k revqlb026p revqlb026q revqlb026t revqlb026u revqlb026v
revqlb026x revqlb026y)
*drop if mpa_2018 == 6

      gen pa_2018 = (revqlb026c + revqlb026d + revqlb026f + revqlb026g
+ revqlb026h + revqlb026k + revqlb026p + revqlb026q + revqlb026t + revqlb026u
+ revqlb026v + revqlb026x + revqlb026y) / 13
gen pa1 = revqlb026c
gen pa2 = revqlb026d
gen pa3 = revqlb026f
gen pa4 = revqlb026g
gen pa5 = revqlb026h
gen pa6 = revqlb026k
gen pa7 = revqlb026p
gen pa8 = revqlb026q
gen pa9 = revqlb026t
gen pa10 = revqlb026u
gen pa11 = revqlb026v
gen pa12 = revqlb026x
gen pa13 = revqlb026y

      revrs qlb026a qlb026b qlb026e qlb026i qlb026j qlb026l qlb026m
qlb026n qlb026o qlb026r qlb026s qlb026w
      gen na_2018 = (revqlb026a + revqlb026b + revqlb026e + revqlb026i
+ revqlb026j + revqlb026l + revqlb026m + revqlb026n + revqlb026o + revqlb026r
+ revqlb026s + revqlb026w) /12

gen na1 = revqlb026a
gen na2 = revqlb026b
gen na3 = revqlb026e
gen na4 = revqlb026i
gen na5 = revqlb026j
gen na6 = revqlb026l
gen na7 = revqlb026m
gen na8 = revqlb026n
gen na9 = revqlb026o
gen na10 = revqlb026r
gen na11 = revqlb026s
```

```
	gen na12 = revqlb026w

	***********************************************
	**	Big 5 OCEAN **
	**	o_2018 c_2018 e_2018 a_2018 n_2018
	***********************************************
	*indicate how well each of the following desribes you 1= alot| 2= some| 3= a little| 4= not at all

	*Big 5 lb031a a...z..._z6
		*1= A lot, 2 = Some, 3 = A little, 4 = Not at all
		*Reverse-code all items EXCEPT Q31c, Q31q, Q31v, and Q31x and average the scores for items within sub-dimensions for

	*Conscientiousness (Q31c, Q31e, Q31i, Q31n, Q31r, Q31v, Q31x, Q31z_1, Q31z_5, and Q31z_6)

	*Neuroticism (Q31d, Q31h, Q31l, Q31q)

	*Set the final score to missing if more than half of the items have missing values within each sub-dimension.
		*Openness to Experience (Q31m, Q31o, Q31s, Q31t, Q31w, Q31z_3, Q31z_4)
		revrs qlb031a qlb031b qlb031d qlb031e qlb031f qlb031g qlb031h qlb031i qlb031j qlb031k qlb031l qlb031m qlb031n qlb031o qlb031p qlb031r qlb031s qlb031t qlb031u qlb031w qlb031y qlb031z_1 qlb031z_2 qlb031z_3 qlb031z_4 qlb031z_5 qlb031z_6


	gen O1_creat = revqlb031m
	gen O2_imagi = revqlb031o
	gen O3_intel = revqlb031s
	gen O4_curio = revqlb031t
	gen O5_broad = revqlb031w
	gen O6_sophi = revqlb031z_3
	gen O7_adven = revqlb031z_4

	gen C1_reckl = qlb031c
	gen C2_carel = qlb031v
	gen C3_impul = qlb031x
	gen C4_organ = revqlb031e
	gen C5_respo = revqlb031i
	gen C6_hardw = revqlb031n
	gen C7_selfd = revqlb031r
	gen C8_cauti = revqlb031z_1
	gen C9_thoro = revqlb031z_5
	gen C10_thri = revqlb031z_6

	gen E1_outgo = revqlb031a
	gen E2_frien = revqlb031f
	gen E3_livel = revqlb031j
	gen E4_activ = revqlb031u
	gen E5_talka = revqlb031z_2

	gen A1_helpf = revqlb031b
	gen A2_warm  = revqlb031g
	gen A3_carin = revqlb031k
```

```
      gen A4_softh = revqlb031p
      gen A5_sympa = revqlb031y

      gen N1_moody = revqlb031d
      gen N2_worry = revqlb031h
      gen N3_nervo = revqlb031l
      gen N4_calm  = qlb031q


            gen o_2018 = (O1_creat + O2_imagi + O3_intel + O4_curio +
O5_broad + O6_sophi + O7_adven)/7

            gen c_2018 = (C1_reckl + C2_carel + C3_impul + C4_organ +
C5_respo + C6_hardw + C7_selfd + C8_cauti + C9_thoro + C10_thri)/10

            gen e_2018 = (E1_outg + E2_frien + E3_livel + A4_softh +
E5_talka)/5

            gen a_2018 = (A1_helpf + A2_warm + A3_carin + A4_softh +
A5_sympa)/5

            gen n_2018 = (N4_calm + N1_moody + N2_worry + N3_nervo)/4

      drop revqlb026c revqlb026d revqlb026f revqlb026g revqlb026h revqlb026k
revqlb026p revqlb026q revqlb026t revqlb026u revqlb026v revqlb026x revqlb026y
qlb026a qlb026b qlb026c qlb026d qlb026e qlb026f qlb026g qlb026h qlb026i
qlb026j qlb026k qlb026l qlb026m qlb026n qlb026o qlb026p qlb026q qlb026r
qlb026s qlb026t qlb026u qlb026v qlb026w qlb026x qlb026y qlb031a qlb031b
qlb031c qlb031d qlb031e qlb031f qlb031g qlb031h qlb031i qlb031j qlb031k
qlb031l qlb031m qlb031n qlb031o qlb031p qlb031q qlb031r qlb031s qlb031t
qlb031u qlb031v qlb031w qlb031x qlb031y qlb031z_1 qlb031z_2 qlb031z_3
qlb031z_4 qlb031z_5 qlb031z_6 revqlb026a revqlb026b revqlb026e revqlb026i
revqlb026j revqlb026l revqlb026m revqlb026n revqlb026o revqlb026r revqlb026s
revqlb026w revqlb031a revqlb031b revqlb031d revqlb031e revqlb031f revqlb031g
revqlb031h revqlb031i revqlb031j revqlb031k revqlb031l revqlb031m revqlb031n
revqlb031o revqlb031p revqlb031r revqlb031s revqlb031t revqlb031u revqlb031w
revqlb031y revqlb031z_1 revqlb031z_2 revqlb031z_3 revqlb031z_4 revqlb031z_5
revqlb031z_6

      ******************************************************************
      **#    Code asset values and percentages for 2018 **
      ** IRAs:        IRAtotval_2018  IRAtotatrisk_2018
      ** NQs:        stockval_2018  NQtotval_2018  riskshare_2018
      ** Combo:   totval_2018    totatrisk_2018   tot_risk_share_2018
      *******************************************************************

      *IRA part starts here
            gen ira1max2018 = qq168_1
            replace ira1max2018 =  400001 if qq168_1 == 99999996
            gen IRAval1_2018DK = .
                  replace IRAval1_2018DK = (qq167_1 + ira1max2018)/2 if
qq166_1 == 9999998

                  rename qq166_1 IRAval1_2018
                  replace IRAval1_2018 = 0 if IRAval1_2018 == .
                  replace IRAval1_2018 = 0 if IRAval1_2018 == -8
```

```
                  replace IRAval1_2018 = IRAval1_2018DK if IRAval1_2018 ==
9999998
                  replace IRAval1_2018 = 0 if IRAval1_2018 == 9999999
                  drop ira1max2018 IRAval1_2018DK

            gen ira2max2018 = qq168_2
            replace ira2max2018 =  400001 if qq168_2 == 99999996
            gen IRAval2_2018DK = .
                  replace IRAval2_2018DK = (qq167_2 + ira2max2018)/2 if
qq166_2 == 9999998

            rename qq166_2 IRAval2_2018
                  replace IRAval2_2018 = 0 if IRAval2_2018 == .
                  replace IRAval2_2018 = 0 if IRAval2_2018 == -8
                  replace IRAval2_2018 = IRAval2_2018DK if IRAval2_2018 ==
9999998
                  replace IRAval2_2018 = 0 if IRAval2_2018 == 9999999
                  drop ira2max2018 IRAval2_2018DK

            gen ira3max2018 = qq168_3
            replace ira3max2018 =  400001 if qq168_3 == 99999996
            gen IRAval3_2018DK = .
                  replace IRAval3_2018DK = (qq167_3 + ira3max2018)/2 if
qq166_3 == 9999998

            rename qq166_3 IRAval3_2018
                  replace IRAval3_2018 = 0 if IRAval3_2018 == .
                  replace IRAval3_2018 = 0 if IRAval3_2018 == -8
                  replace IRAval3_2018 = IRAval3_2018DK if IRAval3_2018 ==
9999998
                  replace IRAval3_2018 = 0 if IRAval3_2018 == 9999999
                  drop ira3max2018 IRAval3_2018DK

            egen IRAtotval_2018 = rowtotal(IRAval1_2018 IRAval2_2018
IRAval3_2018), missing
                  *3.1.2022 maybe do NOT make missing; N=14,196 with 9,578 =0
                  *replace IRAtotval_2018 = . if IRAtotval_2018 == 0
                  *2.11.2022 etl edits: N= 4,618

      *IRA risk share section
      *3.1.2022 first line of IRAriskshare#_2018 I set to 0 instead of '.' to
retain all 14,196

            gen IRAriskshare1_2018 = 0
                  replace IRAriskshare1_2018 = .25 if qq514_1 ==998 & qq515_1
== 1
                  replace IRAriskshare1_2018 = .50 if qq514_1 ==998 & qq515_1
== 3
                  replace IRAriskshare1_2018 = .75 if qq514_1 ==998 & qq515_1
== 5
                  replace IRAriskshare1_2018 = qq514_1 / 100 if qq514_1 >= 0
& qq514_1 < 101
                  drop qq514_1

            gen IRAriskshare2_2018 = 0
                  replace IRAriskshare2_2018 = .25 if qq514_2 ==998 & qq515_2
== 1
```

```
                  replace IRAriskshare2_2018 = .50 if qq514_2 ==998 & qq515_2
== 3
                  replace IRAriskshare2_2018 = .75 if qq514_2 ==998 & qq515_2
== 5
                  replace IRAriskshare2_2018 = qq514_2 / 100 if qq514_2 >= 0
& qq514_2 < 101
                  drop qq514_2

            gen IRAriskshare3_2018 = 0
                  replace IRAriskshare3_2018 = .25 if qq514_3 ==998 & qq515_3
== 1
                  replace IRAriskshare3_2018 = .50 if qq514_3 ==998 & qq515_3
== 3
                  replace IRAriskshare3_2018 = .75 if qq514_3 ==998 & qq515_3
== 5
                  replace IRAriskshare3_2018 = qq514_3 / 100 if qq514_3 >= 0
& qq514_3 < 101
                  drop qq514_3

      *3.1.2022 multiplication here is still okay for keeping 0s. each var
still has 14,196
            gen IRAatrisk1_2018 = 0
                  replace IRAatrisk1_2018 = IRAval1_2018 * IRAriskshare1_2018
            gen IRAatrisk2_2018 = 0
                  replace IRAatrisk2_2018 = IRAval2_2018 * IRAriskshare2_2018
            gen IRAatrisk3_2018 = 0
                  replace IRAatrisk3_2018 = IRAval3_2018 * IRAriskshare3_2018

            egen IRAtotatrisk_2018 = rowtotal(IRAatrisk1_2018 IRAatrisk2_2018
IRAatrisk3_2018), missing
                  *3.1.2022 don't drop 0's yet
                  *replace IRAtotatrisk_2018 = . if IRAtotatrisk_2018 == 0
/*this drops 52 0's)*/
      *3.1.2022 dont do the division yet. End up with N=4,618. Pull these
variables in separatly at the end.

            *gen IRAtotriskshare_2018 = IRAtotatrisk_2018 / IRAtotval_2018
/* N=3,134 2.11.2022*/

      **# Non-qual section starts here
            gen stockmax= qq319
            replace stockmax = 1750000 if qq319 ==99999996
            gen qq317DK =.
            replace qq317DK = ((qq318 + stockmax)/2) if qq317==99999998
/*need to drop the 99999996 from qq319 */

            rename qq317 stockval_2018
                  replace stockval_2018 = 0 if stockval_2018 == .
                  replace stockval_2018 = 0 if stockval_2018 == -8
                  replace stockval_2018 = qq317DK if stockval_2018 ==
99999998
                  replace stockval_2018 = 0 if stockval_2018 == 99999998
                  replace stockval_2018 = 0 if stockval_2018 == 99999999

            gen bondmax = qq333
            replace bondmax = 400000 if qq333 == 99999996
            gen qq331DK =.
```

```
                replace qq331DK = ((qq332 + bondmax)/2) if qq331 ==99999998

            rename qq331 bondval_2018
                replace bondval_2018 = 0 if bondval_2018 == .
                replace bondval_2018 = 0 if bondval_2018 == -8
                replace bondval_2018 = qq331DK if bondval_2018 == 99999998
                replace bondval_2018 = 0 if bondval_2018 == 99999998
                replace bondval_2018 = 0 if bondval_2018 == 99999999

            gen c1max= qq347
            replace c1max = 300001 if qq347 ==99999996
            gen qq345DK =.
            replace qq345DK = ((qq346 + c1max)/2) if qq345 ==99999998

            rename qq345 cash1val_2018
                replace cash1val_2018 = 0 if cash1val_2018 == .
                replace cash1val_2018 = 0 if cash1val_2018 == -8
                replace cash1val_2018 = qq345DK if cash1val_2018 ==
99999998
                replace cash1val_2018 = 0 if cash1val_2018 == 99999998
                replace cash1val_2018 = 0 if cash1val_2018 == 99999999

            gen c2max= qq359
            replace c2max = 250000 if qq347 ==99999996

            gen qq357DK=.
            replace qq357DK = ((qq358 + c2max)/2) if qq357 ==99999998

            rename qq357 cash2val_2018
                replace cash2val_2018 = 0 if cash2val_2018 == .
                replace cash2val_2018 = 0 if cash2val_2018 == -8
                replace cash2val_2018 = qq357DK if cash2val_2018 ==
99999998
                replace cash2val_2018 = 0 if cash2val_2018 == 99999998
                replace cash2val_2018 = 0 if cash2val_2018 == 99999999

            egen NQtotval_2018 = rowtotal(stockval_2018 bondval_2018
cash1val_2018 cash2val_2018), missing
      * 3.1.2022 don't do division yet. bring in each variable separately at
end
      *     gen riskshare_2018 = stockval_2018 / NQtotval_2018
      *           replace riskshare_2018 = . if riskshare_2018 == 0
                *2.11.2022 etl N = 2,524

            *sums all values and all risky share values to establish an all
asset risky share %
            egen totval_2018 = rowtotal(IRAtotval_2018 NQtotval_2018),
missing    /*N=14,196*/
            egen totatrisk_2018 = rowtotal(IRAtotatrisk_2018 stockval_2018),
missing /*N=14,196*/
      *3.1.2022 do this at end
      *     gen tot_riskshare_2018 = totatrisk_2018 / totval_2018 if
totatrisk_2018 /*N=4,396*/
      drop hhidpn
      gen hhidpn = hhid + pn
      merge m:1 moyr18 using "${data_ed}\asset prices\2018.dta", nogen
```

```
            save "${data_ed}\fat18.dta", replace
            clear

            *3.1.2022 this has all 14,196 still in the fat18 edited!

      *                               ***********
      **#                               2020
      *                               ***********
      *======================================================================
========
      *Import/combine 2020 dta files to create 2020 fat
      *======================================================================
========

      *2020 (R)

            *pulling section a
            use hhid pn RA019 RA500 RA501 using
"${data_covid}\STATA_Datasets\h20a_r.dta" , clear
                  rename RA019 age_2020

                  gen moyr20 = ym(RA501,RA500)
                  format %tmCCYY-NN moyr20

                  gen hhidpn = hhid + pn

                  merge m:1 moyr20 using "${data_ed}\asset prices\2020.dta",
nogen
            save "${data_ed}\fat20.dta", replace
            clear

            *pulling section b
            use hhid pn RB014 RB132 using
"${data_covid}\STATA_Datasets\h20b_r.dta"

                  rename RB014 education_2020
                  rename RB132 genrisk_2020
                        replace genrisk_2020 = . if genrisk_2020 >= 98
                  gen hhidpn = hhid + pn
            merge 1:1 hhidpn using "${data_ed}\fat20.dta" , nogen
            save "${data_ed}\fat20.dta", replace
            clear


      **# Bookmark #1
            *pulling section LB

            use hhid pn RLB032_2 /*PANA*/ RLB026A RLB026B RLB026C RLB026D
RLB026E RLB026F RLB026G RLB026H RLB026I RLB026J RLB026K RLB026L RLB026M
RLB026N RLB026O RLB026P RLB026Q RLB026R RLB026S RLB026T RLB026U RLB026V
RLB026W RLB026X RLB026Y /*Big 5*/ RLB031A RLB031B RLB031C RLB031D RLB031E
RLB031F RLB031G RLB031H RLB031I RLB031J RLB031K RLB031L RLB031M RLB031N
RLB031O RLB031P RLB031Q RLB031R RLB031S RLB031T RLB031U RLB031V RLB031W
RLB031X RLB031Y RLB031Z1 RLB031Z2 RLB031Z3 RLB031Z4 RLB031Z5 RLB031Z6 using
"${data_covid}\STATA_Datasets\h20lb_r.dta", clear

      rename RLB032_2 finrisk_2020
```

```
****************************************************
** Positive / Negative Affect **
**      pa_2020   na_2020
****************************************************
*PANA 26a....y
*During the last 30 days, to what degree did you feel....?
      *1 = Very much, 2 = Quite a bit, 3 = Moderately, 4 = A little, 5 = Not at all
      *Create an index of positive affect by reverse-coding items Q27c, d, f, g, h, k, p, q, t, u, v, x, and y and averaging the scores across all 13 items. Set the final score to missing if there are more than six items with missing values.
      *Create an index of negative affect by reverse-coding items Q27 a, b, e, i, j, l, m, n, o, r, s, and w and averaging the scores across all 12 items. Set the final score to missing if there are more than six items with missing values

      revrs RLB026C RLB026D RLB026F RLB026G RLB026H RLB026K RLB026P RLB026Q RLB026T RLB026U RLB026V RLB026X RLB026Y

*drop if there are more than 6 items with missing values. I checked and there are no Obs were this is true
gen pa1_20 = revRLB026C
gen pa2_20 = revRLB026D
gen pa3_20 = revRLB026F
gen pa4_20 = revRLB026G
gen pa5_20 = revRLB026H
gen pa6_20 = revRLB026K
gen pa7_20 = revRLB026P
gen pa8_20 = revRLB026Q
gen pa9_20 = revRLB026T
gen pa10_20 = revRLB026U
gen pa11_20 = revRLB026V
gen pa12_20 = revRLB026X
gen pa13_20 = revRLB026Y

gen pa_2020 = (pa1_20 + pa2_20 + pa3_20 + pa4_20 + pa5_20 + pa6_20 + pa7_20 + pa8_20 + pa9_20 + pa10_20 + pa11_20 + pa12_20 + pa13_20) /13

 revrs RLB026A RLB026B RLB026E RLB026I RLB026J RLB026L RLB026M RLB026N RLB026O RLB026R RLB026S RLB026W

gen na1_20 = revRLB026A
gen na2_20 = revRLB026B
gen na3_20 = revRLB026E
gen na4_20 = revRLB026I
gen na5_20 = revRLB026J
gen na6_20 = revRLB026L
gen na7_20 = revRLB026M
gen na8_20 = revRLB026N
gen na9_20 = revRLB026O
gen na10_20 = revRLB026R
gen na11_20 = revRLB026S
gen na12_20 = revRLB026W
```

```
	gen na_2020 = (na1_20 + na2_20 + na3_20 + na4_20 + na5_20 + na6_20 +
na7_20 + na8_20 + na9_20 + na10_20 + na11_20 + na12_20)/12

	**********************************************
	**	Big 5 OCEAN **
	**	o_2020 c_2020 e_2020 a_2020 n_2020
	**********************************************
	*indicate how well each of the following desribes you 1= alot| 2= some|
3= a little| 4= not at all

	*Big 5 lb031a a...z..._z6
		*1= A lot, 2 = Some, 3 = A little, 4 = Not at all
		*Reverse-code all items EXCEPT Q31c, Q31q, Q31v, and Q31x and
average the scores for items within sub-dimensions for

	*Conscientiousness (Q31c, Q31e, Q31i, Q31n, Q31r, Q31v, Q31x, Q31z_1,
Q31z_5, and Q31z_6)

	*Neuroticism (Q31d, Q31h, Q31l, Q31q)

	*Set the final score to missing if more than half of the items have
missing values within each sub-dimension.
		*Openness to Experience (Q31m, Q31o, Q31s, Q31t, Q31w, Q31z_3,
Q31z_4)

	revrs RLB031A RLB031B RLB031D RLB031E RLB031F RLB031G RLB031H RLB031I
RLB031J RLB031K RLB031L RLB031M RLB031N RLB031O RLB031P RLB031R RLB031S
RLB031T RLB031U RLB031W RLB031Y RLB031Z1 RLB031Z2 RLB031Z3 RLB031Z4 RLB031Z5
RLB031Z6

	gen O1_20 = revRLB031M
	gen O2_20 = revRLB031O
	gen O3_20 = revRLB031S
	gen O4_20 = revRLB031T
	gen O5_20 = revRLB031W
	gen O6_20 = revRLB031Z3
	gen O7_20 = revRLB031Z4

	gen C1_20 = RLB031C
	gen C2_20 = RLB031V
	gen C3_20 = RLB031X
	gen C4_20 = revRLB031E
	gen C5_20 = revRLB031I
	gen C6_20 = revRLB031N
	gen C7_20 = revRLB031R
	gen C8_20 = revRLB031Z1
	gen C9_20 = revRLB031Z5
	gen C10_20 = revRLB031Z6

	gen E1_20 = revRLB031A
	gen E2_20 = revRLB031F
	gen E3_20 = revRLB031J
	gen E4_20 = revRLB031U
	gen E5_20 = revRLB031Z2

	gen A1_20 = revRLB031B
	gen A2_20 = revRLB031G
```

```
      gen A3_20 = revRLB031K
      gen A4_20 = revRLB031P
      gen A5_20 = revRLB031Y

      gen N1_20 = revRLB031D
      gen N2_20 = revRLB031H
      gen N3_20 = revRLB031L
      gen N4_20  = RLB031Q


      gen o_2020 = (O1_20 + O2_20 + O3_20 + O4_20 + O5_20 + O6_20 + O7_20)/7
      gen c_2020 = (C1_20 + C2_20 + C3_20 + C4_20 + C5_20 + C6_20 + C7_20 +
C8_20 + C9_20 + C10_20)/10
      gen e_2020 = (E1_20 + E2_20 + E3_20 + E4_20 + E5_20)/5
      gen a_2020 = (A1_20 + A2_20 + A3_20 + A4_20 + A5_20)/5
      gen n_2020 = (N1_20 + N2_20 + N3_20 + N4_20)/4
      *************************************************************
                  gen hhidpn = hhid + pn
            merge 1:1 hhidpn using "${data_ed}\fat20.dta", nogen
            save "${data_ed}\fat20.dta", replace
            clear

            *pulling section p
            use hhid pn RP047 RP041 RP097 using
"${data_covid}\STATA_Datasets\h20p_r.dta", clear

      * riskperc2020   ~ higher# ~ more bullish outlook
            gen marketexp20 =.
            replace marketexp20 = RP047
            replace marketexp20 = . if marketexp20 ==-8 | marketexp20 ==998|
marketexp20 ==999
      drop RP047

      *financial planning periods time horizon 0: <5 years; 1 = 5yrs+
            gen fpperiods2020=.
                  replace fpperiods2020= RP041
                  replace fpperiods2020 = . if RP041 ==-8
                  replace fpperiods2020 = 0 if RP041 == 1 | RP041 == 2 |
RP041 == 3
                  replace fpperiods2020 = 1 if RP041 == 4 | RP041 == 5 |
RP041 == 8 | RP041 == 9
      drop RP041

      * how closely do you follow the market? 0: not at all, 1: somehwhat, 2:
very closely
            gen fmkt20 =.
            replace fmkt20= RP097
            replace fmkt20 = . if RP097 == -8 | RP097==8 | RP097==9
            revrs fmkt20
            gen followmkt2020 = revfmkt20
            drop RP097
            drop fmkt20
            drop revfmkt20

                  gen hhidpn = hhid + pn
            merge 1:1 hhidpn using "${data_ed}\fat20.dta", nogen
            save "${data_ed}\fat20.dta", replace
```

```
            clear


            *pulling section q

            * For some reason pn is not showing up in this module.
            *Also: only 11,500 hhid's in this section so roughly 5,000 will
not get matched

            use hhid RPN_CS RQ166_1 RQ167_1 RQ168_1 RQ169_1 RQ166_2 RQ167_2
RQ168_2 RQ169_2 RQ166_3 RQ167_3 RQ168_3 RQ169_3 RQ514_1 RQ515_1 RQ514_2
RQ515_2 RQ514_3 RQ515_3 RQ317 RQ318 RQ319 RQ320 RQ331 RQ332 RQ333 RQ334 RQ345
RQ346 RQ347 RQ348 RQ357 RQ358 RQ359 RQ360 using
"${data_covid}\STATA_Datasets\h20q_h2.dta", clear

            gen ira1max2020 = RQ168_1
            replace ira1max2020 =  400001 if RQ168_1 == 99999996
            gen IRAval1_2020DK = .
                  replace IRAval1_2020DK = (RQ167_1 + ira1max2020)/2 if
RQ166_1 == 999999998

            rename RQ166_1 IRAval1_2020
                  replace IRAval1_2020 = 0 if IRAval1_2020 == .
                  replace IRAval1_2020 = 0 if IRAval1_2020 == -8
                  replace IRAval1_2020 = IRAval1_2020DK if IRAval1_2020 ==
999999998
                  replace IRAval1_2020 = 0 if IRAval1_2020 == 999999999
                  drop ira1max2020
                  drop IRAval1_2020DK

            gen ira2max2020 = RQ168_2
            replace ira2max2020 =  400001 if RQ168_2 == 99999996
            gen IRAval2_2020DK = .
                  replace IRAval2_2020DK = (RQ167_2 + ira2max2020)/2 if
RQ166_2 == 999999998

            rename RQ166_2 IRAval2_2020
                  replace IRAval2_2020 = 0 if IRAval2_2020 == .
                  replace IRAval2_2020 = 0 if IRAval2_2020 == -8
                  replace IRAval2_2020 = IRAval2_2020DK if IRAval2_2020 ==
999999998
                  replace IRAval2_2020 = 0 if IRAval2_2020 == 999999999
                  drop ira2max2020
                  drop IRAval2_2020DK

            gen ira3max2020 = RQ168_3
            replace ira3max2020 =  400001 if RQ168_3 == 99999996
            gen IRAval3_2020DK = .
                  replace IRAval3_2020DK = (RQ167_3 + ira3max2020)/2 if
RQ166_3 == 999999998

            rename RQ166_3 IRAval3_2020
                  replace IRAval3_2020 = 0 if IRAval3_2020 == .
                  replace IRAval3_2020 = 0 if IRAval3_2020 == -8
                  replace IRAval3_2020 = IRAval3_2020DK if IRAval3_2020 ==
999999998
                  replace IRAval3_2020 = 0 if IRAval3_2020 == 999999999
```

```
                  drop ira3max2020 IRAval3_2020DK

            egen IRAtotval_2020 = rowtotal(IRAval1_2020 IRAval2_2020
IRAval3_2020), missing
      *3.1.2022 do not set to missing and retain 0s   ; N=11,490
      *           replace IRAtotval_2020 = . if IRAtotval_2020 == 0
                  *3.1.2022 do not set to missing and retain 0s
                  *2.9.2022 etl edits: N=2,868

      *3.1.2022 set to 0 instead of '.'
            gen IRAriskshare1_2020 = 0
                  replace IRAriskshare1_2020 = .25 if RQ514_1 ==998 & RQ515_1
== 1
                  replace IRAriskshare1_2020 = .50 if RQ514_1 ==998 & RQ515_1
== 3
                  replace IRAriskshare1_2020 = .75 if RQ514_1 ==998 & RQ515_1
== 5
                  replace IRAriskshare1_2020 = RQ514_1 / 100 if RQ514_1 >= 0
& RQ514_1 < 101
                  drop RQ514_1

            gen IRAriskshare2_2020 = 0
                  replace IRAriskshare2_2020 = .25 if RQ514_2 ==998 & RQ515_2
== 1
                  replace IRAriskshare2_2020 = .50 if RQ514_2 ==998 & RQ515_2
== 3
                  replace IRAriskshare2_2020 = .75 if RQ514_2 ==998 & RQ515_2
== 5
                  replace IRAriskshare2_2020 = RQ514_2 / 100 if RQ514_2 >= 0
& RQ514_2 < 101
                  drop RQ514_2

            gen IRAriskshare3_2020 = 0
                  replace IRAriskshare3_2020 = .25 if RQ514_3 ==998 & RQ515_3
== 1
                  replace IRAriskshare3_2020 = .50 if RQ514_3 ==998 & RQ515_3
== 3
                  replace IRAriskshare3_2020 = .75 if RQ514_3 ==998 & RQ515_3
== 5
                  replace IRAriskshare3_2020 = RQ514_3 / 100 if RQ514_3 >= 0
& RQ514_3 < 101
                  drop RQ514_3

            gen IRAatrisk1_2020 = 0
                  replace IRAatrisk1_2020 = IRAval1_2020 * IRAriskshare1_2020
            gen IRAatrisk2_2020 = 0
                  replace IRAatrisk2_2020 = IRAval2_2020 * IRAriskshare2_2020
            gen IRAatrisk3_2020 = 0
                  replace IRAatrisk3_2020 = IRAval3_2020 * IRAriskshare3_2020

            egen IRAtotatrisk_2020 = rowtotal(IRAatrisk1_2020 IRAatrisk2_2020
IRAatrisk3_2020), missing
      *3.1.2022 do not set to '.' yet; N-11,490 still
      *     replace IRAtotatrisk_2020 = . if IRAtotatrisk_2020 == 0  /*this
drops 151 0's)*/

      *3.1.2022 do at very end
```

```
      *           gen IRAtotriskshare_2020 = IRAtotatrisk_2020 /
IRAtotval_2020   /* N=1927 2.9.2022*/

            gen stockmax= RQ319
            replace stockmax = 1750000 if RQ319 ==99999996
            gen RQ317DK =.
            replace RQ317DK = ((RQ318 + stockmax)/2) if RQ317==999999998

            gen stockval_2020= RQ317
            recast double stockval_2020
                  replace stockval_2020 = 0 if stockval_2020 == .
                  replace stockval_2020 = 0 if stockval_2020 <= -8
                  replace stockval_2020 = RQ317DK if RQ317 == 999999998
/*if RQ317, not if stockval_2020*/
                  replace stockval_2020 = 0 if stockval_2020 == 999999998
                  replace stockval_2020 = 0 if RQ317 == 999999999
                  drop stockmax RQ317DK RQ317

            gen bondmax = RQ333
            replace bondmax = 400000 if RQ333 == 99999996
            gen RQ331DK =.
            replace RQ331DK = ((RQ332 + bondmax)/2) if RQ331 == 9999998

            gen bondval_2020= RQ331
                  replace bondval_2020 = 0 if bondval_2020 == .
                  replace bondval_2020 = 0 if bondval_2020 == -8
                  replace bondval_2020 = RQ331DK if RQ331 == 9999998
                  replace bondval_2020 = 0 if bondval_2020 == 9999998
                  replace bondval_2020 = 0 if bondval_2020 == 9999999
                  drop bondmax RQ331DK RQ331


            gen cash1max = RQ347
            replace cash1max = 250001 if RQ347 == 99999996
            gen RQ345DK =.
            replace RQ345DK = ((RQ346 + cash1max)/2) if RQ345 ==9999998

            gen cash1val_2020 =RQ345
                  replace cash1val_2020 = 0 if cash1val_2020 == .
                  replace cash1val_2020 = 0 if cash1val_2020 == -8
                  replace cash1val_2020 = RQ345DK if cash1val_2020 == 9999998
                  replace cash1val_2020 = 0 if cash1val_2020 == 9999999
                  drop cash1max RQ345DK RQ345

            gen c2max = RQ359
            replace c2max = 250001 if RQ359 == 99999996
            gen RQ357DK=.
            replace RQ357DK = ((RQ358 + c2max)/2) if RQ357 ==999999998

            gen cash2val_2020= RQ357
                  replace cash2val_2020 = 0 if cash2val_2020 == .
                  replace cash2val_2020 = 0 if cash2val_2020 == -8
                  replace cash2val_2020 = RQ357DK if RQ357 == 999999998
                  replace cash2val_2020 = 0 if RQ357 == 999999999
                  drop c2max RQ357DK RQ357
```

```
            egen NQtotval_2020 = rowtotal(stockval_2020 bondval_2020
cash1val_2020 cash2val_2020), missing
      *3.1.2022 wait to do division after merged;
      *     gen riskshare_2020 = stockval_2020 / NQtotval_2020 /* 0=5,968
N=7,548 so drop 0's*/
      *           replace riskshare_2020 = . if riskshare_2020 == 0
                  *2.9.2022 etl N = 1,580

            *sums all values and all risky share values to establish an all
asset risky share %


            /*gen totval_2020 = IRAtotval_2020 + NQtotval_2020    */
/*N=2,868*/
            egen totval_2020 = rowtotal(IRAtotval_2020 NQtotval_2020),
missing    /*N=11,490*/
            /*gen totatrisk_2020 = IRAtotatrisk_2020 + stockval_2020 */
/*N=1,927*/
            egen totatrisk_2020 = rowtotal(IRAtotatrisk_2020 stockval_2020),
missing /*N=11,490*/
      *3.1.2022 don't do division yet.
      *     gen tot_riskshare_2020 = totatrisk_2020 / totval_2020 if
totatrisk_2020 !=0
                  /*N should be 2,737, which is also 7,766 - 5,029 zeroes)*/

            *I'm adding RPN_CS
            *11/16/2022: there's only 11,485 RPN_CS to merge on
            gen hhidpn = hhid + RPN_CS
            merge 1:1 hhidpn using "${data_ed}\fat20.dta", nogen
            save "${data_ed}\fat20.dta", replace

      *============================================================================
========
      **# Combine fat file data
      *============================================================================
========
      *2/17/2022 etl edit here to see if this merges all edited fat files
      *for now, maybe I should just try merging the 18 and 20 fat files


      /****** this is just the 18&20 combined fat file ******/
      clear
      use "${data_ed}\fat20.dta"
      merge 1:1 hhidpn using "${data_ed}\fat18.dta", nogen
      save "${data_ed}\fat1820.dta", replace
      *matched N=14,257
      *Future research: here is where we could just keep adding the previous
year until we have the fat files combined
      *merge 2016 with 1820 file
      clear
      use "${data_ed}\fat16.dta"
      merge 1:1 hhidpn using "${data_ed}\fat1820.dta", nogen
      save "${data_ed}\fat 161820.dta", replace

      *============================================================================
========
      *Merge RAND and fat data
```

```
	*==========================================================================
========
	clear
	use "${data_ed}\randetl.dta", clear
		merge 1:1 hhidpn using "${data_ed}\fat 161820.dta", nogen

		*matched 21,684
	*clean up dataset for use

	/*					what if I don't do this part
	Example: loginc N=13,218, age_2020 = 12,014
	Running this drops loginc 10,413, more importantly

	keep if spy18 !=.
	keep if spy20!=.
	*/


		save "${data_ed}\varsbeforedrop1.dta", replace


	*==========================================================================
========
	*Performance adjustment section
	*==========================================================================
========

	*Performance adjustment section
		*0th: calculate a stock, bond, and cash return
		*1st: adjust the values using the 2018 and 2019 returns
		*2nd: calculate the performance adjusted weight
		*3rd: that's the weight we need to compare to the next survey
year (2020)

	*0 calculate stock, bond, and cash returns
		gen stockr = spy20/spy18
		gen bondr = agg20/agg18
		gen cashr = bil20/bil18

	*3.1.2022 all good through here
	*major edit to this section starting here

		*Adjust the NQ stock VALUES using the 2018 to 2020 returns (EV =
expected value based on rate of return)
		gen evstock2020 = stockval_2018 * stockr
		*PAstockval_2018_1
		gen evbond2020  = bondval_2018  * bondr
		gen evcash1_2020 = cash1val_2018 * 1.00000
		gen evcash2_2020 = cash2val_2018 * cashr

		*Sum the expected 2020 non-IRA values
		egen evNQtotval2020 = rowtotal(evstock2020 evbond2020
evcash1_2020 evcash2_2020), missing
	*3.1.2022 N still 12,129
```

```
      /*N=5,677 but there are 3,426=0, so N with some NQ value = 2,251. Don't
drop yet because they may have an IRA value. Need to do the math if 'x' !=0,
else =0 */
            * Calculate the performance adjusted NQ stock allocation PERCENT
      *     gen PAriskshare_2018_1 = evstock2020 / evNQtotval2020

      *we could run a paired t-test comparing PAriskshare_2018 to
riskshare_2020 to compare the NQ riskshare change


            *do the same thing for the IRAs
            *the non-IRA portion...assume the bond return

            *IRA performance adjustment section
            *1. adjust the IRA stock VALUE of each account
            gen evIRA1stockval2020 = IRAatrisk1_2018  * stockr
            gen evIRA2stockval2020 = IRAatrisk2_2018  * stockr
            gen evIRA3stockval2020 = IRAatrisk3_2018  * stockr

            *1b. sum the IRA stock Values
            egen evIRAstockval2020 = rowtotal (evIRA1stockval2020
evIRA2stockval2020 evIRA3stockval2020), missing

            *2a. calculate the IRA *NON* stock percentage
            gen IRA1bond_2018 = .
            replace IRA1bond_2018 = (1 - IRAriskshare1_2018) / 100 if
IRAriskshare1_2018 >= 0 & IRAriskshare1_2018 < 101
            gen IRA2bond_2018 = .
            replace IRA2bond_2018 = (1- IRAriskshare2_2018) / 100 if
IRAriskshare2_2018 >= 0 & IRAriskshare2_2018 < 101
            gen IRA3bond_2018 = .
                  replace IRA3bond_2018 = (1- IRAriskshare3_2018) / 100 if
IRAriskshare3_2018 >= 0 & IRAriskshare3_2018 < 101


            *2b. performance adjust the bond IRA values (assume it earned the
bond return)
            gen evIRA1bondval2020 = IRA1bond_2018 * bondr
            gen evIRA2bondval2020 = IRA2bond_2018 * bondr
            gen evIRA3bondval2020 = IRA3bond_2018 * bondr

            *2c. sum the expected IRA bond values
            egen evIRAbondval2020 = rowtotal(evIRA1bondval2020
evIRA2bondval2020 evIRA3bondval2020), missing

            *3. Sum the 2020 expected IRA values adjusted for both stock and
bond returns
            egen evIRAtotval2020 = rowtotal (evIRAstockval2020
evIRAbondval2020), missing

            *4. get the performance adjusted IRA stock percentage
      *           gen PAIRAtotriskshare_2018_1 = PAIRAtotatrisk_2018_1 /
PAIRAtotval_2018_1

      *we could run a paired t-test comparing PAIRAtotriskshare_2018 to
IRAtotriskshare_2020
```

```
      *total 2020 expected stock value (IRA + NQ)
            egen evtotatrisk_2020 = rowtotal(evstock2020 evIRAstockval2020),
missing
      *total 2020 expected portfolio value (IRA + NQ)
            egen evtotval_2020 = rowtotal(evNQtotval2020 evIRAtotval2020),
missing
      *N still 14,257


      *Follow Browning & Finke, 2015

      *3.2.2022 need to drop if they have no assets in both years (maybe even
if <$1,000)
      *drop if they have no assets in 2018 AND 2020
      *actually limit if LNW < $1,000  (also could make a variable of
networth cats)

      /* better not do this for SEM though
      gen zeroboth = 0
      replace zeroboth = 1 if totval_2018 <=1000 & totval_2020 <=1000
      drop if zeroboth == 1
      *drops 3,709
      */

      *(1) Actual % change = 2020 stock% - 2018 stock%
      gen actualpct20to18 = (totatrisk_2020 / totval_2020) - (totatrisk_2018
/ totval_2018)
      *2,192 are 0% of 5,063 total.

      *(2) Expected % change = 2020 expect stock % - 2018 stock%
      gen expectedpct20to18 = (evtotatrisk_2020 / evtotval_2020 ) -
(totatrisk_2018 / totval_2018)
      *4,712 are 0 of 8,674 total.

      *key control: stocks as a % of financial assets in 2018
      gen riskshare_2018 = totatrisk_2018 / totval_2018
      *4,673 are 0

      *********************************************
      **#         dependent variable
      ***                                                  ***
      *********************************************
      *(3) DV = equation 1 - equation 2
      *srdv20to18 means "stock reallocation dependent variable 2020 to 2018"
      *for OLS
      gen stockreallocation = actualpct20to18 - expectedpct20to18
      *N=5,061
      *mean= -7.52%
      *2,176 had 0% change, how to handle?  By having %stocks as a control
variable?


      *N= 1,140 with cog vars (those aged 65+)
      *N=1,867 without cog vars
      *N = 4,876 w/o C & N vars
      *N= 700 if cog vars AND neither == 1
```

```
	*Multi-nomial (Lim advice 3.7/22) based on who owned stock in each year
	*neither
	gen neither = 0
	replace neither =1 if totatrisk_2018 == 0 & totatrisk_2020 ==0

	*2018=yes, 2020 =no stock
	gen y18n20 = 0
	replace y18n20 = 1 if totatrisk_2018 >0 & totatrisk_2020 ==0

	*2018=no, 2020= has stock
	gen n18y20 = 0
	replace n18y20 = 1 if totatrisk_2018 ==0 & totatrisk_2020 >0

	*stock in both 18 and 20
	gen both = 0
	replace both =1 if totatrisk_2018 > 0 & totatrisk_2020 >0

	gen dvmulti4 = 0
	replace dvmulti4 = 1 if y18n20 ==1
	replace dvmulti4 = 2 if n18y20 ==1
	replace dvmulti4 = 3 if both   ==1
	*label define dvmulti4 0 "Neither" 1 "Stock '18 not '20" 2 "No stock
'18 yes '20" 3 "Stock in both years"
	*label values dvmulti4 dvmulti4

	drop if marstat2018 ==. & neither == 0

*=============================================================================
==
* END
*=============================================================================
==

	save "${data_ed}\DissAllVars.dta", replace

/****************************************************************************
*********
*Title: Dissertation
*Created by: Eric
*Created on: 9/7/2023
*Last modified on: 9/7/2023
*Last modified by: Eric
*Purpose: Export file to Mplus; code missings to -9999
*****************************************************************************
*********/
*Purpose: code missings to -9999
*Also: to create CSV file so that you can pull that into Mplus

clear all

*=============================================================================
==
*Set directories
*=============================================================================
==

global projdir "C:\Users\erict\OneDrive\K-State PhD\Dissertation\Data"
```

```
cd "$projdir"
global data_ed "${projdir}\edited"

use "${data_ed}\DissallVars.dta"

*need to limit it to the 17k Rs from 2018 Rand file...how?
*limit on marstat = 2018 = 17,120

keep hhidpn age_2018 gender marstat2018 race3 educ2018 workstat2018 ihst_nw18
healthstat2018 imrc18 dlrc18 identmo18 identdy18 identyr18 identdw18
identpres18 identvp18 mentstatscale numeracy num1 num2 num3 fpperiods2018
sentv2 followmkt2018 riskshare_2018 pa1 pa2 pa3 pa4 pa5 pa6 pa7 pa8 pa9 pa10
pa11 pa12 pa13 na1 na2 na3 na4 na5 na6 na7 na8 na9 na10 na11 na12 O1_creat
O2_imagi O3_intel O4_curio O5_broad O6_sophi O7_adven C1_reckl C2_carel
C3_impul C4_organ C5_respo C6_hardw C7_selfd C8_cauti C9_thoro C10_thri
E1_outgo E2_frien E3_livel E4_activ E5_talka A1_helpf A2_warm A3_carin
A4_softh A5_sympa N1_moody N2_worry N3_nervo N4_calm o_2018 c_2018 e_2018
a_2018 n_2018 marketexp20 stockreallocation neither
save "${data_ed}\DissKeepVars.dta", replace


mvencode hhidpn age_2018 gender marstat2018 race3 educ2018 workstat2018
ihst_nw18 healthstat2018 imrc18 dlrc18 identmo18 identdy18 identyr18
identdw18 identpres18 identvp18 mentstatscale numeracy num1 num2 num3
fpperiods2018 sentv2 followmkt2018 riskshare_2018 pa1 pa2 pa3 pa4 pa5 pa6 pa7
pa8 pa9 pa10 pa11 pa12 pa13 na1 na2 na3 na4 na5 na6 na7 na8 na9 na10 na11
na12 O1_creat O2_imagi O3_intel O4_curio O5_broad O6_sophi O7_adven C1_reckl
C2_carel C3_impul C4_organ C5_respo C6_hardw C7_selfd C8_cauti C9_thoro
C10_thri E1_outgo E2_frien E3_livel E4_activ E5_talka A1_helpf A2_warm
A3_carin A4_softh A5_sympa N1_moody N2_worry N3_nervo N4_calm o_2018 c_2018
e_2018 a_2018 n_2018 marketexp20 stockreallocation neither , mv(-9999)

save "${data_ed}\DissKeepVars.dta", replace

export delimited using "${data_ed}\DissKeepVars.csv", replace

*Then open that file, copy the first row of var names to paste in
usevariables
*Then delete that first row and use that as the use file

*****************************************************************************
*********
*Title: Dissertation
*Created by: Eric
*Created on: 9/7/2023
*Last modified on: 11/2/2023
*Last modified by: Eric
*Purpose: Alphas and descriptives
*****************************************************************************
*********/


clear all

*============================================================================
==
*Set directories
```

```
*=================================================================================
==

global projdir "C:\Users\erict\OneDrive\K-State PhD\Dissertation\Data"
cd "$projdir"
global data_ed "${projdir}\edited"
global data_raw "${projdir}\raw"
global data_covid "${projdir}\2020_HRS_COVID\STATA_Datasets"

use "${data_ed}\DissallVars.dta"


keep hhidpn age_2018 gender marstat2018 race3 educ2018 workstat2018 ihst_nw18
healthstat2018 imrc18 dlrc18 identmo18 identdy18 identyr18 identdw18
identpres18 identvp18 mentstatscale numeracy num1 num2 num3 fpperiods2018
sentv2 followmkt2018 riskshare_2018 pa1 pa2 pa3 pa4 pa5 pa6 pa7 pa8 pa9 pa10
pa11 pa12 pa13 na1 na2 na3 na4 na5 na6 na7 na8 na9 na10 na11 na12 O1_creat
O2_imagi O3_intel O4_curio O5_broad O6_sophi O7_adven C1_reckl C2_carel
C3_impul C4_organ C5_respo C6_hardw C7_selfd C8_cauti C9_thoro C10_thri
E1_outgo E2_frien E3_livel E4_activ E5_talka A1_helpf A2_warm A3_carin
A4_softh A5_sympa N1_moody N2_worry N3_nervo N4_calm o_2018 c_2018 e_2018
a_2018 n_2018 marketexp18 marketexp20 stockreallocation neither

*alphas
*Openness
alpha O1_creat O2_imagi O3_intel O4_curio O5_broad O6_sophi O7_adven, std
item
sum o_2018

*Consientiousness
alpha C1_reckl C2_carel C3_impul C4_organ C5_respo C6_hardw C7_selfd C8_cauti
C9_thoro C10_thri, std item
sum c_2018

*Extraversion
alpha E1_outgo E2_frien E3_livel E4_activ E5_talka, std item
sum e_2018

*Agreeableness
alpha A1_helpf A2_warm A3_carin A4_softh A5_sympa, std item
sum a_2018

*Neuroticism (all 4)
alpha N1_moody N2_worry N3_nervo N4_calm, std item
sum n_2018

*Numeracy
alpha num1 num2 num3, std item

*Mental status
alpha identmo18 identdy18 identyr18 identdw18 identpres18 identvp18 imrc18
dlrc18, std item

*************
*Positive Affect
alpha pa1 pa2 pa3 pa4 pa5 pa6 pa7 pa8 pa9 pa10 pa11 pa12 pa13, std item
```

```
gen pa_2018 = (pa1 + pa2 + pa3 + pa4 + pa5 + pa6 + pa7 + pa8 + pa9 + pa10 +
pa11 + pa12 + pa13)/13
sum pa_2018

*Negative Affect
alpha na1 na2 na3 na4 na5 na6 na7 na8 na9 na10 na11 na12, std item
gen na_2018 = (na1 + na2 + na3 + na4 + na5 + na6 + na7 + na8 + na9 + na10 +
na11 + na12)/12
sum na_2018

*******************
*Need to cobmine PANA and Each Big 5 across waves since only 1/2 used per
waves
*Generate as missing first
gen pacombo =.
gen nacombo = .
gen ocombo = .
gen ccombo = .
gen ecombo = .
gen acombo = .
gen ncombo = .
* Combine the 2018 and 2020 values for each variable
* For Positive Affect
replace pacombo = pa_2018 if pa_2018 != .
replace pacombo = pa_2020 if pacombo == .
* For Negative Affect
replace nacombo = na_2018 if na_2018 != .
replace nacombo = na_2020 if nacombo == .
* For Openness
replace ocombo = o_2018 if o_2018 != .
replace ocombo = o_2020 if ocombo == .
* For Conscientiousness
replace ccombo = c_2018 if c_2018 != .
replace ccombo = c_2020 if ccombo == .
* For Extraversion
replace ecombo = e_2018 if e_2018 != .
replace ecombo = e_2020 if ecombo == .
* For Agreeableness
replace acombo = a_2018 if a_2018 != .
replace acombo = a_2020 if acombo == .
* For Neuroticism
replace ncombo = n_2018 if n_2018 != .
replace ncombo = n_2020 if ncombo == .

sum
*************************************************************************
*Hierarchical linear regression
*Purpose: see if each block adds explanatory power

*make sure you have a consistent N for each of these blocks!
*seems backwards but using full block 4 first to get sample
*then use that sample on remaining blocks

*************************************
*** this is the one to use *********
*2018 OCEAN and PANA but with 2020 stock market expectation, n:991
```

```
*block 4: add stock market outlook (situational trait)
regress stockreallocation age_2018 gender marstat2018 race3 educ2018
workstat2018 ihst_nw18 healthstat2018 mentstatscale numeracy fpperiods2018
sentv2 followmkt2018 riskshare_2018 o_2018 c_2018 e_2018 a_2018 n_2018
pa_2018 na_2018 marketexp20, vce(cluster hhid)

gen regsample = e(sample)

*get descriptives
tab1 stockreallocation marketexp20 age_2018 gender marstat2018 race3 educ2018
workstat2018 ihst_nw18 healthstat2018 fpperiods2018 followmkt2018 if
regsample==1

sum stockreallocation age_2018 gender marstat2018 race3 educ2018 workstat2018
ihst_nw18 healthstat2018 mentstatscale numeracy fpperiods2018 sentv2
followmkt2018 riskshare_2018 o_2018 c_2018 e_2018 a_2018 n_2018 pa_2018
na_2018 marketexp20 if regsample ==1

* pacombo nacombo ocombo ccombo ecombo acombo ncombo
*using combined 2018 and 2020 for personality traits
*dropped mentstatscale
regress stockreallocation age_2018 gender marstat2018 race3 educ2018
workstat2018 ihst_nw18 healthstat2018  numeracy fpperiods2018 sentv2
followmkt2018 riskshare_2018 ocombo ccombo ecombo acombo ncombo

regress stockreallocation age_2018 gender marstat2018 race3 educ2018
workstat2018 ihst_nw18 healthstat2018  numeracy fpperiods2018 sentv2
followmkt2018 riskshare_2018 ocombo ccombo ecombo acombo ncombo pacombo
nacombo

*Block 4: run first to get consistent sample across
regress stockreallocation age_2018 gender marstat2018 i.race3 educ2018
workstat2018 ihst_nw18 healthstat2018  numeracy fpperiods2018 sentv2
i.followmkt2018 riskshare_2018 ocombo ccombo ecombo acombo ncombo pacombo
nacombo marketexp20, vce(cluster hhid)
*R-Square: .2479
gen regsample = e(sample)

*Block 3: PANA
regress stockreallocation age_2018 gender marstat2018 i.race3 educ2018
workstat2018 ihst_nw18 healthstat2018  numeracy fpperiods2018 sentv2
i.followmkt2018 riskshare_2018 ocombo ccombo ecombo acombo ncombo pacombo
nacombo if regsample==1, vce(cluster hhid)
*R-Square: .2406

*Block 2: Big 5
regress stockreallocation age_2018 gender marstat2018 i.race3 educ2018
workstat2018 ihst_nw18 healthstat2018  numeracy fpperiods2018 sentv2
i.followmkt2018 riskshare_2018 ocombo ccombo ecombo acombo ncombo if
regsample==1, vce(cluster hhid)
*R-Square: .2404

*Block 1: Controls
regress stockreallocation age_2018 gender marstat2018 i.race3 educ2018
i.workstat2018 ihst_nw18 healthstat2018  numeracy fpperiods2018 sentv2
i.followmkt2018 riskshare_2018  if regsample==1, vce(cluster hhid)
*R-Square: .2385
```

MPlus

```
TITLE: SEM
! *** with riskshare_2018
! no boots
! no controls
! fitted CFAs from the MM
! full SEM
! 2 MIs at the end

Data:
    File is "C:\Users\erict\OneDrive\K-State PhD\Dissertation\Data\edited\
  DissKeepVars.csv" ;


    Variable:
  Names are
gender race3 marstat2018 educ2018 workstat2018 healthstat2018 ihst_nw18
identmo18 identdy18 identyr18 identdw18 identpres18 identvp18 imrc18
dlrc18 mentstatscale hhidpn marketexp20 sentv2 age_2018 fpperiods2018
followmkt2018 num1 num2 num3 numeracy pa1 pa2 pa3 pa4 pa5 pa6 pa7 pa8
pa9 pa10 pa11 pa12 pa13 na1 na2 na3 na4 na5 na6 na7 na8 na9 na10 na11
na12 O1_creat O2_imagi O3_intel O4_curio O5_broad O6_sophi O7_adven
C1_reckl C2_carel C3_impul C4_organ C5_respo C6_hardw C7_selfd C8_cauti
C9_thoro C10_thri E1_outgo E2_frien E3_livel E4_activ E5_talka A1_helpf
A2_warm A3_carin A4_softh A5_sympa N1_moody N2_worry N3_nervo N4_calm
o_2018 c_2018 e_2018 a_2018 n_2018 riskshare_2018 stockreallocation ;


    Missing are all (-9999) ;
    IDVARIABLE IS hhidpn;


  USEVARIABLES ARE hhidpn

  na1 na2 na3 na4 na5 na6 na7 na8 na9 na10 na11
 na12 pa1 pa2 pa3 pa4 pa5 pa6 pa7 pa8
  pa9 pa10 pa11 pa12 pa13
  N1_moody N2_worry N3_nervo N4_calm
   C4_organ C5_respo C6_hardw C7_selfd C8_cauti
   C9_thoro C10_thri
   O1_creat O2_imagi O3_intel O4_curio O5_broad
   O6_sophi O7_adven
   E1_outgo E2_frien E3_livel E4_activ E5_talka
   A1_helpf A2_warm A3_carin A4_softh A5_sympa
   marketexp20
   riskshare_2018 ! just realized I've been missing this KEY VAR!!!
  stockreallocation
  !adding controls here
 gender race3 marstat2018 educ2018 workstat2018 healthstat2018 ihst_nw18
 mentstatscale sentv2 age_2018 fpperiods2018 followmkt2018 numeracy
;

ANALYSIS:
 TYPE IS General;
```

```
 ESTIMATOR IS ML;
 ! Bootstrap = 2000; ! bootstraps here. do 5000 final time
 ITERATIONS = 1000; ! switching from 2000
 CONVERGENCE = 0.00005;
 COVERAGE = 0.001;
 Processors = 4;

MODEL:
! Openness
Open by O1_creat O2_imagi O3_intel O4_curio O5_broad
O6_sophi O7_adven ;
O1_creat with O2_imagi ; !mod 1
O6_sophi with O7_adven ; !mod 2

!Conscientiousness
Cons by    C4_organ C5_respo C6_hardw C7_selfd C8_cauti
C9_thoro C10_thri ; !dropped 1-3
C9_thoro with C10_thri; ! mod 1
C8_cauti with C10_thri; ! mod 2

! Extraverson
Extra by  E1_outgo E2_frien E3_livel E4_activ E5_talka ;
E3_livel with E4_activ ; ! mod 1
E1_outgo with E5_talka ; ! mod 2
E1_outgo with E4_activ ; ! mod 3

! Agree
Agree by A1_helpf A2_warm A3_carin A4_softh A5_sympa ;
A4_softh with A5_sympa ; !Mod 1

!Neuroticism
NRTCSM by N1_moody N2_worry N3_nervo N4_calm;
N2_worry with N3_nervo;

!Positive Affect
PA by pa1 pa2 pa3 pa4 pa5 pa6 pa7 pa8
pa9 pa10 pa11 pa12 pa13 ;
pa1 with pa2  ; ! mod 1
pa9 with pa10 ; ! mod 2
pa4 with pa5  ; ! mod 3
pa7 with pa8  ; ! mod 4
pa6 with pa8  ; ! mod 5
pa10 with pa11; ! mod 6
pa9 with pa13 ; ! mod 7
pa11 with pa12; ! mod 8
pa8 with pa12 ; ! mod 9
pa6 with pa12 ; ! mod 10
pa12 with pa13; ! mod 11
pa10 with pa13; ! mod 12
pa6 with pa13 ; ! mod 13
pa1 with pa6  ; ! mod 14
pa4 with pa6  ; ! mod 15
pa13 with pa7 ; ! mod 16
pa11 with pa2 ; ! mod 17
pa3 with pa5  ; ! mod 18
pa3 with pa4  ; ! mod 19
pa5 with pa6  ; ! mod 20
```

```
pa1 with pa13 ; ! mod 21
pa10 with pa12; ! mod 22
pa8 with pa10 ; ! mod 23
pa6 with pa10 ; ! mod 24
pa7 with pa9  ; ! mod 25  z. now going to z1...
pa4 with pa7  ; ! mod 26
pa4 with pa13 ; ! mod 27
pa9 with pa12 ; ! mod 28
pa1 with pa8  ; ! mod 29
pa1 with pa12 ; ! mod 30
pa1 with pa11 ; ! mod 31
pa2 with pa12 ; ! mod 32
pa3 with pa6  ; ! mod 33
pa1 with pa3  ; ! mod 34

!Negative Affect
NegA by na1 na2 na3 na4 na5 na6 na7 na8 na9 na10 na11 na12 ;
na1 with na4   ; ! mod 1
na3 with na9   ; ! mod 2
na2 with na5   ; ! mod 3
na8 with na10  ; ! mod 4
na7 with na8   ; ! mod 5
na7 with na9   ; ! mod 6
na1 with na5   ; ! mod 7
na11 with na12 ; ! mod 8 GoF achieved across the board here.
na8 with na9   ; ! mod 9
na2 with na11  ; ! mod 10
na4 with na10  ; ! mod 11
na6 with na11  ; ! mod 12
na7 with na11  ; ! mod 13
na1 with na6   ; ! mod 14
na4 with na9   ; ! mod 15
na5 with na6   ; ! mod 16
na1 with na2   ; ! mod 17
na5 with na11  ; ! mod 18
na2 with na12  ; ! mod 19
na5 with na12  ; ! mod 20
na4 with na6   ; ! mod 21
na3 with na6   ; ! mod 22
na10 with na12 ; ! mod 23
na3 with na7   ; ! mod 24
na9 with na10  ; ! mod 25
na5 with na10  ; ! mod 25

!Modifications
A2_warm with E2_frien; ! Mod 1
A5_SYMPA WITH O5_BROAD; ! Mod 2
A5_SYMPA WITH C8_CAUTI; ! Mod 3
E4_ACTIV WITH C6_HARDW; ! Mod 4
C7_SELFD WITH N4_CALM; ! Mod 5

!now these are the 11f - 11k modifications when I was using parcels
A4_SOFTH WITH N4_CALM;  ! mod 6
A3_CARIN WITH E2_FRIEN; ! mod 7
O7_ADVEN WITH O3_INTEL; ! mod 8
A1_HELPF WITH C6_HARDW; ! mod 9
A3_CARIN WITH C5_RESPO; ! mod 10
```

```
A1_HELPF WITH E2_FRIEN; ! mod 11

! continue
O7_ADVEN WITH C8_CAUTI;  ! 8i
E2_FRIEN WITH C5_RESPO;  ! 8j
O2_IMAGI WITH C6_HARDW;  ! 8k
A1_HELPF WITH E1_OUTGO;  ! 8l
A2_WARM  WITH E1_OUTGO;  ! 8m
A3_CARIN WITH E4_ACTIV;  ! 8n
E5_TALKA WITH E4_ACTIV;  ! 8o
E5_TALKA WITH O6_SOPHI;  ! 8p
E4_ACTIV WITH C7_SELFD;  ! 8q
E4_ACTIV WITH E2_FRIEN;  ! 8r
A2_WARM  WITH E3_LIVEL;  ! 8s
O4_CURIO WITH O3_INTEL;  ! 8t
E1_OUTGO WITH N2_WORRY;  ! 8u

! compound on elemental
PA on NRTCSM Agree Extra Cons Open;
NegA on NRTCSM Agree Extra Cons Open;

! situational on compound
marketexp20 on PA NegA;

! Regression with direct paths to stock reallocation
stockreallocation on Open Cons Extra Agree NRTCSM PA NegA marketexp20
 gender race3 marstat2018 educ2018 workstat2018 healthstat2018 ihst_nw18
 mentstatscale sentv2 age_2018 fpperiods2018 followmkt2018 numeracy
 riskshare_2018
;

! final mod
E4_ACTIV WITH PA3 ;
AGREE    BY N4_CALM ;

MODEL INDIRECT:
! Indirect effects of Big 5 traits on stockreallocation
  stockreallocation IND Open ;
  stockreallocation IND Cons ;
  stockreallocation IND Extra ;
  stockreallocation IND Agree ;
  stockreallocation IND NRTCSM ;

! Indirect effects of Affect traits on stockreallocation through marketexp20
  stockreallocation IND PA marketexp20;
  stockreallocation IND NegA marketexp20;


OUTPUT: STDYX  SAMPSTAT MODINDICES (100);
```