Biopsychosocial determinants of financial well-being in older adults:
A structural equation modeling approach

by

Chet Richard Bennetts

B.S., Bellevue University, 2003

M.S., University of Nebraska-Lincoln, 2020

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Personal Financial Planning

College of Health and Human Sciences

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2024

Abstract

Financial Well-Being (FWB) in older adults is a complex construct influenced by various biological, psychological, and sociological factors. This dissertation employs the Biopsychosocial (BPS) Model to examine the determinants of financial well-being among older adults using Structural Equation Modeling (SEM) techniques. Data from the Health and Retirement Study (HRS), including variables related to physical health, mental health, and social relationships, were used to explore the direct, indirect, and total effects of these factors on financial well-being.

The findings reveal that the integrated BPS Model provides significant explanatory power for financial well-being beyond traditional economic models. Biological factors, such as self-reported health and chronic illness, were found to directly and indirectly influence financial outcomes. Psychological factors, including life satisfaction, depressive symptoms, and anxiety, significantly predicted financial well-being. Sociological factors, particularly the quality of social relationships, also played a crucial role, highlighting the interconnectedness of biopsychosocial determinants in shaping financial health.

This research contributes to the literature by validating the BPS Model in a financial context and identifying key intervention points that can guide policy and practice aimed at improving financial well-being among older adults. The study underscores the importance of a holistic approach to financial well-being, considering the complex interplay of health, psychological resilience, and social support in later life.

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Acknowledgements

The journey of pursuing a PhD in your 40s is one that is not begun nor traveled alone. There were several decisions and life events that led up to this point, many of which had an impact on my family, my friends, my colleagues, and my clients. Acknowledging those life events and thanking those who shaped or helped me navigate them is the least I can do. Having people early on in life that you quietly watched and were inspired by is always a good start.

My parents, Robert and Karla Bennetts, thank you for showing me what service to others and true servant leadership looks like. Your examples of selfless sacrifice to help others instilled what would late be drilled into me while in the Marines; service above self. My aunts and uncles who, while growing up we may not have had the closest of relationships, observing you set educational and career goals when my age is something I have looked back at during this journey and has pushed me forward.

The Marine Corps undoubtedly was an enormous influence in my and my families life. While there were many horrible things that occur when in the business of war and combat, on the whole, serving my country with and for the men and women who serve(d) beside me was a positive and transformative experience. I was able to yet again see amazing and heart breaking examples of the embodiment of "service above self" from leaders, peers, and subordinates alike. I was also able to see the opposite and the impacts that has on others. The transition from this vocation to a civilian career was one that would not have been possible without someone who was willing to take a chance on me.

Going from Marine to financial advisor is not a normal path. Luckily, I was able to convince someone to take that chance and give me an opportunity. Gary Karthauser is an amazing combination of a leader, a brother, a father-figure, and a friend. Gary, thank you for

taking that chance and for mentoring me in the early stages of my career as an advisor. Thank you for then taking another chance and growing me into a leader in the agency and in our profession. We walked through some tough times together as I began working through some of the scars that were left behind from Iraq, and it is during this part of the journey that things began to gain clarity for the next stages of my journey.

To my brothers and sisters in the veteran community, thank you and hang in there. So many of us fight unknown battles, and most of us win them daily. Keep winning and keep helping those around you do the same. It is because of watching and witnessing these internal battles, some won and others lost, that drove me this direction. Financial wellness is not going to solve all of the problems, but my hope, my prayer, my mission is to make sure that the lack of financial well-being does not contribute to the battles we all face. One team. One fight. Keep fighting.

To the academic community and your work, passion and wisdom on which I hope to grow and contribute. Dr. Eric Elbogen, thank you for leading the way within the VA in the conversation of how finances are an integral component of overall care for veterans. Your leadership in this area and your willingness to meet with and informally mentor me has meant the world. We still have a lot of work to do, and I am honored to be able to do it along side of you.

Dr. Michael Thomas, thank you for taking time with me at Reagan Airport in DC. After my fist CFP® Board Academic Research Colloquium as a practitioner still contemplating whether or not to take this journey, you taking that time in the airport to hear my story and what I was thinking of doing meant (means) the world. Your words of, “you can do this” have rang out in my head from that day and throughout this process. Thank you for taking that time and investing in me. Dr. Wade Pfau, thank you for letting me take a selfie with you at some random meeting in Lincoln, NE and then encouraging me to pursue my PhD through The Kansas State University. As a practitioner your work shaped the way I was able to serve my clients, and now is foundational in how I view and perform research that practitioners can use to serve their clients.

To my fellow nerds in the cohort of August 2020, we started in the midst of COVID which made it difficult and yet somehow easy to be able to bond with you all. By the time we went to our first in-person summer, the dreaded second summer, we had a bond already that seemed to defy rationale. Daniel Yerger, thank you for your eloquent bluntness as a consummate contrarian. The way you challenge opinions and thought in our profession is both annoying and yet desperately needed. Keep living that motto of "Persuade, Change and Influence", it suits you well. Dr. Effie Antonoudi, thank you for being the one who pushed us. Your drive and determination was exhausting to keep up with but was something that I know all of us benefited from in the long run. Brandon Ratzlaff, thank you for your friendship and for withstanding hours upon hours of New Girl episodes late into the night as we made it through second summer. Thank you for challenging me, even if I did not listen, about not complicating things, and for allowing me to be the little spoon of our cohort. Dr. Eric Ludwig, thank you for your height. Your tall stature transcends mere linear measurements and shows up in who you are as a student, a researcher, a father, a colleague, and as a friend. We may not be Bill and Ted, but I know we have many excellent adventures still ahead of us.

To the faculty at Kansas State University, both past and present, thank you for what you have built and for what you are amazing stewards of. Being out in the academic community, it is evident just how far the ripples have and can travel when something worth doing is done well.

Dr. Megan McCoy thank you for being our first year professor and for the counseling sessions we all found out we were individually having with you. Your heart for us, your students, and for the work that we do is something that is unmatched. Dr. Meghann Lurtz, thank you for giving me a chance and allowing me the opportunity to serve as your Course Associate for Financial Psychology at CUNY. That was an amazing experience not only because of the work we were able to do but also because of how we grew as friends.

Dr. Michael Kothakota, thank you for your wisdom and expertise, as well as being a role model. Your service to the country in the Army and subsequent journey to where you are now is something I have always looked up to and aspired towards. Dr. HaNa Lim, thank you for your stoic and steadfastness. You too were (are) always able to provide guidance in the most friendly and professional way despite how crazy my ideas were (are). Dr. Maurice MacDonald, thank you for paving the way. Your work and contributions towards this profession of financial planning are instrumental. I will never forget having a beer with you at Manhattan Brewing and sharing some of the ideas I had about future research and methods. Your feedback and genuine enthusiasm about them is a moment I fondly remember.

Dr. Stuart Heckman, thank you for helping me (re)learn statistics after a short 20-year break from any type of formal math. While it was sad to see you go to Tech, it has been great to reconnect on the other side of this journey and I look forward to working professionally with you in the near future. Dr. Chelsea Spencer, thank you for the work you have done and continue to do for the military community. I am so grateful to have you on my committee and for the feedback you have provided thus far. I also look forward to working with you as we both stive to make the lives of servicemembers, veterans, and their families better.

To my committee co-chairs, thank you for your patience and for keeping me moving forward, even if it was not at the pace any of us wanted. Dr. Derek Lawson, thank you for the knowledge you have imparted to us with the use of SEM, the basis of this dissertation. Your willingness to listen to my crazy ideas with no visible judgement followed by mostly calm suggestions surrounding me not complicating things truly has been helpful, whether I fully adhered to your advice or not. Dr. Martin Seay, thank you for your leadership in this program and in the profession as a whole. Thank you for the nights of connect four and yelling "YAHTZEE!" upon destroying me at a children's game. This method of motivation coupled with introducing me as "Mr. Bennetts" at conferences we were both speaking at was (is) the exact type of twisted motivation I needed. Genuinely, thank you for that.

Lastly, and most importantly, to my family. Zachary, Abigail, and Nicholas, it is an honor to be your father, and while I know it was difficult at times being my children, thank you. Thank you for your love and support throughout all of this while I figured out what was important. It has been amazing watching you all grow into the adults you are today. The memories of going to track meets, football games, cross country meets, wrestling matches, and doing cheers on the sideline of football games are ones I cherish. More recently, all four of us being full time college students has been its own adventure. Between meeting in the library to study together, having you take the classes I teach, and having spirited conversations about topics none of us are studying has been and will continue to be something I look forward to. To my bonus daughters, Malia and Izabel, thank you for joining our loud and passionate family of nerds. I love you all so much.

To my bride of 25 years, Sarah Jane, I love you so much. Thank you for being a rock for our children and for me. You are such an amazing mother, wife, and friend. I do not know how I would have done life without you. Thank you for your support in this journey. Quitting a career that I (we) had spent so much time investing in, with the fruits of that labor finally starting to manifest, was not an easy decision. Your patience and encouragement when I expressed the desire to take this path meant so much to me. Thank you for dealing with the highs and lows of this journey and for continuing to be my biggest critic, fan, and cheerleader. I can not wait to see what life has in store for us over the next 25+ years.

Dedication

I dedicate this dissertation to my family, for without them, I feel I would have been lost entirely. Sarah Jane, from Frees Hall to here, I would not have wanted to have it happen any other way. Our 18-year-old selves would not believe what we have gone through together and where we are, and I look forward to finding out together what our 20-year from now selves will think about where we are today and where we go from here.

Chapter 1 - Introduction

Introduction

Financial well-being is a multifaceted construct that is influenced by a myriad of factors. It is not merely a reflection of one's financial status but also involves a sense of security, freedom of choice, and the ability to enjoy life (Netemeyer et al., 2018). Recent research has begun to explore the biological, psychological, and sociological determinants of financial well-being, providing a more comprehensive understanding of this complex phenomenon. These determinants have been used individually, and often in pairings, but research has not yet examined how all three elements might inform our understanding of individuals' financial well-being.

The Biopsychosocial (BPS) Model, which posits that biological, psychological, and sociological factors all play a significant role in human functioning in the context of disease or illness (Engel, 1977), provides a comprehensive framework for understanding the determinants of financial well-being. This dissertation aims to further this understanding by applying the BPS Model to a nationally representative group of older adults within the Health and Retirement Study (HRS) data set using Structural Equation Modeling (SEM) techniques.

Statement of the Problem

Financial well-being has become a growing concern for many Americans. Recent surveys reveal that over 60% of citizens say they live paycheck to paycheck (PYMNTS.com, 2022), over 40% do not have enough savings to cover a $400 emergency expense (Board of Governors of the Federal Reserve System, 2022), and 12.3% live below the federal poverty line (Fontenot et al., 2021). Additionally, consumer debt continues to rise, with United States (U.S.) households owing over $15 trillion in debt including credit cards, student loans, and mortgages (Federal

Reserve Bank of New York, 2022). This paints a picture of a nation filled with financial fragility and lack of preparedness to handle unexpected costs or income disruptions.

Several systemic factors contribute to this precarious state of financial health. Wage growth has stagnated over the past few decades, with hourly earnings only increasing an average of 0.25% per year over the past 46 years when adjusted for inflation (Desilver, 2018). However, costs of living have steadily risen, especially for critical needs like healthcare, housing, childcare, and education. Healthcare premiums and out-of-pocket costs have consistently risen faster than general inflation (Claxton et al., 2022). Over 59 million Americans live in "childcare deserts" with inadequate access to affordable childcare options (Jessen-Howard et al., 2018). The national average cost of university tuition and fees has increased 169% since 1980 (Ma et al., 2022). These rising expenses put pressure on household budgets and make it harder to save or pay down debt.

High levels of education debt also inhibit financial well-being. Over 43 million borrowers hold $1.75 trillion in student loan debt (Friedman, 2022), with an average balance of $39,351 among those with outstanding loans (Hanson, 2022). This debt burden hampers borrowers' ability to achieve other financial goals like buying a home, getting additional education and training, starting a business, or saving for retirement. By age 30, student loan borrowers have accrued nearly $10,000 less in retirement savings compared to non-borrowers (Mezza et al., 2020).

Even those considered "financially literate" struggle with saving, budgeting, and managing competing financial priorities. As of 2022, only 45% of U.S. high school students are required to take a personal finance course (Council for Economic Education, 2022). Credit card debt, payday loans, auto-title loans, and other high-interest debt traps remain problems even for educated consumers. Clearly, knowledge alone is not enough. Psychological and sociological factors also influence financial behaviors and success. As Bottazzi et al. (2006) observed, "Knowledge may be a necessary but not sufficient input into beneficial financial behavior."

This complex, multifactorial nature of financial well-being underscores the need for research utilizing comprehensive frameworks like the biopsychosocial model that incorporate biological, psychological, and sociological determinants. As Engel (1977) described when introducing this model to medicine, reductionist models focusing only on biological factors provide an incomplete understanding of human functioning. Similarly in the field of personal finance, while economic models of rational choice may explain some financial behaviors, psychological biases and sociological constraints also guide decisions and outcomes in significant ways. However, the biological determinants of financial well-being are still a relatively unexplored area. Only by examining financial well-being through an integrated biopsychosocial lens can researchers and policymakers gain a complete picture of the varied individual and systemic drivers, then develop effective solutions that help individuals thrive financially amidst rising costs and inequality. This dissertation applies the biopsychosocial model to elucidate these complex determinants of financial well-being within a nationally representative sample, filling a critical gap in understanding Americans' financial health.

Purpose and Justification of the Study

The concerning state of financial well-being as outlined above underscores the urgent need to advance our theoretical understanding and evidence-based solutions. Despite the growing body of research on the determinants of financial well-being, few studies have examined these determinants in a comprehensive, integrated manner. The biopsychosocial model provides a theoretical framework for doing so. This model posits that biological, psychological, and sociological factors interact in complex ways to influence health and well-being, and also financial well-being. This study aims to make significant headway in that endeavor by applying and testing the explanatory potential of the biopsychosocial model within a nationally representative aging sample using SEM techniques. As will be discussed in detail, this novel framework can provide actionable insights to guide policy and practice in improving older adults' financial health while providing an empirical framework for future research in varying populations. The integrative, multidimensional nature of the model aligns with calls from leading scholars for more comprehensive perspectives to illuminate and address financial capability. By elucidating key determinants and their interactions, this timely study offers a critical step forward.

Rationale

This study applies the biopsychosocial model to further the understanding of financial well-being, examining how biological, psychological, and sociological factors interact to shape financial health outcomes. The rationale stems from recognition of the complex, multidimensional nature of financial well-being. As articulated in the statement of the problem, systemic constraints, psychological biases, lack of knowledge, and biological stress reactions all contribute to the financial struggles many Americans face. To develop solutions that effectively bolster financial health, researchers and policymakers need a comprehensive framework that encapsulates these diverse determinants.

The biopsychosocial model provides this inclusive lens, positing that biological, psychological and social factors all play an integral role in human functioning and health (Engel, 1977). While initially developed for healthcare, this model has been applied to illuminate a wide range of human behaviors and outcomes, from smoking cessation to academic performance (Suls

& Rothman, 2004). This study brings the powerful explanatory potential of the biopsychosocial model to financial well-being research. In doing so, it answers calls from leaders in the field to advance theoretical frameworks for financial capability and consider multidimensional models that capture the full range of factors driving financial behaviors and success (Despard et al., 2020; Friedline & West, 2016).

Significance

This research makes several important contributions. First, it provides empirical testing of the biopsychosocial model in the context of financial well-being using a nationally representative sample. This adds to a small but growing body of literature examining biopsychosocial factors in financial contexts (Nettleton & Burrows, 2001). Second, it demonstrates the utility of applying an established theoretical model from healthcare to illuminate a pressing psychosocial issue, financial fragility. Testing and validating this cross-disciplinary application sets a precedent for other researchers.

Third, by analyzing how biological, psychological, and sociological variables interact to predict financial outcomes, it offers a more complete explanatory model to guide policy and practice. Too often, financial capability interventions target only one dimension, such as building financial knowledge. This study highlights the need for multidimensional solutions spanning educational, relational, psychological, and structural facets. Finally, the findings provide specificity about high-impact intervention points across biopsychosocial dimensions for the population studied, older adults. As such, it delivers actionable guidance to improve financial well-being for a vulnerable demographic.

Need for the Study

Understanding the determinants of financial well-being is not only important for advancing academic knowledge but also has significant policy and societal implications. For instance, it can inform interventions aimed at improving financial well-being and reducing financial disparities. Moreover, it can contribute to the development of policies that promote financial well-being at the societal level.

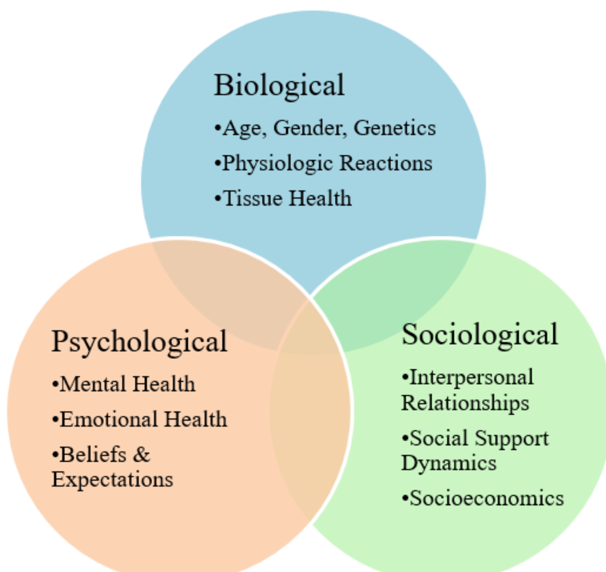
Financial insecurity in later life has serious repercussions for health and quality of life. Financially strained seniors are more likely to report poor physical health, high psychological distress, lower life satisfaction, loneliness, and fatigue (Oddleifson & Sousa-Poza, 2022). Financial distress also reduces healthcare access and exacerbates health disparities. Yet little research has examined the holistic biopsychosocial determinants of financial well-being among older adults. While studies have looked at certain discrete factors like cognition or education, none paints the full picture of how financial health emerges from the interaction of multiple systems and dimensions.

This study addresses that gap by analyzing biological, psychological, and sociological drivers in tandem within a nationally representative aging sample. The integrative application of the biopsychosocial model provides meaningful explanatory power beyond singular variables. Testing interrelationships between key determinants will offer specific guidance for interventions to improve older adult financial well-being. Given demographic trends, this understanding is increasingly urgent. As the U.S. population ages, bolstering seniors' financial health through evidence-based solutions will become more vital for individual, family, community, and societal well-being. This timely study helps build that knowledge base.

Introduction to Theoretical Framework

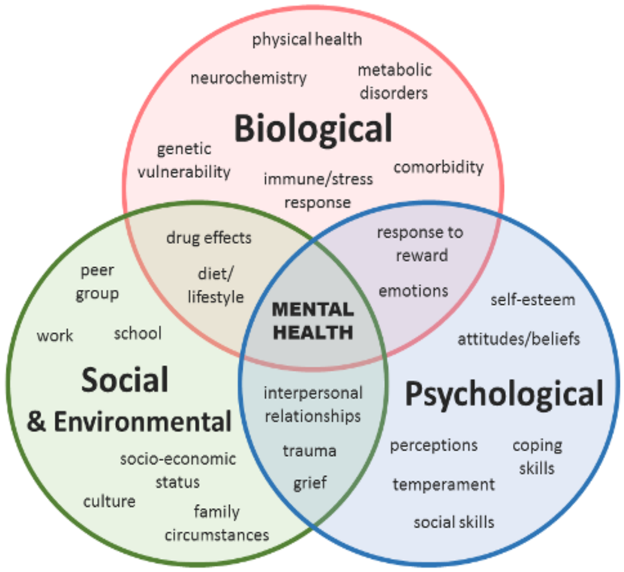
The biopsychosocial model provides a useful framework for understanding the complex interplay of biological, psychological, and social factors that influence health and well-being outcomes in older adults. This model was originally proposed by Engel (1977) as a critique of the traditional biomedical model, which focuses narrowly on biological determinants of disease while minimizing psychological and social influences. Grounded in General Systems Theory, the Biopsychosocial paradigm posits that health and illness are determined by an intricate interaction between biological dispositions, psychological factors (mood, personality, behavior, etc.), and sociological influences (family, culture, economic status, access to healthcare, etc.) (Borrell-Carrió et al, 2004) (Figure 1.1).

Figure 1.1 Biopsychosocial Model (Engler, 1977)



Adaptations of the biopsychosocial model have been used to evaluate everything from chronic pain (Gatchel et al., 2014), addiction (Skewes & Gonzalez, 2013) , diabetes (Powers et al., 2017), and mental health in general (Bashmi et al., 2023; OpenLearn.edu, 2020) (Figure 1.2).

Figure 1.2 Adaptation of Biopsychosocial Model - Mental Health



When applied to the study of financial well-being in later life, the biopsychosocial model suggests that financial security and stability are not merely matters of objective economic resources but are shaped by the interplay of biological, psychological, and social factors. At the biological level, health and physical functioning are critical; older adults with chronic conditions may find it challenging to manage their finances independently, which can lead to financial insecurity (Dumontet, 2023; Garnett et al., 2018; Henager & Cude, 2016). This is particularly relevant as health issues can exacerbate financial difficulties, creating a cycle of stress that further impacts health outcomes (Dumontet, 2023).

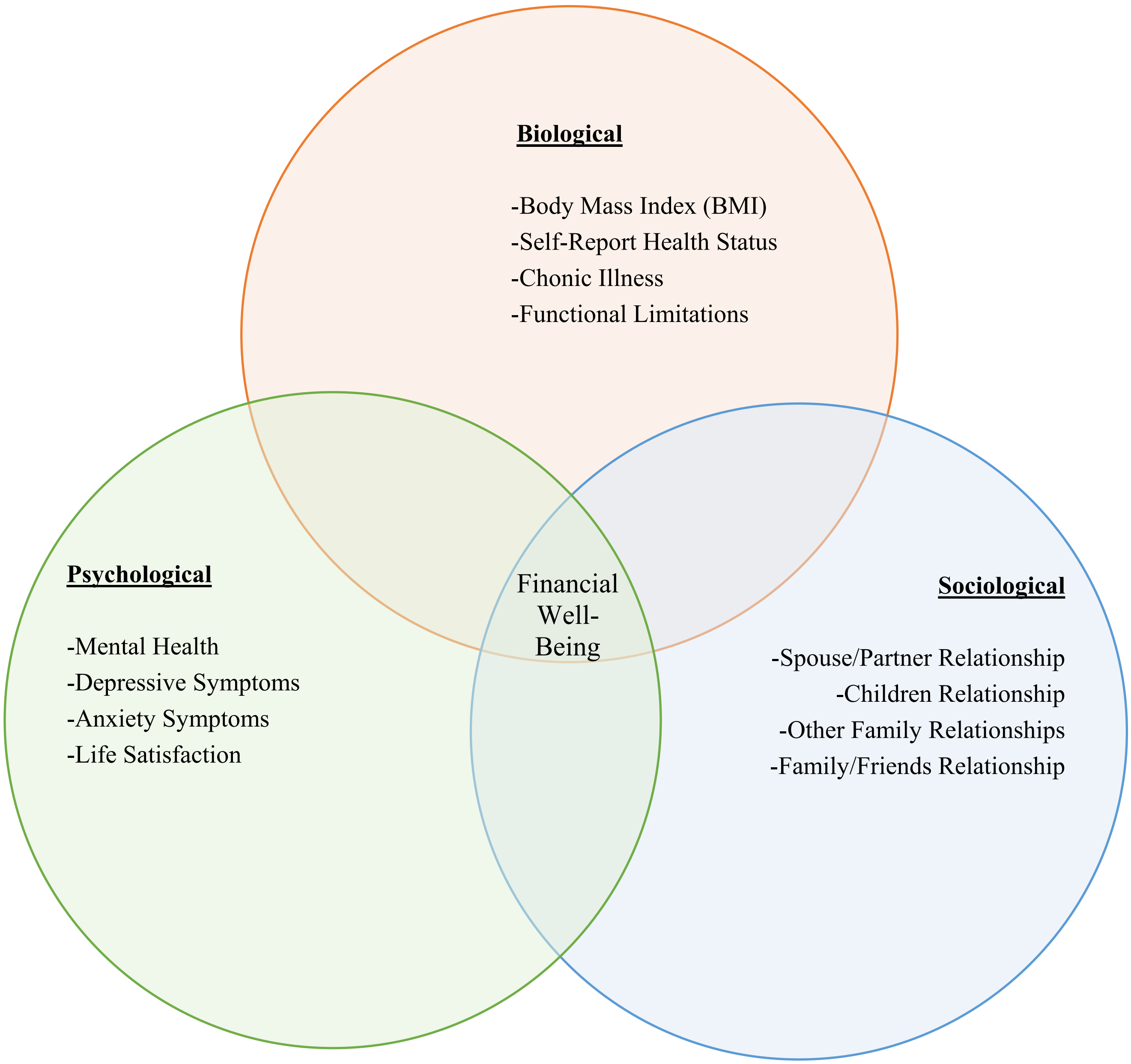
Psychologically, cognitive abilities, financial literacy, and personality traits significantly influence financial behaviors and attitudes among older adults (Hsu & Willis, 2013; Serido et al., 2020). Research indicates that financial literacy is crucial for effective decision-making regarding healthcare, retirement planning, and managing medical expenses, which directly affects economic security (Leung et al., 2022). Additionally, self-efficacy and mood can shape how older adults approach financial management, with positive psychological states promoting better financial behaviors (Leung et al., 2022).

Social factors also play a pivotal role in shaping financial outcomes. Family structure, cultural context, and access to financial services can significantly influence older adults' financial stability. Moreover, social isolation, often exacerbated by life events such as retirement or loss of loved ones, can lead to detrimental financial outcomes, as older adults may lack the social networks necessary to navigate financial challenges (Naito et al., 2021). Access to community resources, including financial advice centers, can mitigate these issues by providing tailored support to those in greater need (Collinge & Bath, 2023).

Financial security and stability in later life are not merely a function of economic resources but are significantly shaped by the interplay of biological health, psychological factors, and social contexts. Understanding these dynamics is essential for developing effective interventions aimed at improving the financial well-being of older adults.

This research uses an adaptation of BPS that incorporates variables provided in the Health and Retirement Study (HRS) data to explore their relationship with financial well-being (Figure 1.3). This study utilizes the biopsychosocial framework to develop a multidimensional model of financial well-being in older adults, with indicators representing key biopsychosocial determinants. The complex interrelationships between these factors is tested using structural equation modeling. This provides greater insight into the mechanisms influencing financial well-being in later life. The Biopsychosocial paradigm offers a valuable theoretical lens through which financial well-being can be examined holistically.

Figure 1.3 Conceptual Model of the Biopsychosocial Model (Initial)



Research Objectives

This study has several key research objectives. The primary goal is to apply and empirically test the biopsychosocial model in the context of financial well-being using a nationally representative sample of older adults. This evaluates the model's utility for explaining variation in financial outcomes. Additionally, the study seeks to examine the complex relationships between biological, psychological, and sociological determinants and financial well-being using structural equation modeling techniques. It aims to analyze the direct, indirect, and total effects among variables within this multidimensional framework. Another objective is to compare the explanatory power of the biopsychosocial model to traditional economic models focused solely on objective financial resources. Finally, the study intends reveals high-impact intervention points across biopsychosocial dimensions to provide actionable guidance for improving older adult financial well-being.

Research Questions

This study addresses key questions about the determinants shaping financial well-being:

- To what extent does the biopsychosocial model explain variation in financial well-being, compared to traditional economic models?
- What are the relationships and effects among biological, psychological, and sociological predictors and financial well-being outcomes?
- Which specific determinants have the strongest influence?
- What are the direct, indirect, and total effects among the variables in the model?

The study addresses these questions using structural equation modeling with a national sample of older adults. Findings provide greater insight into the complex array of factors influencing financial health in later life. Exposing the dynamics within the Biopsychosocial framework can guide efforts to improve financial well-being through a more holistic understanding of its multidimensional drivers.

Hypotheses

H_1 - The combination of all elements (BPS) will have better explanatory power than any individual element.

H_2 - The biopsychosocial model will significantly explain variation in financial well-being among older adults.

H_{3a} - Biological factors will directly predict financial well-being.

H_{3b} - Biological factors will indirectly predict financial well-being.

H_{4a} - Psychological factors will directly predict financial well-being.

H_{4b} - Psychological factors will indirectly predict financial well-being.

H_{5a} - Sociological factors will directly predict financial well-being.

H_{5b} - Sociological factors will indirectly predict financial well-being.

Limitations

Despite the valuable insights provided by this study, several limitations must be acknowledged. First, while the use of Structural Equation Modeling (SEM) allows for the modeling of complex relationships and accounts for measurement error by incorporating latent variables, it does not entirely eliminate the issue of endogeneity inherent in observational data like the Health and Retirement Study (HRS). Endogeneity can still result from omitted variable bias or reverse causality, potentially leading to biased and inconsistent estimators in our models of financial well-being. For instance, unobserved factors such as innate financial acumen or access to informal financial advice might influence both psychological dispositions and financial outcomes, confounding our results. The challenges of endogeneity in SEM frameworks are well-documented, emphasizing the importance of addressing omitted variable bias and reverse causality in observational studies (Angrist & Pischke, 2009; Cheung, 2021; Kline, 2016; McNeish & Hamaker, 2020; Wooldridge, 2020).

Second, although SEM enhances our ability to assess relationships among variables, the cross-sectional nature of the data limits our capacity to draw definitive causal inferences. SEM can test theoretical models and suggest potential causal pathways, but without longitudinal data or experimental manipulation, establishing causality remains challenging. Longitudinal analyses could better address this by tracking changes over time and accounting for unobserved heterogeneity. The limitations of cross-sectional data in SEM applications are highlighted in recent literature, which advocates for the use of longitudinal data to improve causal inference (Kline, 2016; McNeish & Hamaker, 2020; Wooldridge, 2020).

Third, some influences like psychological traits were assessed using brief measures. While SEM helps improve reliability and validity by modeling measurement error and latent constructs, these brief measures may still lack the depth of more comprehensive assessments that could be employed in a purpose-built study using primary data. The use of brief measures can compromise the richness of data collected, potentially leading to oversimplified conclusions about complex psychological constructs (Credé et al., 2012).

Fourth, the specificity of the sample—older adults—may limit the generalizability of our findings to other age groups. Additional research should test the applicability of the biopsychosocial model in different demographic cohorts to enhance external validity. The generalizability of findings from specific populations is a critical consideration in SEM research, as results may not translate across diverse demographic groups (Anglim et al., 2020; Chen et al., 2021).

Fifth, while SEM allows for the inclusion of multiple variables and the examination of their interrelationships, the constraints of secondary data usage limited the variable options for this initial test. Incorporating a broader range of biological, psychological, and social variables could potentially explain more variance in financial well-being. The flexibility of SEM in accommodating various variables is often constrained by the availability of data, which can limit the comprehensiveness of the models (Singh & Khamba, 2019; Tomarken & Waller, 2005).

Moreover, reverse causality remains a challenge. SEM can model reciprocal relationships, but without temporal sequencing from longitudinal data, it is difficult to ascertain the directionality of effects confidently. An individual's financial situation could impact their psychological state, creating a bidirectional relationship that complicates causal interpretations. The complexity of reciprocal relationships in SEM is underscored in recent studies, which advocate for longitudinal designs to clarify these dynamics (Little et al., 2007).

Finally, although SEM accounts for measurement error, self-reported data are still susceptible to response biases such as social desirability or imperfect recall, which may influence results. While these limitations exist, this research still provides valuable initial validation of the biopsychosocial model. The use of SEM enhances our analysis by accounting for measurement error and modeling complex relationships, but future studies employing longitudinal designs, more comprehensive assessments, and methods to address endogeneity will further strengthen the robustness and applicability of the findings (Maccallum & Austin, 2000; Tomarken & Waller, 2005).

Summary

This dissertation investigates the complex biopsychosocial determinants of financial well-being and their interrelationships among older adults, a population facing unique financial challenges. By applying an integrative theoretical framework, this timely research provides invaluable insights to guide future scholarship, inform evidence-based practice and policy, and empower older adults to make informed financial decisions that support their long-term goals. The significance of this study lies in its potential to improve the financial outcomes and retirement security of older investors during volatile market conditions. Through its comprehensive lens and actionable findings, this research delivers a vital step forward in understanding and strengthening financial well-being across the lifespan.

Chapter 2 – Review of Literature

Introduction

Financial well-being has emerged as a significant research area given its implications for overall quality of life and life satisfaction. Prior studies have conceptualized financial well-being as a multidimensional construct encompassing both objective circumstances and subjective evaluations of one's financial status (Joo, 2008). Frameworks posit core elements like perceived control, resilience to shocks, goal progress, and freedom of choice shape financial well-being, alongside current status and future outlook (CFPB, 2015; Kempson et al., 2017). While conceptual models outline key components, additional research is needed to elucidate the complex factors influencing financial well-being over the life course.

For older adults nearing or in retirement, financial well-being holds heightened importance. Diminished income, health declines, caregiving needs, and other challenges can strain limited financial resources. Older individuals with inadequate financial well-being face hardships spanning beyond monetary shortfalls, negatively impacting health, relationships, and overall well-being (Brüggen et al., 2017; Mugenda et al., 1990). A comprehensive understanding of determinants is essential to promote financial security in later life. This review examines prior literature on financial well-being, with a focus on studies using the multidomain Health and Retirement Study. The biopsychosocial model provides a theoretical framework to investigate how biological, psychological, and social factors relate to financial well-being in older adulthood. Investigating these complex interrelationships can inform efforts to bolster financial resiliency and well-being among aging individuals.

Financial Well-Being

Financial Well-Being (FWB) has become a significant topic in consumer research. FWB is an increasingly recognized aspect of overall well-being and quality of life, encapsulating both objective and subjective evaluations of an individual's financial circumstances (Joo, 2008). It reflects an individual's overall financial status, including the ability to control finances, withstand shocks, achieve goals, and obtain freedom (CFPB, 2015). The significance of FWB stretches beyond just monetary considerations, affecting broader subjective well-being and life satisfaction (Brüggen et al., 2017; Kempson et al., 2017; Mugenda et al., 1990; Netemeyer et al., 2018). The understanding of financial well-being, from the perspective of its effect on individuals including their physical health, encompasses a range of financial experiences such as financial hardships, overall financial situation, tension, stress, and ultimately, financial security (Hassan et al., 2021).

Conceptual Frameworks

Various models have been proposed to dissect the multidimensional nature of FWB. The Consumer Financial Protection Bureau (CFPB, 2015) outlines four core elements: control over finances, capacity to absorb financial shocks, being on track to meet financial goals, and having financial freedom to make life-enriching choices. Similar constructs were echoed by Kempson et al. (2017) and Netemeyer et al. (2018), with added emphasis on day-to-day money management behaviors, perceived financial coping efficacy, and perceived financial status/standing. Netemeyer et al. (2018) goes on to define financial well-being through two distinct yet interconnected constructs: a) stress related to money management and b) the level of security one feels with their finances. Utilizing these constructs, Netemeyer et al. (2018) formulated two scales: a) current money management stress and b) expected future financial security. Brüggen et al. (2017), further elucidate that the FWB construct involves both current perceptions of financial status and future financial freedom (Brüggen et al., 2017).

Using Bronfenbrenner's ecological life-course approach (1994), Salignac et al. (2020) proposed the definition of FWB as being, "…when a person is able to meet expenses and has some money left over, is in control of their finances and feels financially secure, now and in the future." Key drivers of FWB include control of finances, low debt-to-income ratio, low financial anxiety, and ability to handle life changes (Vlaev & Elliott, 2014). Additionally, FWB encompasses objective elements such as income and expenditures alongside subjective factors such as financial satisfaction, attitudes, and confidence (Joo, 2008).

A further examination of objective FWB could be viewed through the lens of its inverse relationship to objective financial strain. Tharp (2017) operationalizes financial strain through three ratios found in previous literature. Financially strained households included those with a solvency ratio (total assets/total debt) of less than or equal to 1.0, a liquidity ratio (liquid assets/monthly income) of less than 3.0, and an investment assets ratio (investment assets/net worth) of less than 0.25 (Kim & Lyons, 2008; Garrett & James, 2013; Tharp, 2017).

The existing literature examines FWB through a variety of lenses with some using objective measures and others using subjective measures. This complex relationship between objective and subjective is further complicated when one considers people's perception of FWB. Some individuals might report having sufficient funds, even if objective measures suggest otherwise. On the flip side, some might report a lack of funds despite objective measures indicating they have enough (Szanton et al., 2008). As such, a construct consisting of both objective and subjective elements of FWB is utilized in this study.

Determinants of Financial Well-Being

Prior research shows financial capability, behaviors, confidence, and psychological traits are associated with FWB (CFPB, 2017; Gutter & Copur, 2011; Shim et al., 2009; Xiao & O'Neill, 2018). In young adults, financial knowledge, attitudes, and perceived control were shown as statistically significant predictors of FWB (Shim et al., 2009). Responsible behaviors like savings are also found to be correlated with positive elements of FWB (CFPB, 2017; Gutter & Copur, 2011). Psychological factors including financial stress and self-control connect to both FWB and satisfaction (Archuleta et al., 2013; Strömbäck et al., 2017). Furthermore, studies such as the one conducted by Skinner et al. (2004) demonstrate a significant correlation between financial stress and psychological discomfort, diminished perceived physical well-being, lowered self-esteem and satisfaction, as well as heightened interpersonal conflict.

Income and education are consistently positively associated with financial well-being (Brüggen et al., 2017; Despard et al., 2018). Psychosocial factors like future orientation and perceived control also predict greater financial well-being (Kempson et al., 2017; Netemeyer et al., 2018). Gender differences exist, with women reporting lower financial well-being than men on average (Brüggen et al., 2017). Racial disparities have been documented as well (Rothwell & Han, 2010). Financial knowledge is a critical determinant, with financial literacy enhancing financial behaviors and buffering negative shocks (Henager & Cude, 2016; Lusardi & Mitchell, 2011).

Employing a structural equation model (SEM) approach, Fan & Henager (2022) constructed a framework by which they evaluated the determinants of FWB. The key insights reveal that financial satisfaction, short-term financial behavior, and perceived financial capability are positively and directly correlated with financial well-being. Conversely, financial stress and long-term financial behavior exhibit a negative and direct correlation with financial well-being. Additionally, notable indirect relationships with financial well-being were identified for financial perception and knowledge factors, financial stress, and short-term financial behavior.

Financial Well-Being in Older Adults

While some studies examine financial satisfaction in older Americans, few assess both objective and subjective FWB. Existing research has demonstrated that income and personality (Tharp et al., 2020), and retirement status (Hira & Mugenda, 1998) link to perceived financial satisfaction. Older adult FWB also relates to objective factors like income and subjective factors like social connection (Yeo & Lee, 2019). Using the Chilean data, with similar questions in structure and measurement to that of the U.S. Health and Retirement Study (HRS), there is an indication that FWB systematically differs across age, gender, race, education, and personality traits (Hastings & Mitchell, 2020). Psychological constructs including perceived control shape financial satisfaction in later life (Zurlo, 2009). Income and poverty serve as objective FWB indicators, while perceived hardship acts as a subjective indicator (Prawitz et al., 2006; Roll et al., 2013).

Financial ratios are associated with FWB as well. Tenney & Kalenkoski (2019) found a positive correlation between the investment ratio and the respondents' perceived financial well-being. Another minor, yet statistically notable, increase in financial well-being perception was observed with rising liquidity ratios, and when observing broad categorical distinctions, a positive association was also maintained with the debt-to-asset ratio. Brüggen et al. (2017), assessed objective qualities like income alongside subjective financial perceptions to comprehensively examine older adult FWB. This approach can advance conceptualization of this multifaceted construct.

FWB is widely studied but its definition and measurement need refinement (Brüggen et al., 2017). Prior operationalizations examine objective and subjective financial status (Greninger et al., 1996; Porter & Garman, 1992; Vosloo, 2014) or subjective assessments alone (Kim et, 2003; O'Neill et al., 2005). FWB is a multidimensional construct strongly linked to overall well-being. Key sociodemographic, psychological, and financial knowledge factors shape financial well-being over the life course. Additional research leveraging multidomain measures like those found in the HRS data can further our understanding of financial well-being and its drivers among older adults.

Biopsychosocial Model

The biopsychosocial model, introduced by Engel (1977) as an alternative to the traditional biomedical model, encapsulates the intricate interaction of biological, psychological, and social elements impacting health and well-being (Borrell-Carrió et al., 2004). In the context of financial well-being in later life, this dissertation posits that financial well-being is shaped not merely by objective economic resources or one’s subjective perception of said resources, but by a blend of factors across biological, psychological, and social domains.

The biopsychosocial model provides a useful framework for understanding the complex interplay of biological, psychological, and social factors that influence financial well-being in older adults. This model was originally proposed by Engel (1977) as a critique of the traditional biomedical model, which focused narrowly on biological determinants of disease while minimizing psychological and social influences. The biopsychosocial model posits that health and illness are determined by an intricate interaction between biological dispositions, psychological factors (mood, personality, behavior, etc.), and sociological influences (family, culture, economic status, access to healthcare, etc.) (Borrell-Carrió et al., 2004).

When applied to the study of financial well-being in later life, the biopsychosocial model would suggest that financial security and stability are not simply a matter of objective economic resources, but rather are shaped by the interplay between multiple factors at biological, psychological, and social levels. At the biological level, health and physical functioning capacity may impact older adults' ability to manage finances independently (McInerney et al., 2013). Psychologically, cognitive abilities, financial knowledge, personality traits, self-efficacy, and mood can influence financial behaviors and attitudes (Henager & Cude, 2016; Xiao et al., 2014). Socially, family structure, culture, neighborhood, access to financial services and public benefits all shape financial outcomes (Alley & Kahn, 2012; Dew & Xiao, 2013).

This study utilizes the biopsychosocial framework to test a multidimensional model of financial well-being in older adults, with indicators representing key biopsychosocial determinants as described below. The complex interrelationships between these factors are tested using structural equation modeling and will provide greater insight into the mechanisms influencing financial well-being in later life. The biopsychosocial model offers a valuable theoretical lens through which financial well-being can be examined holistically.

Biological

With the origins of the biopsychosocial model coming from the health care sector as it relates to physiological health, likewise, the focus on one’s physiological health should be included in the utilization of the BPS Model when examining the determinants of FWB. Using the Health and Retirement Study (HRS), Lee (2018) utilized body mass index (BMI) and measures of respondents’ health and found that higher BMI was associated with decreased levels of FWB. While difficult to ascertain directionality, when respondents self-reported their health status, those who stated "fair" or "poor" had a 73% increased likelihood of having medical debt demonstrating the decrease in FWB that physical health can cause (Richard et al., 2018).

As an element of poor FWB, other forms of increased debt had direct and indirect effects on health. Using the HRS, Alley et al., (2011) found that those who were delinquent on their mortgage reported poorer health status, greater food insecurity, and greater occurrences of medication nonadherence due to costs (Alley et al., 2011). When evaluating the health effects of short-term/pay-day loans, Sweet et al. (2018) found that those with this type of debt had increased levels of inflammation, higher BMI, higher blood pressure, and poorer self-reported health status (Sweet et al., 2018). Analyses reveal people with worse self-rated health have lower assets and satisfaction, more debt, and more difficulty paying bills (Pak & Fan, 2022).

An examination of older adults, again using the HRS, and the relationship that self-reported health (SRH) status has with elements of financial well-being was done. When compared to better levels, poor or fair SRH status levels were shown to have decreased total assets and financial satisfaction while showing increased levels of debt, debt-to-asset ratios, and increased responses of having difficulty paying bills (Pak & Fan, 2022).

When evaluating key physiologic pathways that might be contributing to socioeconomic disparities resulting in lower levels of financial well-being, Samuel et al. (2022) found evidence that suggested financial strain resulted in increases of inflammatory biomarkers in older adults (Samuel et al., 2022). This suggests a bi-directional relationship between finances and health. Chronic conditions like hypertension, diabetes, lung disease, arthritis and others are frequently used as markers of health status (Chang et al., 2014; Lee, 2018). Functional limitations in daily activities have also been studied, with difficulty in tasks like walking, dressing and bathing indicating poorer physical capacity (Lee, 2018).

The pathways connecting social relationships and health may be explained in part through leisure activities, which can provide physical and psychological benefits (Chang et al., 2014). Physical leisure activities especially may mediate positive links between social ties and physical health. Personality traits can also influence activity engagement and variety, which in turn predict well-being and retirement outlook (Beier et al., 2018). In summary, the biological domain captures physical health factors that are intricately tied to financial status and behaviors in older adults. Bidirectional relationships likely exist, whereby poor physical health can worsen financial standing, while financial strain can generate physiological stress that undermines health. As people age, maintaining health, independence and an active lifestyle becomes essential for financial well-being.

Psychological

The psychological domain encompasses cognitive, emotional, and personality factors that shape financial behaviors and attitudes. A growing body of research has explored how psychological traits relate to financial outcomes, especially in older adults. Several studies reveal links between poor financial well-being and adverse mental health symptoms. With indebtedness being one of the objective measures of FWB, research relating to short-term, unsecured debt showed a positive correlation between household debt and an increase in depressive symptoms. This relationship was notably prevalent among those with a high school education or less, those who were not in a stable marriage, and those who were over age 50 (Berger et al., 2016). When looking at long-term debt, using the HRS, Alley et al., (2011) found that those who were delinquent on their mortgage had increased levels of depression as compared to those not delinquent (Alley et al., 2011).

Financial strain can diminish overall life satisfaction and heighten anxiety (Chen & Feeley, 2014). Positive psychology factors like optimism, purpose, gratitude and resilience can buffer these effects and promote financial coping (Asebedo & Seay, 2014). Life satisfaction, depression, and anxiety are frequently studied in relation to finances. Life satisfaction scales assess general contentment with one's circumstances (Diener et al., 2018). Depression is measured through validated scales like the Center for Epidemiologic Studies Depression (CES-D) inventory (Radloff 1977). Anxiety is captured through tools like the Beck Anxiety Inventory (BAI) which distinguishes anxiety from depressive symptoms (Beck et al., 1988).

Relationships are critical for well-being. Studies show social support from spouses and children enhances financial self-efficacy more than support from extended family or friends (Asebedo, 2019). This aligns with socioemotional selectivity theory, where older adults derive greater satisfaction from inner circle relationships. Purpose and meaning also relate to retirement satisfaction, helping offset potential losses of purpose after leaving the workforce (Asebedo & Seay, 2014).

The psychological domain encompasses cognitive capacities like financial literacy, along with emotional states, personality traits, and positive psychological resources. These factors intersect to shape financial behaviors and attitudes. Poor financial well-being can generate distress, undermining mental health and satisfaction. But psychosocial resources like optimism and social support can mitigate these effects and promote resilience. Further exploration is needed to disentangle the complex bidirectional relationships between financial well-being and psychological well-being over the life course. Enhanced understanding of these connections can inform interventions that holistically support financial security and mental health among older adults.

Sociological

In exploring the sociological domain of the BPS, again, there is an abundance of literature. O'Connor (1995) found that in the lives of older adults, the quality of friendships had a greater influence on life satisfaction than the quality of their familial ties with their offspring. Moreover, engagement in family-oriented activities was seen to amplify both positive and negative emotions in older adults; conversely, participation in activities with friends not only boosted positive emotions but also diminished negative ones and, furthermore, enhanced life satisfaction (Huxhold et al., 2014). Recent studies have also indicated that the significance of friendships has been growing among the latest cohorts of the elderly population (Fiori et al., 2020).

Chen and Feeley (2014) employed Structural Equation Modeling (SEM) to construct a framework elucidating the determinants of financial well-being. Their reported outcomes delineate the interrelations among various determinants encompassing financial perceptions and knowledge, financial stress, short- and long-term positive financial behavior, and financial satisfaction. The key insights reveal that financial satisfaction, short-term financial behavior, and perceived financial capability are positively and directly correlated with financial well-being.

Conversely, financial stress and long-term financial behavior exhibit a negative and direct correlation with financial well-being. Additionally, notable indirect relationships with financial well-being were identified for financial perception and knowledge factors, financial stress, and short-term financial behavior. Of importance in the sociological domain, they discovered that financial well-being is enhanced with increased levels of social support (Chen & Feeley, 2014). Similarly, Alley and Kahn (2012) found a strong relationship between psychosocial resources like social networks and financial strain. Having more close family and friends, being more extroverted and optimistic, and having higher mastery were protective against financial strain.

The interplay between social support and financial well-being becomes even more pronounced when considering the dual nature of social relationships. Fiori et al. (2020) emphasize the growing significance of friendships in later life, not only as a source of emotional support but also as a buffer against financial stress. Fuller et al. (2020) expand on this by discussing the Convoy Model of Social Relations, which underscores the importance of family and friend networks in providing support throughout life. While these networks often provide critical emotional and practical assistance, they can also introduce stress and conflict, which may negatively impact financial decision-making and well-being. This duality is further explored by Rook (2015), who notes that while social networks generally offer positive support that can enhance financial stability, negative interactions or obligations within these networks can exacerbate financial strain.

Decreases in financial well-being and economic pressure negatively impact relationships. Individuals who reported worsening financial situations showed lower relationship happiness (Dew & Xiao, 2013). As economic pressure rose, individuals practiced less sound financial management to maintain lifestyles, which reduced relationship happiness. This highlights the mediating role of financial behaviors between economic stress and relationship quality. Financial concerns relate negatively to financial management, while relationship happiness relates positively (Wheeler & Brooks, 2023). Relationship happiness can moderate the link between financial concerns and management; with higher relationship happiness, people engage in more positive financial behaviors despite concerns. This illustrates the buffering effect strong relationships can have against financial stressors.

In older populations, an element of FWB is likely going to manifest in their retirement preparations and subsequent retirement satisfaction. While this study initially focuses on those who are not retired, these elements and their psychosocial implications are worth noting. Asebedo and Seay (2014) found that familial social relationships and their support were associated with increased levels of retirement satisfaction, further underscoring the importance of social support in later life. Similarly, Holt-Lunstad (2022) frames social connection as a critical public health issue, noting that strong social ties are associated with lower mortality rates and better overall health, which in turn can lead to more positive financial outcomes in retirement. Conversely, Uchino et al. (2018) highlight the physiological impacts of social support, showing that strong social ties reduce levels of inflammatory cytokines, thereby promoting both physical health and financial stability through reduced healthcare costs.

Positive social support plays a crucial role in enhancing well-being, particularly in older adults, by providing emotional security, practical assistance, and a sense of belonging. Fiori et al., (2020) emphasize the growing significance of friendships in late life, highlighting how these relationships contribute to life satisfaction by fostering positive emotions and reducing loneliness. Holt-Lunstad (2022) extends this discussion by framing social connection as a critical public health issue, demonstrating that strong social ties are linked to better mental and physical health outcomes, including lower mortality rates and improved quality of life. Furthermore, the Convoy Model, as discussed by Fuller et al., (2020), underscores the importance of enduring social networks, such as family and close friends, in providing continuous support throughout life. Rook (2015) adds that positive social interactions within these networks can alleviate stress and contribute to better health outcomes by promoting emotional well-being and reducing the risk of chronic diseases. Uchino et al. (2018) further corroborate these findings by showing that higher levels of positive social support are associated with lower levels of inflammatory cytokines, indicating a protective effect on physical health.

Conversely, negative social support can have detrimental effects on well-being, exacerbating stress and contributing to poorer health outcomes. Fuller et al., (2020) discuss how family relationships, while generally supportive, can also introduce stress and conflict, particularly when caregiving responsibilities become burdensome or when intergenerational tensions arise. Rook (2015) highlights that negative interactions within social networks, such as criticism, excessive demands, or unmet expectations, can lead to increased anxiety, depression, and physical health issues, effectively negating the benefits of social support. Uchino et al. (2018) further support this view by indicating that negative social interactions are associated with higher levels of inflammatory cytokines, which are linked to chronic health conditions. Holt-Lunstad (2022) also acknowledges the risks associated with social isolation and loneliness, often resulting from inadequate or harmful social ties, which can lead to significant public health concerns, including increased morbidity and mortality rates. Thus, while social support is generally beneficial, the negative aspects of these relationships must be carefully managed to avoid adverse health outcomes.

In summary, social support, relationships, and cultural forces shape financial behaviors and satisfaction. Financial difficulties can reciprocally undermine social resources and relationships, but conversely, strong social connections can safeguard financial well-being. Positive social support, whether from family or friends, not only enhances emotional well-being but also serves as a buffer against financial stress. However, negative social interactions can exacerbate financial strain, highlighting the need for a nuanced understanding of the role of social networks in financial well-being.

Intersection

The connectivity of each element in the BPS Model has been well documented. When examining interpersonal relationships and health, Cohen (2004) found that individuals possessing stronger social connections tend to experience not only better psychological well-being, but also improved physical health. The former was hypothesized as being related to feeling more connected and thus mitigating depression while the latter being related to boosting immune system functionality and lowering the risks of heart attacks (Cohen, 2004).

There are several examples where researchers have examined components of the BPS model and their interactions with and among elements of both subjective and objective FWB. For instance, in an arthritis study comprised of patients and healthy control participants, Skinner et. al., (2004) conducted a layered analysis where they found that a decrease in FWB due to a rise in financial stress was linked to an increase in health complaints and negative emotions, but it didn't cause more pain for those with arthritis. There was a notable interaction between relational stress and financial stress. Specifically, during weeks of heightened stress in relationships alongside increased financial stress, there were more reported physiological health symptoms, especially in weeks when pain was worse. Among arthritis patients, their findings hint at the substantial role financial stress plays in affecting both the mental and physical health (Skinner et. al., 2004).

With one's wealth being an element of their FWB, McInerney et al., (2013) found that following the market crash of 2008, older adults who experienced sudden wealth loss reported an increase in depressive sentiments and antidepressant medication usage, with these effects being more pronounced among respondents who had substantial stock holdings before the crash. Using the HRS, their results suggest that abrupt financial losses trigger immediate deteriorations in self-reported mental health indicators among older U.S. adults (McInerney et al., 2013).

Summary

Financial well-being is increasingly recognized as a critical component of overall well-being and quality of life. It encompasses both objective financial circumstances and subjective evaluations of one's financial status. Key frameworks suggest core elements of financial well-being including perceived control, resilience, progress towards goals, and freedom of choice. Both current status and future outlook shape the multidimensional nature of financial well-being.

A range of determinants influence financial well-being, including financial knowledge, attitudes, behaviors, and psychological traits like self-efficacy and perceived control (Shim et al., 2009; Xiao & O'Neill, 2018). Higher income and education positively predict financial well-being, while women and minorities often report lower levels on average (Brüggen et al., 2017; Despard et al., 2018). For older adults specifically, financial ratios, responsible money management, retirement preparations and social connections also connect to financial well-being outcomes (Asebedo & Seay, 2014; Tenney & Kalenkoski, 2019).

The biopsychosocial model posits that financial status results from complex dynamic interactions between biological, psychological and social factors (Borrell-Carrió et al., 2004). At the biological level, health ailments like chronic conditions and functional limitations relate to debt, assets, and financial strain, suggesting bidirectional relationships between physical health and finances (Alley et al., 2011; Lee, 2018). Psychologically, increased debt links to depressive symptoms and lowered life satisfaction, while positive traits can aid coping and retirement outlook (Asebedo & Seay, 2014). Sociologically, social support and strong interpersonal relationships enhance financial self-efficacy, future outlook, and overall well-being.

Financial well-being intricately connects to overall well-being, with evidence of bidirectional effects between finances, health, and psychological resources over the life course. While prior studies have examined singular associations in isolation, structural equation modeling provides a methodology to reveal the complex dynamic interrelationships described by the biopsychosocial model. This systems-based approach will enable greater insight into how biological, psychological and social factors interact to shape financial well-being across the lifespan.

Enhanced understanding of these multidimensional determinants can better inform efforts to improve financial security and resiliency among older adults. Interventions targeting specific biopsychosocial factors may generate positive cascading effects on financial status and overall well-being. However, more research is needed to disentangle the complex linkages between finances, health, social ties, and psychological resources as individuals age. This review conceptualized financial well-being as a multidimensional construct, shaped by various socioeconomic, psychological, and health factors across biological, psychological and social domains. It provides conceptual and empirical validation for using a biopsychosocial framework to comprehensively evaluate determinants of financial well-being in older adults.

Chapter 3 - Methodology

The focus of this dissertation is to empirically test the biopsychosocial model (BPS) as to its predictive capability relating to Financial Well-Being (FWB). While existing measures of FWB incorporate various elements, none have utilized the entire scope of the BPS. By analyzing each component of the BPS and their relationship to FWB followed by evaluating the model as a whole, this research seeks to highlight the multidimensional elements of FWB when looking at the entire person and how FWB interacts with them.

Dataset and Sample Selection

Data utilized in this study were derived from the 2010 to 2018 waves of the Health and Retirement Study (HRS). Conducted by the University of Michigan and sponsored by the National Institute on Aging (grant number NIA U01AG009740), the HRS is a longitudinal panel study that is conducted biennially. The HRS is designed to be a nationally representative sample of people over the age of 50 in the U.S. with over 20,000 participants. The HRS is well suited for this research due to its robust variables that include key financial, health, psychological, sociological, and traditionally used control variables.

Due to the vast quantity of variables and participants in a longitudinal study dating back to 1992, the RAND Center for the Study of Aging provides more user-friendly data file that is consolidated both in terms of traditional control from participants variables (e.g., age, gender, marital status, education, etc.), but also in the creation of commonly used constructs such as total household income, total household debt, household net worth, etc. These consolidated data provided by RAND (RAND HRS 2020 Longitudinal File 2020 (V1), 2023) were used as the primary data file for this study.

The Leave-Behind Psychosocial and Lifestyle Questionnaire (LB) was utilized in this study. Beginning in 2006, the LB was given to half of the study's participants with the other half receiving it in 2008. The first half then received the LB again in 2010 with that pattern repeating through the period(s) of interest for this study. The LB includes several psychosocial and behavioral variables of interest that were used independently and as items in latent constructs for this study.

The combination of the HRS Core data, the RAND data, and the LB data for the periods of 2010 to 2018 are what were used in this study. By only utilizing data collected during the 2010 to 2018 timeframe(s), the goal is to empirically test this model while removing confounding elements due to periods of high market volatility (2008) and/or a global pandemic (2020). As a result, only data from those timeframes are included. While the HRS data sets and their constituent components can be used longitudinally, the current study does not intend to test the BPS model temporally. Each year (wave) of data were evaluated independently to test the hypotheses and model, with a combined data set of all five waves serving as a robust analysis across a larger sample size. The sample was restricted to those who, at any time during the established timeframe, were able to provide answers to the questions that allow us to evaluate the variables of interest. Summary statistics of all six waves are found in Table 3.1.

Data Analysis Procedures

Initial data coding, Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA), and subsequent Structural Equation (SEM) Modeling was completed using Stata 18. EFAs and CFAs are used to validate the measurement model as well as for testing the full structural model. Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) both endeavor to model the observed correlations among a set of indicators using a fewer number of unobserved variables, yet they are distinct in their approach to model specification and constraint imposition.

Table 3.1 Sample Summary Statistics

	2010	2012	2014	2016	2018	Combined
Sample (*n*)	22,034	20,554	18,747	20,912	17,146	99,393
Age (μ/σ)	65.7 12.0	66.8 11.6	67.9 11.3	65.7 11.8	67.0 11.4	66.5 11.7
Gender (%) Male	41.8%	41.6%	41.1%	41.4%	41.0%	41.41%
Female	58.2%	58.5%	58.9%	58.6%	59.0%	58.59%
Marital Status (%) Married/Partnered	63.3%	63.2%	62.5%	60.8%	60.3%	61.1%
Not Married/Partnered	36.7%	36.8%	37.5%	39.2%	39.8%	38.9%
Race (%) White	72.3%	72.0%	71.4%	66.4%	66.1%	69.7%
Black	19.4%	19.4%	19.7%	21.8%	22.2%	20.4%
Other	8.4%	8.6%	8.9%	11.9%	11.7%	9.8%
Education (%) HS or Less	53.6%	53.0%	52.1%	49.8%	48.3%	51.5%
Some College or More	46.4%	47.0%	47.9%	50.2%	51.7%	48.5%
Employment Status (%) Not working for pay	59.4%	61.2%	63.2%	57.8%	60.6%	60.4%
Working for pay	40.6%	38.8%	36.8%	42.2%	39.4%	39.6%

Factor Analysis

EFA operates without preconceived notions about the number of underlying factors or the specific pattern of relationships (i.e., factor loadings) between factors and observed indicators, making it a primarily exploratory or descriptive method. It is utilized to identify the suitable number of latent factors and to discern which observed variables serve as reliable indicators for these latent dimensions through the examination of factor loading sizes and their distinctions. This process is significantly informed by two key elements: Eigen values and factor loadings (λ), which together guide the determination of the number of factors to retain and the strength of the relationship between each factor and the observed variables.

Eigen values are a critical measure in EFA, representing the total variance in the observed variables that can be attributed to each factor. In essence, an Eigen value gauges the relative importance or weight of a factor in explaining the variance observed among the indicators. A common threshold is to consider factors with Eigen values greater than 1.0 as significant, under the rationale that a factor should explain a greater amount of variance than a single observed variable (Kline, 2016). This criterion, often referred to as the Kaiser criterion (Yong & Pearce, 2013), serves as a preliminary guide to determine the number of factors to retain.

Factor Loadings (λ), articulate the degree to which each observed variable is associated with a factor, providing insight into the pattern of relationships between variables and factors. High absolute values of factor loadings, commonly regarded as those above 0.4 (Yong & Pearce, 2013) indicate strong associations, thereby suggesting that the variable is a significant indicator of the factor it loads onto. The pattern of these loadings helps in interpreting the latent dimensions represented by each factor, allowing assignment of meaningful labels and further understanding the underlying structure of the data. Factor loadings are also essential in evaluating the model's adequacy, as they contribute to the calculation of the communality for each variable—representing the proportion of the variable's variance that is explained by the factors, further substantiating the model's explanatory power.

In employing EFA, it is thus not only the identification of a suitable number of latent factors that is of importance but also a thorough examination of Eigen values and factor loadings. These elements collectively inform the decision-making process regarding factor retention, the interpretability of the factor solution, and ultimately, the robustness of the analysis in uncovering the underlying structure of the observed variables.

Conversely, CFA involves the *a priori* determination of factors and the expected pattern of connections between indicators and factors, alongside additional parameters such as factor independence or correlation, and unique variances of indicators. The hypothesized model is assessed based on its capacity to replicate the empirical correlation (or covariance) matrix of the indicators. This necessitates a robust empirical or theoretical basis for the initial model setup and subsequent evaluation, positioning CFA as a tool for later stages in the construct validation process, only utilized once the foundational structure has been delineated through earlier empirical (EFA) and theoretical considerations.

The CFA analyzed the factor structure and construct validity of each latent variable, including those from the biopsychosocial model and their constituent factors. Next, the structural model containing the latent variables was tested. Finally, the fully hypothesized structural model was analyzed. The model fit of the CFA was evaluated using several fit statistics. The chi-square test was sensitive to sample size, so other indices were prioritized (Kline, 2016). Acceptable model fit was indicated by a Root Mean Square Error of Approximation (RMSEA) less than 0.08 and ideally below 0.05. The Standardized Root Mean Square Residual (SRMR) was less than 0.08. The Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI) exceeded 0.90 for acceptable fit and 0.95 for good fit (Kline, 2016). If the initial CFA model did not demonstrate satisfactory fit, modifications to the model were considered based on theoretical justifications and modification indices (Brown, 2015). Any changes to the model were reported, and the revised model was re-evaluated using the same fit indices.

Second-Order Factor Analysis

In structural equation modeling (SEM), second-order factor analysis is used when researchers hypothesize that a set of first-order latent constructs are themselves indicators of a higher-order latent construct. This approach is particularly useful in exploring complex constructs that are multifaceted and cannot be captured by a single dimension (Chen et al, 2006).

Second-order factor models allow for a more nuanced understanding of the relationships between constructs. They can provide a clearer, more parsimonious representation of the data by accounting for the covariance among first-order factors (Rindskopf & Rose, 1988). When constructs are complex and hypothesized to have multiple dimensions that are related to a single overarching concept, a second-order model can be more accurate and meaningful than a first-order model (Marsh & Hocevar, 1985).

The application of second-order factor models has been seen in various fields. For instance, in the study of psychological constructs, a second-order factor might represent an overarching concept such as general intelligence, with first-order factors representing specific abilities like verbal and mathematical skills (Carroll, 1993). Similarly, within the domain of health psychology, the construct of health-related quality of life has been examined through second-order factor modeling, where dimensions such as physical functioning, emotional well-being, and social functioning are seen as first-order factors indicative of the broader construct (Chen et al, 2006).

The use of second-order factors aligns with the theoretical frameworks positing that the complex constructs within the biopsychosocial model are hierarchical in nature. Assessment of model fit was done using the standard indices such as Chi-Square, CFI, TLI, RMSEA, and SRMR (Kline, 2016). First, there was an evaluation of the significance of the loadings of the first-order factors on the second-order factor to determine the contribution of each first-order factor to the higher-order construct. By employing second-order factor analysis, this study captured the essence of the complex phenomena and contributed to a deeper understanding of the constructs of interest and how they might be able to predict Financial Well-Being in the sample of older adults.

Missing Data

Full information maximum likelihood (FIML) was used to estimate any missing data. FIML is a statistical technique commonly employed within Structural Equation Modeling (SEM) to handle missing data. This method is particularly advantageous in this research, where the multiple waves of data sets often have missing values due to nonresponse, timing of the questions being asked every other wave, and attrition. FIML operates under the assumption that the missing data mechanism is ignorable (i.e., missing at random or completely at random), allowing for unbiased parameter estimates and standard errors.

The FIML approach works by utilizing all available information in the dataset, including cases with missing data, to estimate model parameters. It does so by calculating the likelihood of observing the given data for each individual, considering the observed portion of their data. The method maximizes the likelihood function across all individuals in the sample, thus deriving parameter estimates that make the observed data most probable. Unlike traditional methods such as listwise or pairwise deletion, which may discard valuable information and lead to biased estimates, FIML retains and utilizes all data, maximizing statistical power and maintaining sample size. For the purposes of establishing and testing a new model, FIML also allows for easier reproduction since repeating the runs using the same model will produce similar results. (Acock, 2005; Kline, 2106; Medeiros, 2016; StataCorp, 2021).

When using FIML as the estimation method for SEM in STATA, the Standardized Root Mean Square Residual (SRMR) is not available as a fit index due to the presence of missing values. However, other fit indices such as the Root Mean Square Error of Approximation (RMSEA), Comparative Fit Index (CFI), and Tucker-Lewis Index (TLI) can still be evaluated and were used to assess the model fit.

To ensure the robustness of the findings and to compare the performance of different estimation methods, the model fit was assessed using both maximum likelihood (ML) (the default method of SEM in STATA), and full information maximum likelihood (FIML) approaches. While FIML is the preferred method for handling missing data, running the analysis with both ML and FIML will serve as a sensitivity check. In contrast, ML estimation will provide the SRMR, as it treats the data as complete after listwise deletion of cases with missing values. By comparing the results obtained from ML and FIML, we can assess the consistency of the model fit indices and determine if the conclusions drawn from the analysis are robust to the choice of estimation method.

Where the model fit indices from both ML and FIML estimations were similar and indicated an acceptable fit, it provided additional confidence in the validity of the model and the robustness of the findings. However, when there are notable discrepancies between the two estimation methods, further investigation was required in order to understand the reasons behind the differences and to determine the most appropriate approach for the analysis.

Evaluating the model fit using both ML and FIML estimation methods serves as a robustness check and helps to ensure the reliability of the findings. While FIML is the preferred approach for handling missing data, comparing the results with ML estimation provides additional insights into the consistency of the model fit indices and the sensitivity of the conclusions to the choice of estimation method. While running the CFA level analyses of the latent constructs, assuming there is consistency of model fit between ML and FIML, for the full SEM model analysis, only FIML was used.

Variable Measurement

Dependent Variable: Financial Well-Being (FWB)

As was determined by the review of the relevant literature, the dependent variable of FWB was constructed using both objective and subjective measures. (Asebedo & Wilmarth, 2017; Pak & Fan, 2022; Wilkinson, 2016).

Objective Measures of Financial Well-Being

The latent construct of FWB included common elements of objective FWB found in the literature. Those that were included in this study are a) household income, b) total household net worth, c) non-housing net worth, and d) investment assets ratio (Garrett & James, 2013; Kim & Lyons, 2008; Lee, 2018; Pak & Fan, 2022; Tharp, 2017; Tenney & Kalenkoski, 2019; Wilkinson, 2016). Household income is the total of all income earnings from the respondent and his/her partner, if applicable. In older adults, both earned income, as well as capital income (including business or farm income, self-employment earnings, gross rent, dividend and interest income, trust funds or royalties, and other asset income) are considered important (Wilkinson, 2016). This value is labeled as "Total Household Income" in the RAND data file.

Total household net worth and non-housing net worth are combined in the RAND data file and labeled as "Total Wealth", or net worth. Elements include the net values of primary residence, secondary residence, real estate (not primary residence), businesses, any retirement accounts, other investments accounts, liquid savings , etc. The investment assets ratio was constructed by dividing the RAND constructed non-housing net worth variable by the RAND constructed total household net worth variable. Previous research uses this ratio to determine financial strain when this ratio is less than or equal to 0.25 (Garrett & James, 2013; Kim & Lyons, 2008; Todd, 2017). Using the inverse relationship of this ratio, this research codifies those who are not in financial strain as having financial well-being when there is an investment asset ratio of greater than 0.25. Since many people's wealth is associated with their primary residence, the net value of that residence (provided in the RAND data) is also added to the model separately (Wilkinson, 2016).

Household wealth data typically exhibits a skewed distribution (Friedline et al., 2015), which can be addressed using a natural log transformation (Lee and Kim 2016). This skewness in the data is evident as shown by the non-transformed means (μ) and standard deviations (σ) in Table 3.2. A natural log transformation of income was performed to reduce skewness. This was coded such that incomes of $0 were a "1", otherwise it will be the natural logarithm of income. However, natural log transformations are only applicable to positive values, making them unsuitable for net worth measures that may include zeros or negative amounts. To overcome this limitation, an inverse hyperbolic sine (IHS) transformation was employed for the net-worth variables (Friedline et al., 2015; Lee & Kim 2016; Todd et al., 2023). The IHS transformation provides a more appropriate solution for dealing with the skewed nature of these financial variables while accommodating the full range of possible values. Summary statistics of these Objective Financial Well-Being measures can be found in Table 3.2.

To investigate the latent construct of Objective Financial Well-Being (oFWB), an exploratory factor analysis (EFA) was conducted using data from all waves of the data. The observed variables included in the analysis were income, net worth, non-housing net worth, and investment asset ratio. Descriptive statistics and correlations among the variables were examined to assess the suitability of the data for EFA.

Table 3.2 Summary of Objective Measurements of Financial Well-Being

	2010	2012	2014	2016	2018	Combined
Income (μ/σ)	\$62,948 \$97,743	\$64,840 \$100,253	\$67,911 \$127,946	\$74,204 \$159,343	\$75,439 \$163,444	\$74,561 \$142,126
Log of Income (μ/σ)	10.385 1.628	10.401 1.606	10.438 1.605	10.421 1.818	10.416 1.873	10.411 1.705
Net Worth (μ/σ)	\$394,142 \$993,803	\$392,170 \$999,580	\$439,028 \$1,898,284	\$438,146 \$ 1,171,675	\$ 545,131 \$1,862,758	\$456,267 \$1,599,060
IHS of Net Worth (μ/σ)	9.926 6.911	9.959 6.802	10.344 6.337	10.010 6.615	10.172 6.573	10.072 6.664
Non-Housing Net Worth (μ/σ)	\$256,633 \$840,073	\$259,066 \$851,631	\$291,293 \$1,530,076	\$287,545 \$1,017,308	\$357,123 \$1,413,414	\$305,146 \$1,307,432
IHS of Non-Housing Net Worth (μ/σ)	8.366 7.298	8.509 7.103	8.702 6.950	8.095 7.384	8.138 7.440	8.363 7.241
Investment Assets Ratio ($\mu/n>0.25$)	0.288 14,680	0.714 25,865	0.531 21,299	0.535 13,463	0.493 10,940	0.603 14.691

Across all waves, the correlation matrix revealed moderate to strong correlations ($r >$ 0.49) among income, net worth, and non-housing net worth, suggesting that these variables may be measuring a similar underlying construct. In contrast, investment asset ratio exhibited very low correlations with the other variables, indicating a potential lack of association with the oFWB construct. The internal consistency reliability of the scales was assessed using Cronbach's Alpha (α), which yielded coefficients ranging from 0.6511 (2018) to 0.7034 (2016) (Table 3.3). All coefficient values were at or slightly below the commonly accepted threshold of 0.7, suggesting that the scale's reliability could be improved.

EFAs were performed using the principal factors method, and across all waves, two factors were retained based on the Eigen values (Table 3.3). The unrotated factor loadings showed that Factor1 had high loadings for net worth, and non-housing net worth, and a moderate loading for income, suggesting that this factor may represent the objective financial well-being construct. Factor 2 had very low loadings for all variables and did not appear to be meaningful. The variable investment asset ratio had low loadings on both factors and a very high uniqueness value, indicating that it did not contribute substantially to the underlying construct. Based on these findings, investment asset ratio was removed from the analysis, as it does not seem to be a good indicator of the oFWB construct.

Table 3.3 EFA of Objective Measurements of Financial Well-Being (Initial)

	2010	2012	2014	2016	2018	Combined
Cronbach's Alpha (α)	0.6889	0.6911	0.6895	0.7034	0.6511	0.6832
Eigenvalue						
Factor 1	2.1603	2.1631	2.3747	2.1737	1.8444	2.1533
Factor 2	0.0001	0.0094	0.0329	0.0060	0.0021	0.0001
Factor Loadings (λ)						
Income	0.5023	0.4893	0.6352	0.4940	0.3749	0.5062
Net Worth	0.9768	0.9835	0.9960	0.9820	0.9190	0.9736
Non-Housing Net Worth	0.9766	0.9780	0.9892	0.9820	0.9267	0.9742
Investment Assets Ratio	0.0065	-0.0005	0.0286	0.0294	0.0227	0.0026

After removing the investment asset ratio from the analysis, additional EFAs were conducted to investigate the latent construct of Objective Financial Well-Being (oFWB) using the remaining observed variables: income, net worth, and non-housing net worth. The internal consistency reliability of the scales was assessed using Cronbach's Alpha (α), yielding coefficients ranging from 0.7257 (2018) to 0.7845 (2016) (Table 3.4). These values exceed the commonly accepted threshold of 0.7, indicating a satisfactory level of reliability for the three-item scale.

EFAs were performed using the principal factors method, and one factor was retained based on the Eigen values. The factor loadings showed that net worth and non-housing net worth had very high loadings on the single factor. These ranged from 0.9195 (2018) to 0.9960 (2014) for net worth and 0.9269 (2018) to 0.9890 (2014) for non-housing net worth, while income had moderate to high loadings ranging from 0.3790 (2018) to 0.6362 (2014) (Table 3.4).

In summary, the EFA results support a single-factor structure for the oFWB construct across all waves, with net worth and non-housing net worth being very strong indicators and income being a moderate indicator. This single-factor model provides a parsimonious and

Table 3.4 EFA of Objective Measurements of Financial Well-Being (Final)

	2010	2012	2014	2016	2018	Combined
Cronbach's Alpha (α)	0.7698	0.7722	0.7705	0.7845	0.7257	0.7636
Eigenvalue Factor 1	2.1646	2.1679	2.3749	2.1765	1.8481	2.1559
Factor Loadings (λ) Income	0.5066	0.4944	0.6362	0.4982	0.3790	0.5085
Net Worth	0.9770	0.9836	0.9960	0.9822	0.9195	0.9738
Non-Housing Net Worth	0.9764	0.9777	0.9890	0.9816	0.9269	0.9742

interpretable solution, with the three observed variables demonstrating a satisfactory level of internal consistency reliability. Further validation of the model using confirmatory factor analysis (CFA) helped establish the validity and reliability of the oFWB measure and its contribution to the Financial Well-Being (FWB) latent construct after adding the subjective measures of financial well-being (sFWB).

Subjective Measures of Financial Well-Being

The subjective measurement of FWB is consistently measured by a two-item scale within the literature (Pak & Fan, 2022; Wilkinson, 2016) and is comprised of: a) financial strain and b) financial satisfaction. Both of these items are included in the Leave-Behind Psychosocial and Lifestyle Questionnaire (LB). Financial strain is a measure of the respondents' difficulty in meeting monthly payments. Responses were offered in a five-point Likert scale ranging from 1 "not at all difficult" to 5 "completely difficult." Financial Satisfaction was measured as an element of "satisfaction of life" section within the LB survey. Respondents were asked to rate their satisfaction of their present financial situation with similar response options ranging from 1 "not at all satisfied" to 5 "completely satisfied" (Table 3.5). The responses to this were reverse-coded and a subjective FWB scale was created and evaluated. Summary statistics of these Objective Financial Well-Being measures can be found in Table 3.6.

Table 3.5 Subjective Measurements of Financial Well-Being

Variable	Survey Questions	Coding
Financial Strain	"How difficult is it for (you/your family) to meet monthly payments on (your/ your family's) bills?"	1 = not at all difficult, 2 = not very difficult, 3 = somewhat difficult, 4 = very difficult, 5 = completely difficult
Financial Satisfaction	"Please think about your life and situation right now. How satisfied are you with your present financial situation?"	1 = completely satisfied, 2 = very satisfied, 3 = somewhat satisfied, 4 = not very satisfied, 5 = not at all satisfied

Table 3.6 Summary of Subjective Measurements of Financial Well-Being

	2010	2012	2014	2016	2018	Combined
Financial Strain (μ/σ)	3.279 1.163	3.316 1.147	3.326 1.140	3.231 1.139	3.339 1.145	3.298 1.148
Financial Satisfaction (μ/σ)	3.914 1.076	3.931 1.066	4.013 1.020	3.960 1.030	4.093 1.000	3.976 1.044
Subjective Financial Well-Being Scale (μ/σ)	3.597 1.028	3.622 1.001	3.668 0.981	3.590 0.985	3.711 0.975	4.045 1.008

Financial Well-Being

The combination of the latent construct Objective Financial Well-Being (oFWB) and the two observed variables included in Subjective Financial Well-Being (sFWB) are what comprise the latent construct Financial Well-Being (FWB). To investigate the latent construct of Financial Well-Being (FWB), an exploratory factor analysis (EFA) was conducted using data from all waves as well as the combined wave. The observed variables included in the analysis were income, net worth, non-housing net worth, financial strain, and financial satisfaction. Descriptive statistics and correlations among the variables were examined to assess the suitability of the data for EFA.

Across all waves, the correlation matrix revealed strong correlations ($r > 0.732$) among net worth and non-housing net worth, which is not surprising since these variables measure a similar underlying construct. In contrast, the correlations between the other variables exhibited moderate ($0.302 \leq r \leq 0.431$) to low ($0.213 \leq r \leq 0.290$) correlations with the other variables, indicating a potential lack of association with the FWB construct. The internal consistency reliability of the scales was assessed using Cronbach's Alpha (α), which yielded coefficients ranging from 0.6921 (2010) to 0.7133 (2016) (Table 3.3). All coefficient values were at or slightly below the commonly accepted threshold of 0.7, suggesting that the scale's reliability could be improved.

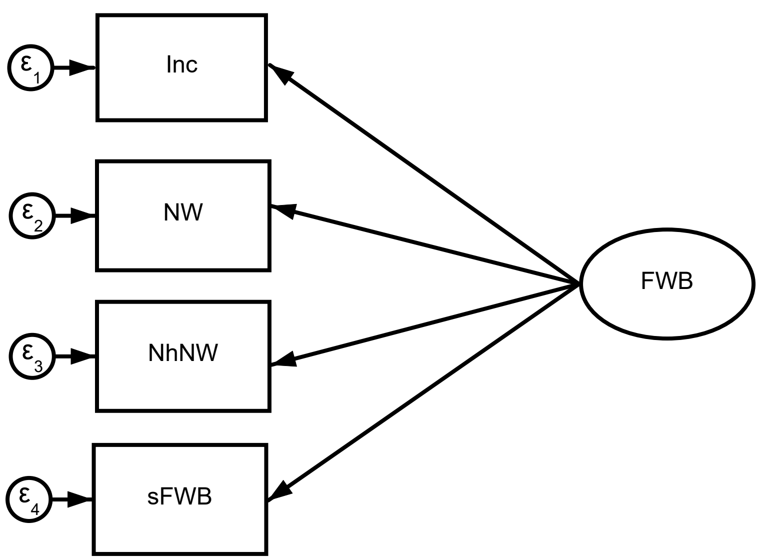
EFAs were performed using the principal factors method, and across all waves, two factors were retained based on the Eigen values (Table 3.7). The unrotated factor loadings showed that Factor1 had high loadings for net worth, and non-housing net worth, and moderate loadings for income and subjective financial well-being, suggesting that this factor may represent the objective financial well-being construct. Factor2 had very low loadings for all variables and did not appear to be meaningful.

Table 3.7 EFA of Financial Well-Being

	2010	2012	2014	2016	2018	Combined
Cronbach's Alpha (α)	0.6921	0.7000	0.6979	0.7133	0.7122	0.7016
Eigenvalue Factor 1	1.6907	1.7064	1.7471	1.7362	1.7553	1.6882
Factor 2	0.0176	0.0216	0.0484	0.0439	-0.0045	0.0218
Factor Loadings (λ) Income (ln)	0.3551	0.3955	0.4087	0.3796	0.4145	0.3859
Net Worth (IHS)	0.8023	0.7858	0.8013	0.8099	0.8090	0.8001
Non-Housing Net Worth (IHS)	0.8291	0.8178	0.8294	0.8333	0.8279	0.8264
Subjective FWB	0.4833	0.5134	0.5000	0.4918	0.4934	0.4650

To further validate the single-factor structure of the Financial Well-Being (FWB) construct identified through the EFA, a confirmatory factor analysis (CFA) was conducted using data from all waves as well as the combined wave. The CFA model was specified based on the results of the EFA, with the log-transformed income, inverse hyperbolic sine-transformed total assets, inverse hyperbolic sine-transformed non-housing assets, and subjective financial well-being (sFWB) as indicators of the latent FWB construct. To ensure the identification of the CFA model, the factor loading of the indicator variable logIncome was fixed to 1. This approach allowed for the estimation of the other factor loadings and the evaluation of their statistical significance. The model was estimated using STATA's maximum likelihood with missing values (MLMV) method, or FIML, which is appropriate for handling missing data. As indicated earlier, for robustness, maximum likelihood (ML) was also be evaluated against FIML. The measurement model for FWB is shown in Figure 3.1.

Figure 3.1 Financial Well-Being (FWB) as a Latent Variable (Initial)



When evaluating the results of the CFAs of FWB using both ML and FIML, overall, the model for all waves indicates it is a good fit (Table 3.8). The comparative fit index (CFI) and Tucker–Lewis index (TLI) results were within the acceptable ranges (0.987-0.997 and 0.961-0.994, respectively) following Kline (2016). The standardized root mean squared residual

Table 3.8 CFA of Measurements of Financial Well-Being (Initial)

	2010		2012		2014		2016		2018		Combined	
	ML	FIML	ML	FIML	ML	FIML	ML	FIML	ML	FIML	ML	FIML
n	8,221	22,034	7,299	20,554	7,439	18,747	6,260	20,912	5,697	17,146	34,916	99,393
RMSEA	0.055	0.035	0.068	0.041	0.088	0.056	0.081	0.045	0.056	0.033	0.060	0.036
CFI	0.995	0.997	0.992	0.997	0.987	0.994	0.989	0.996	0.995	0.998	0.994	0.997
TLI	0.984	0.992	0.975	0.990	0.961	0.981	0.967	0.988	0.984	0.994	0.981	0.992
SRMR	0.019	-	0.024	-	0.031	-	0.029	-	0.018	-	0.022	-

(SRMR) results for the ML model were within the acceptable range (SRMR < 0.05), further supporting a good fit. The root mean squared error of approximation (RMSEA) results were all outside of the acceptable range (RMSEA < 0.05) for the ML model (0.055-0.088) with the FIML model RMSEA results suggesting an overall good fit (0.033-0.056). Since the comparison of goodness of fit results between the ML and FIML models were both within acceptable ranges for all but RMSEA, FIML was utilized to refine the model for FWB by examining the modification indices.

Modification indices (MI) are a diagnostic tool used in structural equation modeling (SEM) to identify potential improvements to the model fit. They provide information about the expected decrease in the model's chi-square value (i.e., the improvement in model fit) if a specific parameter that is currently fixed to zero (such as a path or a covariance) were to be freely estimated. In other words, modification indices suggest how the model fit could be improved by adding additional paths or covariances between variables that are not currently specified in the model. A high modification index (MI > 40) indicates that adding the corresponding parameter to the model would likely result in a significant improvement in model fit. Modifications to the model based on modification indices were guided by theoretical considerations and not solely based on statistical criteria, to avoid overfitting the model to the specific sample.

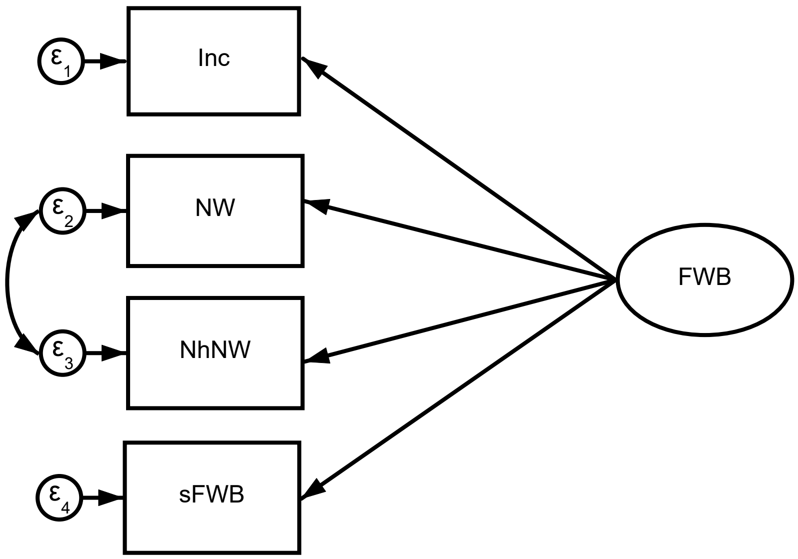
The modification indices (MI) provided by the "estat mi" command in Stata suggest potential improvements to the CFA model fit by identifying additional paths or covariances that could be added to the model. The MI represents the expected decrease in the model's chi-square value if a particular parameter were to be freely estimated. Evaluating the MI results for each wave and the combined wave, the modification indices suggest two potential covariances that could be added to the model. These include the covariance between the error terms of income (Inc) and subjective financial well-being (sFWB) (MI = 18.648-190.314) and covariance between the error terms of net worth (NW) and non-housing net worth (NhNW) (MI = 18.648-190.317) (Table 3.9). The covariance between the error terms of net worth (NW) and non-housing net worth (NhNW) appears to be the most theoretically justifiable, as both variables measure aspects of household assets and are likely to share some common sources of variance not accounted for by the latent variable FWB. The modification to the model is represented in Figure 3.2.

Table 3.9 Modification Indices (MI) of Financial Well-Being

	2010	2012	2014	2016	2018	Combined
n	22,034	20,554	18,747	20,912	17,146	99,393
MI cov(Inc,.sFWB)	34.251	51.648	89.815	58.411	18.648	190.314
cov(NW,NhNW)	34.251	51.649	89.815	58.395	18.648	190.317

The covariance between the error terms of net worth (NW) and non-housing net worth (NhNW) were added, and the model was re-estimated using FIML only. The model fit indices and parameter estimates were re-evaluated to assess the impact of this modification on the overall model fit and the relationships between the observed variables and the latent construct and are reported in Table 3.10. The results suggest that these modifications greatly improve the model with no further modifications required. Based on the modification indices, the covariance

Figure 3.2 Financial Well-Being (FWB) as a Latent Variable (Final)



between the error terms of net worth (NW) and non-housing net worth (NhNW) was added to the CFA model. The modified model was then re-estimated using the maximum likelihood with missing values (mlmv) method (FIML). The standardized factor loadings for the observed variables are reported in Table 3.11.

Table 3.10 CFA of Measurements of Financial Well-Being (Final)

	2010	2012	2014	2016	2018	Combined
n	22,034	20,554	18,747	20,912	17,146	99,393
RMSEA	0.022	0.012	0.000	0.021	0.021	0.004
CFI	0.999	1.000	1.000	1.000	1.000	1.000
TLI	0.997	0.999	1.000	0.997	0.997	1.000
MI cov(NW,NhNW)	>3.84	>3.84	>3.84	>3.84	>3.84	>3.84

Note: STATA reports, "no modification indices to report, all MI values > 3.84145"

Table 3.11 Standardized Factor Loadings of Financial Well-Being

	2010	2012	2014	2016	2018	Combined
n	22,034	20,554	18,747	20,912	17,146	99,393
Income (lnInc)	0.4006	0.4470	0.4673	0.4524	0.4327	0.4374
Net Worth (NW)	0.6606	0.6628	0.6177	0.6571	0.7036	0.6580
Non-Housing Net Worth (NhNW)	0.7549	0.7367	0.7000	0.7042	0.7525	0.7307
Subjective FWB (sFWB)	0.5763	0.6069	0.6293	0.6158	0.5901	0.5659
cov(NW,NhNW)	0.4779	0.4813	0.5456	0.5350	0.4742	0.5042

The re-estimated CFA model revealed that all factor loadings were statistically significant ($p < 0.001$), indicating that each observed variable contributes significantly to the measurement of the latent construct FWB. The standardized factor loadings revealed that non-housing net worth (NhNW) has the strongest relationship with the latent construct FWB, followed by net worth (NW). A one standard deviation increase in FWB was associated with a 0.700 to 0.755 standard deviation increase in non-housing net worth (NhNW) and a 0.618 to 0.704 standard deviation increase in net worth (NW), holding other variables constant. This suggests that non-housing assets and total household assets are the most important indicators of the latent construct FWB.

The subjective financial well-being measure (sFWB) had a moderate relationship with FWB, with standardized factor loadings between 0.576 and 0.629 indicating that a one standard deviation increase in FWB corresponds to a 0.576 to 0.629 standard deviation increase in sFWB, keeping other variables constant. The log-transformed household income (lnInc) had the weakest relationship with FWB among the observed variables, with standardized factor loadings between 0.401 and 0.467. This suggests that income plays a less crucial role in measuring the latent construct FWB compared to the asset-based measures and subjective financial well-being. Lastly, the standardized covariance between the error terms net worth (NW) and non-housing net worth (NhNW) ranged from 0.474 and 0.546, indicating a moderate positive relationship between the unique variances of these two variables that is not accounted for by the latent construct FWB.

In conclusion, the CFA results support the validity of the FWB construct, with all observed variables contributing significantly to its measurement. The asset-based measures (net worth (NW) and non-housing net worth (NhNW)) had the strongest relationships with FWB, followed by the subjective financial well-being measure (sFWB) and the log-transformed household income (Income (lnInc)). The added covariance between the error terms of net worth (NW) and non-housing net worth (NhNW) improved the model fit, indicating that these variables share some common sources of variance not accounted for by the latent construct FWB. These findings highlight the importance of considering both objective and subjective aspects of financial well-being when assessing the overall financial well-being of older adults and were used as the dependent variable in this study.

Predictor Variables

Biological

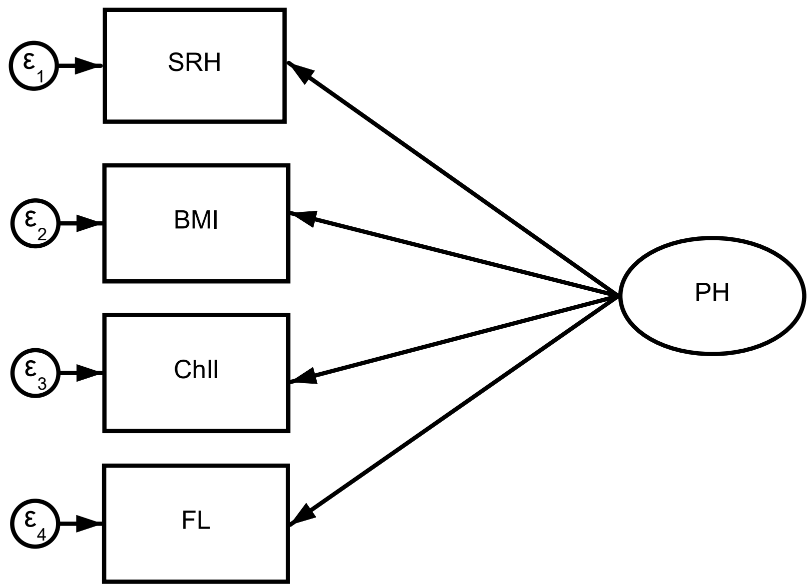
The biological predictor variable was routinely referred to and tested as Physical Health (PH). While the validity of self-reported health has been increasing over time (Schnittker & Bacak, 2014), the inclusion and evaluation of objective measures of physical health is warranted. The biological variable in and of itself is a latent construct within the biopsychosocial model (BPS) in this study (Figure 3.3). Within the biological variable, several observed and latent variables are introduced consistent with the relevant literature. In addition to the observed variable of self-reported health status (SRH), these constructs include a) body mass index (BMI), b) chronic illness (ChIl), and c) functional limitation (FL) (Chang et al., 2014; Lee, 2018; Pak & Fan, 2022; Wilkinson, 2016). The measurement of the elements of PH is described in Table 3.12.

Table 3.12 Physical Health Variable Measurements

Variables	Measurement
Self-Reported Health Status (SRH)	Respondents' self-reported health status. Ordinal Likert-type indicator measured on a 5-point scale with higher scores representing poorer perceived health.
BMI	Respondents' self-reported, squared weight /squared height
Chronic Illness (ChIl)	Latent construct with 8 binary indicators (1-yes, 0-no) of respondent having an occurrence of: high blood pressure, diabetes, cancer, lung

	disease, heart disease, stroke, psychiatric problems, and arthritis. Responses are summed.
Functional Limitation (FL)	Latent construct with 6 indicators (1-yes, 0-no) of respondent indicating having difficulty with an activity of daily living (ADL). ADLs include walking across a room, dressing, bathing, eating, getting in and out of bed, and using the toilet. Responses are summed.

Figure 3.3 Physical Health as a Latent Variable in the Biopsychosocial Model



Self-Reported Health (SRH)

Self-Reported Health (SRH) status as a subjective measure of respondents' overall health has been shown to be highly correlated with otherwise objective measures (Kahn & Pearlin, 2006; Stenholm et al., 2014). Within each survey wave of the Core HRS questions, respondents are asked to rate their health using a five-point Likert scale ranging from 1 (excellent) to 5 (poor). Previous research treats the categorization of these responses differently.

Richard et al. (2018) treated a reported health status of fair or poor coded as 1, and all others (i.e., excellent, very good, and good) were coded as 0. Lee (2018) categorized responses into three dummy categorical variables, including poor, good, and excellent where "poor" included responses of fair/poor, “good” included responses of good/very good, and “excellent” included responses of “excellent.” In this study, the original five-item measure were used for SRH status (Chang et al., 2014) as described in Table 3.13 with summary statistics shown in Table 3.14.

Table 3.13 Self-Reported Health Status Variable Measurement

Variable	Survey Questions	Coding
Self-Reported Health Status	In general, would you say that your health is (a) excellent, (b) very good, (c) good, (d) fair, or (e) poor?	1 = excellent, 2 = very good, 3 = good, 4 = fair, 5 = poor

Table 3.14 Summary of Self-Reported Health Status (SRH)

	2010	2012	2014	2016	2018	Combined
Self-Reported Health Status (SRH) (μ/σ)	2.8936 1.1096	2.8958 1.0990	2.9477 1.0686	2.9517 1.0663	2.9331 1.0502	2.9929 1.0808

Body Mass Index (BMI)

Using the World Health Organization’s definition and categorization of BMI, the value for this variable was constructed using the respondents’ squared height and weight. Dividing the weight by the height provided a result where the larger the score would indicate a riskier BMI value. The results are categorized as: 1 (Underweight, BMI < 18.5), 2 (Healthy Weight, 18.5 ≤ BMI ≤ 24.9), 3 (Overweight, 25.0 ≤ BMI ≤ 29.9), and 4 (Obese, BMI ≥ 30.0) (Chang et al., 2014). Summary statistics of BMI as both a continuous variable as well as BMI in its categorical form are shown in Table 3.15.

Table 3.15 Summary of Body Mass Index (BMI)

	2010	2012	2014	2016	2018	Combined
Body Mass Index (BMI) (μ/σ)	28.5031 6.1968	28.5011 6.2340	28.5733 6.2139	28.9582 6.3576	29.0614 6.4411	28.9604 6.3785
Min	7.0	8.9	11.0	10.3	10.2	7
Max	79.1	83.0	76.6	92.8	103.6	103.6

BMI Categories (*%*) Underweight	1.45	1.69	1.73	1.60	1.67	1.24
Healthy Weight	27.39	27.50	26.72	24.85	24.42	23.70
Overweight	35.99	35.95	36.22	35.96	35.92	34.33
Obese	35.18	34.86	35.33	37.59	37.99	40.73

Chronic Illness (ChIl)

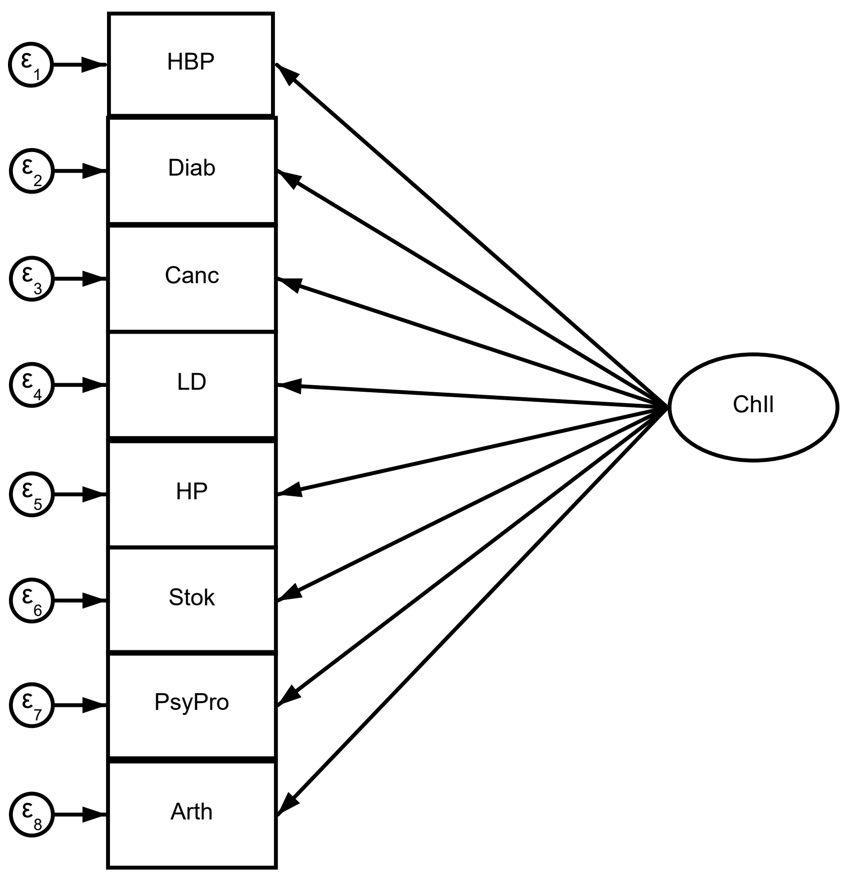
Chronic Illness (ChIl) as a latent variable for physical health in the HRS is frequently used and operationalized similarly (Beier et al., 2018; Chang et al., 2014; Lee, 2018). Respondents are asked if a doctor has ever told them that they have one of the following eight conditions: a) high blood pressure or hypertension, b) diabetes or high blood sugar, c) cancer or a malignant tumor of any kind except skin cancer, d) chronic lung disease except asthma such as chronic bronchitis or emphysema e) heart attack, coronary heart disease, angina, congestive heart failure, or other heart problems, f) stroke or transient ischemic attack (TIA), g) emotional, nervous, or psychiatric problems, and/or h) arthritis or rheumatism. Within the RAND data file, for each/any of those conditions, if a respondent answers “yes” then it is coded as a 1 and is otherwise set to 0. As indicated in Table 3.16, responses are summed with a range of 0 to 8 with lower scores indicating better physical health.

As was be the case with all latent variables in this data analysis, in order to ascertain the reliability and validity of any latent variable, confirmatory factor analysis (CFA) was employed to assess the degree of association between each indicator and the latent variable and the relationships expressed in Figure 3.4. An analysis and reporting was done on the standardized factor loadings, the significance of these loadings, residual variances, and Cronbach’s alpha for the latent variable, as outlined by Kline (2016). To investigate the latent construct of Chronic Illness (ChIl), an exploratory factor analysis (EFA) was conducted using data from all waves as well as the combined wave.

Table 3.16 Summary of Chronic Illness Variables

	2010	2012	2014	2016	2018	Combined
ChIl Categories						
High Blood Pressure	0.5649	0.5937	0.6166	0.5976	0.6238	0.5976
(μ/σ)	0.4958	0.4912	0.4862	0.4904	0.4845	0.4904
Diabetes	0.2148	0.2337	0.2509	0.2617	0.2869	0.2478
(μ/σ)	0.4107	0.4232	0.4336	0.4396	0.4523	0.4318
Cancer	0.1341	0.1450	0.1536	0.1415	0.1519	0.1447
(μ/σ)	0.3407	0.3521	0.3606	0.3485	0.3589	0.3518
Lung Disease	0.0897	0.0977	0.1034	0.1039	0.1130	0.1010
(μ/σ)	0.2858	0.2970	0.3045	0.3051	0.3166	0.3013
Heart Problems	0.2194	0.2358	0.2486	0.2293	0.2460	0.2350
(μ/σ)	0.4139	0.4245	0.4322	0.4204	0.4307	0.4240
Stroke	0.0836	0.0905	0.0943	0.0878	0.0913	0.0893
(μ/σ)	0.2767	0.2869	0.2923	0.2831	0.2880	0.2851
Psych Problems	0.1709	0.1866	0.1986	0.2092	0.2245	0.1967
(μ/σ)	0.3764	0.3896	0.3990	0.4068	0.4173	0.3975
Arthritis	0.5307	0.5624	0.5867	0.5474	0.5875	0.5611
(μ/σ)	0.4991	0.4961	0.4924	0.4978	0.4923	0.4963

Figure 3.4 Chronic Illness (ChIl) as a Latent Variable (Initial)



The observed variables included in the analysis were the binary responses of whether the respondent has ever had high blood pressure, diabetes, cancer, lung disease, heart problems, a stroke, psychological problems, and/or arthritis. Descriptive statistics and correlations among the variables were examined to assess the suitability of the data for EFA.

Across all waves and all variables, the correlation matrix revealed weak correlations ($r < 0.30$). The internal consistency reliability of the scales were assessed using Cronbach's Alpha (α), which yielded coefficients ranging from 0.5073 (2014) to 0.5282 (2016) (Table 3.17). All coefficient values were at or slightly below the commonly accepted threshold of 0.7, suggesting that the scale's reliability could be improved.

EFAs were performed using the principal factors method, and across all waves, three factors were retained based on the Eigen values (Table 3.17). The unrotated factor loadings revealed three to four factors with Eigen values greater than 1. However, the Eigen values for factors 2, 3, and 4 were relatively small compared to factor 1, which accounted for between 82.8% (2016), 85.8% (Combined), 86.7% (2010, 2012), 87.6% (2018) and 88.6% (2014) of the total variance explained by the four factors. The factor loadings showed that all indicators had their highest loadings on factor 1, with loadings ranging from 0.1575 to 0.4440. However, the uniqueness values were relatively high (ranging from 0.7824 to 0.9612), indicating that a substantial portion of the variance in each indicator was not accounted for by the extracted factors. Additionally, the Cronbach's alpha coefficient for the eight indicators ranged from 0.5072 to 0.5282, which is below the generally accepted threshold of 0.70 for internal consistency reliability.

Table 3.17 EFA of Chronic Illness (ChIl)

	2010	2012	2014	2016	2018	Combined
Cronbach's Alpha (α)	0.5153	0.5134	0.5073	0.5282	0.5142	0.5180
Eigenvalue						
Factor 1	0.9325	0.9293	0.9138	0.9872	0.9418	0.9469
Factor 2	0.1376	0.1411	0.1438	0.1528	0.1447	0.1421
Factor 3	0.0160	0.0165	0.0172	0.0216	0.0380	0.0210
Factor 4	-	0.0005	0.0056	0.0142	0.0044	0.0050
ChIl Factor Loadings						
High Blood Pressure	0.4237	0.4179	0.4117	0.4223	0.4164	0.4202
Diabetes	0.3198	0.3153	0.3191	0.3185	0.3084	0.3185
Cancer	0.1892	0.1762	0.1575	0.1809	0.1671	0.1756
Lung Disease	0.2883	0.3017	0.3129	0.3268	0.3212	0.3109
Heart Problems	0.4363	0.4316	0.4288	0.4440	0.4344	0.4352
Stroke	0.3141	0.3182	0.3112	0.3293	0.3212	0.3184
Psych Problems	0.2767	0.2885	0.2941	0.2941	0.2930	0.2911
Arthritis	0.4077	0.4029	0.3905	0.4193	0.4055	0.4071

Given the results of the EFA and the low internal consistency reliability, the eight chronic illness indicators might not be best represented by a single latent construct. As an alternative, a summative scale variable for Chronic Illness (ChIl) was created by summing the binary responses across the eight indicators. This scale reflects the total number of chronic illnesses reported by each respondent, with possible scores ranging from 0 to 8. Descriptive statistics for the ChIl scale revealed means ranging from of 2.008 (2010) to 2.3247 (2018) (Table 3.18), indicating that, on average, respondents reported having approximately two chronic illnesses. The minimum score was 0, and the maximum score was 8, demonstrating that the scale captures the full range of possible values.

The decision to use the summative scale (ChIl) instead of a latent construct was based on several factors. First, the EFA results suggested that the eight chronic illness indicators might not be measuring a single, unified construct, as evidenced by the presence of multiple factors with Eigen values greater than 1 and the high uniqueness values for each indicator. Second, the low

Cronbach's alpha coefficient indicated poor internal consistency reliability among the indicators, further supporting the notion that they may not be capturing a single latent construct.

Table 3.18 Summary of Chronic Illness (ChIl)

	2010	2012	2014	2016	2018	Combined
Chronic Illness (ChIl)	2.0080	2.1455	2.2527	2.1785	2.3247	2.1731
(μ/σ)	1.5093	1.5321	1.5413	1.5656	1.5685	1.5459

By using the summative scale, we can still capture important information about the overall chronic illness burden experienced by respondents without assuming that the eight indicators are measuring a single, unified construct. This approach allows for a more flexible and pragmatic assessment of chronic illness, as it accounts for the cumulative impact of multiple chronic conditions on individuals' health and well-being.

In summary, the decision to use the summative scale (ChIl) instead of a latent construct was based on the results of the EFA, the low internal consistency reliability, and the desire to capture the cumulative burden of chronic illness in a pragmatic manner. This approach allows for a more comprehensive understanding of the impact of chronic illness on the study population and will be further tested when evaluating the entirety of the latent construct of Physical Health (PH).

Functional Limitation (FL)

Functional Limitation (FL) as a latent variable for physical health in the HRS is frequently used and operationalized similarly (Beier et al., 2018; Chang et al., 2014; Lee, 2018). Respondents are asked if they have had any difficulty performing a task within a list containing six activities of daily living (ADL). The list includes, a) walking across a room, b) dressing, c) bathing, d) eating, e) getting in and out of bed, and/or f) using the toilet. Within the RAND data file, for each/any of those conditions, if a respondent answers “yes” then it is coded as a 1 and is otherwise set to 0. Lee (2018) only included four of the six that are available in the HRS (getting out of bed, bathing, dressing, and eating), and categorized respondents into two groups: having some difficulty (ranging from 1 to 4) and having no functional limitations in daily living activities which served as the reference group. Unless otherwise justified in further analyses, as indicated in Table 3.12 above, responses are summed with a range of 0 to 6 with lower scores indicating better physical health. Summary statistics of these Functional Limitation measures can be found below in Table 3.19.

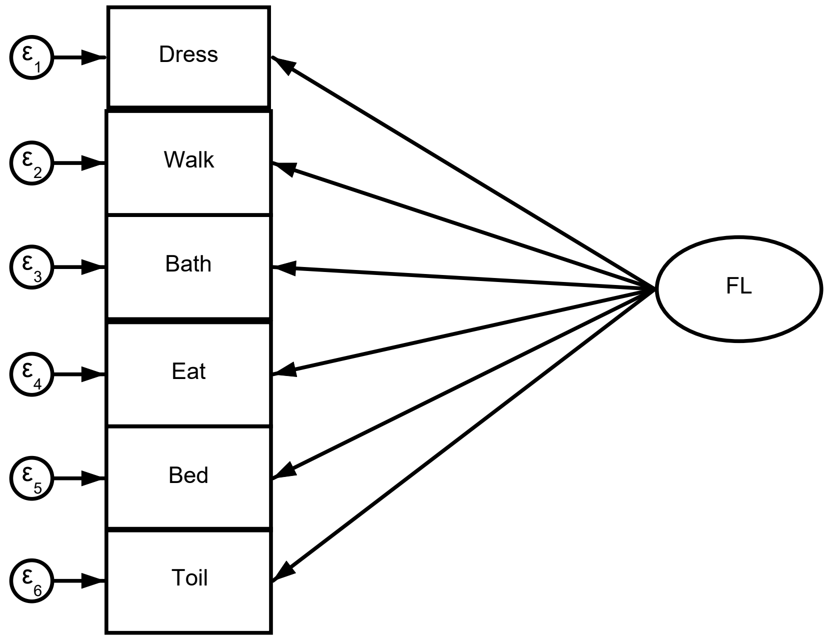
Table 3.19 Summary of Functional Limitation Variables

	2010	2012	2014	2016	2018	Combined
Dress (μ/σ)	0.1174 0.3220	0.1127 0.3162	0.1234 0.3289	0.1160 0.3202	0.1101 0.3131	0.1160 0.3202
Walk (μ/σ)	0.0816 0.2737	0.0820 0.2743	0.0870 0.2818	0.0812 0.2732	0.0839 0.2773	0.0830 0.2759
Bath (μ/σ)	0.0854 0.2795	0.0873 0.2822	0.0922 0.2894	0.0833 0.2763	0.0805 0.2721	0.0858 0.2800
Eat (μ/σ)	0.0437 0.2043	0.0447 0.2066	0.0471 0.2118	0.0408 0.1978	0.0400 0.1960	0.0433 0.2035
Bed (μ/σ)	0.0798 0.2710	0.0806 0.2722	0.0828 0.2756	0.0811 0.2731	0.0821 0.2745	0.0812 0.2731
Toilet (μ/σ)	0.0702 0.2556	0.0712 0.2571	0.0745 0.2625	0.0668 0.2497	0.0659 0.2481	0.0698 0.2547
Scale of FL (μ/σ)	0.4779 1.2118	0.4782 1.2273	0.5067 1.2486	0.4690 1.1972	0.4625 1.1767	0.4789 1.2131

As was the case with all latent variables in this data analysis; in order to ascertain the reliability and validity of any latent variable, confirmatory factor analysis (CFA) was employed to assess the degree of association between each indicator and the latent variable (Figure 3.5). An analysis and reporting were done on the standardized factor loadings, the significance of these loadings, residual variances, and Cronbach's alpha for the latent variable, as outlined by Kline (2016).

To investigate the latent construct of Functional Limitation (FL), an exploratory factor analysis (EFA) was first conducted using data from all waves of the data. The observed variables

Figure 3.5 Functional Limitation (FL) as a Latent Variable (Initial)



included in the analysis were walking across a room, dressing, bathing, eating, getting in and out of bed and using the toilet. Descriptive statistics and correlations among the variables were examined to assess the suitability of the data for EFA. Across all waves, the correlation matrix revealed mostly weak correlations ($r < 0.25$) among all variables, suggesting that these variables are likely measuring a different underlying construct. The internal consistency reliability of the scales were assessed using Cronbach's Alpha (α), which yielded coefficients ranging from 0.8407 (2016) to 0.8515 (2012) (Table 3.20). All coefficient values were above the commonly accepted threshold of 0.7, suggesting that the scale can be viewed as reliable and possibly useful for this analysis.

EFAs were performed using the principal factors method, and across all waves, two factors were retained based on the Eigen values (Table 3.20). The unrotated factor loadings showed that Factor 1 had high loadings for all variables, suggesting that this factor may well

Table 3.20 EFA of Functional Limitation (FL) (Initial)

	2010	2012	2014	2016	2018	Combined
Cronbach's Alpha (α)	0.8430	0.8515	0.8455	0.8407	0.8324	0.8431
Eigenvalue						
Factor 1	2.7935	2.8885	2.8205	2.7689	2.6753	2.7929
Factor 2	0.0026	-0.0451	-0.0354	-0.0115	0.0035	-0.0188
Factor Loadings						
Dress	0.7068	0.7071	0.7067	0.7031	0.6970	0.7044
Walk	0.7060	0.7011	0.7007	0.6895	0.6940	0.6983
Bath	0.7427	0.7487	0.7411	0.7354	0.7290	0.7399
Eat	0.5867	0.6035	0.5994	0.5661	0.5571	0.5838
Bed	0.6752	0.6998	0.6907	0.6880	0.6723	0.6852
Toilet	0.6662	0.6946	0.6667	0.6816	0.6434	0.6717

represent the objective financial well-being construct. Factor 2 had very low loadings for all variables and did not appear to be meaningful.

The EFA results supported a single-factor structure for the FL construct across all waves, with all variables being very strong indicators. This single-factor model provides a parsimonious and interpretable solution, with the six observed variables demonstrating a satisfactory level of internal consistency reliability. Further validation of the model using confirmatory factor analysis (CFA) helped establish the validity and reliability of the FL measure and its contribution to the Physical Health (PH) latent construct after adding the additional measures proposed.

The CFA model was specified based on the results of the EFA, with all observed variables associated with Functional Limitation (FL) as indicators of the latent FL construct. To ensure the identification of the CFA model, the factor loading of the indicator variable 'Dress' was fixed to 1. This approach allows for the estimation of the other factor loadings and the evaluation of their statistical significance. The model was estimated using STATA's maximum likelihood with missing values (MLMV) method, or FIML, which is appropriate for handling missing data. As indicated earlier, for robustness, maximum likelihood (ML) will also be evaluated against FIML. The measurement model for FL is shown in Figure 3.5 above.

When evaluating the results of the CFAs of FL using both ML and FIML, overall, the model for all waves indicates it is a good fit (Tables 3.21 and 3.22). The comparative fit index (CFI) and Tucker–Lewis index (TLI) results were within the acceptable ranges (0.988-0.996 and 0.980-0.993, respectively) following Kline (2016). The standardized root mean squared residual (SRMR) results for the ML model were within the acceptable range (SRMR < 0.05), further supporting a good fit. The root mean squared error of approximation (RMSEA) results were almost all within the acceptable range (RMSEA < 0.05) for both the ML and FIML model (0.053-0.033). Since the comparison of goodness of fit results between the ML and FIML models were both within acceptable ranges for all but RMSEA, FIML was utilized to refine the model for FWB by examining the modification indices.

Table 3.21 ML CFA of Measurements of Functional Limitation (FL) (Initial)

	2010	2012	2014	2016	2018	Combined
n	21,875	20,499	18,685	20,840	17,099	98,998
RMSEA	0.053	0.033	0.036	0.043	0.048	0.042
CFI	0.988	0.996	0.995	0.992	0.989	0.992
TLI	0.980	0.993	0.991	0.986	0.982	0.987
SRMR	0.018	0.010	0.012	0.015	0.017	0.014

Table 3.22 FIML CFA of Measurements of Functional Limitation (FL) (Initial)

	2010	2012	2014	2016	2018	Combined
n	21,902	20,535	18,731	20,876	17,120	99,164
RMSEA	0.053	0.033	0.035	0.043	0.048	0.042
CFI	0.988	0.995	0.995	0.992	0.989	0.992
TLI	0.980	0.992	0.991	0.986	0.982	0.987
SRMR	-	-	-	-	-	-

Modification indices (MI) are a diagnostic tool used in structural equation modeling (SEM) to identify potential improvements to the model fit. They provide information about the expected decrease in the model's chi-square value (i.e., the improvement in model fit) if a specific parameter that is currently fixed to zero (such as a path or a covariance) were to be freely estimated. In other words, modification indices suggest how the model fit could be improved by adding additional paths or covariances between variables that are not currently specified in the model. A high modification index (MI > 40) indicates that adding the corresponding parameter to the model would likely result in a significant improvement in model fit. Modifications to the model based on modification indices were guided by theoretical considerations and not solely based on statistical criteria, to avoid overfitting the model to the specific sample.

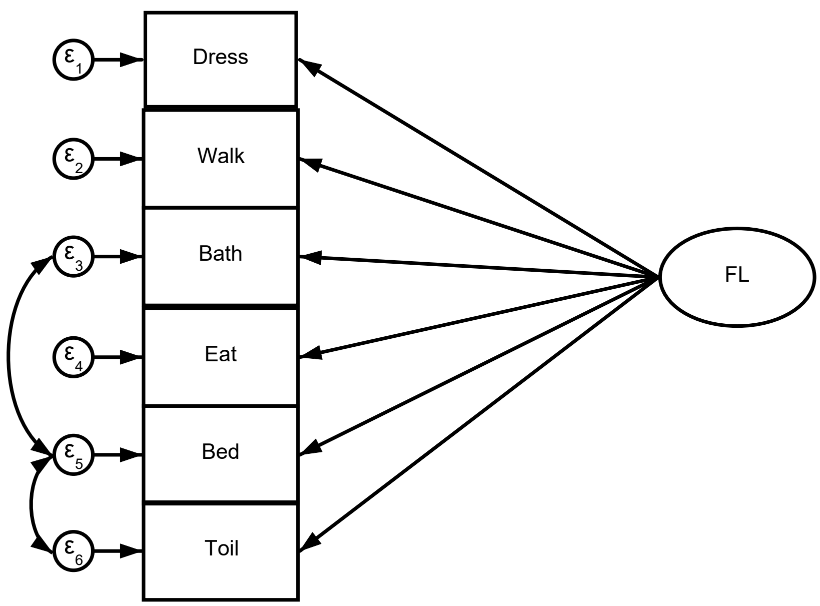
The modification indices (MI) provided by the "estat mi" command in Stata suggest potential improvements to the CFA model fit by identifying additional paths or covariances that could be added to the model. The MI represent the expected decrease in the model's chi-square value if a particular parameter were to be freely estimated. Evaluating the MI results for each wave and the combined wave, the modification indices suggest two potential covariances that are consistent across all waves that could be consideration for additions to the model. These include the covariance between the error terms of 'Bath' and 'Bed' (MI = 119.78 - 943.24) and covariance between the error terms of 'Bed' and 'Toilet' (MI = 49.16 – 387.19) (Table 3.23). The covariance between these error terms involving needing assistance getting into and out of bed ('Bed') appear to be the most theoretically justifiable, as that variable measures aspects of a respondent's ability to safely move and are likely to share some common sources of variance not accounted for by the latent variable FL. The modification to the model is represented in Figure 3.6.

The covariance between the error terms of 'Bed' with 'Bath' and 'Bed' with Toilet ('Toil') were added, and the model was re-estimated using FIML only. The model fit indices and

Table 3.23 Modification Indices (MI) of Chronic Illness

	2010	2012	2014	2016	2018	Combined
n	21,902	20,535	18,731	20,876	17,120	99,164
MI						
cov(e.Dress,e.Bed)	132.11	-	-	100.37	84.41	357.23
cov(e.Dress,e.Toilet)	47.21	-	-	47.68	-	157.09
cov(e.Bath,e.Eat)	180.91	-	50.88	123.59	94.06	423.75
cov(e.Bath,e.Bed)	360.07	143.05	119.78	172.88	176.17	943.24
cov(e.Bed,e.Toilet)	89.25	49.16	53.68	84.74	119.75	387.19
cov(e.Dress,e.Walk)	-	-	-	-	-	76.87
cov(e.Dress,e.Bath)	-	-	-	-	-	77.04
cov(e.Dress,e.Eat)	-	-	-	-	-	78.27
cov(e.Walk,e.Bath)	-	-	-	-	-	107.79

Figure 3.6 Financial Well-Being (FWB) as a Latent Variable (Final)



parameter estimates were re-evaluated to assess the impact of this modification on the overall model fit and the relationships between the observed variables and the latent construct and are reported in Table 3.24.

While the results of the fit statistics suggest that these modifications improved the model, there are additional modifications required based on the MI values. Based on the increased

Table 3.24 CFA of Measurements of Functional Limitation (FL) (Final)

	2010	2012	2014	2016	2018	Combined
n	21,902	20,535	18,731	20,876	17,120	99,164
RMSEA	0.032	0.018	0.023	0.032	0.31	0.26
CFI	0.997	0.999	0.998	0.997	0.997	0.998
TLI	0.993	0.998	0.996	0.993	0.993	0.995
MI cov(e.Dress,e.Bed)	60.52	-	-	82.39	71.92	226.82
cov(e.Walk,e.Toilet)	62.71	-	-	57.38	-	188.25
cov(e.Bath,e.Eat)	83.76	-	-	65.91	41.62	181.89
cov(e.Walk,e.Bed)	-	-	-	-	-	70.54
cov(e.Bath,e.Toilet)	-	-	-	-	-	121.15
cov(e.Bed,e.Eat)	-	-	-	-	-	63.41

Note: MI value not shown if MI values < 40

complexity of the modification indices, and their lack of consistency of these between waves, the six functional limitation indicators might not be best represented by a single latent construct. As an alternative, a summative scale variable for Functional Limitations (FL) was created by summing the binary responses across the six indicators. This scale reflects the total number of functional limitations reported by each respondent, with possible scores ranging from 0 to 6. Descriptive statistics for the FL scale revealed means ranging from 0.4625 (2018) to 0.5067 (2014) (Table 3.25), indicating that, on average, most respondents do not report having functional limitations. The minimum score was 0, and the maximum score was 6, demonstrating that the scale captures the full range of possible values.

Given the skewed distribution of the majority of respondents indicating zero functional limitations, a binary variable was created to measure whether the respondent had any functional limitations or not. A summary of this measure is shown in Table 3.26. The decision was made to use this binary measure (FL_b) instead of the initially proposed latent construct, and was based on several factors.

First, while the EFA results suggested that the six functional limitation indicators seem to be measuring a single, unified construct, as evidenced by the presence of a single factor with an

Table 3.25 Summary of Functional Limitations (FL)

	2010	2012	2014	2016	2018	Combined
FL Scale (μ/σ)	0.4779 1.2118	0.4782 1.2273	0.5067 1.2486	0.4690 1.1972	0.4625 1.1766	0.4789 1.2131
FL Freq (%) 0	80.54	80.71	79.49	80.81	80.61	80.45
1	7.94	8.14	8.47	7.89	8.21	8.12
2	4.23	3.77	4.21	4.06	4.14	4.08
3	2.44	2.49	2.62	2.51	2.64	2.53
4	1.69	1.57	1.88	1.75	1.53	1.69
5	1.59	1.51	1.55	1.52	1.50	1.54
6	1.55	1.80	1.77	1.46	1.37	1.6

Table 3.26 Summary of Functional Limitations, Binary (FL_b)

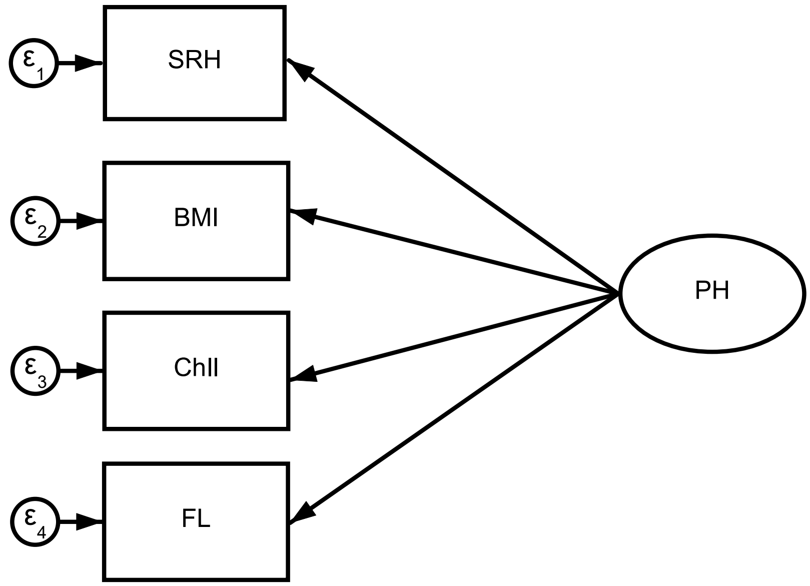
	2010	2012	2014	2016	2018	Combined
Functional Limitations, Binary (FL_b) (μ/σ)	0.1946 0.3959	0.1831 0.3868	0.1704 0.3760	0.1247 0.3304	0.1187 0.3234	0.1475 0.3546

Eigen value greater than 2 and the high factor loadings for each indicator, the modification indices (MI) suggest that the covarying relationship(s) between the observed indicators represent a more complex relationship. Evaluating the presence of functional limitations by looking at it through a binary lens can still capture important information about the overall impact of functional limitation(s) experienced by respondents. This approach allows for a more parsimonious and pragmatic assessment of functional limitation(s), as it still accounts for the presence of these conditions on individuals' health and well-being and is further tested when evaluating the entirety of the latent construct of Physical Health (PH).

Physical Health (PH)

Combining the individual indicators of Body Mass Index (BMI) and Self-Reported Health Status (SRH) with the summed construct of Chronic Illness (ChIl) and the binary construct of Functional Limitation (FL), the latent construct of Physical Health (PH) is the Biological variable in the biopsychosocial model of Financial Well-Being (Figure 3.7). The

Figure 3.7 Physical Health as a Latent Variable in the Biopsychosocial Model (Initial)



measurements of these variables are described in Table 3.27, with summary statistics shown in Table 3.28.

Across all waves, the pairwise correlations with Bonferroni correction show that all four variables (SRH, BMI, ChIl, and FL_b) are significantly correlated with each other at the 0.05 level or better ($p < 0.05$). The strongest correlation was between SRH and ChIl (0.4538 < r > 0.4651), followed by SRH and FL_b (0.3182 < r > 0.4210), suggesting that these variables may be measuring a similar underlying construct. BMI had the weakest, though still significant, correlations with the other variables, indicating a potential lack of association with the PH construct. The initial internal reliability analysis with all four yields Cronbach's Alpha (α), coefficients ranging from 0.1871 (2012) to 0.2161 (2010) (Table 3.29). All coefficient values were below the commonly accepted threshold of 0.7, indicating poor internal consistency.

Table 3.27 Physical Health Variable Measurements (Final)

Variables	Measurement
Self-Reported Health Status (SRH)	Respondents' self-reported health status. Ordinal Likert-type indicator measured on a 5-point scale with higher scores representing poorer perceived health.
BMI	Respondents' self-reported, squared weight /squared height
Chronic Illness (ChIl)	Latent construct with 8 binary indicators (1-yes, 0-no) of respondent having an occurrence of: high blood pressure, diabetes, cancer, lung disease, heart disease, stroke, psychiatric problems, and arthritis. Responses are summed.
Functional Limitation (FL_b)	Binary measurement (1-yes, 0-no) of respondent indicating having difficulty with any activity of daily living (ADL). ADLs include walking across a room, dressing, bathing, eating, getting in and out of bed, and using the toilet.

Table 3.28 Summary of Physical Health (PH)

	2010	2012	2014	2016	2018	Combined
Self-Reported Health (SRH) (μ/σ)	2.894 1.110	2.896 1.099	2.948 1.069	2.952 1.066	2.933 1.050	2.993 1.081
Body Mass Index (BMI) (μ/σ)	28.503 6.197	28.501 6.234	28.573 6.214	28.958 6.358	29.061 6.441	28.960 6.378
Chronic Illness (ChIl) (μ/σ)	2.008 1.509	2.146 1.532	2.253 1.541	2.179 1.566	2.325 1.568	2.173 1.546
Functional Limitations (FL_b) (μ/σ)	0.195 0.396	0.183 0.386	0.170 0.376	0.1257 0.330	0.119 0.323	0.147 0.355

EFAs were performed using the principal factors method, and across all waves, the factor analysis extracted one factor with an Eigen value greater than 1 (Table 3.29). The unrotated factor loadings showed that Factor 1 had moderate to high loadings for self-reported health (SRH) (0.5850-0.6458), chronic illness (ChIl) (0.6015-0.6157), and functional limitations (FL_b) (0.4714-0.5532), and a relatively low loadings for body mass index (BMI) (0.2327-0.2612). Since the internal reliability across all waves showed poor internal consistency, and with BMI having low loadings in all of the factor analyses, BMI was removed from the analysis, as it does not seem to be a good indicator of the PH construct.

Table 3.29 EFA of Physical Health (PH) (Initial)

	2010	2012	2014	2016	2018	Combined
Cronbach's Alpha (α)	0.2161	0.1871	0.1914	0.2007	0.1991	0.2003
Eigenvalue Factor 1	1.1361	1.1442	1.1144	1.0430	1.0260	1.0317
Factor Loadings (λ) Self-Reported Health (SRH)	0.6458	0.6306	0.6152	0.5850	0.5871	0.6176
Body Mass Index (BMI)	0.2327	0.2479	0.2612	0.2537	0.2612	0.2376
Chronic Illness (ChIl)	0.6015	0.6157	0.6094	0.6156	0.6067	0.6096
Functional Limitations (FL_b)	0.5506	0.5532	0.5444	0.5073	0.4950	0.4714

After removing the BMI from the analysis, additional EFAs were conducted to investigate the latent construct of Physical Health (PH) using the remaining observed variables: Self-Reported Health Status (SRH) with the summed construct of Chronic Illness (ChIl) and the binary construct of Functional Limitation (FL). Removing BMI and rerunning the analysis improved the results. The pairwise correlations remained significant ($p < 0.05$) with all Cronbach's alphas increasing with ranges between 0.5527 (combined) to 0.5852 (2012), suggesting moderate internal consistency (Table 3.30).

Table 3.30 EFA of Physical Health (PH) (Final)

	2010	2012	2014	2016	2018	Combined
Cronbach's Alpha (α)	0.5806	0.5852	0.5776	0.5482	0.5426	0.5527
Eigenvalue Factor 1	1.0693	1.0704	1.0313	0.9708	0.9487	0.9652
Factor Loadings (λ) Self-Reported Health (SRH)	0.6405	0.6293	0.6121	0.5774	0.5798	0.6147
Chronic Illness (ChIl)	0.5896	0.6026	0.5984	0.6117	0.6029	0.6019
Functional Limitations (FL_b)	0.5581	0.5579	0.5464	0.5131	0.4991	0.4745

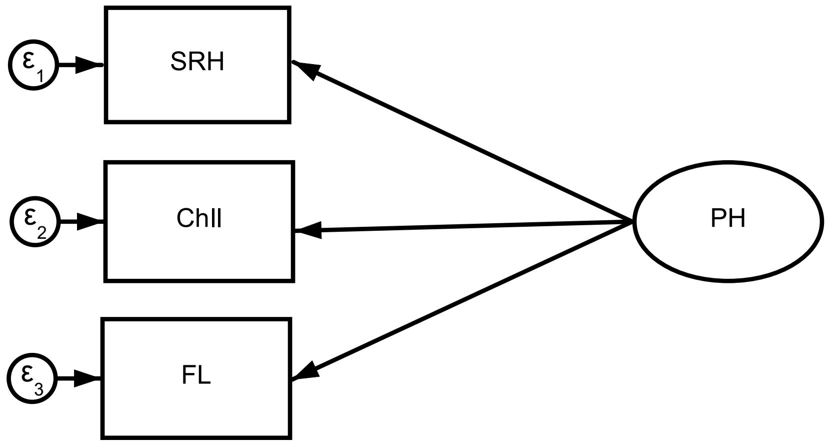
The factor analysis again extracted a single factor with Eigen values ranging from 0.9487 (2018) to 1.0704 (2012), now explaining between 145.65% (2010) to 153.65% (2018) of the variance. The factor loadings for SRH (0.5774-0.6405), ChIl (0.5896-0.6117), and FL_b (0.4745-0.5581) were all moderate to high. The internal consistency reliability of the scales was assessed using Cronbach's Alpha (α), yielding coefficients ranging from 0.7257 (2018) to 0.7845 (2016) (Table 3.30). These values exceed the commonly accepted threshold of 0.7, indicating a satisfactory level of reliability for the three-item scale.

In summary, the final EFA results support a single-factor structure for the Physical Health (PH) construct across all waves, with Self-Reported Health Status (SRH), the summed construct of Chronic Illness (ChIl) and the binary construct of Functional Limitation (FL) being strong indicators. This single-factor model provides a parsimonious and interpretable solution, with the three observed variables demonstrating a satisfactory level of internal consistency reliability. Further validation of the model using confirmatory factor analysis (CFA) helped establish the validity and reliability of the PH latent construct.

The CFA model was specified based on the results of the EFA, with all observed variables associated with Physical Health (PH) as indicators of the latent PH construct. To ensure the identification of the CFA model, the factor loading of the indicator variable Self-Reported Health Status was fixed to 1. This approach allowed for the estimation of the other factor loadings and the evaluation of their statistical significance. The model was estimated using STATA's maximum likelihood with missing values (MLMV) method, or FIML, which is appropriate for handling missing data. As indicated earlier, for robustness, maximum likelihood (ML) was also evaluated against FIML. The final measurement model for FL is shown in Figure 3.8.

When evaluating the results of the CFAs of FL using both ML and FIM, overall, the model for all waves indicates it is a good fit (Tables 3.31 and 3.32). The model fit indices were

Figure 3.8 Physical Health as a Latent Variable in the Biopsychosocial Model (Final)



examined to assess the overall goodness of fit. Examining the ML model first, the likelihood ratio test comparing the model to the saturated model yielded a chi-square value of 0.000 with 0 degrees of freedom, indicating a perfect fit. However, this test is sensitive to sample size and may not be informative with large samples.

The root mean squared error of approximation (RMSEA) results were 0.000, and the probability that RMSEA is less than or equal to 0.05 (pclose) was 1.000, suggesting an excellent fit. The comparative fit index (CFI) and Tucker–Lewis index (TLI) results were both 1.000, indicating a perfect fit compared to the baseline model. The standardized root mean squared residuals (SRMR) were also 0.000, further supporting a good model fit following Kline (2016). The coefficients of determination (CD) ranged between 0.679 (2016) and 0.694 (2012), suggesting that the model explains a substantial proportion of the variance in the indicators. The modification indices (MI) provided by the "estat mi" command in Stata indicates that there are no further improvements to the CFA model fit necessary (MI < 3.841).

In summary, the CFA results provide strong evidence for the unidimensionality of the PH construct, as indicated by the high and significant factor loadings, excellent model fit indices, and a substantial proportion of explained variance. These findings support the use of SRH, ChIl,

Table 3.31 ML CFA of Measurements of Physical Health (PH)

	2010	2012	2014	2016	2018	Combined
n	21,891	20,515	18,716	20,852	17,109	99,105
RMSEA	0.000	0.000	0.000	0.000	0.000	0.000
CFI	1.000	1.000	1.000	1.000	1.000	1.000
TLI	1.000	1.000	1.000	1.000	1.000	1.000
SRMR	0.000	0.000	0.000	0.000	0.000	0.000
CD	0.689	0.694	0.682	0.679	0.681	0.693

Table 3.32 FIML CFA of Measurements of Physical Health (PH)

	2010	2012	2014	2016	2018	Combined
n	22,034	20,554	18,747	20,912	17,146	99,393
RMSEA	0.000	0.000	0.000	0.000	0.000	0.000
CFI	1.000	1.000	1.000	1.000	1.000	1.000
TLI	1.000	1.000	1.000	1.000	1.000	1.000
SRMR	-	-	-	-	-	-

and FL as indicators of the latent PH construct in this sample and a further examination of the strength of the relationship(s).

The standardized coefficients (β) in the CFA represent the magnitude of the relationships between the latent construct Physical Health (PH) and its three indicators: self-reported health (SRH), chronic illness (ChIl), and functional limitations (FL). These coefficients are interpreted as the change in the indicator variable, measured in standard deviation units, associated with a one standard deviation change in the latent construct PH. All coefficients are shown in Table 3.33.

The standardized coefficients for SRH ranged from 0.7112 (2016) to 0.7443 (2012), indicating a strong positive relationship between physical health and self-reported health. An example of interpretation from these results would be that in 2010, a one standard deviation increase in PH is associated with a 0.7357 standard deviation increase in SRH, holding other

Table 3.33 Standardized Coefficients (β) of Measurements of Physical Health (PH)

	2010	2012	2014	2016	2018	Combined
n	22,034	20,554	18,747	20,912	17,146	99,393
SRH	0.7357	0.7443	0.7236	0.7112	0.7197	0.7383
var(e.SRH)	0.4587	0.4460	0.4764	0.4942	0.4820	0.4549
ChIl	0.6168	0.6144	0.6243	0.6371	0.6307	0.6299
var(e.ChIl)	0.6195	0.6226	0.6102	0.5941	0.6023	0.6032
FL	0.5437	0.5408	0.5355	0.5380	0.5315	0.5320
var(e.FL)	0.7043	0.7075	0.7133	0.7105	0.7175	0.7169

indicators constant. This suggests that individuals with better physical health tend to report better self-rated health.

The standardized coefficient for ChIl ranged from 0.6144 (2012) to 0.6371 (2016), indicating a moderately strong positive relationship between PH and ChIl. In 2010, a one standard deviation increase in PH is associated with a 0.6168 standard deviation increase in ChIl, holding other indicators constant. This implies that individuals with better physical health are less likely to have chronic illnesses. The standardized coefficient for FL ranged from 0.5315 (2018) to 0.5437 (2010), indicating a moderate positive relationship between PH and FL. Again, in 2010, a one standard deviation increase in PH is associated with a 0.5437 standard deviation increase in FL, holding other indicators constant. This suggests that individuals with better physical health tend to have fewer functional limitations.

The standardized coefficients also provide information about the relative importance of each indicator in measuring the latent construct PH. In this case, self-reported health (SRH) has the strongest relationship with PH, followed by chronic illness (ChIl) and functional limitations (FL). This implies that self-reported health is the most important indicator of physical health among the three variables considered in this model but a final examination of the CFA results is warranted as a form of robustness of these conclusions.

The variance terms in a CFA output, represent the residual variances or unique variances of the indicator variables. These values indicate the amount of variance in each indicator that is not explained by the latent construct, in this case, Physical Health (PH). In other words, they represent the variability in the indicators that is not accounted for by the common factor and are represented in Table 3.34. Lower residual variances indicate that the indicator variables are better measures of the latent construct, as more of their variability is accounted for by the common factor. Conversely, higher residual variances suggest that the indicators are less reliable measures of the latent construct, as a larger proportion of their variability is not explained by the common factor.

Table 3.34 Standardized Coefficients (β) of Measurements of Physical Health (PH)

	2010	2012	2014	2016	2018	Combined
n	22,034	20,554	18,747	20,912	17,146	99,393
SRH	0.7357	0.7443	0.7236	0.7112	0.7197	0.7383
var(e.SRH)	0.4587	0.4460	0.4764	0.4942	0.4820	0.4549
ChIl	0.6168	0.6144	0.6243	0.6371	0.6307	0.6299
var(e.ChIl)	0.6195	0.6226	0.6102	0.5941	0.6023	0.6032
FL	0.5437	0.5408	0.5355	0.5380	0.5315	0.5320
var(e.FL)	0.7043	0.7075	0.7133	0.7105	0.7175	0.7169

The residual variance for self-reported health (SRH) in the combined wave is 0.4549. This means that approximately 45.49% of the variance in SRH is not explained by the latent construct PH. In other words, 54.51% (1 - 0.4549) of the variance in SRH is accounted for by PH. This suggests that self-reported health is a relatively good indicator of physical health, as more than half of its variance is explained by the latent construct.

The residual variance for chronic illness (ChIl) is 0.6299. This indicates that about 62.99% of the variance in ChIl is not explained by PH, and 37.01% (1 - 0.6299) of its variance is accounted for by the latent construct. This suggests that chronic illness is a weaker indicator of physical health compared to self-reported health, as a smaller proportion of its variance is explained by PH. Lastly, the residual variance for functional limitations (FL) is 0.7169. This means that approximately 71.69% of the variance in FL is not explained by PH, and 28.31% (1 - 0.7169) of its variance is accounted for by the latent construct. Among the three indicators, functional limitations have the weakest relationship with physical health, as it has the highest proportion of unexplained variance.

Based on the CFA results and the interpretation of the standardized coefficients and residual variances, we can summarize the latent construct of Physical Health (PH) as follows. The CFA model suggests that Physical Health (PH) is a unidimensional latent construct that can be measured using three indicator variables: self-reported health (SRH), chronic illness (ChIl), and functional limitations (FL). The model demonstrates a good fit to the data, as evidenced by the perfect fit indices (e.g., RMSEA = 0.000, CFI = 1.000, TLI = 1.000) and the non-significant chi-square test comparing the model to the saturated model.

The standardized coefficients (factor loadings) for the three indicators are all statistically significant ($p < 0.001$) and range from moderate to strong. Self-reported health (SRH) has the strongest relationship with PH ($0.7112 < \beta > 0.7443$), followed by chronic illness (ChIl; $0.6144 < \beta > 0.6371$) and functional limitations (FL; $0.5315 < \beta > 0.5437$). These coefficients indicate that all three indicators are important measures of the latent construct PH, with self-reported health being the most critical indicator.

The residual variances for the three indicators range from 0.4460 (2012) for SRH to 0.7169 (combined) for FL. These values suggest that the proportion of unexplained variance in the indicators varies from 44.60% for self-reported health to 71.69% for functional limitations. The relatively high residual variances, particularly for chronic illness and functional limitations, suggests that these indicators are less reliable measures of PH compared to self-reported health.

In summary, the CFA results support the conceptualization of Physical Health as a unidimensional latent construct that can be adequately measured using self-reported health, chronic illness, and functional limitations as indicators. However, the moderate to high residual variances suggest that there is room for improvement in the measurement of PH. Future research could explore additional indicators that may better capture the underlying construct of Physical Health or refine the existing measures to improve their reliability. Despite these limitations, the current model provides a solid foundation for understanding and assessing Physical Health as a latent construct.

Psychological

The psychological predictor variable was routinely referred to and tested as mental health. Again, while self-reported mental health status has been shown to be correlated with objective measures of mental health in older adults (Schnittker, 2005), the inclusion and evaluation of objective measures of mental health is warranted. The psychological variable in and of itself is a latent construct within the biopsychosocial model (BPS) in this study (Figure 3.9).

Within the psychological variable, several latent variables are introduced consistent with the relevant literature. These constructs include a) Life Satisfaction (LS), b) Depressive Symptoms (DS), and c) Anxiety Symptoms (AS). (Asebedo & Seay, 2014; Asebedo & Seay, 2019; Beier et al., 2018; Chang et al., 2014; Lee, 2018; McInerney et al., 2013; Pak & Fan, 2022; Wilkinson, 2016). The measurement of the elements of MH is described in Table 3.35.

Figure 3.9 Mental Health as a Latent Variable in the Biopsychosocial Model

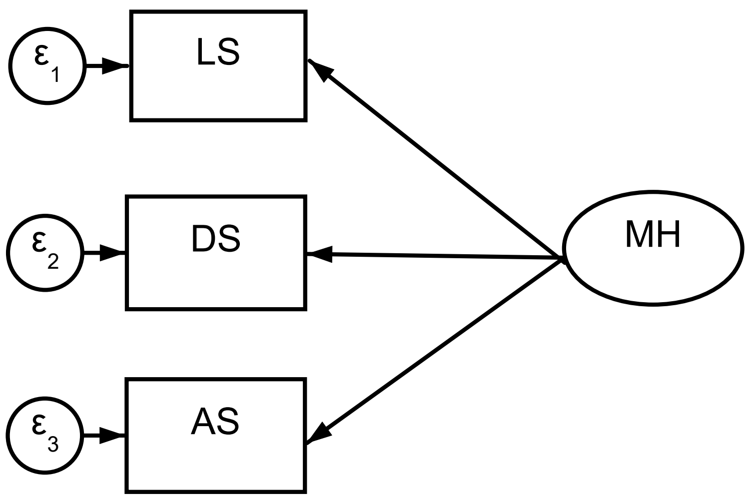


Table 3.35 Mental Health (MH) Variable Measurements

Variables	Measurement
Life Satisfaction (LS)	Respondents' responses to the five Satisfaction With Life Scale (SWLS) questions. Ordinal Likert-type indicators measured on a 7-point scale, with scores averaged and higher scores representing greater LS.
Depressive Symptoms (DS)	Latent construct with eight binary indicators (1-yes, 0-no) of respondents' responses to Center for Epidemiologic Studies Depression (CES-D) inventory questions. Summed responses are averaged with higher scores representing greater DS.
Anxiety Symptoms (AS)	Respondents' responses to the five Beck Anxiety Inventory (BAI) questions. Ordinal Likert-type indicators measured on a 4-point scale, with scores averaged and higher scores representing greater AS.

Life Satisfaction (LS)

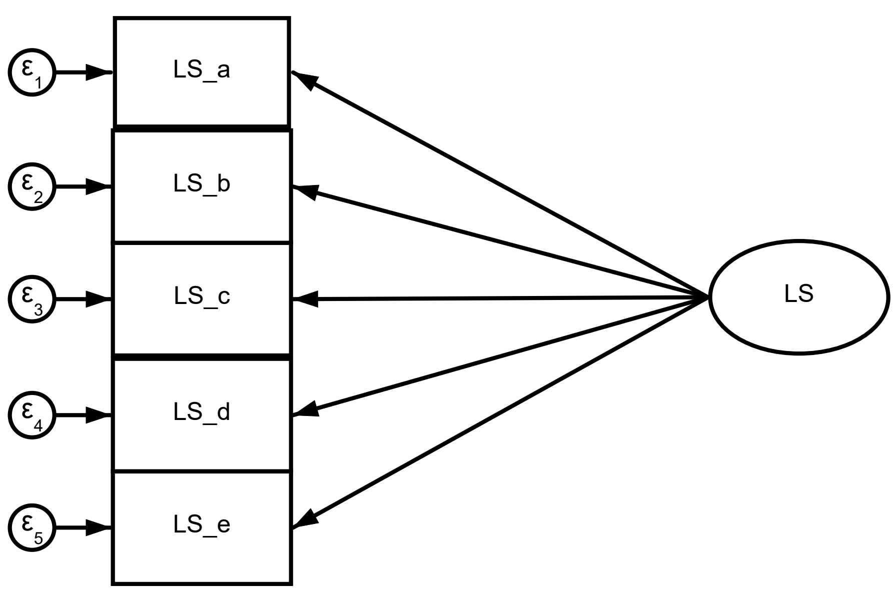
Life Satisfaction is a latent variable constructed within the RAND data file based on responses from the Leave-Behind Psychosocial and Lifestyle Questionnaire (LB). Utilizing five questions from Diener's scale for measuring life satisfaction (Diener et al., 2018), RAND averages the scores to derive the "Satisfied with Life" scale. The five questions in the LB ask respondents to indicate the extent to which they agree with responses ranging from 1 (strongly disagree) to 7 (strongly agree). The total scores for Life Satisfaction were created by summing and then averaging the responses such that higher scores would indicate higher levels of life satisfaction. Table 3.36 lists the questions in detail with coding schema.

Table 3.36 Life Satisfaction Variable Measurement

Variable	Survey Questions	Coding
Life Satisfaction	Please say how much you agree or disagree with the following statements: a) In most ways my life is close to ideal. b) The conditions of my life are excellent. c) I am satisfied with my life. d) So far, I have gotten the important things I want in life. e) If I could live my life again, I would change almost nothing.	1 = Strongly disagree, 2 = Somewhat disagree, 3 = Slightly disagree, 4 = Neither agree nor disagree, 5 = Slightly agree, 6 = Somewhat agree, 7 = Strongly agree

Within the RAND data file, these indicators are consolidated into a singular variable as a validated scale. However, in order to ascertain the reliability and validity of the scale within this data, confirmatory factor analysis (CFA) was employed to assess the degree of association between each indicator and the scale as it represents a latent variable in the model (Figure 3.10).

Figure 3.10 Life Satisfaction (LS) as a Latent Variable



An analysis and reporting was done on the standardized factor loadings, the significance of these loadings, residual variances, and Cronbach's alpha for the latent variable, as outlined by Kline (2016). To investigate the latent construct of Life Satisfaction (LS), an exploratory factor analysis (EFA) was first conducted using data from all waves of the data. The observed variables included in the analysis are listed in Table 3.36. and are summarized in Table 3.37.

Table 3.37 Summary of Life Satisfaction (LS) Variables

	2010	2012	2014	2016	2018	Combined
LS_a (μ/σ)	4.6540 1.8847	4.5234 1.8885	4.8460 1.8136	4.8748 1.8051	4.9181 1.7965	4.7506 1.8480
LS_b (μ/σ)	4.6606 1.9015	4.5323 1.9229	4.8502 1.8222	4.8398 1.8267	4.9339 1.8103	4.7512 1.8667
LS_c (μ/σ)	5.2207 1.8337	5.1684 1.8572	5.3336 1.7685	5.3551 1.7667	5.4010 1.7276	5.2889 1.7980
LS_d (μ/σ)	5.3132 1.7603	5.2644 1.7768	5.3798 1.7153	5.4032 1.6974	5.4354 1.7032	5.3534 1.7348
LS_e (μ/σ)	4.3493 2.0760	4.2834 2.0818	4.4271 2.0298	4.4057 2.0526	4.4653 2.0341	4.3812 2.0573
Scale of LS (μ/σ)	4.8388 1.5721	4.7547 1.5696	4.9657 1.5262	4.9742 1.5129	5.0289 1.5106	4.9037 1.5444

Descriptive statistics and correlations among the variables were examined to assess the suitability of the data for EFA. Across all waves, the correlation matrix revealed moderate to strong correlations ($0.4837 > r < 0.7713$) among all variables, suggesting that these variables are likely measuring a similar underlying construct. The internal consistency reliability of the scales were assessed using Cronbach's Alpha (α), which yielded coefficients ranging from 0.8799 (2012) to 0.8887 (2014) (Table 3.38). All coefficient values were above the commonly accepted threshold of 0.7, suggesting that the scale can be viewed as reliable and possibly useful for this analysis.

EFAs were performed using the principal factors method, and across all waves, two factors were retained based on the Eigen values (Table 3.38). The unrotated factor loadings

Table 3.38 EFA of Life Satisfaction (LS)

	2010	2012	2014	2016	2018	Combined
Cronbach's Alpha (α)	0.8861	0.8799	0.8887	0.8825	0.8861	0.8850
Eigenvalue Factor 1	3.0934	3.0214	3.1234	3.0727	3.0977	3.0841
Factor 2	0.0956	0.1182	0.0871	0.0894	0.0672	0.0936
Factor Loadings (λ) LS_a	0.8112	0.7999	0.8171	0.7939	0.8020	0.8064
LS_b	0.8560	0.8442	0.8607	0.8575	0.8555	0.8552
LS_c	0.8572	0.8548	0.8577	0.8638	0.8608	0.8587
LS_d	0.7679	0.7499	0.7587	0.7610	0.7673	0.7584
LS_e	0.6271	0.6130	0.6352	0.6179	0.6268	0.6243

showed that Factor 1 had high loadings for all variables, suggesting that this factor may represent the Life Satisfaction (LS) construct. Factor 2 had low loadings for all variables and did not appear to be meaningful.

The EFA results support a single-factor structure for the LS construct across all waves, with all variables being very strong indicators. This single-factor model provides a parsimonious and interpretable solution, with the five observed variables demonstrating satisfactory levels of internal consistency and reliability. Given that LS is an established scale in the literature and that the results of the EFA for these data reflect similar validation, a further CFA for this latent variable is not warranted.

Depressive Symptoms (DS)

Depressive symptoms as a latent variable were constructed using a clinically validated measure based on the Center for Epidemiologic Studies Depression (CES-D) scale (Radloff, 1977). As is the standard practice when using the CES-D scale items derived from the HRS, eight items are summed with positive response questions being reverse coded such that the higher scores indicate higher levels of depressive symptoms (Beier et al., 2018; Chang et al., 2014; McInerney et al., 2013; Wilkinson, 2016). The RAND data file creates the index that results from these methods and is inclusive of all waves (RAND HRS Longitudinal File 2020 (V1), 2023). Table 3.39 lists the questions in detail with coding schema.

Table 3.39 Depressive Symptoms Variable Measurement

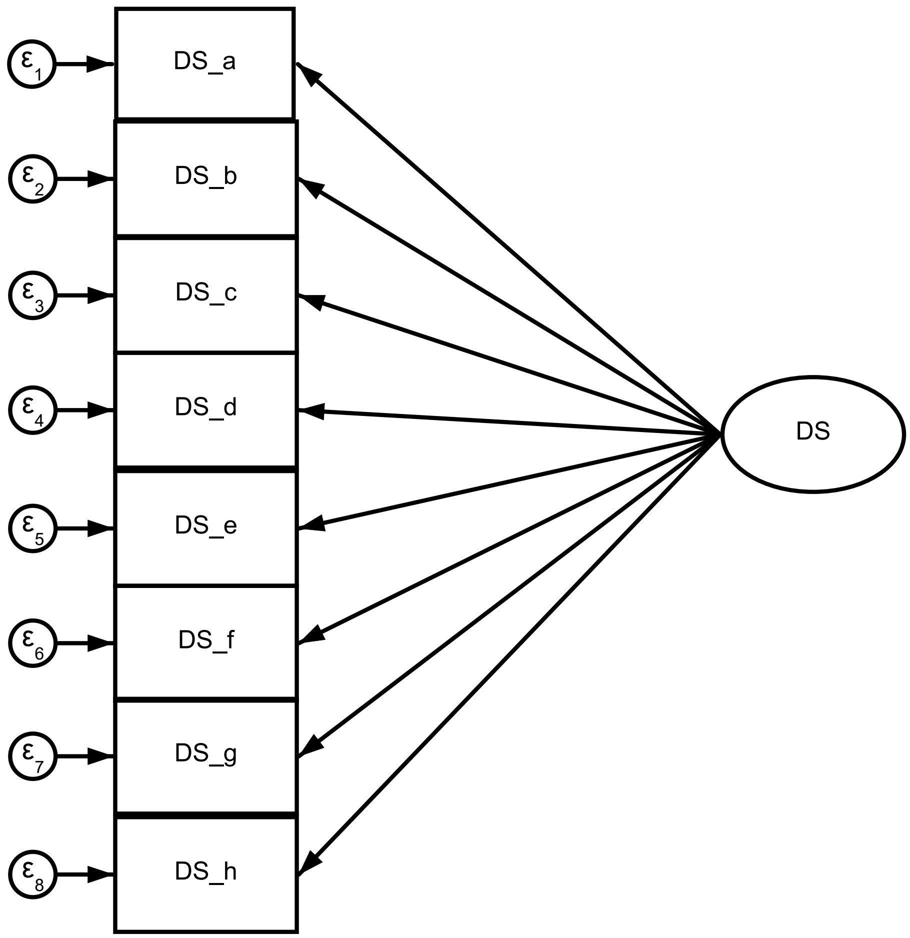
Variable	Survey Questions	Coding
Depressive Symptoms	Now think about the past week and the feelings you have experienced. Please tell me if each of the following was true for you much of the time this past week. Much of the time during the past week ...: a) Felt depressed, b) Everything was an effort, c) Could not get going, d) Enjoyed life (reverse coded), e) Felt happy (reverse coded), f) Felt lonely, g) Sleep was restless, h) Felt sad	0 = No 1 = Yes

Within the RAND data file, these indicators are consolidated into a singular variable as a validated scale. However, in order to ascertain the reliability and validity of the scale within this data, confirmatory factor analyses (CFA) were employed to assess the degree of association between each indicator and the scale as it represents a latent variable in the model (Figure 3.11).

An analysis and reporting was done on the standardized factor loadings, the significance of these loadings, residual variances, and Cronbach's alpha for the latent variable, as outlined by Kline (2016). To investigate the latent construct of Depressive Symptoms (DS), an exploratory factor analysis (EFA) was first conducted using data from all waves of the data. The observed variables included in the analysis are listed in Table 3.39., and are summarized in Table 3.40.

Descriptive statistics and correlations among the variables were examined to assess the suitability of the data for EFA. Across all waves, the correlation matrix revealed weak to

Figure 3.11 Depressive Symptoms (DS) as a Latent Variable



moderate correlations (|*0.2321*| > *r* < |*0.6072*|) among all variables, suggesting that these variables are likely measuring a similar underlying construct. The internal consistency reliability of the scales were assessed using Cronbach's Alpha (α), which yielded coefficients ranging from 0.7978 (2018) to 0.8179 (2014) (Table 3.38). All coefficient values were above the commonly accepted threshold of 0.7, suggesting that the scale can be viewed as reliable and possibly useful for this analysis.

EFAs were performed using the principal factors method, and across all waves, two factors were retained based on the Eigen values (Table 3.41). The unrotated factor loadings showed that Factor 1 had high loadings for all variables, suggesting that this factor may represent

Table 3.40 Summary of Depressive Symptoms (DS) Variables

	2010	2012	2014	2016	2018	Combined
DS_a (μ/σ)	0.1373 0.3442	0.1412 0.3482	0.1343 0.3410	0.1348 0.3415	0.1297 0.3360	0.1357 0.3425
DS_b (μ/σ)	0.2737 0.4459	0.2620 0.4397	0.2691 0.4435	0.2791 0.4486	0.2770 0.4475	0.2722 0.4451
DS_c (μ/σ)	0.2086 0.4063	0.2072 0.4053	0.2051 0.4038	0.1953 0.3965	0.1973 0.3980	0.2029 0.4021
DS_d (μ/σ)	0.9069 0.2906	0.9086 0.2882	0.9045 0.2940	0.9066 0.2910	0.9063 0.2914	0.9066 0.2910
DS_e (μ/σ)	0.8510 0.3561	0.8557 0.3514	0.8562 0.3509	0.8574 0.3497	0.8608 0.3462	0.8560 0.3511
DS_f (μ/σ)	0.1707 0.3762	0.1739 0.3790	0.1724 0.3778	0.1744 0.3795	0.1644 0.3707	0.1714 0.3768
DS_g (μ/σ)	0.3096 0.4623	0.3301 0.4703	0.3128 0.4637	0.3184 0.4659	0.3194 0.4663	0.3180 0.4657
DS_h (μ/σ)	0.1924 0.3942	0.1969 0.3976	0.1915 0.3935	0.2018 0.4014	0.1866 0.3896	0.1941 0.3955
Scale of DS (μ/σ)	3.0448 1.3949	3.0685 1.4159	3.0298 1.4050	3.0611 1.3914	3.0331 1.3838	3.0501 1.3985

Table 3.41 EFA of Depressive Symptoms (DS)

	2010	2012	2014	2016	2018	Combined
Cronbach's Alpha (α)	0.8122	0.8161	0.8179	0.8086	0.7978	0.7994
Eigenvalue Factor 1	2.9971	3.0518	3.0657	2.9627	2.9919	3.0115
Factor 2	0.2653	0.2603	0.2607	0.2426	0.2378	0.2526
Factor Loadings (λ) DS_a	0.7182	0.7317	0.7233	0.7149	0.7160	0.7208
DS_b	0.5079	0.5194	0.5335	0.4957	0.5049	0.5117
DS_c	0.4750	0.4818	0.4819	0.4691	0.4829	0.4777
DS_d	-0.6339	-0.6260	-0.6318	-0.6308	-0.6299	-0.6302
DS_e	-0.6910	-0.6880	-0.6965	-0.6923	-0.6923	-0.6915
DS_f	0.6125	0.6223	0.6258	0.6152	0.6266	0.6201
DS_g	0.4570	0.4559	0.4559	0.4495	0.4397	0.4521
DS_h	0.7310	0.7444	0.7364	0.7269	0.7274	0.7334

the Depressive Symptoms (DS) construct. Factor 2 had low loadings for all variables and did not appear to be meaningful. The EFA results support a single-factor structure for the DS construct across all waves, with all variables being very strong indicators. This single-factor model provides a parsimonious and interpretable solution, with the five observed variables demonstrating satisfactory levels of internal consistency and reliability. Given that DS is an established scale in literature and that the results of the EFA for these data reflect similar validation, a CFA for this latent variable is not warranted.

Anxiety Symptoms (AS)

Anxiety symptoms as a latent variable was constructed using a clinically validated measure based on the Beck Anxiety Inventory (BAI) (Beck et al., 1988) (Figure 3.12). The standard practice when using the BAI scale items derived from the HRS, five items are summed with higher scores indicate higher levels of anxiety symptoms (Chang et al., 2014; Wilkinson, 2016). While depression and anxiety symptomology often express a comorbid relationship, the BAI measure has been able to distinguish symptoms of anxiety from depression in older adults (Wetherell & Areán, 1997). For HRS waves 2014 and 2016 the BAI variables are not available.

In the absence of the exact variables used in the BAI to evaluate the latent relationship "anxiety" in years 2010, 2012, and 2018, a substitute variable needed to be identified. One of the questions in the aforementioned years asks respondents to indicate how often they felt nervous in the past week with responses ranging from '1 - never', '2 - hardly ever', '3 - some of the time', and '4 - most of the time'. These were reverse coded such that higher scores indicated lower levels of anxiety. While the BAI variables are not in the 2014 and 2016 waves of data, there is a single item measure available for measuring anxiety: nervousness. This single item asks the question, “During the past 30 days, to what degree did you feel...***nervous***. Responses to this question ranged from ‘1 - very much’, ‘2 - quite a bit’, ‘3 - moderately’, ‘4 - a little’, and ‘5 - not at all’. Table 3.42 lists the questions in detail with coding schema.

To assess the suitability of using the single item measure (nervousness) as a substitute for the BAI in the survey years where the BAI is not available (2014 and 2016), a series of

Figure 3.12 Anxiety Symptoms (AS) as a Latent Variable

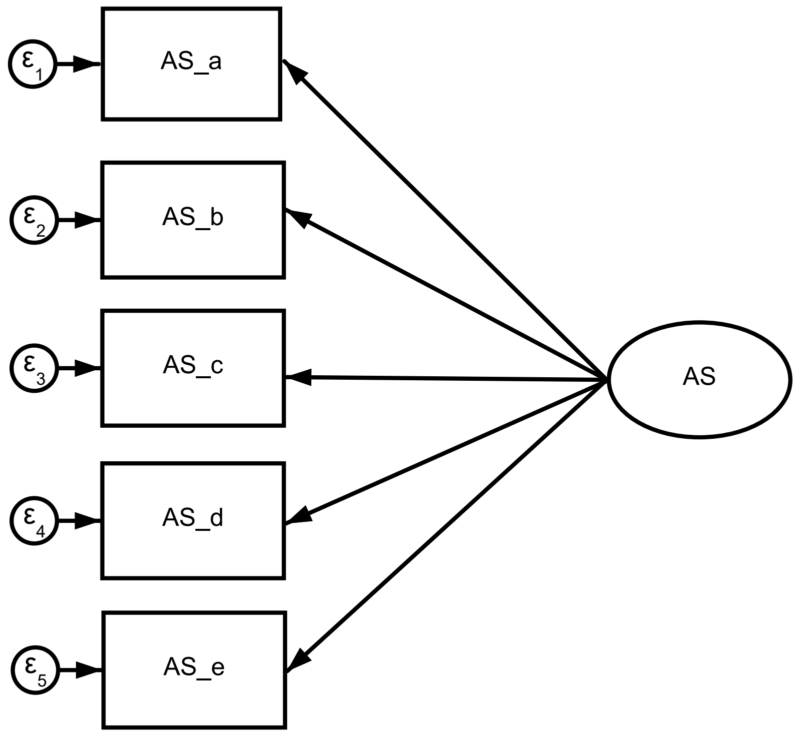


Table 3.42 Anxiety Symptoms Variable Measurement

Variable	Survey Questions	Coding
Anxiety Symptoms *(2010, 2012 & 2018)*	How often did you feel that way during the past week? The best answer is usually the one that comes to your mind first. a) I had fear of the worst happening. b) I was nervous. c) I felt my hands trembling. d) I had a fear of dying. e) I felt faint.	1 = Never 2 = Hardly ever 3 = Some of the time 4 = Most of the time
Anxiety Symptom *(2014 & 2016)*	During the past 30 days, to what degree did you feel...***nervous***.	1 = Very much 2 = Quite a bit 3 = Moderately 4 = A little 5 = Not at all

analyses were conducted using data from the 2010 wave, where both measures were available.

First, descriptive statistics for all waves are shown in Table 3.43.

Table 3.43 Summary of Anxiety Symptoms (AS) Variables

	2010	2012	2014	2016	2018	Combined
AS_a (μ/σ)	3.2419 0.8806	3.2402 0.8777	-	-	3.2910 0.8499	3.2544 0.8717
AS_b (μ/σ)	3.0761 0.8920	3.0784 0.9005	4.1025 1.0042	4.0933 1.0254	3.0733 0.8817	3.4802 1.0665
AS_c (μ/σ)	3.5743 0.7581	3.5670 0.7711	-	-	3.5624 0.7617	3.5686 0.7635
AS_d (μ/σ)	3.6014 0.7261	3.5992 0.7333	-	-	3.6085 0.7161	3.6026 0.7259
AS_e (μ/σ)	3.6556 0.6555	3.6265 0.6848	-	-	3.6057 0.7096	3.6323 0.6806
Scale of AS (μ/σ)	3.4271 0.6059	3.4196 0.6141	4.1025 1.0042	4.0933 1.0254	3.4260 0.5982	3.4309 0.6897

Next, the correlation between the BAI scores and the single-item measure was examined using the Pearson correlation coefficient. The analysis revealed a moderate positive correlation ($0.5241 > r < 0.5430$, $p < 0.05$, Bonferroni corrected), indicating that higher levels of nervousness were associated with higher levels of anxiety. A linear regression analysis was then performed with the BAI scores as the dependent variable and the single item measure as the independent variable. The results showed a significant positive relationship between the two measures ($0.3163 > \beta < 0.3207$, $p < 0.001$ (Table 3.44), with the single item measure explaining roughly 28% of the variance in the BAI scores ($0.2746 > r^2 < 0.2948$, $p < 0.001$).

To further validate the relationship between the single item measure and the BAI, a factor analysis was conducted using the data from the 2010, 2012 and 2018 waves, where both measures were available. The results (Table 3.44) showed that only one factor was retained based on the Eigen value criterion (Eigenvalue > 1). The proportion of variance accounted for by the single factor (Factor 1) was between 1.4209 (2012) and 1.4541 (2018), suggesting that it captured a significant amount of the shared variance among the variables. The factor loadings for both the BAI and the single item measure for all years, were 0.6319 (2018) to 0.6472 (2012),

Table 3.44 Exploratory Factor Analysis of Anxiety Symptom - Nervousness

	2010	2012	2018
Regression Analysis			
β	0.3177	0.3207	0.3163
r^2	0.2886	0.2948	0.2746
p	< 0.001		
Factor Analysis			
Eigenvalue Factor 1	0.8258	0.8378	0.7987
Proportion	1.4307	1.4209	1.4541
Factor Loadings (λ) BAI	0.6426	0.6472	0.6319
AS_2 (Nervousness)	0.6426	0.6472	0.6319

suggesting that both items were strongly related to the underlying factor (anxiety).

The uniqueness values for both items were between 0.5811 (2010) and 0.6006 (2018), indicating that roughly 60% of the variance in each item was not explained by the common factor. This suggests that while the BAI and the single item measure share a common underlying construct, they also have some unique variance not captured by the single factor. The likelihood ratio (LR) test comparing the independent model (where all items are assumed to be uncorrelated) and the saturated model (where all items are allowed to correlate) was significant for all years ($p < 0.001$), indicating that the factor model provided a better fit to the data than the independent model.

In summary, the factor analysis results provide evidence that the BAI and the single item measure of nervousness are capturing the same underlying construct (anxiety) and exhibit a strong unidimensional structure. These findings support the use of the single item measure as a substitute for the BAI in the survey years where the BAI is not available. However, it should be noted that the single item measure may not capture all the unique variance associated with the BAI, as indicated by the uniqueness values. Nevertheless, the strong factor loadings and the significant LR test suggest that the single item measure is a reasonable proxy for assessing anxiety levels in the HRS sample when the BAI is not available.

For the waves that have the full Beck's Anxiety Inventory, descriptive statistics and correlations among the variables were examined to assess the suitability of the data for EFA. Across all waves, the correlation matrix revealed weak to moderate correlations (*0.2321 > r < 0.6072*) among all variables, suggesting that these variables are likely measuring a similar underlying construct. The internal consistency and reliability of the scales were assessed using Cronbach's Alpha (α), which yielded coefficients ranging from 0.8143 (2018) to 0.8226 (2012) (Table 3.45). All coefficient values were above the commonly accepted threshold of 0.7, suggesting that the scale can be viewed as reliable and possibly useful for this analysis.

Table 3.45 EFA of Anxiety Symptoms (AS)

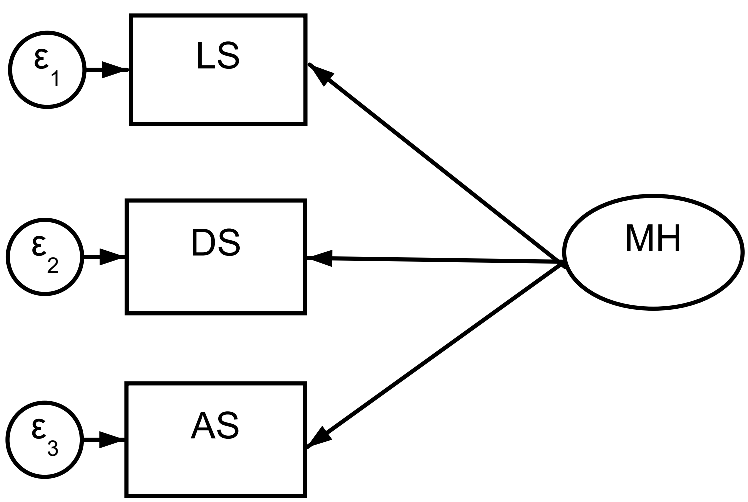
	2010	2012	2014	2016	2018	Combined
Cronbach's Alpha (α)	0.8211	0.8226	-	-	0.8143	0.7692
Eigenvalue Factor 1	2.3519	2.3642	-	-	2.2958	2.3395
Factor 2	0.1160	0.1482	-	-	0.1732	0.1423
Factor Loadings (λ) AS_a	0.7253	0.7185	-	-	0.7206	0.7213
AS_b	0.7424	0.7442	-	-	0.7228	0.7378
AS_c	0.6838	0.6787	-	-	0.6626	0.6764
AS_d	0.6594	0.6628	-	-	0.6520	0.6586
AS_e	0.6102	0.6278	-	-	0.6245	0.6193

EFAs were performed using the principal factors method, and across all waves, two factors were retained based on the Eigen values (Table 3.45). The unrotated factor loadings showed that Factor 1 had high loadings for all variables, suggesting that this factor may represent the Anxiety Symptoms (AS) construct. Factor 2 had low loadings for all variables and did not appear to be meaningful. The EFA results support a single-factor structure for the AS construct across all waves, with all variables being very strong indicators. This single-factor model provides a parsimonious and interpretable solution, with the five observed variables demonstrating satisfactory levels of internal consistency and reliability. Given that AS is an established scale in the literature and that the results of the EFA for these data reflect similar validation, a further CFA for this latent variable is not warranted. The combination of the validated BAI scale for years 2010, 2012 and 2018 in conjunction with the single item measure for years 2014 and 2016 are what was used for the Anxiety Symptom(s) (AS) variable

Mental Health (MH)

Combining the individual elements of Life Satisfaction (LS), Depressive Symptoms (DS) and Anxiety Symptoms (AS), the latent construct of Mental Health (MH) is the psychological variable in the biopsychosocial model of Financial Well-Being (Figure 3.13). The measurements of these variables are described in Table 3.46, with summary statistics shown in Table 3.47.

Figure 3.13 Mental Health as a Latent Variable in the Biopsychosocial Model



Across all waves, the pairwise correlations with Bonferroni correction show that all four variables (LS, DS and AS) are significantly correlated with each other at the 0.05 level. LS and DS exhibited a significant negative correlation ($-0.4114 < r > -0.3907$), indicating that higher life satisfaction is associated with lower depressive symptoms. This negative correlation is consistent

Table 3.46 Mental Health (MH) Variable Measurement (Final)

Variables	Measurement
Life Satisfaction (LS)	Respondents' responses to the five Satisfaction With Life Scale (SWLS) questions. Ordinal Likert-type indicators measured on a 7-point scale, with scores averaged and higher scores representing greater LS.
Depressive Symptoms (DS)	Latent construct with eight binary indicators (1-yes, 0-no) of respondents' responses to Center for Epidemiologic Studies Depression (CES-D) inventory questions. Summed responses are averaged with higher scores representing greater DS.
Anxiety Symptoms (AS) *(2010, 2012 & 2018)*	Respondents' responses to the five Beck Anxiety Inventory (BAI) questions. Ordinal Likert-type indicators measured on a 4-point scale, with scores averaged and higher scores representing greater AS.
Anxiety Symptoms *(2014 & 2016)*	Respondents' responses to, "[d]uring the past 30 days, to what degree did you feel...***nervous***." Respondents' responses to the five Beck Anxiety Inventory (BAI) questions. Ordinal Likert-type indicators measured on a 5-point scale, with higher scores representing greater AS.

with the expectation that increased life satisfaction corresponds with decreased depressive symptoms.

Table 3.47 Summary of Mental Health (MH)

<table>
<tr><th></th><th>2010</th><th>2012</th><th>2014</th><th>2016</th><th>2018</th><th>Combined</th></tr>
<tr><td>Life Satisfaction (LS) (μ/σ)</td><td>4.8362
1.5759</td><td>4.7491
1.5746</td><td>4.9641
1.5283</td><td>4.9722
1.5162</td><td>5.0297
1.5108</td><td>4.9037
1.5444</td></tr>
<tr><td>Depressive Symptoms (DS) (μ/σ)</td><td>3.0448
1.3949</td><td>3.068
1.4159</td><td>3.0398
1.4050</td><td>3.0611
1.3913</td><td>3.0331
1.3838</td><td>3.0501
1.3985</td></tr>
<tr><td>Anxiety Symptoms (AS) (2010, 2012 & 2018) (μ/σ)</td><td>3.4271
0.6056</td><td>3.4196
0.6141</td><td>-</td><td>-</td><td>3.4260
0.5982</td><td rowspan="2">3.4309
0.6897</td></tr>
<tr><td>Anxiety Symptoms (2014 & 2016) (μ/σ)</td><td>-</td><td>-</td><td>4.1025
1.0042</td><td>4.0934
1.0254</td><td>-</td></tr>
</table>

LS and AS were also negatively correlated ($-0.3564 < r > -0.2731$) suggesting that higher life satisfaction is also associated with lower anxiety. DS and AS showed a significant positive correlation ($0.3873 < r > 0.4806$), with higher depressive symptoms associated with higher anxiety symptoms. These findings suggest that life satisfaction, depressive symptoms, and anxiety symptoms are interrelated in meaningful ways. Higher life satisfaction is generally linked with lower levels of depressive and anxiety symptoms, while depressive and anxiety symptoms are strongly related.

EFAs were performed using the principal factors method, and across all waves, the factor analysis extracts one factor with an Eigen value greater than 1, with the exception of the 2014, 2016 and combined waves. Those Eigen values were 0.9317, 0.9098, and 0.9944, respectively (Table 3.48). The unrotated factor loadings showed that Factor 1 had moderate to high loadings for life satisfaction (LS) (0.5237-0.5442), depressive symptoms (DS) (0.6115-0.6426), and anxiety symptoms (AS) (0.5114-0.6128). While the Eigen values are borderline, with all factors showing moderate to high loadings, the latent health construct of mental health (MH) shows the complex interactions between these mental health variables in respondents.

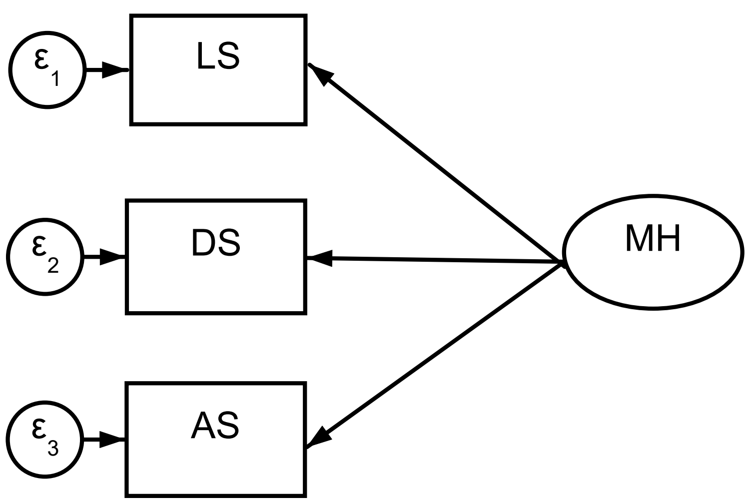
Table 3.48 EFA of Mental Health (MH)

<table>
<tr><th></th><th>2010</th><th>2012</th><th>2014</th><th>2016</th><th>2018</th><th>Combined</th></tr>
<tr><td>Cronbach’s Alpha (α)</td><td>0.4791</td><td>0.4791</td><td>0.5209</td><td>0.4984</td><td>0.4751</td><td>0.4069</td></tr>
<tr><td>Eigenvalue
Factor 1</td><td>1.0555</td><td>1.0685</td><td>0.9317</td><td>0.9098</td><td>1.0654</td><td>0.9944</td></tr>
<tr><td>Factor Loadings (λ)
Life Satisfaction (LS)</td><td>0.5356</td><td>0.5292</td><td>0.5237</td><td>0.5239</td><td>0.5442</td><td>0.5341</td></tr>
<tr><td>Depressive Symptoms (DS)</td><td>0.6352</td><td>0.6426</td><td>0.6184</td><td>0.6115</td><td>0.6473</td><td>0.6306</td></tr>
<tr><td>Anxiety Symptoms (AS) (2010, 2012 & 2018)</td><td>0.6043</td><td>0.6128</td><td>-</td><td>-</td><td>0.5918</td><td rowspan="2">0.5581</td></tr>
<tr><td>Anxiety Symptoms (2014 & 2016)</td><td>-</td><td>-</td><td>0.5245</td><td>0.5114</td><td>-</td></tr>
</table>

In summary, the final EFA results support a single-factor structure for the Mental Health (MH) construct across all waves, with Life Satisfaction (LS), Depressive Symptoms (DS) and Anxiety Symptoms (AS) being strong indicators. This single-factor model provides a parsimonious and interpretable solution, with the three observed variables demonstrating a satisfactory level of internal consistency reliability. Further validation of the model using confirmatory factor analysis (CFA) helped establish the validity and reliability of the MH latent construct.

The CFA model was specified based on the results of the EFA, with all observed variables associated with Mental Health (MH) as indicators of the latent MH construct. To ensure the identification of the CFA model, the factor loading of the indicator variable Self-Reported Health Status was fixed to 1. This approach allows for the estimation of the other factor loadings and the evaluation of their statistical significance. The model was estimated using STATA's maximum likelihood with missing values (MLMV) method, or FIML, which is appropriate for handling missing data. As indicated earlier, for robustness, maximum likelihood (ML) will also be evaluated against FIML. The final measurement model for MH is shown in Figure 3.14.

Figure 3.14 Mental Health as a Latent Variable in the Biopsychosocial Model (Final)



When evaluating the results of the CFAs of MH using both ML and FIM, overall, the model for all waves indicates it is a good fit (Tables 3.49 and 3.50). The model fit indices were examined to assess the overall goodness of fit. Examining the ML model first, the likelihood ratio test comparing the model to the saturated model yielded a chi-square value of 0.000 with 0

Table 3.49 ML CFA of Measurements of Mental Health (MH)

	2010	2012	2014	2016	2018	Combined
n	7,924	6,938	7,190	6,192	5,565	28,200
RMSEA	0.000	0.000	0.000	0.000	0.000	0.000
CFI	1.000	1.000	1.000	1.000	1.000	1.000
TLI	1.000	1.000	1.000	1.000	1.000	1.000
SRMR	0.000	0.000	0.000	0.000	0.000	0.000
CD	0.691	0.698	0.680	0.673	0.703	0.687

degrees of freedom, indicating a perfect fit. However, this test is sensitive to sample size and may not be informative with large samples.

Table 3.50 FIML CFA of Measurements of Mental Health (MH)

	2010	2012	2014	2016	2018	Combined
n	20,887	19,574	17,896	19,967	16,479	94,802
RMSEA	0.000	0.000	0.000	0.000	0.000	0.000
CFI	1.000	1.000	1.000	1.000	1.000	1.000
TLI	1.000	1.000	1.000	1.000	1.000	1.000
SRMR	-	-	-	-	-	-
CD	0.708	0.715	0.696	0.688	0.716	0.693

The root mean squared error of approximation (RMSEA) results were 0.000, and the probability that RMSEA is less than or equal to 0.05 (pclose) was 1.000, suggesting an excellent fit. The comparative fit index (CFI) and Tucker–Lewis index (TLI) results were both 1.000, indicating a perfect fit compared to the baseline model. The standardized root mean squared residuals (SRMR) were also 0.000, further supporting a good model fit following Kline (2016). The coefficients of determination (CD) ranged between 0.673 (2016) and 0.703 (2018), suggesting that the model explains a substantial proportion of the variance in the indicators. The modification indices (MI) provided by the "estat mi" command in Stata indicates that there are no further improvements to the CFA model fit necessary (MI < 3.841).

In summary, the CFA results provide strong evidence for the unidimensionality of the MH construct, as indicated by the high and significant factor loadings, excellent model fit indices, and a substantial proportion of explained variance. These findings support the use of LS, DS, and AS as indicators of the latent MH construct in this sample and a further examination of the strength of the relationship(s).

The standardized coefficients (β) in the CFA represent the magnitude of the relationships between the latent construct Mental Health (MH) and its three indicators: Life Satisfaction (LS), Depressive Symptoms (DS) and Anxiety Symptoms (AS). These coefficients are interpreted as the change in the indicator variable, measured in standard deviation units, associated with a one standard deviation change in the latent construct MH. All coefficients are shown in Table 3.51.

The standardized coefficients for LS ranged from 0.5391 (2014) to 0.5593 (2018), indicating a strong positive relationship between mental health and life satisfaction. An example of interpretation from these results would be that in 2010, a one standard deviation increase in PH is associated with a 0.5546 standard deviation increase in LS, holding other indicators constant. This suggests that individuals with better mental health tend to report better life satisfaction.

Table 3.51 Standardized Coefficients (β) of Measurements of Physical Health (PH)

	2010	2012	2014	2016	2018	Combined
n	20,887	19,574	17,896	19,967	16,479	94,802
LS	0.5546	0.5449	0.5391	0.5395	0.5593	0.5503
var(e.LS)	0.6924	0.7030	0.7094	0.7089	0.6871	0.6971
DS	-0.7381	-0.7491	-0.7711	-0.7657	-0.7649	-0.7544
var(e.DS)	0.4552	0.4388	0.4055	0.4138	0.4149	0.4309
AS	-0.6618	-0.6673	-0.5406	-0.5258	-0.6308	-0.5791
var(e.AS)	0.5620	0.5547	0.7077	0.7236	0.6021	0.6647

The standardized coefficient for DS ranged from -0.7381 (2010) to -0.7711 (2014), indicating a strong positive relationship between MH and DS. In 2010, a one standard deviation increase in MH is associated with a -0.7381 standard deviation decrease in DS, holding other indicators constant. This implies that individuals with better mental health are less likely to have depressive symptoms. The standardized coefficient for AS ranged from -0.5258 (2016) to -0.6673 (2012), indicating a moderate positive relationship between MH and AS. Again, in 2010, a one standard deviation increase in MH is associated with a -0.6618 standard deviation decrease in AS, holding other indicators constant. This suggests that individuals with better mental health tend to have fewer anxiety symptoms.

The standardized coefficients also provide information about the relative importance of each indicator in measuring the latent construct MH. In this case, depressive symptoms (DS) had the strongest (inverse) relationship with MH, followed by anxiety symptoms (AS) and life satisfaction (LS). This implies that depressive symptoms is the most important indicator of mental health among the three variables considered in this model but a final examination of the CFA results is warranted as a form of robustness of these conclusions.

The variance terms in a CFA output, represent the residual variances or unique variances of the indicator variables. These values indicate the amount of variance in each indicator that is not explained by the latent construct, in this case, Mental Health (MH). In other words, they represent the variability in the indicators that is not accounted for by the common factor and are represented in Table 3.52. Lower residual variances indicate that the indicator variables are better measures of the latent construct, as more of their variability is accounted for by the common factor. Conversely, higher residual variances suggest that the indicators are less reliable measures of the latent construct, as a larger proportion of their variability is not explained by the common factor.

The residual variance for Life Satisfaction (LS) in the combined wave is 0.6971. This means that approximately 69.71% of the variance in LS is not explained by the latent construct MH. In other words, 30.29% (1 - 0.6971) of the variance in LS is accounted for by PH. This

Table 3.52 Standardized Coefficients (β) of Measurements of Physical Health (PH)

	2010	2012	2014	2016	2018	Combined
n	20,887	19,574	17,896	19,967	16,479	94,802
LS	0.5546	0.5449	0.5391	0.5395	0.5593	0.5503
var(e.LS)	0.6924	0.7030	0.7094	0.7089	0.6871	0.6971
DS	-0.7381	-0.7491	-0.7711	-0.7657	-0.7649	-0.7544
var(e.DS)	0.4552	0.4388	0.4055	0.4138	0.4149	0.4309
AS	-0.6618	-0.6673	-0.5406	-0.5258	-0.6308	-0.5791
var(e.AS)	0.5620	0.5547	0.7077	0.7236	0.6021	0.6647

suggests that life satisfaction is a relatively poor indicator of mental health, as more than two-thirds of its variance is not explained by the latent construct.

The residual variance for Depressive Symptoms (DS) is 0.4309. This indicates that about 43.09% of the variance in DS is not explained by MH, and 56.91% (1 - 0.4309) of its variance is accounted for by the latent construct. This suggests that depressive symptoms is a stronger indicator of mental health compared to life satisfaction, as a smaller proportion of its variance is explained by MH. Lastly, the residual variance for Anxiety Symptoms (AS) is 0.6647. This means that approximately 66.47% of the variance in AS is not explained by MH, and 33.53% (1 - 0.6647) of its variance is accounted for by the latent construct. Among the three indicators, life satisfaction had the weakest relationship with mental health, as it has the highest proportion of unexplained variance.

Based on the CFA results and the interpretation of the standardized coefficients and residual variances, we can summarize the latent construct of Mental Health (MH) as follows: The CFA model suggests that Mental Health (MH) is a unidimensional latent construct that can be measured using three indicator variables: Life Satisfaction (LS), Depressive Symptoms (DS) and Anxiety Symptoms (AS). The model demonstrates a good fit to the data, as evidenced by the perfect fit indices (e.g., RMSEA = 0.000, CFI = 1.000, TLI = 1.000) and the non-significant chi-square test comparing the model to the saturated model.

The standardized coefficients (factor loadings) for the three indicators were all statistically significant ($p < 0.001$) and range from moderate to strong. Depressive Symptoms (DS) has the strongest (negative) relationship with MH ($-0.7491 < \beta > -0.7711$), followed by Anxiety Symptoms (AS) ($-0.5258 < \beta > -0.6673$) and Life Satisfaction (LS) ($0.5391 < \beta > 0.5593$). These coefficients indicate that all three indicators are important measures of the latent construct MH, with Depressive Symptoms being the most critical indicator.

The residual variances for the three indicators range from 0.4055 (2014) for DS to 0.7236 (2016) for AS. These values suggest that the proportion of unexplained variance in the indicators varies from 40.55% for depressive symptoms to 72.36% for anxiety symptoms. The relatively high residual variances, particularly for anxiety symptoms and life satisfaction, suggest that these indicators are less reliable measures of MH compared to depressive symptoms.

In summary, the CFA results support the conceptualization of Mental Health as a unidimensional latent construct that can be adequately measured using self-reported health, chronic illness, and functional limitations as indicators. However, the moderate to high residual variances suggest that there is room for improvement in the measurement of PH. Future research could explore additional indicators that may better capture the underlying construct of Mental Health, or refine the existing measures to improve their reliability. Despite these limitations, the current model provides a solid foundation for understanding and assessing Mental Health as a latent construct.

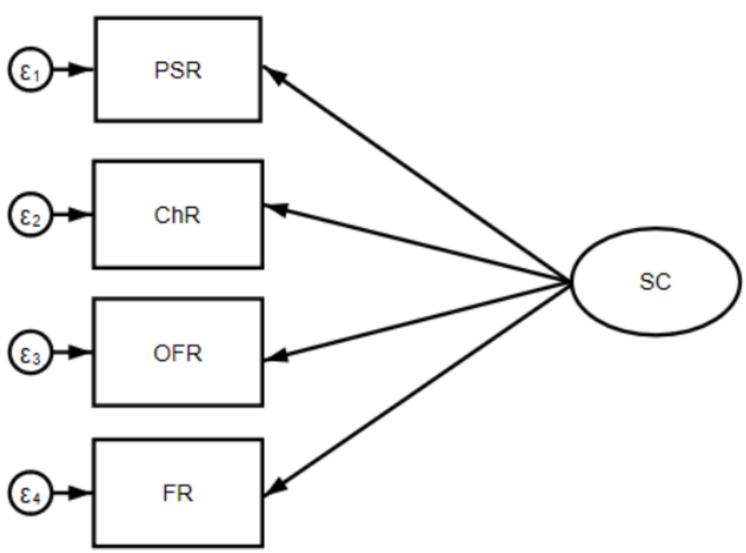
Sociological

The sociological predictor variable was routinely a component of relationships. Holt-Lunstad (2022) provides a structured approach to understanding social connectedness and compiles a body of evidence underscoring its critical importance to health in their Social

Connection (SC) model. Social Connection is a latent construct containing elements from a structural, functional, and qualitative standpoint. Structural elements contain the presence and interplay of various social relationships and roles. Functional elements are provided by or perceived to be available because of social relationships. The qualitative elements are the positive and negative aspects of social relationships (Holt-Lunstad, 2022).

The sociological variable in and of itself is a latent construct within the biopsychosocial model (BPS) in this study (Figure 3.15). Within the sociological variable, several latent variables are introduced, consistent with the relevant literature. These constructs represent various relationships in respondents' lives and include a) Partner/Spouse Relationship (PSR), b) Child(ren) Relationship(s) (ChR), c) Other Immediate Family Relationships (OFR), and d) Friend Relationships (FR) (Alley & Kahn, 2012; Asebedo & Seay, 2014; Asebedo & Seay, 2019; Chang et al., 2014; Dew & Xiao, 2013; Lee, 2018; McInerney et al., 2013; Wheeler & Brooks, 2023; Wilkinson, 2016).

Figure 3.15 Social Connection as a Latent Variable in the Biopsychosocial Model



Each relationship category includes two latent components that represent the relationship quality, or perceived social support, of that relationship The quality of these relationships is divided into positive and negative social support elements, following the methods established in the HRS literature (Alley & Kahn, 2012; Asebedo & Seay, 2014; Asebedo & Seay, 2019; Chang et al., 2014; Dew & Xiao, 2013; Lee, 2018; McInerney et al., 2013; Schuster et al., 1990; Smith et al., 2023; Turner et al., 1983; Wheeler & Brooks, 2023; Wilkinson, 2016).

The measurement and coding of the two perceived social support elements, Positive Social Support (PSS) and Negative Social Support (NSS), is described in Table 3.53 with further labeling definitions of the variables found in Table 3.54. These schemas were applied to all relationship types being evaluated. Descriptive statistics and correlations among the variables within each relationship type were examined to assess the suitability of the data for EFA and are reported in the respective relationship sections.

In order to ascertain the reliability and validity of any latent variable, confirmatory factor analyses (CFA) were employed to assess the degree of association between each indicator and the latent variable and the relationships expressed in Figure 3.15. As outlined by Kline (2016), an analysis and reporting were done on the standardized factor loadings, the significance of these loadings, residual variances, and Cronbach's alpha for each of the latent variables associated with the various relationship types. To investigate the latent construct of Social Connection (SC), an exploratory factor analysis (EFA) was conducted using data from all waves as well as the combined wave.

Partner/Spouse Relationships (PSR)

Partner/Spouse Relationships (PSR) is comprised of two latent constructs surrounding the Social Connection (SC) between a partner/spouse, as measured by their level of Perceived Social Support. All observed variables are derived from the RAND data and are inclusive of all waves (RAND HRS Longitudinal File 2020 (V1), 2023). Following the methods established when

Table 3.53. Perceived Social Support (Relationship Quality) Variable Measurement

<table>
<tr><th>Variable</th><th colspan="2">Survey Questions</th><th>Coding</th></tr>
<tr><td rowspan="3">Perceived Social Support for all relationship types:

-Partner/Spouse (PSR)
-Child(ren) (ChR)
-Other Family (OFR)
-Friend(s) (FR)</td><td colspan="2">We would now like to ask you some questions about your [relationship]. Please mark the answer which best shows how you feel about each statement:</td><td rowspan="3">1 = Not at all,
2 = A little,
3 = Some,
4 = A lot</td></tr>
<tr><td>Positive Social Support</td><td>a.) How much do they really understand the way you feel about things?

b.) How much can you rely on them if you have a serious problem?

c.) How much can you open up to them if you need to talk about your worries?</td></tr>
<tr><td>Negative Social Support</td><td>d.) How often do they make too many demands on you?
e.) How much do they criticize you?
f.) How much do they let you down when you are counting on them?
g.) How much do they get on your nerves?</td></tr>
</table>

Table 3.54. Perceived Social Support (Relationship Quality) Variable Labeling

Perceived Social Support (Relationship Quality)	Partner/Spouse Relationship (PSR)	Children Relationships (ChR)	Other Family Relationships (OFR)	Friend Relationships (FR)
Positive Social Support	PSR_p	ChR_p	OFR_p	FR_p
Negative Social Support	PSR_n	ChR_n	OFR_n	FR_n
Net Social Support (_p - _n)	PSR_net	ChR_net	OFR_net	FR_net

using these scales in the HRS (Asebedo & Seay, 2019; Schuster et al., 1990; Smith et al., 2023; Turner et al., 1983), two scales were created for each; positive support and negative support.

First, the latent construct of Positive Social Support (PSS) between the respondent and their partner/spouse is established. Three questions are asked to assess the level of PSS. Second, a latent construct of Negative Social Support (NSS) between the respondent and their partner/spouse is established with four questions asked. In each case, these questions are asked surrounding how respondents felt about a statement regarding the level of (perceived) support they received. Responses ranged from 1 (a lot) to 4 (not at all) and were reversed coded such that higher scores indicated greater levels of PSS and NSS. Table 3.53 lists the questions in detail with their coding schema.

In order to ascertain the reliability and validity of any latent variable, confirmatory factor analysis (CFA) was employed to assess the degree of association between each indicator and the latent variable. An analysis and reporting was done on the standardized factor loadings, the significance of these loadings, residual variances, and Cronbach’s alpha for the latent variable, as outlined by Kline (2016). To investigate the latent construct of SC in the PSR, an exploratory factor analysis (EFA) was first conducted using data from all waves.

Summative statistics and correlations among the variables were examined to assess the suitability of the data for EFA. The means and standard deviations for each variable and wave can be found in Table 52. Across all waves, the correlation matrix revealed moderate to strong correlations ($0.4993 > r < 0.6589$) among all variables, suggesting that these variables are likely measuring a similar underlying construct. The internal consistency reliability of the scales were assessed using Cronbach's Alpha (α), which yielded coefficients ranging from 0.7996 (2012) to 0.8237 (2018) for PSS (Table 3.53) and 0.7832 (2018) to 0.7939 (2012) for NSS (Table 3.55). All coefficient values were above the commonly accepted threshold of 0.7, suggesting that the scale can be viewed as reliable and possibly useful for this analysis.

EFAs were performed using the principal factors method, and across all waves, two factors were retained based on the Eigen values (Tables 3.56 and 3.57). For both latent constructs (PSS and NSS), only Factor 1 had a value greater than one supporting a single-factor structure

Table 3.55. Summary of Partner/Spouse Relationship Quality (PSR)

	2010	2012	2014	2016	2018	Combined
Positive Social Support (PSS) (μ/σ) a.)	3.2930 0.8197	3.2874 0.8151	3.2672 0.8252	3.3070 0.7990	3.2870 0.8300	3.2878 0.8180
b.)	3.7000 0.6883	3.7028 0.6684	3.6846 0.6881	3.6920 0.6808	3.6858 0.6833	3.6936 0.6820
c.)	3.3944 0.8388	3.3893 0.8238	3.3855 0.8336	3.4110 0.8150	3.3985 0.8319	3.3950 0.8292
Negative Social Support (NSS) (μ/σ) d.)	2.0282 0.9216	2.0540 0.9144	2.0154 0.9007	2.0361 0.9272	2.0064 0.9092	2.0287 0.9147
e.)	2.0513 0.8968	2.0779 0.8929	2.0309 0.8829	2.0340 0.8924	2.0067 0.8875	2.0423 0.8910
f.)	1.6581 0.8592	1.6763 0.8577	1.6776 0.8646	1.6898 0.8788	1.6640 0.8453	1.6729 0.8615
g.)	2.0530 0.8420	2.0762 0.8425	2.0544 0.8368	2.0789 0.8427	2.0635 0.8320	2.0644 0.8395
Net Social Support (μ/σ)	1.5146 1.1783	1.4895 1.1633	1.5025 1.1621	1.5134 1.1600	1.5250 1.1607	1.5083 1.1656

Table 3.56. EFA of Positive Social Support (PSS) for PSR

	2010	2012	2014	2016	2018	Combined
Cronbach's Alpha (α)	0.8147	0.7996	0.8142	0.8043	0.8237	0.8113
Eigenvalue Factor 1	1.6607	1.6041	1.6672	1.6183	1.7269	1.6533
PSS Factor Loadings (λ) a.)	0.7314	0.7029	0.7273	0.7192	0.7479	0.7253
b.)	0.7031	0.6963	0.7060	0.6881	0.7244	0.7030
c.)	0.7946	0.7906	0.7999	0.7922	0.8018	0.7956

for the PSR construct across all waves, for both PSS and NSS, with all variables being very strong indicators. This suggests that this single factor may well represent the social support perceived in a spousal/partner relationship among our respondents for both PSS and NSS. Summary statistics for each are found in Table 3.58.

Table 3.57. EFA of Negative Social Support (NSS) for PSR

	2010	2012	2014	2016	2018	Combined
Cronbach's Alpha (α)	0.7861	0.7939	0.7889	0.7919	0.7832	0.7889
Eigenvalue Factor 1	1.8080	1.8635	1.8277	1.8507	1.7906	1.8280
PSS Factor Loadings d.)	0.6496	0.6560	0.6514	0.6666	0.6591	0.6559
e.)	0.6805	0.6925	0.6709	0.6926	0.6682	0.6811
f.)	0.6530	0.6671	0.6689	0.6506	0.6577	0.6594
g.)	0.7047	0.7132	0.7112	0.7095	0.6908	0.7065

Table 3.58. Summary of PSR Social Support Indices

	2010	2012	2014	2016	2018	Combined
Positive Social Support (PSS) (μ/σ)	3.4623 0.6719	3.4595 0.6542	3.4443 0.6744	3.4703 0.6535	3.4573 0.6765	3.4585 0.6663
Negative Social Support (NSS) (μ/σ)	1.9484 0.6877	1.9711 0.6906	1.9446 0.6825	1.9599 0.6959	1.9351 0.6779	1.9522 0.6871
Net Social Support (μ/σ)	1.5146 1.1783	1.4895 1.1633	1.5025 1.1621	1.5134 1.1600	1.5250 1.1607	1.5083 1.1656

This single-factor model provides a parsimonious and interpretable solution, with the three observed variables for PSS and the four observed variables for NSS demonstrating satisfactory levels of internal consistency and reliability. Given these results and the fact that Perceived Social Support is an established scale in the literature with the results of the EFA for these data reflect similar validation, a CFA for this latent variable is not warranted.

Child(ren) Relationships (ChR)

Child(ren) Relationships (ChR) is/are comprised of two latent constructs surrounding the Social Connection (SC) between a respondent and any living child(ren), as measured by their level of Perceived Social Support. All observed variables are derived from the RAND data and are inclusive of all waves (RAND HRS Longitudinal File 2020 (V1), 2023). Following the methods established when using these scales in the HRS (Asebedo & Seay, 2019; Schuster et al., 1990; Smith et al., 2023; Turner et al., 1983), two scales were created for each; positive support and negative support.

First, the latent construct of Positive Social Support (PSS) between the respondent and their living child(ren) was established. Three questions are asked to assess the level of PSS. Second, a latent construct of Negative Social Support (NSS) between the respondent and their living child(ren) was established with four questions asked. In each case, the questions are asked surrounding how respondents felt about a statement regarding the level of (perceived) support they received. Responses ranged from 1 (a lot) to 4 (not at all) and were reverse coded such that higher scores indicated greater levels of PSS and NSS. Table 3.53 lists the questions in detail with their coding schema.

In order to ascertain the reliability and validity of any latent variable, confirmatory factor analysis (CFA) was employed to assess the degree of association between each indicator and the latent variable. An analysis and reporting was done on the standardized factor loadings, the significance of these loadings, residual variances, and Cronbach's alpha for the latent variable, as outlined by Kline (2016). To investigate the latent construct of SC in the ChR, an exploratory factor analysis (EFA) was first conducted using data from all waves.

Summative statistics and correlations among the variables were examined to assess the suitability of the data for EFA. The means and standard deviations for each variable and wave can be found in Table 59. Across all waves, the correlation matrix revealed moderate to strong correlations ($0.5539 > r < 0.6660$) among all variables, suggesting that these variables are likely measuring a similar underlying construct. The internal consistency reliability of the scales were

Table 3.59 Summary of Child(ren) Relationship Quality (ChR) Variables

	2010	2012	2014	2016	2018	Combined
Positive Social Support (PSS) (μ/σ) a.)	3.1710 0.8230	3.1735 0.8254	3.1701 0.8327	3.1683 0.8343	3.1648 0.8198	3.1699 0.8271
b.)	3.4134 0.8670	3.4267 0.8518	3.4238 0.8588	3.4071 0.8606	3.4071 0.8644	3.4164 0.8604
c.)	3.0985 0.9100	3.1261 0.9242	3.1326 0.9081	3.1355 0.9244	3.0872 0.9325	3.1166 0.9188
Negative Social Support (NSS) (μ/σ) d.)	1.7662 0.9019	1.7393 0.8882	1.6983 0.8808	1.7337 0.8810	1.6792 0.8634	1.7267 0.8853
e.)	1.6846 0.8038	1.6756 0.8081	1.6671 0.8119	1.6711 0.8176	1.6527 0.7999	1.6716 0.8084
f.)	1.6971 0.8506	1.6820 0.8563	1.7039 0.8549	1.7555 0.8775	1.6999 0.8571	1.7063 0.8589
g.)	1.7859 0.8242	1.7746 0.8292	1.7452 0.7993	1.7859 0.8222	1.7419 0.8035	1.7678 0.8165
Net Social Support (μ/σ)	1.4950 1.1595	1.5244 1.1735	1.5403 1.1792	1.5045 1.1806	1.5276 1.1598	1.5177 1.1706

assessed using Cronbach's Alpha (α), which yielded coefficients ranging from 0.8185 (2010) to 0.8310 (2018) for PSS (Table 3.60) and 0.7647 (2016) to 0.7868 (2012) for NSS (Table 3.61). All coefficient values were above the commonly accepted threshold of 0.7, suggesting that the scale can be viewed as reliable and possibly useful for this analysis.

Table 3.60. EFA of Positive Social Support (PSS) for ChR

	2010	2012	2014	2016	2018	Combined
Cronbach's Alpha (α)	0.8185	0.8230	0.8290	0.8278	0.8310	0.8253
Eigenvalue Factor 1	1.6640	1.6897	1.7159	1.7132	1.7316	1.6993
PSS Factor Loadings (λ) a.)	0.7110	0.7107	0.7332	0.7154	0.7220	0.7181
b.)	0.7400	0.7526	0.7399	0.7583	0.7543	0.7481
c.)	0.7816	0.7863	0.7943	0.7914	0.8009	0.7899

Table 3.61. EFA of Negative Social Support (NSS) for ChR

	2010	2012	2014	2016	2018	Combined
Cronbach's Alpha (α)	0.7759	0.7868	0.7826	0.7647	0.7684	0.7766
Eigenvalue Factor 1	1.7506	1.8185	1.7957	1.6882	1.7081	1.7553
PSS Factor Loadings (λ) d.)	0.6288	0.6294	0.6301	0.6017	0.6080	0.6211
e.)	0.6174	0.6358	0.6300	0.6101	0.6171	0.6224
f.)	0.6804	0.7008	0.6816	0.6667	0.6644	0.6793
g.)	0.7149	0.7260	0.7330	0.7137	0.7185	0.7216

EFAs were performed using the principal factors method, and across all waves, two factors were retained based on the Eigen values (Tables 3.60 and 3.61). For both latent constructs (PSS and NSS), only Factor 1 had a value greater than one supporting a single-factor structure for the ChR construct across all waves, for both PSS and NSS, with all variables being strong indicators. This suggests that this single factor may well represent the social support perceived in a child(ren) relationship among our respondents for both PSS and NSS. Summary statistics for each are found in Table 3.62.

Table 3.62. Summary of ChR Social Support Indices

	2010	2012	2014	2016	2018	Combined
Positive Social Support (PSS) (μ/σ)	3.4623 0.6719	3.4595 0.6542	3.4443 0.6744	3.4703 0.6535	3.4573 0.6765	3.4585 0.6663
Negative Social Support (NSS) (μ/σ)	1.9484 0.6877	1.9711 0.6906	1.9446 0.6825	1.9599 0.6959	1.9351 0.6779	1.9522 0.6871
Net Social Support (μ/σ)	1.4950 1.1595	1.5244 1.1735	1.5403 1.1792	1.5045 1.1806	1.5276 1.1598	1.5177 1.1706

This single-factor model provides a parsimonious and interpretable solution, with the three observed variables for PSS and the four observed variables for NSS demonstrating satisfactory levels of internal consistency and reliability. Given these results and the fact that

Perceived Social Support is an established scale in the literature with the results of the EFA for these data reflect similar validation, a CFA for this latent variable is not warranted.

Other Family Relationships (OFR)

Other Family Relationships (OFR) is comprised of two latent constructs surrounding the Social Connection (SC) between a respondent and any other family members, as measured by their level of Perceived Social Support. All observed variables are derived from the RAND data and are inclusive of all waves (RAND HRS Longitudinal File 2020 (V1), 2023). Following the methods established when using these scales in the HRS (Asebedo & Seay, 2019; Schuster et al., 1990; Smith et al., 2023; Turner et al., 1983), two scales were created for each; positive support and negative support.

First, the latent construct of Positive Social Support (PSS) between the respondent and their other family members is established. Three questions are asked to assess the level of PSS. Second, a latent construct of Negative Social Support (NSS) between the respondent and their other family members is established with four questions asked. In each case, the questions are asked surrounding how respondents felt about a statement regarding the level of (perceived) support they received. Responses ranged from 1 (a lot) to 4 (not at all) and were reverse coded such that higher scores indicated greater levels of PSS and NSS. Table 3.53 lists the questions in detail with their coding schema.

In order to ascertain the reliability and validity of any latent variable, confirmatory factor analysis (CFA) was employed to assess the degree of association between each indicator and the latent variable. An analysis and reporting was done on the standardized factor loadings, the significance of these loadings, residual variances, and Cronbach’s alpha for the latent variable, as outlined by Kline (2016). To investigate the latent construct of SC in the OFR, an exploratory factor analysis (EFA) was first conducted using data from all waves.

Summative statistics and correlations among the variables were examined to assess the suitability of the data for EFA. The means and standard deviations for each variable and wave can be found in Table 3.63. Across all waves, the correlation matrix revealed moderate to strong correlations ($0.6177 > r < 0.7330$) among all variables, suggesting that these variables are likely measuring a similar underlying construct.

Table 3.63 Summary of Other Family Relationship Quality (OFR) Variables

	2010	2012	2014	2016	2018	Combined
Positive Social Support (PSS) (μ/σ)						
a.)	2.8508 0.9084	2.8616 0.9107	2.8406 0.9175	2.8151 0.9222	2.8600 0.9205	2.8460 0.9153
b.)	3.0122 1.0275	3.0302 1.0171	2.9917 1.0219	3.0043 1.0307	3.0331 1.0109	3.0136 1.0221
c.)	2.8251 1.0202	2.8484 1.0217	2.8117 1.0190	2.8310 1.0193	2.8349 1.0090	2.8297 1.0183
Negative Social Support (NSS) (μ/σ)						
d.)	1.4666 0.7561	1.4641 0.7632	1.4336 0.7357	1.4683 0.7780	1.4578 0.7578	1.4579 0.7576
e.)	1.5868 0.8031	1.5889 0.8035	1.5496 0.7908	1.6054 0.8174	1.5918 0.8138	1.5835 0.8051
f.)	1.6012 0.8474	1.6026 0.8504	1.5706 0.8238	1.6387 0.8830	1.6067 0.8597	1.6026 0.8518
g.)	1.7643 0.8562	1.7484 0.8516	1.7127 0.8238	1.7775 0.8688	1.7649 0.8493	1.7525 0.8499
Net Social Support (μ/σ)	1.2935 1.1873	1.3114 1.2014	1.3152 1.1841	1.2626 1.2375	1.3038 1.2163	1.2980 1.2035

The internal consistency reliability of the scales were assessed using Cronbach's Alpha (α), which yielded coefficients ranging from 0.8580 (2012) to 0.8684 (2014) for PSS (Table 3.64) and 0.7647 (2016) to 0.7868 (2012) for NSS (Table 3.65). All coefficient values were above the commonly accepted threshold of 0.7, suggesting that the scale can be viewed as reliable and possibly useful for this analysis.

Table 3.64. EFA of Positive Social Support (PSS) for OFR

	2010	2012	2014	2016	2018	Combined
Cronbach's Alpha (α)	0.8598	0.8580	0.8684	0.8596	0.8676	0.8625
Eigenvalue Factor 1	1.9023	1.8863	1.9538	1.8960	1.9453	1.9153
PSS Factor Loadings (λ) a.)	0.7604	0.7612	0.7692	0.7511	0.7706	0.7623
b.)	0.7870	0.7876	0.7997	0.7991	0.8013	0.7943
c.)	0.8394	0.8286	0.8501	0.8326	0.8423	0.8386

EFAs were performed using the principal factors method, and across all waves, two factors were retained based on the Eigen values (Tables 3.64 and 3.65). For both latent constructs (PSS and NSS), only Factor 1 had a value greater than one**,** supporting a single-factor structure for the OFR construct across all waves, for both PSS and NSS, with all variables being strong indicators. This suggests that this single factor may well represent the social support perceived in a child(ren) relationship among our respondents for both PSS and NSS. Summary statistics for each are found in Table 3.66.

Table 3.65. EFA of Negative Social Support (NSS) for OFR

	2010	2012	2014	2016	2018	Combined
Cronbach's Alpha (α)	0.7899	0.8068	0.8026	0.8096	0.7959	0.8009
Eigenvalue Factor 1	1.8303	1.9384	1.9163	1.9601	1.8740	1.9023
PSS Factor Loadings (λ) d.)	0.5906	0.6231	0.6055	0.6133	0.5971	0.6059
e.)	0.6892	0.7074	0.7131	0.7219	0.7042	0.7065
f.)	0.6978	0.7032	0.7091	0.7166	0.6937	0.7043
g.)	0.7208	0.7452	0.7336	0.7412	0.7350	0.7348

This single-factor model provides a parsimonious and interpretable solution, with the three observed variables for PSS and the four observed variables for NSS demonstrating satisfactory levels of internal consistency and reliability. Given these results and the fact that Perceived Social Support is an established scale in the literature with the results of the EFA for these data reflect similar validation, a CFA for this latent variable is not warranted.

Table 3.66. Summary of OFR Social Support Indices

	2010	2012	2014	2016	2018	Combined
Positive Social Support (PSS) (μ/σ)	3.4623 0.6719	3.4595 0.6542	3.4443 0.6744	3.4703 0.6535	3.4573 0.6765	3.4585 0.6663
Negative Social Support (NSS) (μ/σ)	1.9484 0.6877	1.9711 0.6906	1.9446 0.6825	1.9599 0.6959	1.9351 0.6779	1.9522 0.6871
Net Social Support (μ/σ)	1.2935 1.1873	1.3114 1.2014	1.3152 1.1841	1.2626 1.2375	1.3038 1.2163	1.2980 1.2035

Friend Relationships (FR)

Friend Relationships (FR) is comprised of two latent constructs surrounding the Social Connection (SC) between a respondent and any friends they have, as measured by their level of Perceived Social Support. All observed variables are derived from the RAND data and are inclusive of all waves (RAND HRS Longitudinal File 2020 (V1), 2023). Following the methods established when using these scales in the HRS (Asebedo & Seay, 2019; Schuster et al., 1990; ; Smith et al., 2023; Turner et al., 1983), two scales were created for each; positive support and negative support.

First, the latent construct of Positive Social Support (PSS) between the respondent and their friends is established. Three questions are asked to assess the level of PSS. Second, a latent construct of Negative Social Support (NSS) between the respondent and their friends is established with four questions asked. In each case, the questions are asked surrounding how respondents felt about a statement regarding the level of (perceived) support they received.

Responses ranged from 1 (a lot) to 4 (not at all) and were reverse coded such that higher scores indicated greater levels of PSS and NSS. Table 3.53 lists the questions in detail with their coding schema.

In order to ascertain the reliability and validity of any latent variable, confirmatory factor analysis (CFA) was employed to assess the degree of association between each indicator and the latent variable. An analysis and reporting was done on the standardized factor loadings, the significance of these loadings, residual variances, and Cronbach's alpha for the latent variable, as outlined by Kline (2016). To investigate the latent construct of SC in the FR, an exploratory factor analysis (EFA) was first conducted using data from all waves.

Summative statistics and correlations among the variables were examined to assess the suitability of the data for EFA. The means and standard deviations for each variable and wave can be found in Table 3.67. Across all waves, the correlation matrix revealed moderate to strong correlations ($0.5821 > r < 0.6689$) among all variables, suggesting that these variables are likely measuring a similar underlying construct. The internal consistency reliability of the scales were assessed using Cronbach's Alpha (α), which yielded coefficients ranging from 0.8403 (2012 & 2018) to 0.8425 (2016) for PSS (Table 3.68) and 0.7581 (2010) to 0.7776 (2016) for NSS (Table 3.69). All coefficient values were above the commonly accepted threshold of 0.7, suggesting that the scale can be viewed as reliable and possibly useful for this analysis.

EFAs were performed using the principal factors method, and across all waves, two factors were retained based on the Eigen values (Tables 3.68 and 3.69). For both latent constructs (PSS and NSS), only Factor 1 had a value greater than one supporting a single-factor structure

Table 3.67 Summary of Friend Relationship Quality (FR) Variables

	2010	2012	2014	2016	2018	Combined
Positive Social Support (PSS) (μ/σ)						
a.)	3.0687 0.8124	3.0954 0.8028	3.0551 0.8045	3.0813 0.8131	3.0668 0.8109	3.0733 0.8086
b.)	3.0826 0.8785	3.1031 0.8741	3.0698 0.8799	3.0890 0.8694	3.0927 0.8734	3.0869 0.8745
c.)	2.9933 0.9161	3.0311 0.9099	2.9749 0.9029	3.0360 0.9023	3.0119 0.8915	3.0079 0.9059
Negative Social Support (NSS) (μ/σ)						
d.)	1.3390 0.6205	1.3434 0.6317	1.3169 0.6022	1.3194 0.6143	1.3221 0.6129	1.3290 0.6168
e.)	1.3920 0.6230	1.3965 0.6308	1.3632 0.6108	1.4025 0.6496	1.3859 0.6250	1.3877 0.6273
f.)	1.4746 0.7161	1.4725 0.7147	1.4404 0.6937	1.4739 0.7273	1.4571 0.7062	1.4640 0.7116
g.)	1.5445 0.6770	1.5453 0.6952	1.5231 0.6780	1.5502 0.6963	1.5403 0.6781	1.5405 0.6847
Net Social Support (μ/σ)	1.6135 0.9461	1.6373 0.9557	1.6240 0.9367	1.6340 0.9552	1.6308 0.9507	1.6271 0.9485

Table 3.68. EFA of Positive Social Support (PSS) for FR

	2010	2012	2014	2016	2018	Combined
Cronbach's Alpha (α)	0.8598	0.8580	0.8684	0.8596	0.8676	0.8625
Eigenvalue Factor 1	1.9023	1.8863	1.9538	1.8960	1.9453	1.9153
PSS Factor Loadings (λ)						
a.)	0.7604	0.7612	0.7692	0.7511	0.7706	0.7623
b.)	0.7870	0.7876	0.7997	0.7991	0.8013	0.7943
c.)	0.8394	0.8286	0.8501	0.8326	0.8423	0.8386

for the FR construct across all waves, for both PSS and NSS, with all variables being strong indicators. This suggests that this single factor may well represent the social support perceived in a friend relationship among our respondents for both PSS and NSS. Summary statistics for each are found in Table 3.67.

Table 3.69. EFA of Negative Social Support (NSS) for FR

	2010	2012	2014	2016	2018	Combined
Cronbach's Alpha (α)	0.7581	0.7748	0.7704	0.7776	0.7644	0.7689
Eigenvalue Factor 1	1.6402	1.7435	1.7179	1.7514	1.6848	1.7053
PSS Factor Loadings (λ) d.)	0.6035	0.6131	0.6245	0.6102	0.6001	0.6103
e.)	0.6463	0.6798	0.6747	0.6710	0.6762	0.6686
f.)	0.6406	0.6650	0.6487	0.6818	0.6364	0.6546
g.)	0.6692	0.6807	0.6722	0.6811	0.6800	0.6763

Table 3.70. Summary of FR Social Support Indices

	2010	2012	2014	2016	2018	Combined
Positive Social Support (PSS) (μ/σ)	3.0483 0.7596	3.0768 0.7520	3.0333 0.7525	3.0686 0.7513	3.0571 0.7482	3.0561 0.7535
Negative Social Support (NSS) (μ/σ)	1.4382 0.5049	1.4399 0.5178	1.4106 0.4978	1.4368 0.5224	1.4269 0.5036	1.4306 0.5092
Net Social Support (μ/σ)	1.6135 0.9461	1.6373 0.9557	1.6240 0.9367	1.6340 0.9552	1.6308 0.9507	1.6271 0.9485

This single-factor model provides a parsimonious and interpretable solution, with the three observed variables for PSS and the four observed variables for NSS demonstrating satisfactory levels of internal consistency and reliability. Given these results and the fact that Perceived Social Support is an established scale in the literature with the results of the EFA for these data reflect similar validation, a CFA for this latent variable is not warranted.

Social Connection (SC)

Social Connection (SC) as a latent sociological construct of the biopsychosocial model consists of several latent variables that were introduced consistent with the relevant literature. These constructs focused on the quality of relationships as measured by the net Perceived Social Support (PSS) respondents indicated pertaining to the relationships of, a) Partner/Spouse Relationship (PSR), b) Child(ren) Relationship(s) (ChR), c) Other Family Relationships (OFR), and d) Friend Relationships (FR) as shown in Figure 3.16 (Alley & Kahn, 2012; Asebedo & Seay, 2014; Asebedo & Seay, 2019; Chang et al., 2014; Dew & Xiao, 2013; Lee, 2018; ; McInerney et al., 2013; Wheeler & Brooks, 2023; Wilkinson, 2016). The net PSS was derived by subtracting any Negative Social Support (NSS) in a given relationship from the Positive Social Support (PSS) in that same relationship. In general, all relationships across all waves show a net positive score for PSS. Summary statistics for each relationship, for each wave are found in Table 3.71.

Figure 3.16 Social Connection as a Latent Variable in the Biopsychosocial Model

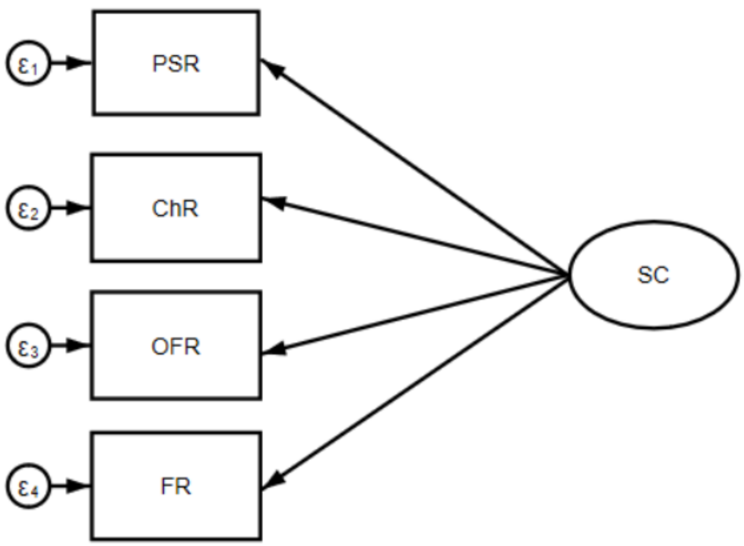


Table 3.71. Summary of Social Connection (Net Perceived Social Support)

	2010	2012	2014	2016	2018	Combined
Partner/Spouse Relationship (PSR) (μ/σ)	1.5146 1.1783	1.4895 1.1633	1.5025 1.1621	1.5134 1.6000	1.5250 1.1607	1.5083 1.1656
Child(ren) Relationship (ChR) (μ/σ)	1.4950 1.1595	1.5244 1.1735	1.5403 1.1792	1.5045 1.1806	1.5276 1.1598	1.5177 1.1706
Other Family Relationship (OFR) (μ/σ)	1.2935 1.1873	1.3114 1.2014	1.3152 1.1841	1.2626 1.2375	1.3038 1.2163	1.2980 1.2035
Friend Relationship (FR) (μ/σ)	1.6135 0.9461	1.6373 0.9557	1.6240 0.9367	1.6340 0.9552	1.6308 0.9507	1.6271 0.9485

Across all waves, the pairwise correlations with Bonferroni correction show that all relationship variables of net PSS (PSR, ChR, OFR, and FR) are significantly correlated with each other at the 0.05 level. Consistently across waves, the strongest correlation is between ChR and OFR ($0.4197 < r > 0.4810$), suggesting that the PSS of child(ren) and other family relationships are strongly related. Also consistent was the weakest correlation being between PSR and FR ($0.1993 < r > 0.2335$), indicating a lower degree of association between the PSS of partner/spouse relationships and friend relationships, in terms of their net effect.

As with all of the aforementioned latent variables, reliability and validity of the Social Connection latent variable was assessed using confirmatory factor analysis (CFA) to assess the degree of association between each indicator and the latent variable. An analysis and reporting was done on the standardized factor loadings, the significance of these loadings, residual variances, and Cronbach's alpha for the latent variable, as outlined by Kline (2016).

The initial internal reliability analysis with all four net PSS relationships across all waves show that the scale reliability is moderate ($0.6435 < \alpha > 0.6755$), indicating that the net PSS variables are largely consistent in measuring the underlying construct of Social Connection

Table 3.72 EFA of Social Connection (Net Perceived Social Support)

	2010	2012	2014	2016	2018	Combined
Cronbach's Alpha (α)	0.6444	0.6755	0.6723	0.6435	0.6549	0.6586
Eigenvalue Factor 1	1.1849	1.2778	1.2768	1.1256	1.1966	1.2136
Factor Loadings (λ) Partner/Spouse Relationship (PSR)	0.4051	0.4556	0.4600	0.4513	0.4468	0.4420
Child(ren) Relationship (ChR)	0.6322	0.6537	0.6462	0.5985	0.6300	0.6335
Other Family Relationship (OFR)	0.5996	0.6100	0.6205	0.5706	0.6095	0.6022
Friend Relationship (FR)	0.5113	0.5204	0.5123	0.4880	0.4781	0.5042

(SC) (Table 3.72). The factor analysis retained one factor with a value greater than zero, suggesting that the net PSS variables for each relationship load onto a single underlying construct, which aligns with the concept of Social Connection (SC). Child(ren) Relationship (ChR) had the highest loading ($0.5985 < \lambda > 0.6322$), followed by Other Family Relationship (OFR) ($0.5706 < \lambda > 0.6205$). This indicates that relationships with child(ren) and other family contribute more strongly to the overall Social Connection construct compared to partner/spouse and friend relationships.

In summary, the EFA results support a single-factor structure for the Social Connection (SC) construct across all waves, with the Net Perceived Social Support (PSS) variable for all relationships being strong indicators. This single-factor model provides a parsimonious and interpretable solution, with the four variables demonstrating a satisfactory level of internal consistency reliability. Further validation of the model using confirmatory factor analysis (CFA) helped establish the validity and reliability of the SC latent construct.

The CFA model was specified based on the results of the EFA, with all observed variables associated with Social Connection (SC) as indicators of the latent SC construct. To ensure the identification of the CFA model, the factor loading of the indicator variable Partner/Spouse Relationship (PSR) was fixed to 1. This approach allows for the estimation of the other factor loadings and the evaluation of their statistical significance. The model was estimated using STATA's maximum likelihood with missing values (MLMV) method, or FIML, which is appropriate for handling missing data. As indicated earlier, for robustness, maximum likelihood (ML) was also evaluated against FIML. The final measurement model for FL is shown in Figure 3.16 above.

When evaluating the results of the CFAs of Social Connection (SC) using both ML and FIML, overall, the model for all waves indicates it is a good fit (Tables 3.73 and 3.71). The model fit indices were examined to assess the overall goodness of fit. Examining the ML model first, the likelihood ratio test comparing the model to the saturated model yielded chi-square values that ranged from 12.22 ($df = 2$, $p = 0.002$) in 2018 to 144.83 ($df = 2$, $p < 0.0001$) in the combined dataset, reflecting varying levels of model fit across different years. Each model consistently demonstrated a statistically significant difference from the saturated model ($p < 0.0001$ for most years), implying that while the models are good, they are not perfect representations of the observed data. This is typical in large samples, where the chi-square test is highly sensitive to small discrepancies between the model and the data. The degrees of freedom remained consistent at 2 across all models, reflecting the simplicity of the model specification relative to the data. Despite the significant chi-square values, other fit indices were considered for a more comprehensive evaluation of model fit.

The goodness-of-fit indices for the Confirmatory Factor Analysis (CFA) models measuring Social Connection (SC) across multiple years and using two estimation methods—Maximum Likelihood (ML) and Full Information Maximum Likelihood (FIML)—are summarized in Tables 3.73 and 3.74 below.

Table 3.73 ML CFA of Measurements of Social Connection (SC)

	2010	2012	2014	2016	2018	Combined
n	4,462	3,837	3,831	3,171	2,798	18,099
RMSEA	0.065	0.052	0.070	0.073	0.043	0.063
CFI	0.984	0.991	0.984	0.978	0.993	0.986
TLI	0.952	0.973	0.951	0.933	0.980	0.957
SRMR	0.020	0.016	0.021	0.023	0.014	0.019
CD	0.691	0.711	0.708	0.663	0.693	0.694

Table 3.74 FIML CFA of Measurements of Social Connection (SC)

	2010	2012	2014	2016	2018	Combined
n	8,292	7,373	7,503	6,345	5,708	35,221
RMSEA	0.053	0.054	0.049	0.052	0.035	0.050
CFI	0.986	0.988	0.990	0.985	0.994	0.988
TLI	0.959	0.963	0.969	0.956	0.982	0.965
SRMR	-	-	-	-	-	-

For the ML estimation (Table 3.73), the Root Mean Square Error of Approximation (RMSEA) values ranged from 0.043 in 2018 to 0.073 in 2016, indicating a generally acceptable fit across the years, though 2016's RMSEA suggests a slightly poorer fit. The Comparative Fit Index (CFI) remained consistently high across all years, ranging from 0.978 to 0.993, indicating excellent model fit. The Tucker-Lewis Index (TLI) values were slightly lower, ranging from 0.933 in 2016 to 0.980 in 2018, but still within acceptable limits, indicating good fit, though the 2016 model is on the lower end of acceptability. The Standardized Root Mean Square Residual (SRMR) values were all below 0.025, with the highest being 0.023 in 2016, indicating a very good fit across all years. The Coefficient of Determination (CD) values ranged from 0.663 to 0.711, suggesting that the models explained a substantial portion of the variance in the observed variables.

For the FIML estimation (Table 3.74), the RMSEA values ranged from 0.035 in 2018 to 0.054 in 2012, consistently indicating a good fit across all years. The CFI values were slightly higher than those in the ML estimation, ranging from 0.985 in 2016 to 0.994 in 2018, further supporting excellent model fit. The TLI values were also strong, ranging from 0.956 in 2016 to 0.982 in 2018, indicating that the models fit the data well. Notably, SRMR values were not reported due to missing data, but given the other indices, the overall fit is likely very good. The CD values were the same as the ML models, explaining a significant portion of the variance in the observed variables.

Both ML and FIML estimation methods demonstrated strong model fit across the years, with FIML generally providing slightly better fit indices, particularly in terms of RMSEA, CFI, and TLI. The consistent strength of the fit indices across both methods and multiple years underscores the robustness of the models in measuring the construct of Social Connection (SC). In summary, the CFA results provide strong evidence for the unidimensionality of the SC construct, as indicated by the high and significant factor loadings, strong model fit indices, and a substantial proportion of explained variance. These findings support the use of the net PSS scores for all relationships evaluated as indicators of the latent SC construct in this sample and a further examination of the strength of the relationship(s).

The standardized coefficients (β) in the CFA represent the magnitude of the relationships between the latent construct Social Connection (SC) and its four indicators: Partner/Spouse Relationship (PSR), Child(ren) Relationship(s) (ChR), Other Family Relationship(s) (OFR), and Friend Relationship(s) (FR). These coefficients are interpreted as the change in the indicator variable, measured in standard deviation units, associated with a one standard deviation change in the latent construct SC. Table 3.75 presents the standardized coefficients (β) and error variances for the latent construct of SC measured across all waves, using the four indicators.

Table 3.75 Standardized Coefficients (β) of Measurements of Social Connection (SC)

	2010	2012	2014	2016	2018	Combined
n	8,292	7,373	7,503	6,345	5,708	35,221
PSR	0.3967	0.4514	0.4686	0.4606	0.4628	0.4449
var(e.PSR)	0.8426	0.7962	0.7804	0.7879	0.7859	0.8020
ChR	0.7073	0.7140	0.7080	0.6624	0.7044	0.7009
var(e.ChR)	0.4997	0.4903	0.4988	0.5613	0.5038	0.5087
OFR	0.6527	0.6778	0.6827	0.6402	0.6763	0.6655
var(e.OFR)	0.5739	0.5406	0.5340	0.5901	0.5426	0.5571
FR	0.4868	0.5099	0.4916	0.5032	0.4720	0.4931
var(e.OFR)	0.7630	0.7400	0.7584	0.7468	0.7772	0.7568

The standardized coefficients for PSR were consistent across the years, ranging from 0.3967 in 2010 to 0.4686 in 2014. The combined dataset shows a coefficient of 0.4449. These values indicate that PSR consistently contributes to the SC construct, with a moderate impact across all years. The error variances for PSR are consistently high across the years, ranging from 0.7804 in 2014 to 0.8426 in 2010, with a combined variance of 0.8020. This indicates that a significant portion of the variance in PSR was not explained by the SC construct, suggesting the influence of other factors.

An example of interpretation from these results would be that in 2010, the β of 0.3967 indicates that the quality of the partner/spouse relationship has a moderate positive relationship with the overall SC construct. For every 1 standard deviation increase in the quality of the partner/spouse relationship, the SC construct increases by approximately 0.40 standard deviations. In other words, if a person reports improved quality in their relationship with their partner/spouse (e.g., better communication, more support), this improvement is moderately associated with an increase in their overall sense of social connection.

The standardized coefficients for ChR were the highest among the four indicators, ranging from 0.6624 in 2016 to 0.7140 in 2012. The combined dataset has a coefficient of 0.7009, demonstrating that child relationships are a strong and stable contributor to the SC construct over time. The error variances for ChR are lower compared to other indicators, ranging from 0.4903 in 2012 to 0.5613 in 2016, with a combined variance of 0.5087. This reflects that ChR was more closely aligned with the SC construct, with less unexplained variance.

Again, for 2010, the β of 0.7073 indicates a strong positive relationship between the quality of relationships with children and the SC construct. For every 1 standard deviation increase in the quality of child relationships, the SC construct increased by approximately 0.71

standard deviations. If a person experiences better relationships with their children (e.g., more frequent and positive interactions, feeling closer to their children), this improvement is strongly associated with a significant increase in their overall social connection.

The standardized coefficients for OFR were also relatively high, ranging from 0.6402 in 2016 to 0.6827 in 2014, with a combined coefficient of 0.6655. These values suggest that relationships with other family members are a significant component of SC, though slightly less than child relationships. The error variances for OFR were moderate, ranging from 0.5340 in 2014 to 0.5901 in 2016, with a combined variance of 0.5571. This suggests that while OFR is a significant part of SC, there remains some unexplained variance.

Again, for 2010, the β of 0.6527 suggests a strong positive relationship between the quality of other family relationships and the SC construct. For every 1 standard deviation increase in the quality of these family relationships, the SC construct increased by approximately 0.65 standard deviations. In other words, if a person has stronger bonds with other family members, this is strongly linked to a significant increase in their overall sense of social connection.

Lastly, the standardized coefficients for FR were the lowest among the four indicators, ranging from 0.4720 in 2018 to 0.5099 in 2012, with a combined coefficient of 0.4931. Although friend relationships contribute to SC, their impact is relatively weaker compared to family relationships. The error variances for FR were the highest among the four indicators, ranging from 0.7400 in 2012 to 0.7772 in 2018, with a combined variance of 0.7568. This high variance indicates that FR had the most unexplained variance, reflecting its relatively weaker contribution to the SC construct.

Again, for 2010, the β of 0.4868 indicated a moderate positive relationship between the quality of friendships and the SC construct. For every 1 standard deviation increase in the quality of friend relationships, the SC construct increased by approximately 0.49 standard deviations. If a person has stronger friendships, this enhancement is moderately associated with an increase in their overall social connection.

The comprehensive analysis of Social Connection (SC) across various relationships (Partner/Spouse Relationship (PSR), Child Relationships (ChR), Other Family Relationships (OFR), and Friend Relationships (FR)) provides a detailed understanding of how these relationships contribute to the overall construct of SC over time. Using both Maximum Likelihood (ML) and Full Information Maximum Likelihood (FIML) estimation methods, the analysis consistently demonstrated that relationships with children and other family members were the strongest contributors to an individual's sense of social connection. These findings are supported by high standardized coefficients (β), particularly in 2010 where ChR and OFR had coefficients of 0.7073 and 0.6527, respectively.

The model fit indices, including RMSEA, CFI, TLI, and SRMR, indicated good to excellent fit across the years, with FIML slightly outperforming ML in terms of model fit. The RMSEA values were consistently within acceptable ranges, and the CFI values were above 0.98, suggesting that the models reliably capture the underlying construct of SC. Despite significant chi-square values across models, which is expected given the large sample sizes, the other fit indices reinforced the robustness of the models. Error variances associated with the relationships highlight the complexity of the SC construct. While child and other family relationships have lower error variances, indicating a closer alignment with SC, partner/spouse and friend relationships exhibit higher error variances, suggesting that additional factors influence these relationships.

In 2010, for example, the moderate contribution of the partner/spouse relationship ($\beta = 0.3967$) and friend relationships ($\beta = 0.4868$) to SC underscores the multifaceted nature of social connection, where different relationships play varying roles. In these data, improvements in child and family relationships were more strongly linked to increases in social connection, while partner and friend relationships, though important, had a somewhat lesser impact.

The CFA results support the conceptualization of Social Connection (SC) as a unidimensional latent construct that can be adequately measured using the net Perceived Social Support (PSS) scores for the four relationship types examined as indicators. Overall, this analysis underscores the central role of family dynamics, particularly relationships with children and other family members, in fostering social connection. As we observe consistency across multiple years and robust model fit, these findings provide valuable insights into the enduring nature of social connection and its determinants. This understanding can inform future research and interventions aimed at enhancing social connection through targeted improvements in key relationships. For the purposes of this research, the current model provides a solid foundation for understanding and assessing Social Connection as a latent construct in the biopsychosocial model.

Control variables

In addition to the latent variables operationalized for the empirical testing of the biopsychosocial model for Financial Well-Being, a variety of control variables were added consistent with the literature on this topic. Socioeconomic variables for age, gender, marital status, race, education, and employment status were also included and their coding schema are summarized in Table 3.73.

Table 3.76 Measurement of Control Variables

Variable	Measurement
Age	Continuous variable ranging from age 50 to 104
Gender	0 for female; 1 for male
Marital Status	1 for coupled household; otherwise, 0
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
Employment Status	1 if respondent is working for pay; 0 if not

Chapter 4 – Findings and Results

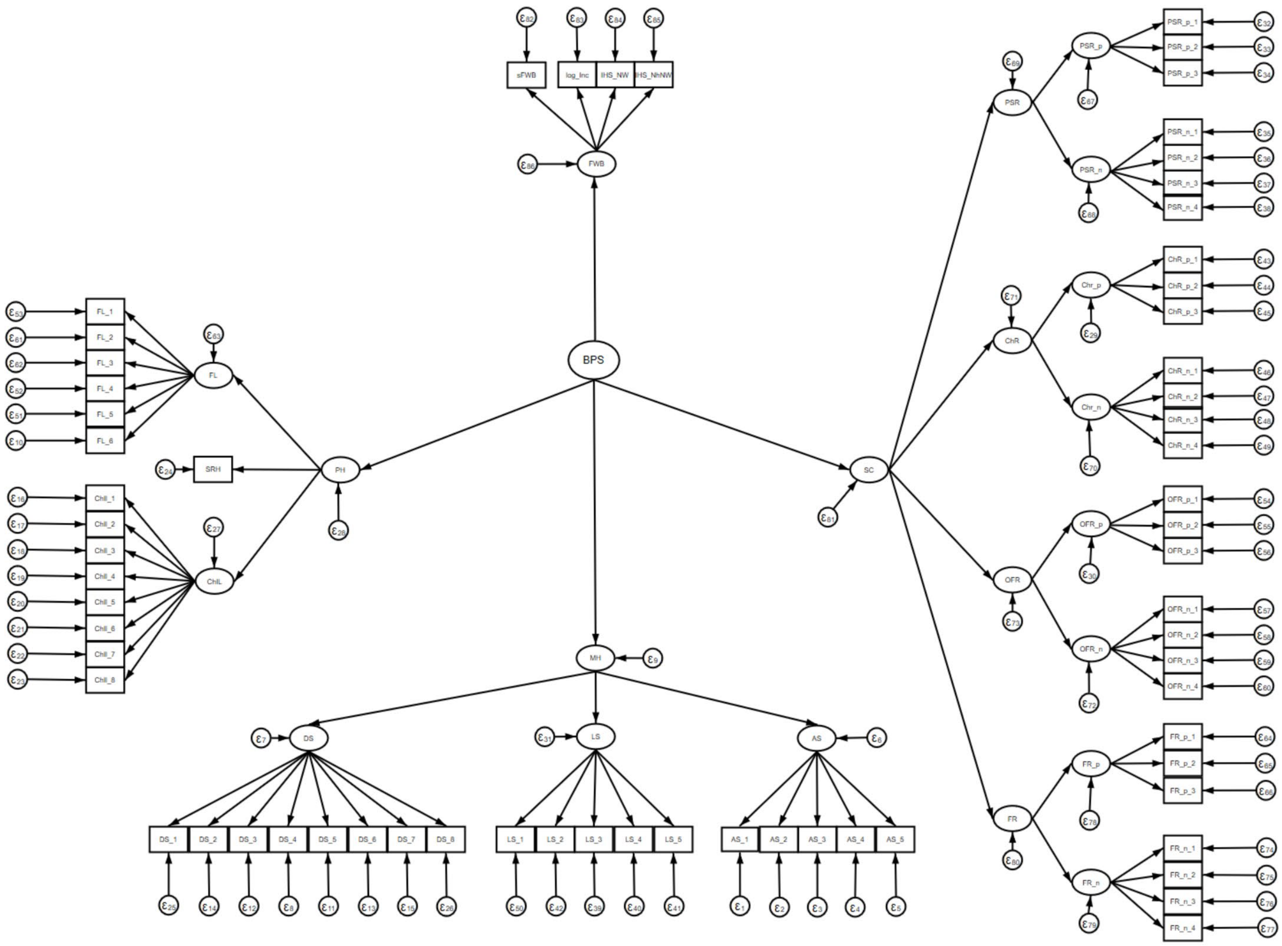
This chapter reports on the results of the analyses beginning with a summary of the individual components of the BPS Model followed by an analysis of the entire model. This analysis consists of an examination of the measurement model fit followed by reporting on the structural model. Evaluating the result of the full structural model, the associations between elements of the BPS and FWB are discussed. Lastly, a summary of the results as they related to the hypothesis are discussed.

Biopsychosocial Model

The Biopsychosocial Model (BPS) as introduced by Engel (1977) has been utilized to explore the complex relationship(s) of the three components within the BPS, and a multitude of outcomes. This research sought to operationalize the complexity of the BPS and its relationship with Financial Well-Being among older adults. Using data from the Health and Retirement Study (HRS) and components from HRS found in the RAND data, five organic waves, with a synthetic combined sixth wave, the individual components of the BPS were tested, with their relationships shown in Figure 4.1.

As with all of the previous latent relationships, in order to ascertain the reliability and validity of the BPS latent variable, confirmatory factor analysis (CFA) was employed to assess the degree of association between each indicator and the latent variable. An analysis and reporting were done on the standardized factor loadings, the significance of these loadings, residual variances, and Cronbach's alpha for the latent variable, as outlined by Kline (2016). To investigate the latent construct of BPS, an exploratory factor analysis (EFA) was first conducted using data from all waves.

Figure 4.1 Biopsychosocial Model of Financial Well-Being

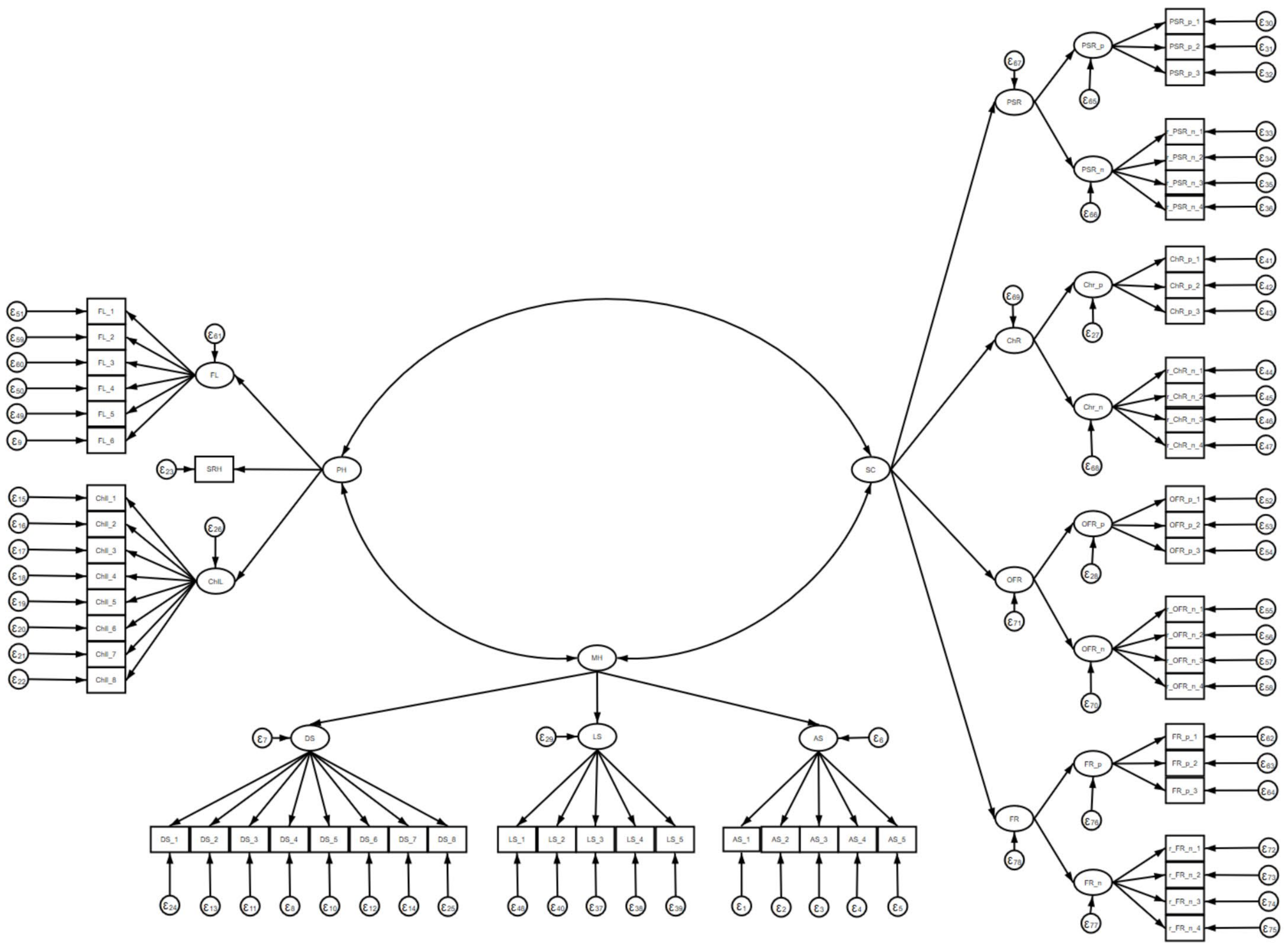


Prior to accessing the full BPS Model and its relationship with FWB, an analysis of BPS is in order. The measurement model as shown in Figure 4.2 was evaluated using STATA v.18.5 with the both the 2-core and 4-core license. While the saturated model and baseline model(s) for each wave were able to be fitted, the target model(s) never were able to achieve convergence. This was the case when running both maximum likelihood (ML) and maximum likelihood with missing values (FIML) methods using the Newton-Raphson* optimization technique with a

*In the context of Structural Equation Modeling (SEM) in STATA, the Newton-Raphson method is employed to maximize the likelihood function, thereby estimating model parameters efficiently. The method's ability to handle complex models with multiple equations and parameters makes it particularly suitable for SEM applications, where the relationships between variables can be nonlinear and intricate (Mehtre, 2019; Souza et al., 2018).

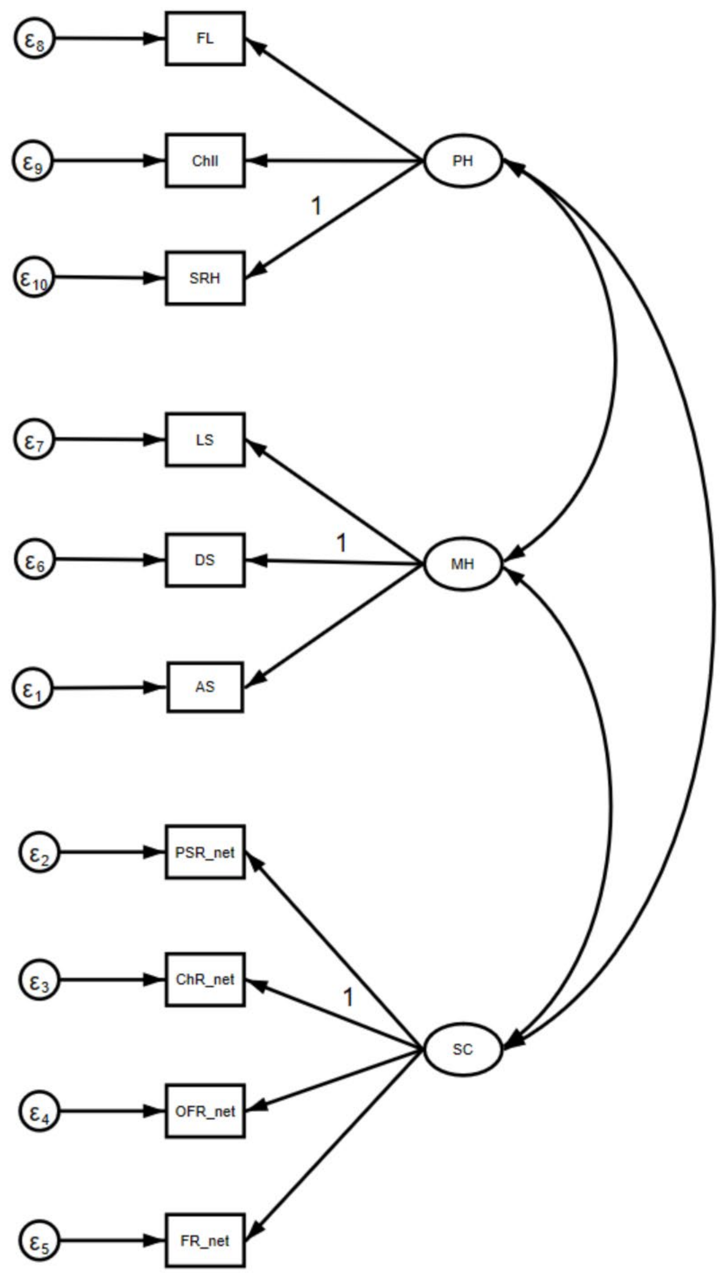
maximum of 300 iterations. As a result of the complexity of the full model with all the individual observed variables and their latent relationships, the full model was not able to be evaluated, prompting a need to use a truncated version of it.

Figure 4.2 Biopsychosocial Model – Measurement Model



In light of the full BPS Model not being able to run in STATA, modifying the model to a simpler form was required. While ideally, we would have been able to explore the intricacies of each component of the BPS and their constituent elements, we are able to still capture the relationships given the results of the EFAs and CFAs described in Chapter 3. The components of the BPS include; Biological, as measure by Physical Health (PH), Psychological, as measured by Mental Health (MH), and Sociological, as measured by Social Connection (SC). Since each of those were shown to be valid and reliable measurements of their underlying latent relationship, the observed variables constructed to represent the latent was utilized for simplicity. These simplified relationships are shown in Figure 4.3 with their CFA results in Table 4.1.

Figure 4.3 Biopsychosocial Model – Measurement Model



Reporting of Results

Measurement Model

The measurement component of the structural model was evaluated using Confirmatory Factor Analysis (CFA), as discussed in Chapter 3. Factor loadings of the "observed" variables (validated latent constructs) for each BPS element was fixed to one (1) based on the results of the highest factor loading(s) from Chapter 3 (SRH, PH; DS, MH; ChR, SC). The fit statistics were within the ranges suggested by Kline (2016), with the models of all waves explaining a substantial proportion of the variance in the observed variables (CD), as illustrated in Table 4.1.

Table 4.1 Confirmatory Factor Analyses of all BPS Components (FIML)

Wave (*n*)	$\chi2$ [df]	*p*	RMSEA	CFI	TLI	CD
2010 (8,250)	935.67 [32]	<0.001	0.059	0.938	0.913	0.956
2012 (7,252)	858.76 [32]	<0.001	0.060	0.941	0.916	0.958
2014 (7,465)	1004.25 [32]	<0.001	0.064	0.925	0.958	0.952
2016 (6,306)	686.06 [32]	<0.001	0.064	0.925	0.958	0.952
2018 (5,674)	689.57 [32]	<0.001	0.060	0.935	0.909	0.952
Combined (99,393)	4597.14 [32]	<0.001	0.038	0.953	0.934	0.943

The results from the BPS measurement model offer insights into how Physical Health (PH), Mental Health (MH), and Social Connection (SC) interact (Table 4.2). The coefficients in the BPS measurement model provide insight into the strength and direction of relationships between latent factors and their respective observed variables. All were found to be statistically significant ($p < 0.001$).

Physical Health (PH)

Functional Limitations (FL)

The standardized coefficients for FL ranged from 0.4572 to 0.5512. The consistently strong relationship between PH and FL across all years suggests that functional limitations are a central component of physical health. This indicates a moderately strong relationship between Physical Health (PH) and Functional Limitations (FL). A higher coefficient means that as PH

Table 4.2 Standardized Coefficients (β) of BPS Measurement Model

	2010	2012	2014	2016	2018	Combined
n	8,250	7,252	7,465	6,306	5,674	99,393
PH						
FL	0.5198	0.5474	0.5275	0.4572	0.4869	0.5512
var(e.FL)	0.7298	0.7003	0.7217	0.7910	0.7629	0.6914
ChIl	0.5521	0.5736	0.5833	0.5940	0.5875	0.5971
var(e.ChIl)	0.6952	0.6710	0.6598	0.6472	0.6549	0.6435
SRH	0.7889	0.7787	0.7551	0.7372	0.7590	0.7523
var(e.SRH)	0.3777	0.3937	0.4299	0.4566	0.4239	0.4340
MH						
LS	0.5870	0.5787	0.5901	0.5896	0.5880	0.5728
var(e.LS)	0.6555	0.6652	0.6518	0.6523	0.6543	0.6718
DS	0.6890	0.7118	0.7172	0.7054	0.7002	-0.6188
var(e.DS)	0.5253	0.4934	0.4856	0.5024	0.5097	0.6171
AS	0.6485	0.6478	0.5114	0.4966	0.6333	-0.5662
var(e.AS)	0.5795	0.5804	0.7384	0.7533	0.5989	0.6794
SC						
PSR	0.4635	0.5178	0.5447	0.5535	0.5409	0.5110
var(e.PSR)	0.7852	0.7319	0.7033	0.6937	0.7074	0.7389
ChR	0.7023	0.7110	0.7031	0.6678	0.6996	0.7014
var(e.ChR)	0.5067	0.4945	0.5056	0.5540	0.5105	0.5081
OFR	0.6172	0.6436	0.6386	0.5902	0.6361	0.6347
var(e.OFR)	0.6191	0.5858	0.5922	0.6517	0.5953	0.5972
FR	0.4955	0.5014	0.4932	0.4875	0.4706	0.4959
var(e.FR)	0.7545	0.7486		0.7624	0.7786	0.7540
BPS						
cov(MH,PH)	-0.7181	-0.7539	-0.7228	-0.6676	-0.7363	-0.8062
cov(MH,SC)	0.5301	0.5380	0.5768	0.6509	0.5968	0.5758
cov(PH,SC)	-0.2359	-0.2138	-0.2546	-0.2694	-0.2565	-0.2615

improves, FL decreases significantly. If a person's physical health improves, they are likely to. experience fewer difficulties in daily activities. The high variance of errors indicates that while Functional Limitation (FL) is a key indicator of Physical Health (PH), other unmeasured factors might also influence physical health outcomes

Chronic Illness (ChIl)

Chronic Illnesses (ChIl) had a strong and consistent impact on Physical Health (PH) with coefficients ranging from 0.5521 to 0.5971. A higher coefficient means that chronic conditions, such as diabetes or hypertension, significantly lower an individual's overall Physical Health (PH) status. As with FL, the high error variances indicate that while Chronic Illness (ChIl) is a key indicator of Physical Health (PH), other unmeasured factors might also influence physical health outcomes.

Self-Reported Health (SRH)

Self-Reported Health (SRH) was a very strong predictor of overall Physical Health (PH) with coefficients ranging from 0.7372 to 0.7889. A higher coefficient suggests that individuals' perceptions of their health closely align with their actual physical health. SRH had the strongest association with physical health, reflecting its reliability as a strong indicator of an individual's overall health status. The lower error variance, combined with the higher coefficients, suggests that respondents in this sample are generally accurate in accessing their own health when their functional limitations and chronic illnesses are taken into consideration.

Mental Health (MH)

Life Satisfaction (LS)

Life Satisfaction (LS) maintained a stable and significant relationship with Mental Health (MH) across the years, indicating that it is a robust indicator of overall mental well-being. With the coefficients for LS ranging from 0.5728 to 0.5901, the higher coefficients suggest that individuals who are satisfied with their lives tend to have better Mental Health (MH). The consistent error variance implies that the measurement of Life Satisfaction (LS) relative to Mental Health (MH) remained stable, with little influence from external variables.

Depressive Symptoms (DS)

Depressive Symptoms (DS) were strongly related to Mental Health (MH), with higher levels of depression indicating poorer mental health. The strong relationship between depressive symptoms and mental health is evident, with coefficients ranging from 0.6890 to 0.7172. This suggests that, in general, when depressive symptoms increase, mental health worsens. The error variances suggest that depressive symptoms are influenced by other, unmeasured factors, complicating their direct relationship with overall Mental Health (MH).

Anxiety Symptoms (AS)

Anxiety Symptoms (AS) had a moderate to strong relationship with Mental Health with coefficients ranging from 0.4966 to 0.6485. With some variability across years, the relationship is less stable than that of Depressive Symptoms (DS). The high error variance, especially in later waves (years), indicates growing complexity in how anxiety symptoms relate to overall mental health, potentially reflecting broader social or environmental stressors.

Social Connection (SC)

Partner/Spouse Relationships (PSR)

The perceived social support from a Partner/Spouse Relationship (PSR) had a moderate impact on social connection. With coefficients for PSR ranging from 0.4635 to 0.5535, a higher coefficient indicates that individuals who perceive they have strong social support from a PSR tend to have better Social Connection (SC). The error variance trend implies that while PSR became more significant, there was still considerable variation in how individuals perceived and utilized their social resources.

Child(ren) Relationship(s) (ChR)

The stable relationship between Child(ren) Relationship(s) (ChR) and Social Connection (SC) indicates that respondents' relationship(s) with living children consistently impacted Social Connection (SC). The low and consistent error variance suggests Child(ren) Relationship(s) (ChR) is a well-defined and stable component of Social Connection (SC), with little influence from other factors.

Other Family Relationships (OFR)

The stable but slightly fluctuating coefficients, ranging from 0.5902 to 0.6436, indicate that Other Family Relationships (OFR) maintained their importance in Social Connection (SC), but with minor variations over time, possibly reflecting changing family dynamics or societal shifts. The consistent error variance suggests that the impact of Other Family Relationships (OFR) on Social Connection (SC) was stable, with few external influences.

Friend Relationships (FR)

The relatively lower coefficients for Friend Relationships (FR), coefficients for FR ranged from 0.4706 to 0.5014, implying that while friends are part of Social Connection (SC), they might not be as central as the other factors in the model. The stable error variances indicate that Friend Relationships (FR) role in Social Connection (SC) was consistent, though possibly less variable than other Social Connection (SC) components.

Biopsychosocial (BPS)

Mental Health (MH) and Physical Health (PH) Covariance

The strong and negative covariance between Mental Health (MH) and Physical Health (PH) underscores the close interdependence between these two domains ($-0.8062 < \beta > -0.6676$). When Physical Health (PH) worsens, Mental Health (MH) tends to follow, and vice versa. The slight decrease in covariance over time could reflect the increasing complexity in the relationship, possibly due to the growing influence of unmeasured factors like chronic stress or societal changes.

Mental Health (MH) and Social Connection (SC) Covariance

The consistently positive covariance (0.5301 $< \beta >$ 0.6509) between Mental Health (MH) and Social Connection (SC) indicates a relationship whereby as Social Connection (SC) increases, Mental Health (MH) tends to increase, and vice versa. The strengthening of this relationship over time could indicate rising social pressures or the increasingly stressful nature of social interactions in contemporary society.

Physical Health (PH) and Social Connection (SC) Covariance

The weak and negative covariance (-0.2138 $< \beta >$ -0.2694) between Physical Health (PH) and Social Connection (SC) suggests that these two domains are largely independent, with only a minor inverse relationship. This could indicate that improving physical health might not necessarily enhance social connection and vice versa. The consistency of this relationship over time suggests that the interaction between physical health and social connection remained stable but minor.

Summary

The measurement model of the BPS model highlights the intricate and evolving relationships between physical health, mental health, and social connection . Each relationship provides insight into how different aspects of an individual's life contribute to their overall well-being. Physical Health (PH) consistently showed strong associations with its indicators, particularly Self-Reported Health (SRH). Mental Health (MH) showed more variability, particularly in its relationship with Anxiety (AS) and Depressive Symptoms (DS), suggesting changing dynamics in mental well-being. Social Connections (SC) importance grew over time, particularly Partner/Spousal Relationships (PSR), while Friend Relationships (FR) played a more minor role.

The covariances between latent factors revealed the complex interplay between these domains, with Mental Health (MH) and Physical Health (PH) being closely linked, while Social Connection (SC) had a more nuanced and sometimes inverse relationship with Mental (MH) and Physical Health (PH). On their own, these results underscore the importance of considering the multifaceted nature of health and well-being, particularly in how social factors might influence or interact with Mental (MH) and Physical Health (PH).

Biopsychosocial Model of Financial Well-Being

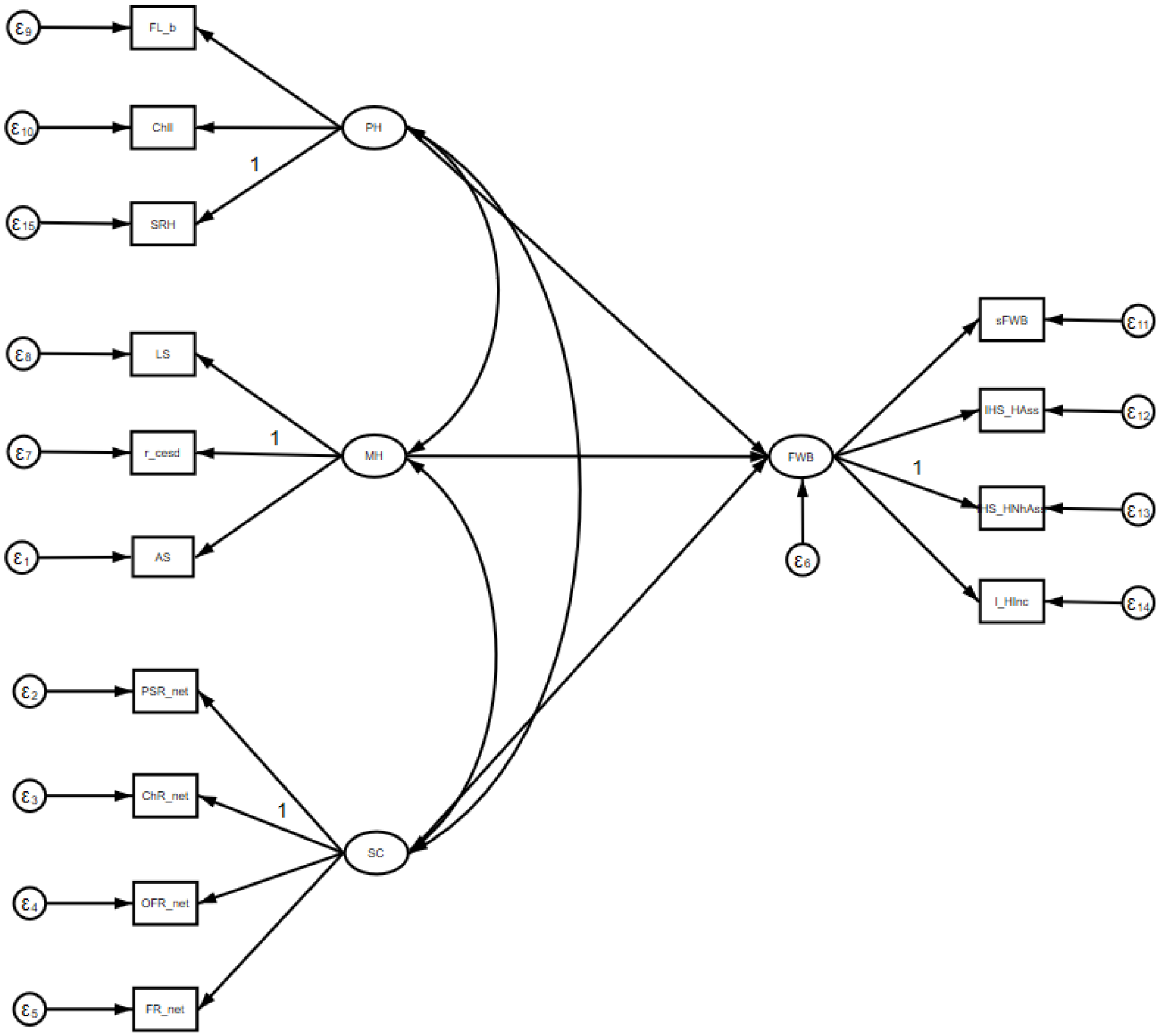
With the measurement model of the biopsychosocial (BPS) relationships being tested and shown to have fit statistics that were acceptable in accordance with Kline (2016), we can now evaluate the full structural model inclusive of Financial Well-Being (FWB) (Figure 4.4). The initial run of the structural model only includes covarying relationships of the components of study; Biological as measured by Physical Health (PH), Psychological as measured by Mental Health (MH), and Sociological as measured by Social Connection (SC). Based on the goodness of fit of the model(s), modification indices were evaluated according to Kline (2016) for any additional covarying relationships among observed variables and/or their error terms.

Reporting of Results

Structural Model

The initial results of the full structural model without covarying relationships showed mixed results (Table 4.3). Most of the waves had poor fit statistics with the exception of the combined wave. As a result of this, covarying relationships were added based on the results of

Figure 4.4 Biopsychosocial Model of Financial Well-Being – Initial Structural Model



The initial relationship that was consistent with all waves included covarying the inverse hyperbolic sine of household net worth (IHS_NW) and non-housing net worth (IHS_NhNW). While this improved the model(s) performance of goodness of fit (Table 4.4), there were still improvements that needed to be made to account for additional relationships that had high modification indices and were justifiable within the literature. These included subjective financial well-being (sFWB) with the natural log transformed household income (l_HInc),

Table 4.3 SEM of BPS Model of FWB – Initial (FIML)

Wave (n)	$\chi2$ [df]	p	RMSEA	CFI	TLI	CD
2010 (8,250)	3112.90 [71]	<0.001	0.072	0.889	0.857	0.959
2012 (7,243)	2951.53 [71]	<0.001	0.075	0.885	0.853	0.960
2014 (25,521)	3163.71 [71]	<0.001	0.041	0.875	0.840	0.955
2016 (6,302)	2578.16 [71]	<0.001	0.075	0.873	0.837	0.946
2018 (18,658)	2165.11 [71]	<0.001	0.040	0.892	0.861	0.956
Combined (99,393)	12777.73 [71]	<0.001	0.042	0.941	0.924	0.956

Table 4.4 SEM of BPS Model of FWB – Initial Covariance (FIML)

Wave (n)	$\chi2$ [df]	p	RMSEA	CFI	TLI	CD
2010 (8,250)	2047.98 [70]	<0.001	0.059	0.928	0.906	0.968
2012 (7,243)	1998.74 [70]	<0.001	0.062	0.923	0.900	0.967
2014 (25,521)	2134.42 [70]	<0.001	0.034	0.917	0.892	0.961
2016 (6,302)	1537.59 [70]	<0.001	0.058	0.926	0.903	0.957
2018 (18,658)	1443.12 [70]	<0.001	0.032	0.929	0.908	0.964
Combined (99,393)	8022.30 [70]	<0.001	0.034	0.963	0.952	0.959

functional limitations (FL) with self-reported health status (SRH), anxiety symptoms (AS) with depressive symptoms (DS), and life satisfaction (LS) with partner/spouse relationship quality (PSR_net). The final structural model is shown in Figure 4.5.

The inclusion of the covarying relationships listed above brought the goodness of fit (GoF) statistics into more acceptable ranges in accordance with Kline (2016) (Table 4.5). While each of the GoF statistics measures a different element of fit, it is the combination of all of them that indicates whether a model fits the data or not.

Figure 4.5 Biopsychosocial Model of Financial Well-Being – Final Structural Model

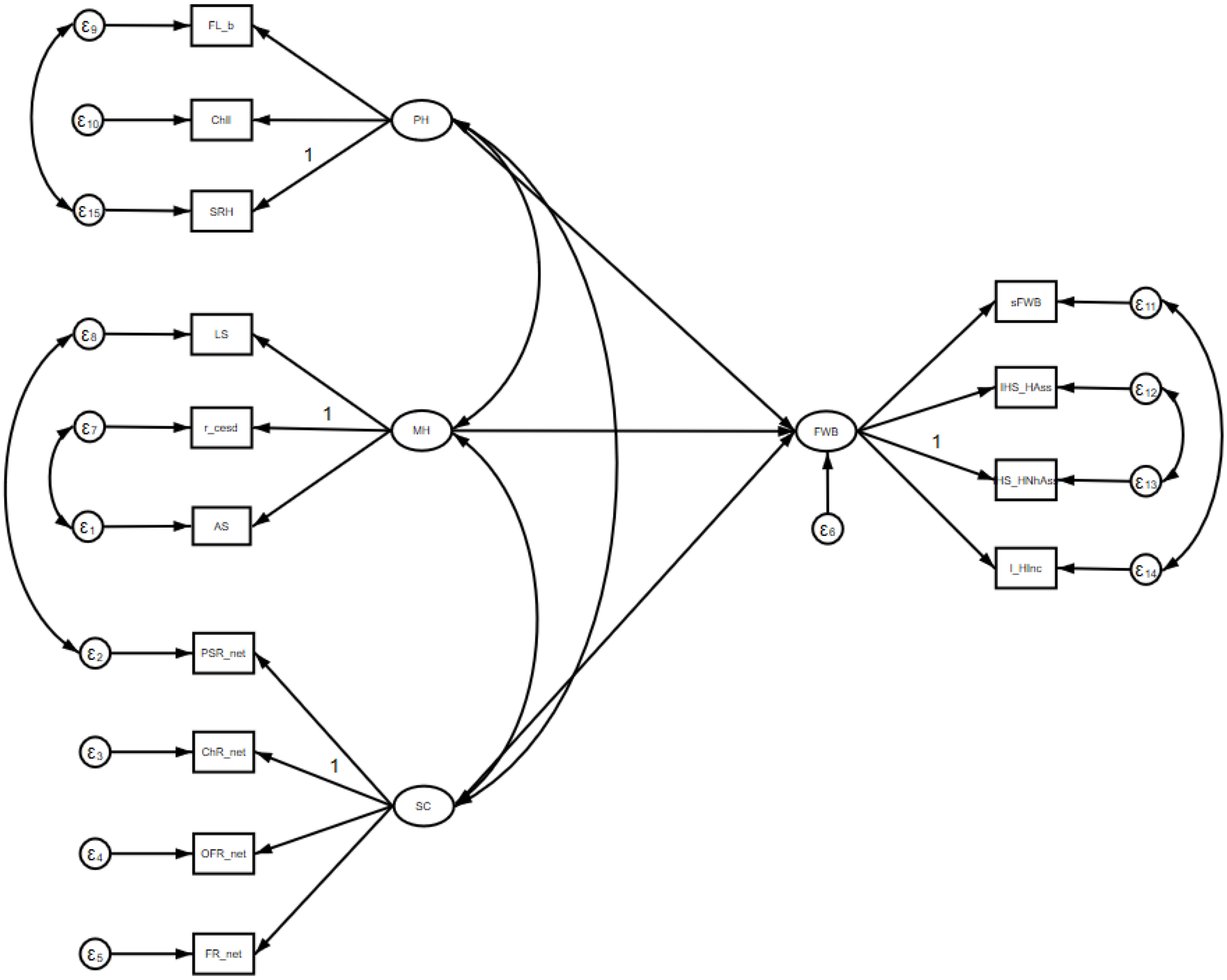


Table 4.5 SEM of BPS Model of FWB – Final Model (FIML)

				90% CI					
Wave (*n*)	χ2 [df]	*p*	RMSEA	LB	UB	*pClose*	CFI	TLI	CD
2010 (8,250)	1400.38 [66]	<0.001	0.050	0.047	0.052	0.635	0.951	0.933	0.992
2012 (7,243)	1379.04 [66]	<0.001	0.052	0.050	0.055	0.048	0.948	0.928	0.988
2014 (25,521)	1581.04 [66]	<0.001	0.030	0.029	0.031	1.000	0.939	0.916	0.985
2016 (6,302)	1067.11 [66]	<0.001	0.049	0.046	0.052	0.719	0.949	0.930	0.979
2018 (18,658)	969.40 [66]	<0.001	0.027	0.026	0.029	1.000	0.953	0.936	0.981
Combined (99,393)	4725.13 [66]	<0.001	0.027	0.026	0.027	1.000	0.978	0.970	0.978

Root Mean Square Error of Approximation (RMSEA) estimates how well the model, with unknown but optimally chosen parameter estimates, would fit the population covariance matrix. It is sensitive to model complexity and, generally, penalizes models with more parameters. Despite that, across all waves, the RMSEA values ranging from 0.032 (2018) to 0.062 (2012) indicate a close fit, meaning the model fits the data very well. The 90% confidence interval (CI) for RMSEA ranges from 0.026 (2018) to 0.055 (2012) with p-close values between 0.048 (2012) and 1.000 (2014, 2018, and combined) (probability RMSEA ≤ 0.05), meaning the fit is very likely to be good for the population data as well and the model does not have major misspecifications.

Comparative Fit Index (CFI) compares the fit of a model to a baseline model (the "null model") where all variables are assumed to be uncorrelated. CFI adjusts for model complexity, rewarding models that explain more variance with fewer parameters. Kline (2016) suggests that CFI values should be greater than or equal to 0.90 for an acceptable fit. With these models' CFI values ranging from 0.939 (2014) to 0.978 (combined), this would suggest that our models fit the data extremely well when compared to the baseline model. In other words, based on CFI, our model explains much more of the covariances among variables than would be expected by chance or an uncorrelated baseline model.

The Tucker-Lewis Index (TLI) is similar to CFI but introduces a stronger penalty for model complexity. It compares the fit of the model against a null model while accounting for the number of parameters. TLI is often called a "parsimony fit index" because it rewards simpler models that fit well. Similar to CFI, Kline (2016) suggests that CFI values should be greater than or equal to 0.90 for an acceptable fit. Our models' have TLI values that range from 0.916 (2014) to 0.970 (combined), indicating an acceptable fit, especially given the complexity of the relationships being modeled.

Lastly, the Coefficient of Determination (CD) in structural equation modeling (SEM) is a measure of how well the model explains the variance in the observed variables. A CD value close to 1 indicates that the model explains almost all of the variance in the data, while a value closer to 0 suggests the model explains very little variance. In our model, the CD values ranging from 0.978 (combined) to 0.992 (2010) means that the model explains 97.8% to 99.2% of the variance in the observed variables. In other words, the latent factors (Financial Well-Being, Mental Health, Physical Health, and Social Connection) do an excellent job of accounting for the variability in the observed measures related to these constructs, suggesting that the model is a very good fit for the data and captures the underlying relationships between the factors effectively. A high CD like this indicates that the structural paths and measurement indicators included in the model are highly predictive of the observed variables, suggesting a strong explanatory power of the SEM.

The goodness of fit statistics for the BPS FWB model indicate that it fits the data very well. The RMSEA being ≤ 0.050 suggests a close fit, with minimal error in approximation, and the 90% confidence intervals support this conclusion, as do the p-close values being ≤ 0.05. The CFI values being ≥ 0.939 reflects an excellent fit of the model compared to the baseline model, demonstrating that the model explains much of the covariances among variables beyond what would be expected by chance. The TLI values being ≥ 0.916 indicates a good, but slightly less stringent, fit compared to the CFI, penalizing the model for its complexity. Overall, these statistics suggest that the model captures the underlying structure of the data effectively and provides a strong representation of the relationships between the latent and observed variables.

As a result of acceptable model fit across all waves, we can begin to interpret the standardized coefficients from the model that are found in Table 4.6.

Physical Health (PH)

Functional Limitations (FL)

The standardized coefficients for FL ranged from 0.5674 (2016) to 0.6522 (2012). The consistently strong relationship between PH and FL across all years suggests that functional limitations are a central component of physical health. This indicates a moderately strong relationship between Physical Health (PH) and Functional Limitations (FL). A higher coefficient means that as PH improves, FL decreases significantly. If a person's physical health improves, they are likely to experience fewer difficulties in daily activities. The high variance of errors indicates that while Functional Limitation (FL) is a key indicator of Physical Health (PH), other unmeasured factors might also influence physical health outcomes.

Chronic Illness (ChIl)

Chronic Illnesses (ChIl) had a strong and consistent impact on Physical Health (PH) with coefficients ranging from 0.4919 (2010) to 0.5424 (2018). A higher coefficient means that chronic conditions, such as diabetes or hypertension, significantly lower an individual's overall Physical Health (PH) status. As with FL, the high error variances indicated that while Chronic Illness (ChIl) is a key indicator of Physical Health (PH), other unmeasured factors might also influence physical health outcomes.

Self-Reported Health (SRH)

Self-Reported Health (SRH) was a strong predictor of overall Physical Health (PH) with coefficients ranging from 0.8596 (2018) to 0.9159 (2010). A higher coefficient suggests that

Table 4.6 Standardized Coefficients (β) - BPS of FWB Model

	2010	2012	2014	2016	2018	Combined
n	8,250	7,252	7,465	6,306	5,674	99,393
FWB						
sFWB	0.8149	0.8190	0.8245	0.8519	0.8101	0.7373
var(e.sFWB)	0.3360	0.3292	0.3202	0.2742	0.3437	0.4564
IHS_NW	0.4887	0.4986	0.4888	0.4741	0.5230	0.5307
var(e. IHS_NW)	0.7612	0.7514	0.7610	0.7753	0.7265	0.7184
IHS_NhNW	0.5356	0.5540	0.5393	0.5200	0.5612	0.5836
var(e. IHS_NhNW)	0.7132	0.6931	0.7092	0.7296	0.6850	0.6595
l_HInc	0.4779	0.5266	0.5425	0.5099	0.5238	0.5277
var(e. l_HInc)	0.7716	0.7227	0.7057	0.7399	0.7257	0.7216
PH						
FL	0.6347	0.6522	0.6476	0.5674	0.5947	0.5686
var(e.FL)	0.5972	0.5746	0.5807	0.6780	0.6463	0.6767
ChIl	0.4919	0.5182	0.5235	0.5176	0.5424	0.5354
var(e.ChIl)	0.7580	0.7315	0.7260	0.7321	0.7058	0.7134
SRH	0.9159	0.8953	0.8797	0.8683	0.8596	0.8743
var(e.SRH)	0.1612	0.1985	0.2261	0.2460	0.2611	0.2356
MH						
LS	0.6164	0.5996	0.6090	0.6210	0.6116	0.6110
var(e.LS)	0.6201	0.6405	0.6291	0.6143	0.6259	0.6267
DS	0.6113	0.6350	0.6549	0.6319	0.6340	0.6617
var(e.DS)	0.6264	0.5967	0.5711	0.6007	0.5980	0.5621
AS	0.5764	0.5764	0.4301	0.4134	0.5777	0.5215
var(e.AS)	0.6678	0.6677	0.8150	0.8291	0.6663	0.7280
SC						
PSR	0.4476	0.5037	0.5327	0.5343	0.5180	0.4967
var(e.PSR)	0.7997	0.7463	0.7162	0.7145	0.7317	0.7533
ChR	0.7074	0.7131	0.7087	0.6737	0.7067	0.7058
var(e.ChR)	0.4996	0.4915	0.4978	0.5461	0.5006	0.5019
OFR	0.6197	0.6459	0.6362	0.5937	0.6370	0.6365
var(e.OFR)	0.6160	0.5828	0.5952	0.6475	0.5942	0.5948
FR	0.4952	0.5055	0.4960	0.4934	0.4759	0.4982
var(e.FR)	0.7548	0.7444	0.7540	0.7565	0.7735	0.7518
Covariance						
BPS						
cov(MH,PH)	-0.6650	-0.7126	-0.6847	-0.6247	-0.6985	-0.7144
cov(MH,SC)	0.5716	0.5824	0.6116	0.6750	0.6335	0.5921
cov(PH,SC)	-0.2181	-0.1992	-0.2364	-0.2448	-0.2387	-0.2497
cov(e.IHS_NW, e.IHS_NhNW)	0.6681	0.6312	0.6667	0.6854	0.6560	0.6252
cov(e.sFWB_10, e.l_HInc)	-0.3477	-0.3640	-0.3548	-0.3914	-0.3694	-0.2553
cov(e.AS, e.DS)	0.1801	0.1862	0.1806	0.1797	0.1578	0.1489
cov(e.LS, e.PSR_net)	0.1927	0.2156	0.1753	0.1854	0.2095	0.2085
cov(e.FL, e.SRH)	-0.6363	-0.5556	-0.5564	-0.4547	-0.4276	-0.4168

individuals' perceptions of their health closely align with their actual physical health. SRH had the strongest association with physical health, reflecting its reliability as a strong indicator of an individual's overall health status. The lower error variance, combined with the higher coefficients, suggests that respondents in this sample are generally accurate in accessing their own health when their functional limitations and chronic illnesses are taken into consideration with their Financial Well-Being (FWB).

Mental Health (MH)

Life Satisfaction (LS)

Life Satisfaction (LS) maintained a stable and significant relationship with Mental Health (MH) across all waves, indicating that it is a robust indicator of overall mental well-being. With the coefficients for LS ranging from 0.5996 (2012) to 0.6210 (2106), the higher coefficients suggest that individuals who are satisfied with their lives tend to have better Mental Health (MH). The consistent error variance implies that the measurement of Life Satisfaction (LS) relative to Mental Health (MH) remained stable, with little influence from external variables.

Depressive Symptoms (DS)

Depressive Symptoms (DS) were strongly related to Mental Health (MH), with higher levels of depression indicating poorer mental health. The strong relationship between depressive symptoms and mental health was evident, with coefficients ranging from 0.6113 (2010) to 0.6617 (combined). This suggests that, in general, when depressive symptoms increase, mental health worsens. The error variances suggest that depressive symptoms are influenced by other, unmeasured factors, complicating their direct relationship with overall Mental Health (MH).

Anxiety Symptoms (AS)

Anxiety Symptoms (AS) had a moderate to strong relationship with Mental Health with coefficients ranging from 0.4966 to 0.6485. With some variability across years., the relationship was less stable than that of Depressive Symptoms (DS). The high error variance, especially in later years, indicates growing complexity in how anxiety symptoms relate to overall mental health, potentially reflecting broader social or environmental stressors.

Social Connection (SC)

Partner/Spouse Relationships (PSR)

The perceived social support from a Partner/Spouse Relationship (PSR) had a moderate impact on social connection. With coefficients for PSR ranging from 0.4479 (2010) to 0.5343 (2016), a higher coefficient indicates that individuals who perceive they have strong social support from a PSR tend to have better Social Connection (SC) as a whole. The error variance trend implies that while PSR became more significant, there was still considerable variation in how individuals perceived and utilized their social resources.

Child(ren) Relationship(s) (ChR)

The stable relationship between Child(ren) Relationship(s) (ChR) and Social Connection (SC) with coefficients ranging from 0.6737 (2016) to 0.7131 (2012) indicates that respondents' relationship(s) with living children strongly and consistently impacted Social Connection (SC). The low and consistent error variance suggests Child(ren) Relationship(s) (ChR) is a well-defined and stable component of Social Connection (SC), with little influence from other factors.

Other Family Relationships (OFR)

In the full model, Other Family Relationships (OFR) had less fluctuation and moderate to high coefficient values. The stable coefficients, ranging from 0.5937 (2016) to 0.6459 (2012), indicate that Other Family Relationships (OFR) maintained their importance in Social Connection (SC). The consistent error variance suggests that the impact of Other Family Relationships (OFR) on Social Connection (SC) was stable, with few external influences.

Friend Relationships (FR)

The relatively lower coefficients for Friend Relationships (FR), coefficients for FR ranged from 0.4759 (2018) to 0.5055 (2012), imply that while friends are part of Social Connection (SC), they might not be as central as the other factors in the model. The stable error variances indicate that Friend Relationships (FR) role in Social Connection (SC) was consistent, though possibly less variable than other Social Connection (SC) components.

Biopsychosocial (BPS)

Mental Health (MH) and Physical Health (PH) Covariance

The strong and negative covariance between Mental Health (MH) and Physical Health (PH) underscores the close interdependence between these two domains [-0.7144 (combined) < β > -0.6247 (2016)]. This suggests that improvements in one dimension (e.g., better physical health) are associated with decreases in the other. When Physical Health (PH) worsens, Mental Health (MH) tends to follow, and vice versa.

Mental Health (MH) and Social Connection (SC) Covariance

The consistently positive covariance [0.5716 (2010) < β > 0.6750 (2016)] between Mental Health (MH) and Social Connection (SC) indicates a relationship whereby as Social Connection (SC) increases, Mental Health (MH) tends to increase, and vice versa. This could mean that individuals with better mental health are more likely to engage in and maintain social relationships, which in turn strengthens their Social Connection. Likewise, is could mean that being more socially connected, ones mental health improves.

Physical Health (PH) and Social Connection (SC) Covariance

The weak and negative covariance [-0.2497 (combined) < β > -0.1992 (2012)] between Physical Health (PH) and Social Connection (SC) suggests that these two domains are largely independent, with only a minor inverse relationship. This could indicate that improving physical health might not necessarily enhance social connection and vice versa. This could suggest that individuals with better physical health may rely less on social networks for support, or that strong social networks might not be as necessary for those in good physical condition. The consistency of this relationship over time suggests that the interaction between physical health and social connection remained stable but minor.

Financial Well-Being (FWB)

The measurement indicators for Financial Well-Being (FWB) in the structural equation model highlighted how various financial aspects contribute to an individual's overall financial well-being. The standardized coefficients for these indicators reflected the strength of the relationships between subjective financial well-being, household assets, household income, and the latent FWB construct. These relationships provide insights into how different facets of financial status influence individuals' perceptions of their financial security and stability.

Subjective Financial Well-Being (sFWB)

With standardized coefficients ranging from 0.7373 (combined) to 0.8519 (2016), Subjective Financial Well-Being (sFWB) was strongly associated with the overall FWB construct. This suggests that individuals' perceptions of their financial security are closely aligned with their actual financial circumstances. In practical terms, people who feel financially stable and secure are likely to report higher levels of subjective financial well-being. This is critical because financial perceptions often drive other elements of one's life such as decision-making behavior, emotional stress, and life satisfaction. For example, an individual who feels they have enough financial resources to cover emergencies, future plans, and daily expenses will likely report higher subjective financial well-being, even if their income or assets are not the highest among their peers. This strong relationship highlights the importance of financial self-assessment in determining overall financial well-being. The low and stable error variances indicate that Subjective Financial Well-Being (sFWB) role in Financial Well-Being (FWB) was consistent, though possibly less variable than other Financial Well-Being (FWB) components.

<u>Inverse Hyperbolic Sine of Household Net Worth (IHS_NW) and Inverse Hyperbolic Sine of Household Non-Housing Net Worth (IHS_NhNW)</u>

Household Net Worth, both inclusive of house as an asset (e.g., home ownership) and outside the value of the house, were moderately associated with financial well-being, with coefficients ranging from 0.4741 (2016) to 0.5307 (combined) and 0.5356 (2010) to 0.5836 (combined), respectively. These coefficients suggest that individuals with higher levels of financial well-being tend to accumulate more assets, indicating a positive relationship between asset ownership and perceived financial stability. Having significant household and non-household assets provides a buffer against financial uncertainty, contributing to a sense of security. However, while the association is moderate, it suggests that asset accumulation is an important but not dominant factor in determining overall financial well-being. This moderate relationship might reflect that not everyone with high assets necessarily feels financially well-off, and some individuals may prioritize other aspects of financial stability, such as income or financial literacy, in their self-assessment of financial well-being. The high error variances suggest that there was considerable variation in how individuals' net worth contributed to their Financial Well-Being (FWB).

Natural Log of Household Income (l_Inc)

Household income was also moderately related to financial well-being, with coefficients ranging from 0.4779 (2010) to 0.5277 (combined). While higher income generally leads to improved financial well-being, it is not the sole determining factor. The moderate strength of this relationship indicates that income plays a crucial role in shaping financial well-being, but other factors may also influence perceptions of financial stability. For instance, a person with a relatively high income but poor financial management skills or high debt may not perceive themselves as financially secure. Conversely, an individual with a modest income but a strong sense of financial control, fewer liabilities, and lower expectations for wealth accumulation may report higher financial well-being. This suggests that while income is essential, financial well-being is a multidimensional construct influenced by a combination of objective financial indicators and subjective perceptions. That said, the high error variances suggest that there was considerable variation in how individuals' net worth contributed to their Financial Well-Being (FWB).

Biopsychosocial (BPS) Model of Financial Well-Being (FWB)

The main purpose of this study was to employ a structural equation model (SEM) to examine the complex relationships between Financial Well-Being (FWB), Physical Health (PH), Mental Health (MH), and Social Connection (SC) using the biopsychosocial model. The model aims to explore how these domains influence an individual's financial well-being, with a particular focus on how physical and mental health, as well as social connection, contribute to financial outcomes. Provided below is an in-depth interpretation of the results and their implications for financial well-being with the findings found in Table 4.7. Unless otherwise noted, all results had significance values of $p \leq 0.05$.

Table 4.7 Standardized Coefficients (β) **-** BPS of FWB Structural Model

	2010	2012	2014	2016	2018	Combined
n	8,250	7,252	7,465	6,306	5,674	99,393
Structural - FWB						
PH	0.2371	0.2131	0.0874*	0.0729	0.1764	0.0315***
MH	0.9680	0.9325	0.7709	0.8648	0.9803	0.7153
SC	-0.1548	-0.1232	-0.0585**	-0.1678	-0.1930	-0.0668

* $p = 0.016$; ** $p = 0.080$; ***$p = 0.051$

Physical Health (PH) → FWB

The relationship between Physical Health (PH) and Financial Well-Being (FWB) was positive but varied in strength over time, with coefficients ranging from 0.0729 (2016) to 0.2371 (2010), and a significant drop to 0.0315 in the combined model. The 2014 coefficient was also notably lower (0.0874, $p = 0.016$), indicating a weaker but still significant effect in that year.

The results suggest that the impact of Physical Health (PH) and Financial Well-Being (FWB) is consistently positive but fluctuates across time. In 2010 and 2018, individuals with better physical health experienced greater financial well-being, which could be due to fewer health-related expenses and better employment capacity. For example, healthier individuals may be more productive and able to sustain steady work, leading to financial stability. However, in certain years like 2014 and 2016, the influence of physical health was weaker, potentially due to external factors such as economic downturns or changes in healthcare costs that may have diluted the connection between health and financial stability.

In the combined model, the effect of Physical Health (PH) on Financial Well-Being (FWB) remained modest ($\beta = 0.0315$, $p = 0.051$), indicating that while important, physical health is not the primary driver of financial well-being in the broader context. While the coefficient is still positive, indicating that better physical health is associated with better financial well-being, the fact that it is not statistically significant suggests that the relationship is weak or inconsistent when looking at the combined data set as a whole. This could indicate that other factors, such as mental health or social connection, play a more dominant role in shaping financial well-being, or that the impact of physical health fluctuates too much across time to have a consistent, significant effect in the combined model.

Mental Health (MH) → FWB

Mental Health (MH) consistently exhibited the strongest positive relationship with Financial Well-Being (FWB) across all waves, with coefficients ranging from 0.7153 (combined) to 0.9803 (2018). Although the strength of the relationship fluctuated somewhat, it remained highly significant (all $p \leq 0.0001$), with the combined wave showing a robust positive association.

The results strongly suggest that Mental Health (MH) plays a critical role in financial well-being, and vice versa. In each wave, better Mental Health (MH) was associated with higher Financial Well-Being (FWB), reflecting the importance of psychological stability for financial decision-making and stress management. For example, individuals with fewer symptoms of anxiety or depression are more likely to effectively manage their financial resources, avoid impulsive spending, and plan for the future, all of which contribute to better financial outcomes. The coefficient for 2018 was particularly high (0.9803), possibly indicating a growing recognition of mental health's importance in financial well-being in recent years. The combined coefficient (0.7153) reinforces the idea that mental health is a key driver of financial security across time, though fluctuations suggest that external circumstances (e.g., economic stressors) might occasionally moderate this relationship.

Social Connection (SC) → FWB

Social Connection (SC) had a consistently negative relationship with Financial Well-Being (FWB) across all years, with coefficients ranging from -0.0585 (2014, $p = 0.080$) to -

0.1930 (2018). The combined wave showed a moderate negative coefficient of -0.0668, suggesting that stronger social ties generally correspond to lower financial well-being over time.

In 2014 and in the combined wave, the relationship between Social Connection (SC) and Financial Well-Being (FWB) was negative but not statistically significant ($p > 0.05$). These non-significant results suggest that, in those waves, the data did not provide strong enough evidence to conclude that social connection had a reliable impact on financial well-being. The negative coefficients imply a potential financial burden from social obligations, but the lack of significance may indicate that this effect was less pronounced or more variable in those years. External factors could have played a larger role, or the financial demands associated with maintaining social ties may not have been as strong during those periods. Essentially, the relationship was not consistent enough to meet the threshold for significance, suggesting a weaker or more context-dependent association.

The negative relationship between Social Connection (SC) and Financial Well-Being (FWB) suggests that maintaining strong social networks may come with financial burdens. For instance, individuals who are closely tied to their social groups may experience financial obligations, such as supporting family members or participating in costly social events, which can strain personal financial resources. The coefficient for 2018 (-0.1930) highlights the strong negative impact that social ties may have in certain periods, possibly due to economic pressures that exacerbate the financial demands of maintaining social connections, and possibly even supporting those relationships financially. The weak but consistent negative relationship across most waves indicates that, over time, higher Social Connection (SC) may detract from Financial Well-Being (FWB) for individuals who prioritize social obligations over financial goals.

Summary

The results of the SEM model across multiple waves provided important insights into how Physical Health (PH), Mental Health (MH), and Social Connection (SC) influence Financial Well-Being (FWB). Mental Health (MH) consistently showed the strongest positive effect on Financial Well-Being (FWB), underscoring its critical role in enabling individuals to manage financial stress and make sound decisions. Physical Health (PH), while positively associated with Financial Well-Being (FWB), showed more variability in its impact, suggesting that external factors may moderate this relationship in certain years. Social Connection (SC), by contrast, had a consistently negative effect, reflecting the financial costs that may accompany maintaining strong social networks. Overall, these findings highlight the complex and multifaceted nature of Financial Well-Being (FWB), with health and social factors playing distinct and evolving roles in shaping financial outcomes across time.

Reporting of Hypotheses

In this section, the results from the structural equation models (SEM) exploring the elements within the biopsychosocial model (BPS) and their relationship(s) with Financial Well-Being (FWB) across multiple waves are used to evaluate the proposed hypotheses. Each hypothesis is assessed based on whether the findings support or reject it. While most of the hypotheses were supported, there were a few that were only partially supported as indicated by the summary below in Table 4.8.

Hypothesis 1 - The combination of all elements (BPS) will have better explanatory power than any individual element

The BPS model, which incorporated the biological (PH), psychological (MH), and sociological (SC) elements, demonstrated better explanatory power for Financial Well-Being

Table 4.8 Hypotheses Summary

	Hypotheses (#)	Result
1	The combination of all elements (BPS) will have better explanatory power than any individual element	Supported
2	The Biopsychosocial Model will significantly explain variation in financial well-being among older adults	Supported
3_a	Biological factors will directly predict financial well-being	Partially Supported
3_b	Biological factors will indirectly predict financial well-being	Supported
4_a	Psychological factors will directly predict financial well-being	Supported
4_b	Psychological factors will indirectly predict financial well-being	Supported
5_a	Sociological factors will directly predict financial well-being	Partially Supported
5_b	Sociological factors will indirectly predict financial well-being	Supported

(FWB) compared to any single component alone. When evaluating the full BPS model across all waves, the model consistently produced fit statistics that reflected a good overall model fit. Specifically, the RMSEA values ranged from 0.027 to 0.052, and the CFI and TLI values were consistently above 0.90 across all waves, showing that the combined model fits the data well. Moreover, the Coefficient of Determination (CD), which measures the percentage of variance explained by the model, ranged from 0.946 to 0.992, indicating that the BPS model explains nearly all the variance in financial well-being in our data.

The results show that no individual element—whether biological, psychological, or sociological—had as much explanatory power on its own as the full BPS model did when all components were included. For instance, while Mental Health (MH) had the strongest direct effect on FWB, with coefficients ranging from 0.7153 to 0.9803, including Physical Health (PH) and Social Connection (SC) improved the overall explanatory power of the model. Each domain contributed to explaining different facets of financial well-being, and their combined impact provides a more comprehensive understanding of financial well-being.

The combined BPS model, by integrating the effects of physical, mental, and social factors, captures the multifaceted nature of FWB. This is evident from the improvement in model fit when all elements are included, reinforcing the idea that FWB is shaped by a complex interplay of biological, psychological, and social factors. Therefore, H_1 is accepted, as the combination of all elements in the BPS model provided significantly better explanatory power than any individual element alone.

Hypothesis 2 - The Biopsychosocial Model will significantly explain variation in financial well-being among older adults

The Biopsychosocial (BPS) model demonstrated a strong capacity to explain the variation in Financial Well-Being (FWB) among older adults. Across all waves, the model showed excellent goodness-of-fit statistics, with RMSEA values ranging from 0.027 to 0.052, indicating a close fit, and CFI values consistently above 0.90, confirming a good model fit when compared to a baseline model. Furthermore, the Coefficient of Determination (CD) ranged from 0.946 to 0.992, meaning the model explained between 94.6% and 99.2% of the variance in FWB across different time points. This high explanatory power highlights that the integration of biological, psychological, and social factors significantly contributes to understanding financial well-being in this population.

The strong model fit and high variance explained by the BPS model indicate that older adults' financial well-being is driven by a combination of physical, mental, and social factors. Each component plays a distinct role in shaping financial outcomes, and their collective influence provides a comprehensive view of the factors impacting financial well-being in later life. Therefore, H_2 is accepted, as the BPS model significantly explains variation in financial well-being among older adults.

Hypothesis 3_a - Biological factors will directly predict financial well-being

The direct impact of biological factors, as measured by Physical Health (PH), on financial well-being (FWB) was positive across all waves but varied in strength. The standardized coefficients for PH ranged from 0.0729 to 0.2371, with a significant but weaker effect in some years (e.g., 0.0874 in 2014, $p = 0.016$) and a marginally non-significant effect in the combined model (0.0315, $p = 0.051$). These results suggest that while PH consistently predicts FWB, its influence fluctuates across the waves and is not as strong as psychological factors.

The variability in PH's impact could be explained by external factors, such as economic conditions or healthcare access, that may moderate the relationship between physical health and financial outcomes. For instance, in years where healthcare costs were high or employment opportunities for older adults were limited, the relationship between PH and FWB may have been weaker. Nevertheless, H_{3a} is partially accepted, as PH does directly predict FWB, though its effect is inconsistent and weaker compared to other factors.

Hypothesis 3_b - Biological factors will indirectly predict financial well-being

The results indicate that biological factors, as measured by Physical Health (PH), indirectly affect financial well-being (FWB) through their interactions with Mental Health (MH) and Social Connection (SC). The strong negative covariances between PH and MH (ranging from -0.7144 to -0.6247) show that declines in physical health often coincide with poorer mental health, which in turn can negatively impact financial well-being. Similarly, the negative relationship between PH and SC (e.g., -0.2497 in the combined wave) suggests that poor physical health may reduce social engagement, further influencing financial outcomes.

These indirect pathways demonstrate that while PH may not always have a strong direct effect on FWB, it exerts a significant influence through its impact on Mental Health (MH) and Social Connections (SC). This supports the idea that biological factors shape Financial Well-Being (FWB) not only by affecting physical functioning but also by influencing psychological and social dynamics. Therefore, H_{3b} is accepted.

Hypothesis 4_a - Psychological factors will directly predict financial well-being

Psychological factors, as measured by Mental Health (MH), consistently had the strongest direct influence on Financial Well-Being (FWB) across all waves. The standardized coefficients for MH ranged from 0.7153 to 0.9803, indicating a robust and highly significant positive relationship between Mental Health (MH) and Financial Well-Being (FWB) (all *p*-values < 0.001). This strong association reflects that individuals with better mental health are more likely to manage their finances effectively, avoid financial stress, and make sound financial decisions.

The consistently high impact of MH on FWB suggests that psychological well-being is a key driver of financial outcomes. For example, individuals with fewer symptoms of anxiety or depression may have greater emotional and cognitive capacity to manage financial risks, plan for the future, and maintain stability during economic downturns. The strength of this relationship across all years confirms that Mental Health is central to understanding financial well-being, especially in older adults. Thus, H_{4a} is accepted.

Hypothesis 4_b - Psychological factors will indirectly predict financial well-being

The results indicate that psychological factors, measured by Mental Health (MH), also indirectly influence Financial Well-Being (FWB) through their impact on Social Connection (SC). The consistently positive covariances between MH and SC (ranging from 0.5716 to

0.6750) suggest that better mental health enhances social engagement, which can contribute to financial well-being, either through emotional support, advice, or tangible financial assistance from social networks.

These findings demonstrate that Mental Health (MH) indirectly supports Financial Well-Being (FWB) by fostering stronger social ties, which may provide additional resources or support in managing financial responsibilities. The indirect effects of psychological factors highlight the broader role that Mental Health plays in influencing financial outcomes through its interaction with social networks. Therefore, H_{4b} is accepted.

Hypothesis 5$_a$ - Sociological factors will directly predict financial well-being

Social Connection (SC), representing sociological factors, had a negative direct relationship with Financial Well-Being (FWB) in all waves, with coefficients ranging from -0.0585 to -0.1930. The negative association suggests that stronger social ties may impose financial obligations, such as caregiving responsibilities or financial support for family members, which can strain personal financial resources. However, this relationship was not always statistically significant, as seen in 2014 ($\beta = -0.0585$, $p = 0.080$) and the combined wave ($\beta = -0.0668$, $p > 0.05$).

The variability in significance across waves indicates that while Social Connections (SC) can have a financial cost, this effect may depend on other contextual factors, such as the economic climate or personal circumstances. Therefore, H_{5a} is partially accepted, as SC does directly predict FWB, though its effect is not always significant and varies in strength.

Hypothesis 5$_b$ - Sociological factors will indirectly predict financial well-being

Sociological factors, as measured by Social Connection (SC), indirectly influence Financial Well-Being (FWB) through their relationships with Mental Health (MH) and Physical

Health (PH). The positive covariance between SC and MH (ranging from 0.5716 to 0.6750) indicates that social connections improve mental health, which then contributes to better financial outcomes. Similarly, the negative covariance between SC and PH (e.g., -0.2497 in the combined wave) shows that declines in physical health can weaken social connections, indirectly affecting financial well-being.

These findings demonstrate that while Social Connections (SC) may not always have a direct positive effect on Financial Well-Being (FWB), they contribute indirectly by improving Mental Health (MH) and influencing Physical Health (PH) outcomes. This supports the idea that sociological factors affect Financial Well-Being (FWB) through complex interactions with other health domains. Thus, H_{5b} is accepted.

Summary

Structural equation models (SEM) were employed to evaluate the proposed hypotheses about the Biopsychosocial (BPS) model and its relationship with Financial Well-Being (FWB) across multiple waves. The results supported the majority of the hypotheses, confirming the complexity and multifaceted nature of financial well-being. The BPS model demonstrated better explanatory power than any individual element, confirming H_1. The model consistently explained nearly all the variance in FWB, reinforcing the idea that FWB is shaped by the interplay of these factors. The model also significantly explained variations in FWB among older adults, confirming H_2.

Biological factors, as measured by Physical Health (PH), directly predicted Financial Well-Being (FWB), though with varying strength, partially supporting H_{3a}. Physical Health (PH) also indirectly influenced Financial Well-Being (FWB) through its interactions with Mental Health (MH) and Social Connections (SC), fully supporting H_{3b}. Psychological factors, represented by Mental Health (MH), had the strongest direct impact on FWB, confirming H_{4a}, and also exerted indirect effects through social connections, supporting H_{4b}.

Sociological factors, represented by Social Connections (SC), had a negative direct effect on FWB, though this relationship varied in significance, partially supporting H_{5a}. However, Social Connections (SC) indirectly impacted FWB through their effects on mental and physical health, supporting H_{5b}.

Overall, the results highlight the importance of understanding Financial Well-Being (FWB) as a product of interconnected physical, mental, and social dynamics, with Mental Health (MH) emerging as the strongest predictor of financial outcomes.

Chapter 5 – Discussion and Implications

By examining the intersection of Biological, Psychological, and Sociological factors through the lens of the biopsychosocial model, this study aimed to uncover the complex relationships that contribute to Financial Well-Being in later life. The results provide evidence supporting the hypotheses and offer critical insights into how these multidimensional determinants interact to influence financial health, and thus, psychological and physiological health. This chapter explores each hypothesis, discuss the broader implications of the findings, address the study's limitations, and suggest directions for future research.

Discussion of Research Findings

The findings of this study provide an understanding of financial well-being in older adults, highlighting the interconnected nature of Biopsychosocial factors. The application of the biopsychosocial model to a nationally representative sample demonstrates the significant role of Biological, Psychological, and Sociological factors, both independently and collectively, in predicting financial outcomes. Structural Equation Modeling (SEM) results reveal the explanatory power of the model, emphasizing the importance of adopting a holistic approach to financial well-being research. These are born from the Hypotheses that were tested.

Hypothesis 1: The combination of all elements (BPS) will have better explanatory power than any individual element

The results supported Hypothesis 1, confirming that the combined effect of Biological, Psychological, and Sociological factors provides superior explanatory power compared to any individual domain. The integration of these elements captures the complex and multifaceted nature of Financial Well-Being, offering a more comprehensive view than traditional models that focus on isolated factors. This finding aligns with previous research that underscores the importance of multidimensional approaches in understanding complex human outcomes. By testing and validating the Biopsychosocial Model of Financial Well-Being, this study sets a precedent for future research to incorporate multiple determinants in examining Financial Well-Being, recognizing the cumulative impact of physical health, mental states, and social contexts.

Hypothesis 2: The biopsychosocial model will significantly explain variation in financial well-being among older adults

Hypothesis 2 is strongly supported, with the biopsychosocial model demonstrating significant explanatory power for Financial Well-Being among older adults. The model's fit indices and path coefficients confirm that Biological, Psychological, and Sociological predictors collectively explain a substantial portion of the variance in financial well-being. This finding challenges reductionist approaches that prioritize economic or psychological determinants alone, advocating for a more integrated perspective. The evidence suggests that policies and interventions aimed at improving Financial Well-Being should address not just economic factors but also health, mental resilience, and social support systems.

Hypothesis 3a & 3b: Biological factors directly and indirectly predicting financial well-being

Biological factors, including self-reported health status, body mass index, and functional limitations, were found to have both direct and indirect effects on financial well-being, supporting Hypotheses 3a and 3b. Directly, poor Physical Health was associated with lower Financial Well-Being, indicating that health challenges limit older adults' ability to manage finances effectively. Indirectly, biological factors influenced Financial Well-Being through their impact on psychological states, such as increased depressive symptoms and anxiety, which in turn impacted Financial Well-Being, highlighting the complex pathways through which health affects financial outcomes. These findings underscore the bidirectional relationship between health and Financial Well-Being, suggesting that interventions aimed at improving Physical Health could have broader benefits for financial stability.

Hypothesis 4a & 4b: Psychological factors directly and indirectly predicting financial well-being

Psychological factors, including life satisfaction, depressive symptoms, and anxiety, were found to be significant predictors of Financial Well-Being, supporting Hypotheses 4a and 4b. The direct effects indicate that Mental Health plays a critical role in shaping financial behaviors and perceptions, with higher life satisfaction correlating with better financial outcomes. Indirect effects were observed through the mediation of social factors, suggesting that Psychological Well-Being enhances social connections, which in turn supports financial stability. These results highlight the importance of addressing Mental Health as part of financial planning and advising, particularly for older adults who may face unique psychological stressors in later life.

Hypothesis 5a & 5b: Sociological factors directly and indirectly predicting financial well-being

Sociological factors, including the quality of spouse/partner relationships, social connections, and support from family and friends, were found to significantly influence financial well-being, supporting Hypotheses 5a and 5b. Directly, strong social networks and positive relationship quality were associated with better financial outcomes, emphasizing the protective role of social support. Indirectly, social factors mediated the effects of both biological and psychological determinants, highlighting the complex interplay between health, mental states, and social contexts in shaping financial well-being. These findings suggest that enhancing social support systems could be a valuable strategy for improving financial health among older adults.

Summary

In summary, the discussion of research findings confirms that Financial Well-Being in older adults is shaped by a dynamic interplay of Biopsychosocial factors. Each domain—Biological, Psychological, and Sociological—contributes both directly and indirectly to financial outcomes, validating the holistic approach of the biopsychosocial model. The evidence supports the need for integrated interventions that address Physical Health, Mental Health, and Social Connections to enhance financial stability in later life.

Implications of Findings

Financial well-being in older adults is a complex issue shaped by the intricate interplay of biological, psychological, and social factors. This research leverages the integrative biopsychosocial model to provide a comprehensive framework that transcends singular variables, offering meaningful explanatory power. By examining the interrelationships between key determinants, the study delivers actionable insights for researchers, policymakers, financial practitioners, and older adults themselves. The empirical validation of this novel framework not only enhances our understanding of financial well-being but also has significant multidisciplinary implications for interventions aimed at improving financial resilience across the life course.

This research has important potential implications across multiple domains. The integrative application of the biopsychosocial model to financial well-being provides meaningful explanatory power beyond singular variables. Testing interrelationships between key determinants offers specific guidance for interventions to improve older adult financial well-being across biological, psychological, and sociological dimensions. The empirical validation and elaboration of this novel framework thus has important multidisciplinary implications.

For academic researchers, validating the biopsychosocial model in the context of financial well-being provides a useful framework for future studies. The model can be tested with different age groups and populations beyond older adults. Research illuminating biopsychosocial determinants in one population may inform studies in other groups. Findings may also spur new directions exploring mediators and moderators of relationships between variables.

For policymakers, results can point to high-impact areas for intervention across biological, psychological and social levels. Policies and programs targeting specific factors identified as most influential can be developed and evaluated. For instance, findings may highlight priorities like reducing healthcare costs, strengthening financial literacy education, or increasing access to financial advising.

For financial practitioners, understanding biopsychosocial determinants of financial well-being can help identify client needs and tailor solutions. Advisors could screen for psychological traits like conscientiousness and self-efficacy that may impact financial behaviors. Knowledge of biological factors can cause practitioners to assess or accommodate for potential health or cognitive issues. Awareness of social determinants can prompt connecting clients to relevant community resources.

For older adults and their family members, this research underscores the importance of proactively addressing financial well-being through multiple avenues. Seeking medical care, cognitive training, financial education, social engagement and other steps can all contribute. Even small improvements across biopsychosocial dimensions may cumulatively strengthen financial resilience.

At a societal level, these findings highlight the need for multi-pronged solutions to bolster Americans' financial health across the life course. No single program or policy will solve such a complex issue. Concerted, collaborative efforts spanning from the biology of the brain to the culture of our communities will be required to help citizens thrive financially. This study provides an empirical foundation to guide such comprehensive efforts.

By illuminating key biopsychosocial determinants of financial well-being and their interactions, this research has diverse implications for research, policy, practice and the public. It delivers actionable insights while laying groundwork for ongoing scholarship in this critical domain impacting individual and societal well-being.

Limitations of the Study

As discussed in Chapter 1, while this study provides valuable insights, several limitations must be acknowledged. The cross-sectional nature of the data limits the ability to infer causality, and the reliance on self-reported measures may introduce response biases. Additionally, the study's focus on older adults may limit the generalizability of findings to younger populations. Future research should consider longitudinal approaches to better capture the causal relationships between biopsychosocial factors and financial well-being and expand the model to include other age groups and more diverse samples.

Recommendation for Future Studies

Future research should explore the applicability of the biopsychosocial model in different contexts, including younger populations and various cultural settings. Looking at how the model would work by running it conditionally for employment status (working versus not) may shed light on just how much various types of income related to financial well-being. Further, the act of being gainfully employed could also impact the other components of the model by contributing to physical health or mental health.

While the results of the model seemed to maintain their significance and magnitude from wave to wave, longitudinal studies are needed to understand the temporal dynamics of biopsychosocial influences on financial fell-being. As individuals are evaluated across time, the results could provide a clearer picture as to the directionality of the elements' impact and how events over time (i.e. a health decline, loss of a spouse, being the recipient of an inheritance, etc.) contribute to that impact. Doing so could also get closer to being able to examine causal relationships in the model.

Lastly, future studies should investigate potential mediators and moderators, such as resilience and coping strategies, that may further expound upon the pathways through which biopsychosocial factors impact financial outcomes. Examining these relationships using this model across more robust and generalizable data sets would also advance this model and the research associated with it.

Conclusion

This dissertation has explored the complex Biopsychosocial determinants of Financial Well-Being in older adults, providing a comprehensive analysis of how Biological, Psychological, and Sociological factors interact to shape financial health. The findings confirm the value of the biopsychosocial model in explaining Financial Well-Being, highlighting the need for holistic approaches in research, policy, and practice. By advancing our understanding of the multidimensional drivers of Financial Well-Being, this study offers critical insights that can inform efforts to improve financial stability and quality of life for older adults, and for society as a whole.

References

Acock, A. C. (2005). Working with missing values. *Journal of Marriage and Family*, 67(4), 1012–1028. https://doi.org/10.1111/j.1741-3737.2005.00191.x

Alley, D., & Kahn, J. R. (2012). *Demographic and psychosocial predictors of financial strain in older adults* [Paper presentation]. Population Association of America 2012 Annual Meeting, San Francisco, CA https://paa2012.populationassociation.org/papers/121818

Anglim, J., Horwood, S., Smillie, L. D., Marrero, R. J., & Wood, J. K. (2020). Predicting psychological and subjective well-being from personality: a meta-analysis. *Psychological Bulletin*, *146*(4), 279-323. https://doi.org/10.1037/bul0000226

Angrist, J. D., & Pischke, J. S. (2009). Mostly harmless econometrics: An empiricist's companion. Princeton University Press.

Asebedo, S., & Wilmarth, M. (2017). Does how we feel about financial strain matter for mental health? *Journal of Financial Therapy,8*(1). https://doi.org/10.4148/1944-9771.1130

Bashmi, L., Cohn, A., Chan, S. T., Tobia, G., Gohar, Y., Herrera, N., Wen, R. Y., IsHak, W. W., & DeBonis, K. (2023). The biopsychosocial model of evaluation and treatment in psychiatry. In *Atlas of psychiatry* (pp. 57-89). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-031-15401-0_3

Beck, A. T., Epstein, N., Brown, G., & Steer, R. A. (1988). An inventory for measuring clinical anxiety: Psychometric properties. *Journal of Consulting and Clinical Psychology, 56*(6), 893–897. https://doi.org/10.1037/0022-006X.56.6.893

Board of Governors of the Federal Reserve System. (2022). *Report on the economic well-being of U.S. households in 2022*. https://www.federalreserve.gov/publications/files/2022-report-economic-well-being-us-households-202305.pdf

Borrell-Carrió, F., Suchman, A. L., & Epstein, R. M. (2004). The biopsychosocial model 25 years later: Principles, practice, and scientific inquiry. *Annals of Family Medicine, 2*(6), 576-582. https://doi.org/10.1370/afm.245

Bottazzi, L., Jappelli, T., & Padula, M. (2006). Retirement expectations, pension reforms, and their impact on private wealth accumulation. *Journal of Public Economics, 90*(12), 2187-2212. https://doi.org/10.1016/j.jpubeco.2006.03.005

Bronfenbrenner, Urie. (1994). Ecological models of human development. International Encyclopedia of education, 3(2), 37-43. https://www.ncj.nl/wp-content/uploads/media-import/docs/6a45c1a4-82ad-4f69-957e-1c76966678e2.pdf

Brown, T. A. (2015). *Confirmatory factor analysis for applied research* (2nd ed.). Guilford Publications.

Brüggen, E. C., Hogreve, J., Holmlund, M., Kabadayi, S., & Löfgren, M. (2017). Financial well-being: A conceptualization and research agenda. *Journal of Business Research, 79*, 228–237. https://doi.org/10.1016/j.jbusres.2017.03.013

Carroll, J. B. (1993). H*uman cognitive abilities: A survey of factor-analytic studies.* Cambridge University Press.

Chen, R., Chen, G., & Yu, M. (2023). A generalizability score for aggregate causal effect. *Biostatistics*, *24*(2), 309-326. https://doi.org/10.1093/biostatistics/kxab029

Chen, F. F., West, S. G., & Sousa, K. H. (2006). A comparison of bifactor and second-order models of quality of life. *Multivariate Behavioral Research*, *41*(2), 189–225. https://doi.org/10.1207/s15327906mbr4102_5

Cheung, M. (2021). Meta-analytic structural equation modeling. In *Oxford Research Encyclopedia of Business and Management*. https://doi.org/10.1093/acrefore/9780190224851.013.225

Claxton, G., Rae, M., Panchal, N., Damico, A., Whitmore, H., Foster, G., & Broaddus, M. (2022). *2022 employer health benefits survey*. Kaiser Family Foundation. https://files.kff.org/attachment/Report-Employer-Health-Benefits-Annual-Survey-2022.pdf

Collinge, A. N., & Bath, P. A. (2023). Socioeconomic background and self-reported sleep quality in older adults during the COVID-19 pandemic: An analysis of the English longitudinal study of ageing (ELSA). *International Journal of Environmental Research and Public Health, 20*(5), 4534. https://doi.org/10.3390/ijerph20054534

Council for Economic Education. (2022). *Survey of the states: Economic and personal finance education in our nation's schools 2022*. https://www.councilforeconed.org/survey-of-the-states-2022/

Desilver, D. (2018, August 7). For most U.S. workers, real wages have barely budged in decades. *Pew Research Center*. https://www.pewresearch.org/fact-tank/2018/08/07/for-most-us-workers-real-wages-have-barely-budged-for-decades/

Despard, M. R., Friedline, T., & Martin-West, S. (2020). Why do households lack emergency savings? The role of financial capability. *Journal of Family and Economic Issues, 41*(3), 542-557. https://doi.org/10.1007/s10834-020-09679-8

Diener, E., Oishi, S., & Tay, L. (2018). Advances in subjective well-being research. *Nature Human Behaviour, 2*(4), 253–260. https://doi.org/10.1038/s41562-018-0307-6

Dumontet, M., Henchoz, Y., & Santos-Eggimann, B. (2024). Do financial hardships affect health? A study among older adults in Switzerland. *European Journal of Public Health, 34*(1), 7-13. https://doi.org/10.1093/eurpub/ckad202

Engel, G. L. (1977). The need for a new medical model: a challenge for biomedicine. *Science, 196*(4286), 129-136. https://doi.org/10.1126/science.847460

Federal Reserve Bank of New York. (2022). *Quarterly report on household debt and credit.* https://www.newyorkfed.org/microeconomics/hhdc

Fiori, K. L., Windsor, T. D., & Huxhold, O. (2020). The increasing importance of friendship in late life: Understanding the role of sociohistorical context in social development. *Gerontology, 66*(3), 286–294. https://doi.org/10.1159/000505547

Fontenot, K., Semega, J., & Kollar, M. (2021). *Income and poverty in the United States: 2020.* United States Census Bureau. https://www.census.gov/library/publications/2021/demo/p60-273.html

Friedline, T., & West, S. (2016). Financial education is not enough: Millennials may need financial capability to demonstrate healthier financial behaviors. *Journal of Family and Economic Issues, 37*(4), 649-671. https://doi.org/10.1007/s10834-015-9475-y

Friedline, T., Masa, R. D., & Chowa, G. A. N. (2015). Transforming wealth: Using the inverse hyperbolic sine (IHS) and splines to predict youth's math achievement. *Social Science Research, 49*, 264–287. https://doi.org/10.1016/j.ssresearch.2014.08.018

Friedman, Z. (2022, June 14). Student loan debt statistics in 2022: A record $1.75 trillion. *Forbes.* https://www.forbes.com/sites/zackfriedman/2022/05/16/student-loan-debt-statistics-in-2022-a-record-17-trillion/?sh=3db96bba4d5a

Fuller, H. R., Ajrouch, K. J., & Antonucci, T. C. (2020). The convoy model and later-life family relationships. *Journal of Family Theory & Review, 12*(2), 126-146. https://doi.org/10.1111/jftr.12376

Garrett, S., & James, R. (2013). Financial ratios and perceived household financial satisfaction. *Journal of Financial Therapy*, *4*(1). https://doi.org/10.4148/jft.v4i1.1839

Garnett, A., Ploeg, J., Markle-Reid, M., & Strachan, P. H. (2018). Self-management of multiple chronic conditions by community-dwelling older adults: A concept analysis. *SAGE Open Nursing, 4*, 2377960817752471. https://doi.org/10.1177/2377960817752471

Gatchel, R. J., McGeary, D. D., McGeary, C. A., & Lippe, B. (2014). Interdisciplinary chronic pain management: Past, present, and future. *American Psychologist, 69*(2), 119–130. https://doi.org/10.1037/a0035514

Greninger, S. A., Hampton, V. L., Kitt, K. A., & Achacoso, J. A. (1996). Ratios and benchmarks for measuring the financial well-being of families and individuals. *Financial Services Review, 5*(1), 57–70. https://doi.org/10.1016/S1057-0810(96)90027-X

Hanson, M. (2022, August 12). Student loan debt by age and state 2022. *EducationData.org.* https://educationdata.org/student-loan-debt-by-age

Hastings, J., & Mitchell, O. S. (2020). How financial literacy and impatience shape retirement wealth and investment behaviors. *Journal of Pension Economics & Finance, 19*(1), 1-20. https://doi.org/10.1017/S1474747218000227

Henager, R., & Cude, B. J. (2016). Financial literacy and long- and short-term financial behavior in different age groups. *Journal of Financial Counseling and Planning*, *27*(1), 3–19. https://doi.org/10.1891/1052-3073.27.1.3

Hira, T., & Mugenda, O. (1998). Predictors of financial satisfaction: Differences between retirees and non-retirees. *Financial Counseling and Planning*, *9*, 75–83.

Holt-Lunstad, J. (2022). Social connection as a public health issue: The evidence and a systemic framework for prioritizing the "social" in social determinants of health. *Annual Review of Public Health, 43*, 193-213. https://doi.org/10.1146/annurev-publhealth-052020-110732

Hsu, J. W., & Willis, R. (2013). Dementia risk and financial decision making by older households: The impact of information. *Journal of Human Capital, 7*(4), 340-377. https://doi.org/10.1086/674105

Huxhold, O., Miche, M., & Schüz, B. (2014). Benefits of having friends in older ages: Differential effects of informal social activities on well-being in middle-aged and older adults. *The Journals of Gerontology: Series B*, *69*(3), 366–375. https://doi.org/10.1093/geronb/gbt029

Jessen-Howard, S., Malik, R., Workman, S., & Hamm, K. (2018). *Understanding infant and toddler child care deserts.* Center for American Progress. https://www.americanprogress.org/article/understanding-infant-toddler-child-care-deserts/

Kim, J., Garman, E. T., & Sorhaindo, B. (2003). Relationships among credit counseling clients' financial wellbeing, financial behaviors, financial stressor events, and health. *Journal of Financial Counseling and planning*, *14*(2). Available at SSRN: https://ssrn.com/abstract=2265623

Kim, H., & Lyons, A. C. (2008). No pain, no strain: Impact of health on the financial security of older Americans. *Journal of Consumer Affairs*, *42*(1), 9–36. https://doi.org/10.1111/j.1745-6606.2007.00092.x

Kline, R. B. (2016). *Principles and practice of structural equation modeling* (4th ed.). Guilford Press.

Krajbich, I., Bartling, B., Hare, T., & Fehr, E. (2015). Rethinking fast and slow based on a critique of reaction-time reverse inference. *Nature Communications, 6*(1), 7455. https://doi.org/10.1038/ncomms8455.

Lee, Y. G. (2018). Financial status and body mass index of middle-aged and older men and women. *Journal of Financial Counseling and Planning*, *29*(1), 19–35. https://doi.org/10.1891/1052-3073.29.1.19

Lee, J. M., & Kim, K. T. (2016). The role of propensity to plan on retirement savings and asset accumulation. *Family and Consumer Sciences Research Journal*, *45*(1), 34–48. https://doi.org/10.1111/fcsr.12179

Leung, A. Y., Parial, L. L. B., Szeto, S. S., & Koduah, A. O. (2022). Understanding the role of financial health literacy in midlife and old age: A scoping review. *Health & Social Care in the Community, 30*(6), e3921-e3933.https://doi.org/10.1111/hsc.14101

Little, T., Preacher, K., Selig, J., & Card, N. (2007). New developments in latent variable panel analyses of longitudinal data. *International Journal of Behavioral Development, 31*(4), 357 - 365. https://doi.org/10.1177/0165025407077757.

Ma, J., Pender, M., & Libassi, C.J. (2022). *Trends in college pricing and student aid 2022.* College Board. https://research.collegeboard.org/media/pdf/trends-in-college-pricing-student-aid-2022.pdf

Maccallum, R., & Austin, J. (2000). Applications of structural equation modeling in psychological research. *Annual Review of Psychology, 51*, 201-26 . https://doi.org/10.1146/ANNUREV.PSYCH.51.1.201.

Marsh, H. W., & Hocevar, D. (1985). Application of confirmatory factor analysis to the study of self-concept: First- and higher order factor models and their invariance across groups. *Psychological Bulletin, 97*(3), 562–582. https://doi.org/10.1037/0033-2909.97.3.562

McNeish, D. and Hamaker, E. L. (2020). A primer on two-level dynamic structural equation models for intensive longitudinal data in Mplus. *Psychological Methods, 25*(5), 610-635. https://doi.org/10.1037/met0000250

Medeiros, R. (2016). *Handling missing data in Stata: Imputation and likelihood-based approaches* [Conference presentation]. Swiss Stata Users Group Meeting, Bern, Switzerland.

Mehtre, V. (2019). Newton Raphson single and multiple variable methods to obtain the solutions of linear and non-linear equations. *International Journal for Research in Applied Science and Engineering Technology, 7*(11), 926-929. https://doi.org/10.22214/ijraset.2019.11156

Mezza, A., Ringo, D., Sherlund, S., & Sommer, K. (2020). Student loans and homeownership. *Journal of Labor Economics*, *38*(1), 215–260. https://doi.org/10.1086/704609

Naito, R., Leong, D. P., Bangdiwala, S. I., McKee, M., Subramanian, S. V., Rangarajan, S., ... & Yusuf, S. (2021). Impact of social isolation on mortality and morbidity in 20 high-income, middle-income and low-income countries in five continents. *BMJ global health, 6*(3), e004124. https://doi.org/10.1136/bmjgh-2020-004124

Netemeyer, R. G., Warmath, D., Fernandes, D., & Lynch, J. G. (2018). How am I doing? Perceived financial well-being, its potential antecedents, and its relation to overall well-being. *Journal of Consumer Research*, *45*(1), 68–89. https://doi.org/10.1093/jcr/ucx109

Nettleton, S., & Burrows, R. (2001). Families coping with the experience of mortgage repossession in the “new landscape of precariousness.” *Community, Work & Family*, *4*(3), 253–272. https://doi.org/10.1080/01405110120089332

O'Connor, B. P. (1995). Family and friend relationships among older and younger adults: Interaction motivation, mood, and quality. *The International Journal of Aging & Human Development*, *40*(1), 9–29. https://doi.org/10.2190/B37N-K317-KY8Q-0TNW

OpenLearn. (2020). *Exploring the relationship between anxiety and depression*. https://www.open.edu/openlearn/science-maths-technology/exploring-the-relationship-between-anxiety-and-depression/content-section-0

Pak, T.-Y., & Fan, L. (2022). Childhood experience of parental affection and financial well-being in later life: Evidence from the Health and Retirement Study. *Journal of Consumer Affairs*, *56*(4), 1433–1453. https://doi.org/10.1111/joca.12463

Porter, N. M., & Garman, E. T. (1992). Money as part of a measure of financial well-being. *American Behavioral Scientist*, *35*(6), 820–826. https://doi.org/10.1177/0002764292035006016

Powers, M. A., Bardsley, J., Cypress, M., Duker, P., Funnell, M. M., Fischl, A. H., Maryniuk, M. D., Siminerio, L., & Vivian, E. (2017). Diabetes self-management education and support in type 2 diabetes: A joint position statement. *The Diabetes Educator*, *43*(1), 40–53. https://doi.org/10.1177/0145721716689694

Prawitz, A. D., Garman, E. T., Sorhaindo, B., O'Neill, B., Kim, J., & Drentea, P. (2006). InCharge financial distress/financial well-being scale: Development, administration, and score interpretation. *Financial Counseling and Planning*, *17*(1), 34–50. https://doi.org/10.1037/t60365-000

RAND Center for the Study of Aging. (2023). *RAND HRS longitudinal file 2020 (V1)* [Data set]. https://www.rand.org/labor/aging/dataprod/hrs-data.html

Richard, P., Patel, N., Lu, Y.-C., & Alexandre, P. (2018). Self-reported health status and medical debt. *Journal of Financial Counseling and Planning*, *29*(1), 36–44. https://doi.org/10.1891/1052-3073.29.1.36

Rindskopf, D., & Rose, T. (1988). Some theory and applications of confirmatory second-order factor analysis. *Multivariate Behavioral Research*, *23*(1), 51–67. https://doi.org/10.1207/s15327906mbr2301_3

Roll, S., Kondratjeva, O., & Grinstein-Weiss, M. (2019). *Financial well-being: Measuring financial perceptions and experiences in low- and moderate-income households*. Social Policy Institute, Washington University in St. Louis. https://policycommons.net/artifacts/4144695/financial-well-being/4952702/

Rook, K. S. (2015). Social networks in later life: Weighing positive and negative effects on health and well-being. *Current Directions in Psychological Science, 24*(1), 45–51. https://doi.org/10.1177/0963721414551364

Ryff, C. D. (1989). Happiness is everything, or is it? Explorations on the meaning of psychological well-being. *Journal of Personality and Social Psychology*, *57*(6), 1069–1081. https://doi.org/10.1037/0022-3514.57.6.1069

Salignac, F., Hamilton, M., Noone, J., Marjolin, A., & Muir, K. (2020). Conceptualizing financial wellbeing: An ecological life-course approach. *Journal of Happiness Studies*, *21*(5), 1581–1602. https://doi.org/10.1007/s10902-019-00145-3

Serido, J., Shim, S., Mishra, A., & Tang, C. (2010). Financial parenting, financial coping behaviors, and well-being of emerging adults. *Family Relations*, *59*(4), 453–464. https://doi.org/10.1111/j.1741-3729.2010.00615.x

Singh, C., & Khamba, J. (2019). Structural equation modeling. In V. Zeigler-Hill & T. K. Shackelford (Eds.), *Encyclopedia of personality and individual differences*. Springer. https://doi.org/10.1201/9780429486302-7.

Skewes, M. C., & Gonzalez, V. M. (2013). The biopsychosocial model of addiction. In P. M. Miller (Ed.), *Principles of addiction* (pp. 61–70). Academic Press. https://doi.org/10.1016/B978-0-12-398336-7.00006-1

Skinner, M. A., Zautra, A. J., & Reich, J. W. (2004). Financial stress predictors and the emotional and physical health of chronic pain patients. *Cognitive Therapy and Research*, *28*(5), 695–713. https://doi.org/10.1023/B:COTR.0000045572.33750.6c

Smith, J., Ryan, L., Larkina, M., Sonnega, A., & Weir, D. (2023). *HRS 2006-2022 SAQ user guide* (Core Section LB). Institute for Social Research, University of Michigan. https://hrs.isr.umich.edu/sites/default/files/biblio/HRS%202006-2022%20SAQ%20User%20Guide.pdf

Souza, L., Castelani, E., Shirabayashi, W., Filho, A., & Machado, R. (2018). Trusses nonlinear problems solution with numerical methods of cubic convergence order. *TEMA*, *19*(1), 161–172. https://doi.org/10.5540/tema.2018.019.01.161

StataCorp. (2021). *Stata structural equation modeling reference manual* (Version 17). StataCorp LLC. https://www.stata.com/manuals/sem.pdf

Stenholm, S., Pentti, J., Kawachi, I., Westerlund, H., Kivimäki, M., & Vahtera, J. (2014). Self-rated health in the last 12 years of life compared to matched surviving controls: The Health and Retirement Study. *PLOS ONE*, *9*(9), e107879. https://doi.org/10.1371/journal.pone.0107879

Suls, J., & Rothman, A. (2004). Evolution of the biopsychosocial model: Prospects and challenges for health psychology. *Health Psychology*, *23*(2), 119–125. https://doi.org/10.1037/0278-6133.23.2.119

Tenney, J. A., & Kalenkoski, C. M. (2019). Financial ratios and financial satisfaction: Exploring associations between objective and subjective measures of financial well-being among older Americans. *Journal of Financial Counseling and Planning*, *30*(2), 231–243. https://doi.org/10.1891/1052-3073.30.2.231

Tharp, D. T. (2017). *Three essays on personality characteristics and financial satisfaction* [Doctoral dissertation, Kansas State University]. K-State Research Exchange. http://hdl.handle.net/2097/38235

Tharp, D. T., Seay, M. C., Carswell, A. T., & MacDonald, M. (2020). Big Five personality traits, dispositional affect, and financial satisfaction among older adults. *Personality and Individual Differences*, *166*, Article 110211. https://doi.org/10.1016/j.paid.2020.110211

Tomarken, A. J., & Waller, N. G. (2005). Structural equation modeling: Strengths, limitations, and misconceptions. *Annual Review of Clinical Psychology*, *1*, 31–65. https://doi.org/10.1146/annurev.clinpsy.1.102803.144239

Uchino, B. N., Trettevik, R., Kent de Grey, R. G., Cronan, S., Hogan, J., & Baucom, B. R. (2018). Social support, social integration, and inflammatory cytokines: A meta-analysis. *Health Psychology*, *37*(5), 462–471. https://doi.org/10.1037/hea0000594

Vosloo, W. (2014). The relationship between financial efficacy, satisfaction with remuneration and personal financial well-being [Thesis]. https://repository.nwu.ac.za/handle/10394/13455

Vosloo, W. (2014). *The relationship between financial efficacy, satisfaction with remuneration and personal financial well-being* [Master's thesis, North-West University]. NWU Institutional Repository. https://repository.nwu.ac.za/handle/10394/13455

Wilkinson, L. R. (2016). Financial strain and mental health among older adults during the Great Recession. *The Journals of Gerontology: Series B*, *71*(4), 745–754. https://doi.org/10.1093/geronb/gbw001

Wooldridge, J. M. (2020). *Introductory econometrics: A modern approach* (7th ed.). Cengage.

Xiao, J. J., & O'Neill, B. (2016). Consumer financial education and financial capability. *International Journal of Consumer Studies*, *40*(6), 712–721. https://doi.org/10.1111/ijcs.12285

Xiao, J. J., & O'Neill, B. (2018). Propensity to plan, financial capability, and financial satisfaction. *International Journal of Consumer Studies*, *42*(5), 501–512. https://doi.org/10.1111/ijcs.12461

Yeo, J., Lee, Y. G., & Kim, J. (2019). Understanding the association between perceived financial well-being and life satisfaction among older adults: Does social capital play a role? *Journal of Family and Economic Issues*, *40*(4), 592–608. https://doi.org/10.1007/s10834-019-09634-2

Yong, A. G., & Pearce, S. (2013). A beginner's guide to factor analysis: Focusing on exploratory factor analysis. *Tutorials in Quantitative Methods for Psychology*, *9*(2), 79–94. https://doi.org/10.20982/tqmp.09.2.p079

Zurlo, K. A. (2009). *Personal attributes and the financial well-being of older adults: The effects of control beliefs* [Doctoral dissertation, University of Pennsylvania]. ScholarlyCommons. https://repository.upenn.edu/handle/20.500.14332/42317

Appendix A: Variable Cleaning & Analysis Coding

Variable Cleaning

```
/****************************************************************************
*Title: dissertation.do
*Created by: Chet Bennetts
*Created on: 12/21/2023
*Last modified on: 03/23/2024
*Last modified by: Chet Bennetts
*Purpose: Imports and cleans variables from HRS (2010-2020)
****************************************************************************/

clear all

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

global projdir "C:\Users\crben\Dropbox\Grad\KSU\0-Dissertation\data"
	cd "$projdir"
global data_ed "${projdir}\edited"
global data_raw "${projdir}\raw"

*===========================================================================
*Define locals
*===========================================================================

*local waves "m n o p q r"
local years "10 12 14 16 18"

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

use hhid pn hhidpn /*Control Variables*/ ragender raracem rahispan ravetrn raedyrs raedegrm
raeduc r10mstat r11mstat r12mstat r13mstat r14mstat r10mpart r11mpart r12mpart r13mpart
r14mpart r10work r11work r12work r13work r14work r10lbrf r11lbrf r12lbrf r13lbrf r14lbrf
r10sayret r11sayret r12sayret r13sayret r14sayret r10higov r11higov r12higov r13higov r14higov
r10prpcnt r11prpcnt r12prpcnt r13prpcnt r14prpcnt r10covr r11covr r12covr r13covr r14covr
r10hiothp r11hiothp r12hiothp r13hiothp r14hiothp r10agey_b r11agey_b r12agey_b r13agey_b
r14agey_b /*Objective FWB*/ h10itot h11itot h12itot h13itot h14itot *10ipena *11ipena
*12ipena *13ipena *14ipena *10ipen *11ipen *12ipen *13ipen *14ipen *10iann *11iann
*12iann *13iann *14iann *10issdi *11issdi *12issdi *13issdi *14issdi *10isret *11isret *12isret
*13isret *14isret *10iunwc *11iunwc *12iunwc *13iunwc *14iunwc *10igxfr *11igxfr *12igxfr
```

```
*13igxfr *14igxfr h10iothr h11iothr h12iothr h13iothr h14iothr h10inpov h11inpov h12inpov
h13inpov h14inpov h10inpova h11inpova h12inpova h13inpova h14inpova h10inpvra h11inpvra
h12inpvra h13inpvra h14inpvra h10inpovr h11inpovr h12inpovr h13inpovr h14inpovr h10povhhi
h11povhhi h12povhhi h13povhhi h14povhhi h10atotf h11atotf h12atotf h13atotf h14atotf
h10atotb h11atotb h12atotb h13atotb h14atotb h10adebt h11adebt h12adebt h13adebt h14adebt
h10atotw h11atotw h12atotw h13atotw h14atotw h10atotn h11atotn h12atotn h13atotn h14atotn
h10adebt h11adebt h12adebt h13adebt h14adebt h10atoth h11atoth h12atoth h13atoth h14atoth
/*Self-Reported Health Status*/ r10shlt r11shlt r12shlt r13shlt r14shlt /*BMI*/ r10bmi r11bmi
r12bmi r13bmi r14bmi /*Chronic Illness*/ r10conde r11conde r12conde r13conde r14conde
r10hibpe r11hibpe r12hibpe r13hibpe r14hibpe r10diabe r11diabe r12diabe r13diabe r14diabe
r10cancre r11cancre r12cancre r13cancre r14cancre r10lunge r11lunge r12lunge r13lunge
r14lunge r10hearte r11hearte r12hearte r13hearte r14hearte r10stroke r11stroke r12stroke
r13stroke r14stroke r10psyche r11psyche r12psyche r13psyche r14psyche r10arthre r11arthre
r12arthre r13arthre r14arthre /*Functional Limitation*/ r10dress r11dress r12dress r13dress
r14dress r10walkr r11walkr r12walkr r13walkr r14walkr r10bath r11bath r12bath r13bath
r14bath r10eat r11eat r12eat r13eat r14eat r10bed r11bed r12bed r13bed r14bed r10toilt r11toilt
r12toilt r13toilt r14toilt /*Life Satisfaction*/ r10lbsatwlf r11lbsatwlf r12lbsatwlf r13lbsatwlf
r14lbsatwlf /***components of r`i'lbsatwlf*** r10lbsathome r11lbsathome r12lbsathome
r13lbsathome r14lbsathome r10lbsatcity r11lbsatcity r12lbsatcity r13lbsatcity r14lbsatcity
r10lbsatleisure r11lbsatleisure r12lbsatleisure r13lbsatleisure r14lbsatleisure r10lbsatfam
r11lbsatfam r12lbsatfam r13lbsatfam r14lbsatfam r10lbsatfin r11lbsatfin r12lbsatfin r13lbsatfin
r14lbsatfin r10lbsatinc r11lbsatinc r12lbsatinc r13lbsatinc r14lbsatinc r10lbsathlth r11lbsathlth
r12lbsathlth r13lbsathlth r14lbsathlth r10lbsatlife r11lbsatlife r12-r14lbsatlife not in RAND*/
/*Depressive Symptoms*/ r10cesd r11cesd r12cesd r13cesd r14cesd r10depres r11depres
r12depres r13depres r14depres r10effort r11effort r12effort r13effort r14effort r10going
r11going r12going r13going r14going r10enlife r11enlife r12enlife r13enlife r14enlife
r10whappy r11whappy r12whappy r13whappy r14whappy r10flone r11flone r12flone r13flone
r14flone r10sleepr r11sleepr r12sleepr r13sleepr r14sleepr r10fsad r11fsad r12fsad r13fsad
r14fsad using "${data_raw}\randhrs1992_2020v1.dta", clear

/***Creating/cleaning/naming of fixed vars***/
	/*Control Variables*/
		***Education***
		gen educ = .
		  replace educ = 0 if raedegrm == 0			/*No HS Grad*/
		  replace educ = 0 if raedegrm == 1			/*GED*/
		  replace educ = 0 if raedegrm == 2			/*HS Grad*/
		  replace educ = 0 if raedegrm == 3 & raeduc == 3	/*HS Grad*/
		  replace educ = 1 if raedegrm == 3 & raeduc == 4	/*Some College*/
		  replace educ = 1 if raedegrm == 4 & raeduc == 4	/*Some College*/
		  replace educ = 1 if raedegrm == 5			/*Bachelors*/
		  replace educ = 1 if raedegrm > 5			/*Grad Degree*/
			label variable educ "Education"
			label define educ 0 "HS or Less" 1 "Some College or More"
			label values educ educ
		***Education Categories***
```

```
gen educ_cat = .
  replace educ_cat = 1 if raedegrm == 0                    /*No HS Grad*/
  replace educ_cat = 2 if raedegrm == 1                    /*GED*/
  replace educ_cat = 3 if raedegrm == 2                    /*HS Grad*/
  replace educ_cat = 3 if raedegrm == 3 & raeduc == 3       /*HS Grad*/
  replace educ_cat = 4 if raedegrm == 3 & raeduc == 4      /*Some College*/
  replace educ_cat = 4 if raedegrm == 4 & raeduc == 4      /*Some College*/
  replace educ_cat = 5 if raedegrm == 5                    /*Bachelors*/
  replace educ_cat = 6 if raedegrm > 5                     /*Grad Degree*/
        label variable educ_cat "Education"
        label define educ_cat 1 "No HS Grad" 2 "GED" 3 "HS Grad" 4 "Some
College" 5 "Bachelors" 6 "Grad Degree"
        label values educ_cat educ_cat

***Label Gender***
label variable ragender "Gender"
label define ragender 1 "Male" 2 "Female"
label values ragender ragender

***Label Race***
label variable raracem "Race"
label define raracem 1 "White" 2 "Black" 3 "Other"
label values raracem raracem

***Label Ethnicity***
label variable rahispan "Race"
label define rahispan 0 "Not Hispanic" 1 "Hispanic"
label values rahispan rahispan

***Create and Label Race/Eth***
gen r_race_eth = .
  replace r_race_eth = 1 if raracem == 1 & rahispan == 0    /*White, NH*/
  replace r_race_eth = 2 if raracem == 1 & rahispan == 1    /*White, Hispanic*/
  replace r_race_eth = 3 if raracem == 2 & rahispan == 0    /*Black, NH*/
  replace r_race_eth = 4 if raracem == 2 & rahispan == 1    /*Black, Hispanic*/
  replace r_race_eth = 5 if raracem == 3 & rahispan == 0    /*Other, NH*/
  replace r_race_eth = 6 if raracem == 3 & rahispan == 1    /*Other, Hispanic*/
        label variable r_race_eth "Race and Ethnicity"
        label define r_race_eth 1 "White, NH" 2 "White, Hisp" 3 "Black, NH" 4
"Black, Hisp" 5 "Other, NH" 6 "Other, Hisp"
        label values r_race_eth r_race_eth

/***Creating/cleaning/naming of YYYY specific vars***/
    /*Beginning of looping routine*/
    local i = 8                 /*Variation to account for wave/year in Core*/
    local w = 9                 /*Variation to account for wave/year in RAND*/
```

```
	foreach y in `years' {
		local i = `i' + 2
		local w = `w' + 1


	/*Control Variables*/
		***Rename Age***
		rename r`w'agey_b r`i'age

		***Marital Status***
		gen r`i'marstat = .
		  replace r`i'marstat = 0 if r`w'mstat != 1 & r`w'mstat != .
		  replace r`i'marstat = 0 if r`w'mstat != 3 & r`w'mstat != .
		  replace r`i'marstat = 1 if r`w'mstat == 1 | r`w'mstat == 3
		  replace r`i'marstat = . if r`w'mstat == .m
			label variable r`i'marstat "Coupled Household Status"
			label define r`i'marstat 0 "Married/Partnered Household" 1 "Non-
Married/Partnered Household"
			label values r`i'marstat r`i'marstat

		***Marital Status Categories***
		gen r`i'marstat_cat = .
		  replace r`i'marstat_cat = 1 if r`w'mstat < 3			/*Married*/
		  replace r`i'marstat_cat = 2 if r`w'mstat == 3			/*Partnered*/
		  replace r`i'marstat_cat = 3 if inrange(r`w'mstat,4,6)	/*Separated/Divorced*/
		  replace r`i'marstat_cat = 4 if r`w'mstat == 7			/*Widowed*/
		  replace r`i'marstat_cat = 5 if r`w'mstat == 8			/*Never Married*/
			label variable r`i'marstat_cat "Marital Status Categories"
			label define r`i'marstat_cat 1 "Married" 2 "Partnered" 3
"Separated/Divorced" 4 "Widowed" 5 "Never Married"
			label values r`i'marstat_cat r`i'marstat_cat

	/*Objective FWB*/
		***Income and Assets***

		***Creating sum of household pension/annuities
		  egen h`i'ipena = rowtotal(r`w'ipena s`w'ipena), missing
			label variable h`i'ipena "Income from ER Pension or Annuity"

		***Creating bianary var of pension/annuities
		  gen h`i'ipena_b = 0
			replace h`i'ipena_b = 1 if h`i'ipena > 0
				label variable h`i'ipena_b "Has an ER Pension or Annuity"

		***Creating z-score normalization of income and assets***
		  egen z_h`i'HInc = std(h`w'itot)
```

```
        egen z_h`i'HAss = std(h`w'atotb)
        egen z_h`i'HNhAss = std(h`w'atotn)
        egen z_h`i'HNW = std(h`w'atotf)
        egen z_h`i'HNHoEq = std(h`w'atoth)

      ***Creating log of income and assets***
        generate l_h`i'HInc = log(h`w'itot + 1)
        generate l_h`i'HAss = log(h`w'atotb + 1)
        generate l_h`i'HNhAss = log(h`w'atotn + 1)
        generate l_h`i'HNW = log(h`w'atotf + 1)
        generate l_h`i'HNHoEq = log(h`w'atoth + 1)

      ***Generating debt-to-asset ratio***
        gen h`i'd2a = cond(h`w'atotb != 0 & !missing(h`w'atotb), h`w'adebt / h`w'atotb,
.)
      ***renaming RAND oFWB vars***
        gen h`i'HInc = h`w'itot
        gen h`i'HAss = h`w'atotb
        gen h`i'HNhAss = h`w'atotn
        gen h`i'HNW = h`w'atotf
        gen h`i'HNHoEq = h`w'atoth

  /*Biological [All vars...lower are better]*/
  ***Self-Reported Health Status (r`i'SRH)***
    gen r`i'SRH = .
      replace r`i'SRH = 1 if r`w'shlt == 1
      replace r`i'SRH = 2 if r`w'shlt == 2
      replace r`i'SRH = 3 if r`w'shlt == 3
      replace r`i'SRH = 4 if r`w'shlt == 4
      replace r`i'SRH = 5 if r`w'shlt == 5
        label variable r`i'SRH "Self-Reported Health"
        label define r`i'SRH 1 "Excellent" 2 "Very Good" 3 "Good" 4 "Fair" 5 "Poor"
        label values r`i'SRH r`i'SRH

  ***BMI Categories***
  *From CDC:
  *BMI              Weight Status
  *Below 18.5       Underweight
  *18.5 – 24.9   Healthy Weight
  *25.0 – 29.9   Overweight
  *30.0 +                   Obesity
    gen r`i'BMI_cat = .
      replace r`i'BMI_cat = 1 if r`w'bmi < 18.5                  /*Underweight*/
      replace r`i'BMI_cat = 2 if inrange(r`w'bmi,18.5,24.9)      /*Healthy Weight*/
      replace r`i'BMI_cat = 3 if inrange(r`w'bmi,25.0,29.9)      /*Overweight*/
      replace r`i'BMI_cat = 4 if r`w'bmi > 30.0                  /*Obese*/
```

```
                    label variable r`i'BMI_cat "BMI Categories"
                    label define r`i'BMI_cat 1 "Underweight" 2 "Healthy Weight" 3
"Overweight" 4 "Obese"
                    label values r`i'BMI_cat r`i'BMI_cat

    ***BMI Rename***
     gen r`i'BMI = r`w'bmi

    ***Chronic Illness (ChIL)***
     rename r`w'hibpe ChIl_`i'_1
     rename r`w'diabe ChIl_`i'_2
     rename r`w'cancre ChIl_`i'_3
     rename r`w'lunge ChIl_`i'_4
     rename r`w'hearte ChIl_`i'_5
     rename r`w'stroke ChIl_`i'_6
     rename r`w'psyche ChIl_`i'_7
     rename r`w'arthre ChIl_`i'_8

    ***Composite of ChIl***
    *Unlike funcitonal limitation (below), ChIl has composite already built in RAND*
     rename r`w'conde ChIl_`i'_r
          label variable ChIl_`i'_r "# of Chronic Illnesses(Rand)"

    *Built composite for robustness check*
    *First step gives the number of missing values in varlist for each observation
     egen ChIl_`i'_miss = rowmiss(ChIl_`i'_1 ChIl_`i'_2 ChIl_`i'_3 ChIl_`i'_4 ChIl_`i'_5
ChIl_`i'_6 ChIl_`i'_7 ChIl_`i'_8)
    *Second step creates 'sum' var as long at not all vals are missing
     egen ChIl_`i' = rowtotal(ChIl_`i'_1 ChIl_`i'_2 ChIl_`i'_3 ChIl_`i'_4 ChIl_`i'_5
ChIl_`i'_6 ChIl_`i'_7 ChIl_`i'_8) if ChIl_`i'_miss != 8
          label variable ChIl_`i' "# of Chronic Illnesses"

    ***Functional Limitation (FL)***
     gen FL_`i'_1 = .
          replace FL_`i'_1 = 0 if r`w'dress == 0
          replace FL_`i'_1 = 1 if inrange(r`w'dress,1,9)
     gen FL_`i'_2 = .
          replace FL_`i'_2 = 0 if r`w'walkr == 0
          replace FL_`i'_2 = 1 if inrange(r`w'walkr,1,9)
     gen FL_`i'_3 = .
          replace FL_`i'_3 = 0 if r`w'bath == 0
          replace FL_`i'_3 = 1 if inrange(r`w'bath,1,9)
     gen FL_`i'_4 = .
          replace FL_`i'_4 = 0 if r`w'eat == 0
          replace FL_`i'_4 = 1 if inrange(r`w'eat,1,9)
     gen FL_`i'_5 = .
```

```
            replace FL_`i'_5 = 0 if r`w'bed == 0
            replace FL_`i'_5 = 1 if inrange(r`w'bed, 1,9)
      gen FL_`i'_6 = .
            replace FL_`i'_6 = 0 if r`w'toilt == 0
            replace FL_`i'_6 = 1 if inrange(r`w'toilt,1,9)
    ***Composite of FL***
    *First step gives the number of missing values in varlist for each observation
      egen FL_`i'_miss = rowmiss(FL_`i'_1 FL_`i'_2 FL_`i'_3 FL_`i'_4 FL_`i'_5 FL_`i'_6)
    *Second step creates 'sum' var as long at not all vals are missing
      egen FL_`i' = rowtotal(FL_`i'_1 FL_`i'_2 FL_`i'_3 FL_`i'_4 FL_`i'_5 FL_`i'_6) if
FL_`i'_miss != 6
            label variable FL_`i' "# of Functional Limitations"

    /*Psychological*/
    ***Life Satisfaction***
    *The RAND var is different than the Core vars*
      rename r`w'lbsatwlf LS_`i'_r

    ***Depressive Symptoms (DS)***
      gen DS_`i'_1 = .
            replace DS_`i'_1 = 0 if r`w'depres == 0
            replace DS_`i'_1 = 1 if r`w'depres == 1
      gen DS_`i'_2 = .
            replace DS_`i'_2 = 0 if r`w'effort == 0
            replace DS_`i'_2 = 1 if r`w'effort == 1
     gen DS_`i'_3 = .
            replace DS_`i'_3 = 0 if r`w'going == 0
            replace DS_`i'_3 = 1 if r`w'going == 1
      gen DS_`i'_4 = .
            replace DS_`i'_4 = 0 if r`w'enlife == 0
            replace DS_`i'_4 = 1 if r`w'enlife == 1
      gen DS_`i'_5 = .
            replace DS_`i'_5 = 0 if r`w'whappy == 0
            replace DS_`i'_5 = 1 if r`w'whappy == 1
      gen DS_`i'_6 = .
            replace DS_`i'_6 = 0 if r`w'flone == 0
            replace DS_`i'_6 = 1 if r`w'flone == 1
      gen DS_`i'_7 = .
            replace DS_`i'_7 = 0 if r`w'sleepr == 0
            replace DS_`i'_7 = 1 if r`w'sleepr == 1
      gen DS_`i'_8 = .
            replace DS_`i'_8 = 0 if r`w'fsad == 0
            replace DS_`i'_8 = 1 if r`w'fsad == 1

    ***Composite of DS***
    *First step gives the number of missing values in varlist for each observation
```

```
            egen DS_`i'_miss = rowmiss(DS_`i'_1 DS_`i'_2 DS_`i'_3 DS_`i'_4 DS_`i'_5 DS_`i'_6
DS_`i'_7 DS_`i'_8)
          *Second step creates 'sum' var as long at not all vals are missing
            egen DS_`i' = rowtotal(DS_`i'_1 DS_`i'_2 DS_`i'_3 DS_`i'_4 DS_`i'_5 DS_`i'_6
DS_`i'_7 DS_`i'_8) if DS_`i'_miss != 8
                  label variable DS_`i' "# of Depressive Symptoms"
                  }

tempfile rand
save "${data_ed}\rand.2.dta", replace
save `rand', replace

*=====================================================================
*=====================================================================
*Import fat file data
*=====================================================================
*=====================================================================

*2010 (m)

          use hhid hhidpn pn /*Control Variables*/ ma019 mb014 /*Subjective FWB*/ mlb040
mlb039e /*Functinal Limitation*/ mg014 mg016 mg021 mg023 mg025 mg030 /*Life
Satisfaction*/ mlb003a mlb003b mlb003c mlb003d mlb003e /*Depressive Symptoms*/ md110
md111 md117 md115 md113 md114 md112 md116 /*Anxiety Symptoms*/ mlb041a mlb041b
mlb041c mlb041d mlb041e /*Partner/Spouse Closeness*/ mlb006 /*Partner/Spouse Relationship
Quality*/ mlb005a mlb005b mlb005c mlb005d mlb005e mlb005f mlb005g /*Children Contact*/
mlb009a mlb009b mlb009c /*Children Relationship*/ mlb008a mlb008b mlb008c mlb008d
mlb008e mlb008f mlb008g /*Other Immediate Family Contact*/  mlb013a mlb013b mlb013c
/*Other Immediate Family Relationship Quality*/ mlb012a mlb012b mlb012c mlb012d mlb012e
mlb012f mlb012g /*Friend Contact*/ mlb017a mlb017b mlb017c /*Friend Relationship
Quality*/ mlb016a mlb016b mlb016c mlb016d mlb016e mlb016f mlb016g /*Partner/Spouse
Closeness*/ mlb006 /*Number of Close Relationships*/ mlb010 mlb014 mlb018 /*Veteran
Benefits-for future use*/ *q120 *q121 *q122 *q123 *q124 *q127 *q128 *q129 *q13* using
"${data_raw}\h10f.dta", clear

/*Financial Wellbeing*/
          /*Subjective FWB (sFWB)*/
                  ***reverse coding so that higher scores indicate a better situation
                  gen r_mlb039e = 6 - mlb039e
                  gen r_mlb040 = 6 - mlb040
                  gen sFWB_10_1 = 6 - mlb039e
                  gen sFWB_10_2 = 6 - mlb040

                  *generating composite score for msFWB
                  egen sFWB_10 = rowmean(sFWB_10_1 sFWB_10_2)
```

```
/*Psychological*/
	/*Life Satisfaction (LS)*/
	***r`i'lbsatwlf = "the higher the score, the higher the Respondent's self-assessed quality
of life"***
	  rename mlb003a LS_10_1
	  rename mlb003b LS_10_2
	  rename mlb003c LS_10_3
	  rename mlb003d LS_10_4
	  rename mlb003e LS_10_5
		egen LS_10_sum = rowtotal(LS_10_1 LS_10_2 LS_10_3 LS_10_4 LS_10_5),
missing
		egen LS_10_count = anycount(LS_10_1 LS_10_2 LS_10_3 LS_10_4 LS_10_5),
values(1/7)
		gen LS_10 = LS_10_sum / LS_10_count

	/*Anxiety Symptoms (AS)*/
	***Vars in years 2010, 2012, 2018***
	***Reverse coding so higher scores indicate lower anxiety***
	gen AS_10_1 = mlb041a
	  recode AS_10_1 (1=4)(2=3)(3=2)(4=1)
	gen AS_10_2 = mlb041b
	  recode AS_10_2 (1=4)(2=3)(3=2)(4=1)
	gen AS_10_3 = mlb041c
	  recode AS_10_3 (1=4)(2=3)(3=2)(4=1)
	gen AS_10_4 = mlb041d
	  recode AS_10_4 (1=4)(2=3)(3=2)(4=1)
	gen AS_10_5 = mlb041e
	  recode AS_10_5 (1=4)(2=3)(3=2)(4=1)

	egen AS_10_sum = rowtotal(AS_10_1 AS_10_2 AS_10_3 AS_10_4 AS_10_5), missing
	egen AS_10_count = anycount(AS_10_1 AS_10_2 AS_10_3 AS_10_4 AS_10_5),
values(1/4)
	gen AS_10 = AS_10_sum / AS_10_count

/*Sociological (Social Connection) (SC)*/
***Higher scores indicate higher levels of social connection***

	/*Partner/Spouse Closeness (PS)*/
	/*Partner/Spouse Closeness (PSc)*/
	***Only one var in 2010 & 2012. Three in 2014-2018***
	***Reverse coded***
	  gen PSc_10_1 = mlb006
		recode PSc_10_1 (1=4)(2=3)(3=2)(4=1)

	/*Partner/Spouse Relationship Quality (PSq)*/
	***mlb005a-c are reverse coded***
```

```
gen PSq_10_1 = mlb005a
        recode PSq_10_1 (1=4)(2=3)(3=2)(4=1)
gen PSq_10_2 = mlb005b
        recode PSq_10_2 (1=4)(2=3)(3=2)(4=1)
gen PSq_10_3 = mlb005c
        recode PSq_10_3 (1=4)(2=3)(3=2)(4=1)
gen PSq_10_4 = mlb005d
gen PSq_10_5 = mlb005e
gen PSq_10_6 = mlb005f
gen PSq_10_7 = mlb005g

egen PSq_10_sum = rowtotal(PSq_10_1 PSq_10_2 PSq_10_3 PSq_10_4 PSq_10_5
PSq_10_6 PSq_10_7), missing
egen PSq_10_count = anycount(PSq_10_1 PSq_10_2 PSq_10_3 PSq_10_4 PSq_10_5
PSq_10_6 PSq_10_7), values(1/4)
gen PSq_10 = PSq_10_sum / PSq_10_count

/*Children Relationships (Ch)*/
/*Children Contact (Chc)*/
***Three vars in 2010 & 2012. Four vars in 2014-2018***
***Reverse coded***
  gen Chc_10_1 = mlb009a
        recode Chc_10_1 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)
  gen Chc_10_2 = mlb009b
        recode Chc_10_2 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)
  gen Chc_10_3 = mlb009c
        recode Chc_10_3 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)

  egen Chc_10_sum = rowtotal(Chc_10_1 Chc_10_2 Chc_10_3), missing
  egen Chc_10_count = anycount(Chc_10_1 Chc_10_2 Chc_10_3), values(1/6)
  gen Chc_10 = Chc_10_sum / Chc_10_count

/*Children Relationship (Chr)*/
***mlb009a-c are reverse coded***
  gen Chr_10_1 = mlb008a
        recode Chr_10_1 (1=4)(2=3)(3=2)(4=1)
  gen Chr_10_2 = mlb008b
        recode Chr_10_2 (1=4)(2=3)(3=2)(4=1)
  gen Chr_10_3 = mlb008c
        recode Chr_10_3 (1=4)(2=3)(3=2)(4=1)
  gen Chr_10_4 = mlb008d
  gen Chr_10_5 = mlb008e
  gen Chr_10_6 = mlb008f
  gen Chr_10_7 = mlb008g
```

```
		egen Chr_10_sum = rowtotal(Chr_10_1 Chr_10_2 Chr_10_3 Chr_10_4 Chr_10_5 Chr_10_6 Chr_10_7), missing
		egen Chr_10_count = anycount(Chr_10_1 Chr_10_2 Chr_10_3 Chr_10_4 Chr_10_5 Chr_10_6 Chr_10_7), values(1/4)
		gen Chr_10 = Chr_10_sum / Chr_10_count

	/*Other Family Relationships (OFR)*/
	/*Other Immediate Family Contact (OFRc)*/
	***Three vars in 2010 & 2012. Four vars in 2014-2018***
	***Reverse coded***
		gen OFRc_10_1 = mlb013a
			recode OFRc_10_1 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)
		gen OFRc_10_2 = mlb013b
			recode OFRc_10_2 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)
		gen OFRc_10_3 = mlb013c
			recode OFRc_10_3 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)

		egen OFRc_10_sum = rowtotal(OFRc_10_1 OFRc_10_2 OFRc_10_3), missing
		egen OFRc_10_count = anycount(OFRc_10_1 OFRc_10_2 OFRc_10_3), values(1/6)
		gen OFRc_10 = OFRc_10_sum / OFRc_10_count

	/*Other Immediate Family Relationship Quality (OFRq)*/
	***mlb012a-c are reverse coded***
		gen OFRq_10_1 = mlb012a
			recode OFRq_10_1 (1=4)(2=3)(3=2)(4=1)
		gen OFRq_10_2 = mlb012b
			recode OFRq_10_2 (1=4)(2=3)(3=2)(4=1)
		gen OFRq_10_3 = mlb012c
			recode OFRq_10_3 (1=4)(2=3)(3=2)(4=1)
		gen OFRq_10_4 = mlb012d
		gen OFRq_10_5 = mlb012e
		gen OFRq_10_6 = mlb012f
		gen OFRq_10_7 = mlb012g

		egen OFRq_10_sum = rowtotal(OFRq_10_1 OFRq_10_2 OFRq_10_3 OFRq_10_4 OFRq_10_5 OFRq_10_6 OFRq_10_7), missing
		egen OFRq_10_count = anycount(OFRq_10_1 OFRq_10_2 OFRq_10_3 OFRq_10_4 OFRq_10_5 OFRq_10_6 OFRq_10_7), values(1/4)
		gen OFRq_10 = OFRq_10_sum / OFRq_10_count

	/*Friend Relationships (FR)*/
	/*Friend Contact (FRc)*/
	***Three vars in 2010 & 2012. Four vars in 2014-2018***
	***Reverse coded***
		gen FRc_10_1 = mlb017a
			recode FRc_10_1 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)
```

```
    gen FRc_10_2 = mlb017b
        recode FRc_10_2 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)
    gen FRc_10_3 = mlb017c
        recode FRc_10_3 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)

    egen FRc_10_sum = rowtotal(FRc_10_1 FRc_10_2 FRc_10_3), missing
    egen FRc_10_count = anycount(FRc_10_1 FRc_10_2 FRc_10_3), values(1/6)
    gen FRc_10 = FRc_10_sum / FRc_10_count

  /*Friend Relationship Quality (FRq)*/
  ***mlb012a-c are reverse coded***
    gen FRq_10_1 = mlb016a
        recode FRq_10_1 (1=4)(2=3)(3=2)(4=1)
    gen FRq_10_2 = mlb016b
        recode FRq_10_2 (1=4)(2=3)(3=2)(4=1)
    gen FRq_10_3 = mlb016c
        recode FRq_10_3 (1=4)(2=3)(3=2)(4=1)
    gen FRq_10_4 = mlb016d
    gen FRq_10_5 = mlb016e
    gen FRq_10_6 = mlb016f
    gen FRq_10_7 = mlb016g

    egen FRq_10_sum = rowtotal(FRq_10_1 FRq_10_2 FRq_10_3 FRq_10_4 FRq_10_5
FRq_10_6 FRq_10_7), missing
    egen FRq_10_count = anycount(FRq_10_1 FRq_10_2 FRq_10_3 FRq_10_4
FRq_10_5 FRq_10_6 FRq_10_7), values(1/4)
    gen FRq_10 = FRq_10_sum / FRq_10_count


  /*Closeness of Relationships (CoR)*/
  /*Partner/Spouse Closeness (CoRPS)*/
  ***Only one var in 2010 & 2012. Three in 2014-2018***
  ***Reverse coded***
    gen CoRPS_10_1 = mlb006
        recode CoRPS_10_1 (1=4)(2=3)(3=2)(4=1)

  /*Number of Close Relationships (CoRn)*/
  ***These are continuous but have wide range***
  ***Will need to do some sort of transformation***
    gen CoRn_10_1 = mlb010
        replace CoRn_10_1 = 1 if inrange(mlb010,1,2)
        replace CoRn_10_1 = 2 if inrange(mlb010,3,4)
        replace CoRn_10_1 = 3 if inrange(mlb010,5,9)
        replace CoRn_10_1 = 4 if inrange(mlb010,10,14)
        replace CoRn_10_1 = 5 if mlb010 > 14
        replace CoRn_10_1 = . if mlb010 == .
```

```
            label variable CoRn_10_1 "n Close Children Relationships"
            label define CoRn_10_1 0 "0" 1 "1-2" 2 "3-4" 3 "5-9" 4 "10-14" 5 "15+"
            label values CoRn_10_1 CoRn_10_1
    gen CoRn_10_2 = mlb014
        replace CoRn_10_2 = 1 if inrange(mlb014,1,2)
        replace CoRn_10_2 = 2 if inrange(mlb014,3,4)
        replace CoRn_10_2 = 3 if inrange(mlb014,5,9)
        replace CoRn_10_2 = 4 if inrange(mlb014,10,14)
        replace CoRn_10_2 = 5 if mlb014 > 14
        replace CoRn_10_2 = . if mlb014 == .
            label variable CoRn_10_2 "n Close Family Relationships"
            label define CoRn_10_2 0 "0" 1 "1-2" 2 "3-4" 3 "5-9" 4 "10-14" 5 "15+"
            label values CoRn_10_2 CoRn_10_2
    gen CoRn_10_3 = mlb018
        replace CoRn_10_3 = 1 if inrange(mlb018,1,2)
        replace CoRn_10_3 = 2 if inrange(mlb018,3,4)
        replace CoRn_10_3 = 3 if inrange(mlb018,5,9)
        replace CoRn_10_3 = 4 if inrange(mlb018,10,14)
        replace CoRn_10_3 = 5 if mlb018 > 14
        replace CoRn_10_3 = . if mlb018 == .
            label variable CoRn_10_3 "n Close Family Relationships"
            label define CoRn_10_3 0 "0" 1 "1-2" 2 "3-4" 3 "5-9" 4 "10-14" 5 "15+"
            label values CoRn_10_3 CoRn_10_3

    egen CoRn_10_sum = rowtotal(CoRn_10_1 CoRn_10_2 CoRn_10_3), missing
    egen CoRn_10_count = anycount(CoRn_10_1 CoRn_10_2 CoRn_10_3), values(0/5)
    gen CoRn_10 = CoRn_10_sum / CoRn_10_count

gen year = 2010
gen hhidpn_year = string(hhidpn,"%09.0f") + "_" + string(year,"%04.0f")
merge 1:1 hhidpn using "${data_ed}\rand.2.dta"

/*Depressive Symptoms*/
***"the higher the score, the more negative the Respondent's feelings in the past week"***
***as a result...have to reverse code
    gen temp = r10cesd + 1
    gen r_r10cesd = 10 - temp
    drop temp

keep if !missing(hhidpn_year)
keep /*RAND Vars*/ hhid hhidpn* year hhidpn_year pn ragender raracem rahispan ravetrn
raedyrs raedegrm raeduc educ r10* h10* Ch*_10* FL_10* LS_10* DS_10* z_h10* l_h10*
/*Core Vars*/ m* sFWB* AS* PS* OFR* FR* Co* r_*

***append seems to be the solution
*** append using "${data_raw}\h12f3a.dta"
```

save "${data_ed}\fat10.2.dta", replace

*2012 (n)

use hhid hhidpn pn /*Control Variable*/ na019 nb014 /*Subjective FWB*/ nlb040 nlb039e /*Functinal Limitation*/ ng014 ng016 ng021 ng023 ng025 ng030 /*Life Satisfaction*/ nlb003a nlb003b nlb003c nlb003d nlb003e /*Depressive Symptoms*/ nd110 nd111 nd117 nd115 nd113 nd114 nd112 nd116 /*Anxiety Symptoms*/ nlb041a nlb041b nlb041c nlb041d nlb041e /*Partner/Spouse Closeness*/ nlb006 /*Partner/Spouse Relationship Quality*/ nlb005a nlb005b nlb005c nlb005d nlb005e nlb005f nlb005g /*Children Contact*/ nlb009a nlb009b nlb009c /*Children Relationship*/ nlb008a nlb008b nlb008c nlb008d nlb008e nlb008f nlb008g /*Other Immediate Family Contact*/ nlb013a nlb013b nlb013c /*Other Immediate Family Relationship Quality*/ nlb012a nlb012b nlb012c nlb012d nlb012e nlb012f nlb012g /*Friend Contact*/ nlb017a nlb017b nlb017c /*Friend Relationship Quality*/ nlb016a nlb016b nlb016c nlb016d nlb016e nlb016f nlb016g /*Partner/Spouse Closeness*/ nlb006 /*Number of Close Relationships*/ nlb010 nlb014 nlb018 using "${data_raw}\h12f.dta", clear

```
/*Financial Wellbeing*/
	/*Subjective FWB (sFWB)*/
		***reverse coding so that higher scores indicate a better situation
		gen sFWB_12_1 = 6 - nlb039e
		gen sFWB_12_2 = 6 - nlb040

		*generating composite score for msFWB
		egen sFWB_12 = rowmean(sFWB_12_1 sFWB_12_2)

/*Psychological*/
	/*Life Satisfaction (LS)*/
		***From RAND-r`i'lbsatwlf = "the higher the score, the higher the Respondent's 
self-assessed quality of life"***
		***wlb003 in 2010 & 2012 and then wlb002 in 2014-2018***
		rename nlb003a LS_12_1
		rename nlb003b LS_12_2
		rename nlb003c LS_12_3
		rename nlb003d LS_12_4
		rename nlb003e LS_12_5

		egen LS_12_sum = rowtotal(LS_12_1 LS_12_2 LS_12_3 LS_12_4 LS_12_5), 
missing
		egen LS_12_count = anycount(LS_12_1 LS_12_2 LS_12_3 LS_12_4 LS_12_5), 
values(1/7)
		gen LS_12 = LS_12_sum / LS_12_count
```

```
	/*Anxiety Symptoms (AS)*/
	***Vars in years 2010, 2012, 2018***
		***Reverse coding so higher scores indicate lower anxiety***
		gen AS_12_1 = nlb041a
			recode AS_12_1 (1=4)(2=3)(3=2)(4=1)
		gen AS_12_2 = nlb041b
			recode AS_12_2 (1=4)(2=3)(3=2)(4=1)
		gen AS_12_3 = nlb041c
			recode AS_12_3 (1=4)(2=3)(3=2)(4=1)
		gen AS_12_4 = nlb041d
			recode AS_12_4 (1=4)(2=3)(3=2)(4=1)
		gen AS_12_5 = nlb041e
			recode AS_12_5 (1=4)(2=3)(3=2)(4=1)

		egen AS_12_sum = rowtotal(AS_12_1 AS_12_2 AS_12_3 AS_12_4 AS_12_5),
missing
		egen AS_12_count = anycount(AS_12_1 AS_12_2 AS_12_3 AS_12_4
AS_12_5), values(1/4)
		gen AS_12 = AS_12_sum / AS_12_count

/*Sociological (Social Connection) (SC)*/
***Higher scores indicate higher levels of social connection***

	/*Partner/Spouse Closeness (PS)*/
		/*Partner/Spouse Closeness (PSc)*/
		***Only one var in 2010 & 2012. Three in 2014-2018***
		***Reverse coded***
			gen PSc_12_1 = nlb006
				recode PSc_12_1 (1=4)(2=3)(3=2)(4=1)

		/*Partner/Spouse Relationship Quality (PSq)*/
		***nlb005a-c are reverse coded***
			gen PSq_12_1 = nlb005a
				recode PSq_12_1 (1=4)(2=3)(3=2)(4=1)
			gen PSq_12_2 = nlb005b
				recode PSq_12_2 (1=4)(2=3)(3=2)(4=1)
			gen PSq_12_3 = nlb005c
				recode PSq_12_3 (1=4)(2=3)(3=2)(4=1)
			gen PSq_12_4 = nlb005d
			gen PSq_12_5 = nlb005e
			gen PSq_12_6 = nlb005f
			gen PSq_12_7 = nlb005g

			egen PSq_12_sum = rowtotal(PSq_12_1 PSq_12_2 PSq_12_3 PSq_12_4
PSq_12_5 PSq_12_6 PSq_12_7), missing
```

```
			egen PSq_12_count = anycount(PSq_12_1 PSq_12_2 PSq_12_3
PSq_12_4 PSq_12_5 PSq_12_6 PSq_12_7), values(1/4)
			gen PSq_12 = PSq_12_sum / PSq_12_count

	/*Children Relationships (Ch)*/
		/*Children Contact (Chc)*/
		***Three vars in 2010 & 2012. Four vars in 2014-2018***
		***Reverse coded***
			gen Chc_12_1 = nlb009a
				recode Chc_12_1 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)
			gen Chc_12_2 = nlb009b
				recode Chc_12_2 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)
			gen Chc_12_3 = nlb009c
				recode Chc_12_3 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)

			egen Chc_12_sum = rowtotal(Chc_12_1 Chc_12_2 Chc_12_3), missing
			egen Chc_12_count = anycount(Chc_12_1 Chc_12_2 Chc_12_3),
values(1/6)
			gen Chc_12 = Chc_12_sum / Chc_12_count

		/*Children Relationship (Chr)*/
		***nlb009a-c are reverse coded***
			gen Chr_12_1 = nlb008a
				recode Chr_12_1 (1=4)(2=3)(3=2)(4=1)
			gen Chr_12_2 = nlb008b
				recode Chr_12_2 (1=4)(2=3)(3=2)(4=1)
			gen Chr_12_3 = nlb008c
				recode Chr_12_3 (1=4)(2=3)(3=2)(4=1)
			gen Chr_12_4 = nlb008d
			gen Chr_12_5 = nlb008e
			gen Chr_12_6 = nlb008f
			gen Chr_12_7 = nlb008g

			egen Chr_12_sum = rowtotal(Chr_12_1 Chr_12_2 Chr_12_3 Chr_12_4
Chr_12_5 Chr_12_6 Chr_12_7), missing
			egen Chr_12_count = anycount(Chr_12_1 Chr_12_2 Chr_12_3 Chr_12_4
Chr_12_5 Chr_12_6 Chr_12_7), values(1/4)
			gen Chr_12 = Chr_12_sum / Chr_12_count

	/*Other Family Relationships (OFR)*/
		/*Other Immediate Family Contact (OFRc)*/
		***Three vars in 2010 & 2012. Four vars in 2014-2018***
		***Reverse coded***
			gen OFRc_12_1 = nlb013a
				recode OFRc_12_1 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)
			gen OFRc_12_2 = nlb013b
```

```
				recode OFRc_12_2 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)
			gen OFRc_12_3 = nlb013c
				recode OFRc_12_3 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)

			egen OFRc_12_sum = rowtotal(OFRc_12_1 OFRc_12_2 OFRc_12_3),
missing
			egen OFRc_12_count = anycount(OFRc_12_1 OFRc_12_2 OFRc_12_3),
values(1/6)
			gen OFRc_12 = OFRc_12_sum / OFRc_12_count

		/*Other Immediate Family Relationship Quality (OFRq)*/
		***nlb012a-c are reverse coded***
			gen OFRq_12_1 = nlb012a
				recode OFRq_12_1 (1=4)(2=3)(3=2)(4=1)
			gen OFRq_12_2 = nlb012b
				recode OFRq_12_2 (1=4)(2=3)(3=2)(4=1)
			gen OFRq_12_3 = nlb012c
				recode OFRq_12_3 (1=4)(2=3)(3=2)(4=1)
			gen OFRq_12_4 = nlb012d
			gen OFRq_12_5 = nlb012e
			gen OFRq_12_6 = nlb012f
			gen OFRq_12_7 = nlb012g

			egen OFRq_12_sum = rowtotal(OFRq_12_1 OFRq_12_2 OFRq_12_3
OFRq_12_4 OFRq_12_5 OFRq_12_6 OFRq_12_7), missing
			egen OFRq_12_count = anycount(OFRq_12_1 OFRq_12_2 OFRq_12_3
OFRq_12_4 OFRq_12_5 OFRq_12_6 OFRq_12_7), values(1/4)
			gen OFRq_12 = OFRq_12_sum / OFRq_12_count

	/*Friend Relationships (FR)*/
		/*Friend Contact (FRc)*/
		***Three vars in 2010 & 2012. Four vars in 2014-2018***
		***Reverse coded***
			gen FRc_12_1 = nlb017a
				recode FRc_12_1 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)
			gen FRc_12_2 = nlb017b
				recode FRc_12_2 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)
			gen FRc_12_3 = nlb017c
				recode FRc_12_3 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)

			egen FRc_12_sum = rowtotal(FRc_12_1 FRc_12_2 FRc_12_3), missing
			egen FRc_12_count = anycount(FRc_12_1 FRc_12_2 FRc_12_3),
values(1/6)
			gen FRc_12 = FRc_12_sum / FRc_12_count

		/*Friend Relationship Quality (FRq)*/
```

```
***nlb012a-c are reverse coded***
        gen FRq_12_1 = nlb016a
                recode FRq_12_1 (1=4)(2=3)(3=2)(4=1)
        gen FRq_12_2 = nlb016b
                recode FRq_12_2 (1=4)(2=3)(3=2)(4=1)
        gen FRq_12_3 = nlb016c
                recode FRq_12_3 (1=4)(2=3)(3=2)(4=1)
        gen FRq_12_4 = nlb016d
        gen FRq_12_5 = nlb016e
        gen FRq_12_6 = nlb016f
        gen FRq_12_7 = nlb016g

        egen FRq_12_sum = rowtotal(FRq_12_1 FRq_12_2 FRq_12_3 FRq_12_4
FRq_12_5 FRq_12_6 FRq_12_7), missing
        egen FRq_12_count = anycount(FRq_12_1 FRq_12_2 FRq_12_3
FRq_12_4 FRq_12_5 FRq_12_6 FRq_12_7), values(1/4)
        gen FRq_12 = FRq_12_sum / FRq_12_count

/*Closeness of Relationships (CoR)*/
        /*Partner/Spouse Closeness (CoRPS)*/
        ***Only one var in 2010 & 2012. Three in 2014-2018***
        ***Reverse coded***
                gen CoRPS_12_1 = nlb006
                        recode CoRPS_12_1 (1=4)(2=3)(3=2)(4=1)

        /*Number of Close Relationships (CoRn)*/
        ***These are continuous but have wide range***
        ***Will need to do some sort of transformation. Starting by doing categorical
vars***
                gen CoRn_12_1 = nlb010
                        replace CoRn_12_1 = 1 if inrange(nlb010,1,2)
                        replace CoRn_12_1 = 2 if inrange(nlb010,3,4)
                        replace CoRn_12_1 = 3 if inrange(nlb010,5,9)
                        replace CoRn_12_1 = 4 if inrange(nlb010,10,14)
                        replace CoRn_12_1 = 5 if nlb010 > 14
                        replace CoRn_12_1 = . if nlb010 == .
                                label variable CoRn_12_1 "n Close Children
Relationships"
                                label define CoRn_12_1 0 "0" 1 "1-2" 2 "3-4" 3 "5-9" 4
"10-14" 5 "15+"
                                label values CoRn_12_1 CoRn_12_1
                gen CoRn_12_2 = nlb014
                        replace CoRn_12_2 = 1 if inrange(nlb014,1,2)
                        replace CoRn_12_2 = 2 if inrange(nlb014,3,4)
                        replace CoRn_12_2 = 3 if inrange(nlb014,5,9)
                        replace CoRn_12_2 = 4 if inrange(nlb014,10,14)
```

```
				replace CoRn_12_2 = 5 if nlb014 > 14
				replace CoRn_12_2 = . if nlb014 == .
					label variable CoRn_12_2 "n Close Family Relationships"
					label define CoRn_12_2 0 "0" 1 "1-2" 2 "3-4" 3 "5-9" 4
"10-14" 5 "15+"
					label values CoRn_12_2 CoRn_12_2
			gen CoRn_12_3 = nlb018
				replace CoRn_12_3 = 1 if inrange(nlb018,1,2)
				replace CoRn_12_3 = 2 if inrange(nlb018,3,4)
				replace CoRn_12_3 = 3 if inrange(nlb018,5,9)
				replace CoRn_12_3 = 4 if inrange(nlb018,10,14)
				replace CoRn_12_3 = 5 if nlb018 > 14
				replace CoRn_12_3 = . if nlb018 == .
					label variable CoRn_12_3 "n Close Family Relationships"
					label define CoRn_12_3 0 "0" 1 "1-2" 2 "3-4" 3 "5-9" 4
"10-14" 5 "15+"
					label values CoRn_12_3 CoRn_12_3

			egen CoRn_12_sum = rowtotal(CoRn_12_1 CoRn_12_2 CoRn_12_3),
missing
			egen CoRn_12_count = anycount(CoRn_12_1 CoRn_12_2 CoRn_12_3),
values(0/5)
			gen CoRn_12 = CoRn_12_sum / CoRn_12_count


gen year = 2012
gen hhidpn_year = string(hhidpn,"%09.0f") + "_" + string(year,"%04.0f")

merge 1:1 hhidpn using "${data_ed}\rand.2.dta"

/*Depressive Symptoms*/
	***"the higher the score, the more negative the Respondent's feelings in the past
week"***
	***as a result...have to reverse code
	gen temp = r11cesd + 1
	gen r_r11cesd = 10 - temp
	drop temp

keep if !missing(hhidpn_year)

keep /*RAND Vars*/ hhid hhidpn* year hhidpn_year pn ragender raracem rahispan ravetrn
raedyrs raedegrm raeduc educ r11* r12* h11* h12* Ch*_12* FL_12* LS_12* DS_12* z_h12*
l_h12* /*Core Vars*/ n* sFWB* AS* PS* OFR* FR* Co* r_*

***append seems to be the solution
*** append using "${data_raw}\h12f3a.dta"
```

save "${data_ed}\fat12.2.dta", replace

*2014 (o)

use hhid hhidpn pn /*Control Variable*/ oa019 ob014 /*Subjective FWB*/ olb035 olb034e /*Functinal Limitation*/ og014 og016 og021 og023 og025 og030 /*Life Satisfaction*/ olb002a olb002b olb002c olb002d olb002e /*Depressive Symptoms*/ od110 od111 od117 od115 od113 od114 od112 od116 /*Anxiety Symptoms - no Vars in this wave*/ olb026r /*Partner/Spouse Closeness*/ olb005 olb005a olb005b /*Partner/Spouse Relationship Quality*/ olb004a olb004b olb004c olb004d olb004e olb004f olb004g /*Children Contact*/ olb008a olb008b olb008c olb008d /*Children Relationship*/ olb007a olb007b olb007c olb007d olb007e olb007f olb007g /*Other Immediate Family Contact*/ olb012a olb012b olb012c olb012d /*Other Immediate Family Relationship Quality*/ olb011a olb011b olb011c olb011d olb011e olb011f olb011g /*Friend Contact*/ olb016a olb016b olb016c olb016d /*Friend Relationship Quality*/ olb015a olb015b olb015c olb015d olb015e olb015f olb015g /*Partner/Spouse Closeness*/ olb005 olb005a olb005b /*Number of Close Relationships*/ olb009 olb013 olb017 using "${data_raw}\h14f.dta", clear

```
/*Financial Wellbeing*/
	/*Subjective FWB (sFWB)*/
		***reverse coding so that higher scores indicate a better situation
		gen sFWB_14_1 = 6 - olb034e
		gen sFWB_14_2 = 6 - olb035

		*generating composite score for msFWB
		egen sFWB_14 = rowmean(sFWB_14_1 sFWB_14_2)

/*Psychological*/
	/*Life Satisfaction (LS)*/
		***From RAND-r`i'lbsatwlf = "the higher the score, the higher the Respondent's self-assessed quality of life"***
		***wlb003 in 2010 & 2012 and then wlb002 in 2014-2018***
		rename olb002a LS_14_1
		rename olb002b LS_14_2
		rename olb002c LS_14_3
		rename olb002d LS_14_4
		rename olb002e LS_14_5

		egen LS_14_sum = rowtotal(LS_14_1 LS_14_2 LS_14_3 LS_14_4 LS_14_5), missing
		egen LS_14_count = anycount(LS_14_1 LS_14_2 LS_14_3 LS_14_4 LS_14_5), values(1/7)
		gen LS_14 = LS_14_sum / LS_14_count

	/*Anxiety Symptoms (AS)*/
```

```
	***These are possible substitute variables for the AS var***
	***No need to reverse code as in previous waves. Higher scores indicate lower
anxiety***
		rename olb026r AS_14_2

/*Sociological (Social Connection) (SC)*/
***Higher scores indicate higher levels of social connection***

	/*Partner/Spouse Closeness (PS)*/
		/*Partner/Spouse Closeness (PSc)*/
		***Only one var in 2010 & 2012. Three in 2014-2018***
		***Reverse coded***
			gen PSc_14_1 = olb005
				recode PSc_14_1 (1=4)(2=3)(3=2)(4=1)
			gen PSc_14_2 = olb005a
				recode PSc_14_2 (1=4)(2=3)(3=2)(4=1)
			gen PSc_14_3 = olb005b
				recode PSc_14_3 (1=3)(3=1)

			egen PSc_14_sum = rowtotal(PSc_14_1 PSc_14_2 PSc_14_3), missing
			egen PSc_14_count = anycount(PSc_14_1 PSc_14_2 PSc_14_3),
values(1/4)
			gen PSc_14 = PSc_14_sum / PSc_14_count

		/*Partner/Spouse Relationship Quality (PSq)*/
		***olb005a-c are reverse coded***
			gen PSq_14_1 = olb004a
				recode PSq_14_1 (1=4)(2=3)(3=2)(4=1)
			gen PSq_14_2 = olb004b
				recode PSq_14_2 (1=4)(2=3)(3=2)(4=1)
			gen PSq_14_3 = olb004c
				recode PSq_14_3 (1=4)(2=3)(3=2)(4=1)
			gen PSq_14_4 = olb004d
			gen PSq_14_5 = olb004e
			gen PSq_14_6 = olb004f
			gen PSq_14_7 = olb004g

			egen PSq_14_sum = rowtotal(PSq_14_1 PSq_14_2 PSq_14_3 PSq_14_4
PSq_14_5 PSq_14_6 PSq_14_7), missing
			egen PSq_14_count = anycount(PSq_14_1 PSq_14_2 PSq_14_3
PSq_14_4 PSq_14_5 PSq_14_6 PSq_14_7), values(1/4)
			gen PSq_14 = PSq_14_sum / PSq_14_count

	/*Children Relationships (Ch)*/
		/*Children Contact (Chc)*/
		***Three vars in 2010 & 2012. Four vars in 2014-2018***
```

```
***Reverse coded***
        gen Chc_14_1 = olb008a
                recode Chc_14_1 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)
        gen Chc_14_2 = olb008b
                recode Chc_14_2 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)
        gen Chc_14_3 = olb008c
                recode Chc_14_3 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)
        gen Chc_14_4 = olb008d
                recode Chc_14_4 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)


        egen Chc_14_sum = rowtotal(Chc_14_1 Chc_14_2 Chc_14_3 Chc_14_4),
missing
        egen Chc_14_count = anycount(Chc_14_1 Chc_14_2 Chc_14_3
Chc_14_4), values(1/6)
        gen Chc_14 = Chc_14_sum / Chc_14_count

/*Children Relationship (Chr)*/
***olb009a-c are reverse coded***
        gen Chr_14_1 = olb007a
                recode Chr_14_1 (1=4)(2=3)(3=2)(4=1)
        gen Chr_14_2 = olb007b
                recode Chr_14_2 (1=4)(2=3)(3=2)(4=1)
        gen Chr_14_3 = olb007c
                recode Chr_14_3 (1=4)(2=3)(3=2)(4=1)
        gen Chr_14_4 = olb007d
        gen Chr_14_5 = olb007e
        gen Chr_14_6 = olb007f
        gen Chr_14_7 = olb007g

        egen Chr_14_sum = rowtotal(Chr_14_1 Chr_14_2 Chr_14_3 Chr_14_4
Chr_14_5 Chr_14_6 Chr_14_7), missing
        egen Chr_14_count = anycount(Chr_14_1 Chr_14_2 Chr_14_3 Chr_14_4
Chr_14_5 Chr_14_6 Chr_14_7), values(1/4)
        gen Chr_14 = Chr_14_sum / Chr_14_count

/*Other Family Relationships (OFR)*/
    /*Other Immediate Family Contact (OFRc)*/
    ***Three vars in 2010 & 2012. Four vars in 2014-2018***
    ***Reverse coded***
        gen OFRc_14_1 = olb012a
                recode OFRc_14_1 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)
        gen OFRc_14_2 = olb012b
                recode OFRc_14_2 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)
        gen OFRc_14_3 = olb012c
                recode OFRc_14_3 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)
```

```
            gen OFRc_14_4 = olb012d
                recode OFRc_14_4 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)


            egen OFRc_14_sum = rowtotal(OFRc_14_1 OFRc_14_2 OFRc_14_3
OFRc_14_4), missing
            egen OFRc_14_count = anycount(OFRc_14_1 OFRc_14_2 OFRc_14_3
OFRc_14_4), values(1/6)
            gen OFRc_14 = OFRc_14_sum / OFRc_14_count

        /*Other Immediate Family Relationship Quality (OFRq)*/
        ***olb012a-c are reverse coded***
            gen OFRq_14_1 = olb011a
                recode OFRq_14_1 (1=4)(2=3)(3=2)(4=1)
            gen OFRq_14_2 = olb011b
                recode OFRq_14_2 (1=4)(2=3)(3=2)(4=1)
            gen OFRq_14_3 = olb011c
                recode OFRq_14_3 (1=4)(2=3)(3=2)(4=1)
            gen OFRq_14_4 = olb011d
            gen OFRq_14_5 = olb011e
            gen OFRq_14_6 = olb011f
            gen OFRq_14_7 = olb011g

            egen OFRq_14_sum = rowtotal(OFRq_14_1 OFRq_14_2 OFRq_14_3
OFRq_14_4 OFRq_14_5 OFRq_14_6 OFRq_14_7), missing
            egen OFRq_14_count = anycount(OFRq_14_1 OFRq_14_2 OFRq_14_3
OFRq_14_4 OFRq_14_5 OFRq_14_6 OFRq_14_7), values(1/4)
            gen OFRq_14 = OFRq_14_sum / OFRq_14_count

    /*Friend Relationships (FR)*/
        /*Friend Contact (FRc)*/
        ***Three vars in 2010 & 2012. Four vars in 2014-2018***
        ***Reverse coded***
            gen FRc_14_1 = olb016a
                recode FRc_14_1 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)
            gen FRc_14_2 = olb016b
                recode FRc_14_2 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)
            gen FRc_14_3 = olb016c
                recode FRc_14_3 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)
            gen FRc_14_4 = olb016d
                recode FRc_14_4 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)


            egen FRc_14_sum = rowtotal(FRc_14_1 FRc_14_2 FRc_14_3
FRc_14_4), missing
```

```
				egen FRc_14_count = anycount(FRc_14_1 FRc_14_2 FRc_14_3
FRc_14_4), values(1/6)
				gen FRc_14 = FRc_14_sum / FRc_14_count

			/*Friend Relationship Quality (FRq)*/
			***olb012a-c are reverse coded***
				gen FRq_14_1 = olb015a
					recode FRq_14_1 (1=4)(2=3)(3=2)(4=1)
				gen FRq_14_2 = olb015b
					recode FRq_14_2 (1=4)(2=3)(3=2)(4=1)
				gen FRq_14_3 = olb015c
					recode FRq_14_3 (1=4)(2=3)(3=2)(4=1)
				gen FRq_14_4 = olb015d
				gen FRq_14_5 = olb015e
				gen FRq_14_6 = olb015f
				gen FRq_14_7 = olb015g

				egen FRq_14_sum = rowtotal(FRq_14_1 FRq_14_2 FRq_14_3 FRq_14_4
FRq_14_5 FRq_14_6 FRq_14_7), missing
				egen FRq_14_count = anycount(FRq_14_1 FRq_14_2 FRq_14_3
FRq_14_4 FRq_14_5 FRq_14_6 FRq_14_7), values(1/4)
				gen FRq_14 = FRq_14_sum / FRq_14_count

		/*Closeness of Relationships (CoR)*/
			/*Partner/Spouse Closeness (CoRPS)*/
			***Only one var in 2010 & 2012. Three in 2014-2018***
			***Reverse coded***
				gen CoRPS_14_1 = olb005
					recode PSc_14_1 (1=4)(2=3)(3=2)(4=1)
				gen CoRPS_14_2 = olb005a
					recode PSc_14_1 (1=4)(2=3)(3=2)(4=1)
				gen CoRPS_14_3 = olb005b
					recode PSc_14_3 (1=3)(3=1)

				egen CoRPS_14_sum = rowtotal(CoRPS_14_1 CoRPS_14_2
CoRPS_14_3), missing
				egen CoRPS_14_count = anycount(CoRPS_14_1 CoRPS_14_2
CoRPS_14_3), values(0/5)
				gen CoRPS_14 = CoRPS_14_sum / CoRPS_14_count


			/*Number of Close Relationships (CoRn)*/
			***These are continuous but have wide range***
			***Will need to do some sort of transformation. Starting by doing categorical
vars***
				gen CoRn_14_1 = olb009
```

```
replace CoRn_14_1 = 1 if inrange(olb009,1,2)
replace CoRn_14_1 = 2 if inrange(olb009,3,4)
replace CoRn_14_1 = 3 if inrange(olb009,5,9)
replace CoRn_14_1 = 4 if inrange(olb009,10,14)
replace CoRn_14_1 = 5 if olb009 > 14
replace CoRn_14_1 = . if olb009 == .
	label variable CoRn_14_1 "n Close Children
Relationships"
	label define CoRn_14_1 0 "0" 1 "1-2" 2 "3-4" 3 "5-9" 4
"10-14" 5 "15+"
	label values CoRn_14_1 CoRn_14_1
gen CoRn_14_2 = olb013
replace CoRn_14_2 = 1 if inrange(olb013,1,2)
replace CoRn_14_2 = 2 if inrange(olb013,3,4)
replace CoRn_14_2 = 3 if inrange(olb013,5,9)
replace CoRn_14_2 = 4 if inrange(olb013,10,14)
replace CoRn_14_2 = 5 if olb013 > 14
replace CoRn_14_2 = . if olb013 == .
	label variable CoRn_14_2 "n Close Family Relationships"
	label define CoRn_14_2 0 "0" 1 "1-2" 2 "3-4" 3 "5-9" 4
"10-14" 5 "15+"
	label values CoRn_14_2 CoRn_14_2
gen CoRn_14_3 = olb017
replace CoRn_14_3 = 1 if inrange(olb017,1,2)
replace CoRn_14_3 = 2 if inrange(olb017,3,4)
replace CoRn_14_3 = 3 if inrange(olb017,5,9)
replace CoRn_14_3 = 4 if inrange(olb017,10,14)
replace CoRn_14_3 = 5 if olb017 > 14
replace CoRn_14_3 = . if olb017 == .
	label variable CoRn_14_3 "n Close Family Relationships"
	label define CoRn_14_3 0 "0" 1 "1-2" 2 "3-4" 3 "5-9" 4
"10-14" 5 "15+"
	label values CoRn_14_3 CoRn_14_3

egen CoRn_14_sum = rowtotal(CoRn_14_1 CoRn_14_2 CoRn_14_3),
missing
egen CoRn_14_count = anycount(CoRn_14_1 CoRn_14_2 CoRn_14_3),
values(0/5)
gen CoRn_14 = CoRn_14_sum / CoRn_14_count


gen year = 2014
gen hhidpn_year = string(hhidpn,"%09.0f") + "_" + string(year,"%04.0f")

merge 1:1 hhidpn using "${data_ed}\rand.2.dta"
```

```
/*Depressive Symptoms*/
	***"the higher the score, the more negative the Respondent's feelings in the past week"***
	***as a result...have to reverse code
	gen temp = r12cesd + 1
	gen r_r12cesd = 10 - temp
	drop temp

keep if !missing(hhidpn_year)

keep /*RAND Vars*/ hhid hhidpn* year hhidpn_year pn ragender raracem rahispan ravetrn raedyrs raedegrm raeduc educ r12* r14* h12* h14* Ch*_14* FL_14* LS_14* DS_14* z_h14* l_h14* /*Core Vars*/ o* sFWB* AS* PS* OFR* FR* Co* r_*

	save "${data_ed}\fat14.2.dta", replace

*2016 (p)

	use hhid hhidpn pn /*Control Variable*/ pa019 pb014 /*Subjective FWB*/ plb035 plb034e /*Functinal Limitation*/ pg014 pg016 pg021 pg023 pg025 pg030 /*Life Satisfaction*/ plb002a plb002b plb002c plb002d plb002e /*Depressive Symptoms*/ pd110 pd111 pd117 pd115 pd113 pd114 pd112 pd116 /*Anxiety Symptoms - no Vars in this wave*/ plb026r /*Partner/Spouse Closeness*/ plb005 plb005a plb005b /*Partner/Spouse Relationship Quality*/ plb004a plb004b plb004c plb004d plb004e plb004f plb004g /*Children Contact*/ plb008a plb008b plb008c plb008d /*Children Relationship*/ plb007a plb007b plb007c plb007d plb007e plb007f plb007g /*Other Immediate Family Contact*/  plb012a plb012b plb012c plb012d /*Other Immediate Family Relationship Quality*/ plb011a plb011b plb011c plb011d plb011e plb011f plb011g /*Friend Contact*/ plb016a plb016b plb016c plb016d /*Friend Relationship Quality*/ plb015a plb015b plb015c plb015d plb015e plb015f plb015g /*Partner/Spouse Closeness*/ plb005 plb005a plb005b /*Number of Close Relationships*/ plb009 plb013 plb017 using "${data_raw}\h16f.dta", clear

/*Financial Wellbeing*/
	/*Subjective FWB (sFWB)*/
		***reverse coding so that higher scores indicate a better situation
		gen sFWB_16_1 = 6 - plb034e
		gen sFWB_16_2 = 6 - plb035

		*generating composite score for msFWB
		egen sFWB_16 = rowmean(sFWB_16_1 sFWB_16_2)

/*Psychological*/
	/*Life Satisfaction (LS)*/
		***From RAND-r`i'lbsatwlf = "the higher the score, the higher the Respondent's self-assessed quality of life"***
		***wlb003 in 2010 & 2012 and then wlb002 in 2014-2018***
```

```
		rename plb002a LS_16_1
		rename plb002b LS_16_2
		rename plb002c LS_16_3
		rename plb002d LS_16_4
		rename plb002e LS_16_5

		egen LS_16_sum = rowtotal(LS_16_1 LS_16_2 LS_16_3 LS_16_4 LS_16_5),
missing
		egen LS_16_count = anycount(LS_16_1 LS_16_2 LS_16_3 LS_16_4 LS_16_5),
values(1/7)
		gen LS_16 = LS_16_sum / LS_16_count

	/*Anxiety Symptoms (AS)*/
	***These are possible substitute variables for the AS var***
	***No need to reverse code as in previous waves. Higher scores indicate lower
anxiety***
		rename plb026r AS_16_2

/*Sociological (Social Connection) (SC)*/
***Higher scores indicate higher levels of social connection***

	/*Partner/Spouse Closeness (PS)*/
		/*Partner/Spouse Closeness (PSc)*/
		***Only one var in 2010 & 2012. Three in 2014-2018***
		***Reverse coded***
			gen PSc_16_1 = plb005
				recode PSc_16_1 (1=4)(2=3)(3=2)(4=1)
			gen PSc_16_2 = plb005a
				recode PSc_16_2 (1=4)(2=3)(3=2)(4=1)
			gen PSc_16_3 = plb005b
				recode PSc_16_3 (1=3)(3=1)

			egen PSc_16_sum = rowtotal(PSc_16_1 PSc_16_2 PSc_16_3), missing
			egen PSc_16_count = anycount(PSc_16_1 PSc_16_2 PSc_16_3),
values(1/4)
			gen PSc_16 = PSc_16_sum / PSc_16_count

		/*Partner/Spouse Relationship Quality (PSq)*/
		***plb005a-c are reverse coded***
			gen PSq_16_1 = plb004a
				recode PSq_16_1 (1=4)(2=3)(3=2)(4=1)
			gen PSq_16_2 = plb004b
				recode PSq_16_2 (1=4)(2=3)(3=2)(4=1)
			gen PSq_16_3 = plb004c
				recode PSq_16_3 (1=4)(2=3)(3=2)(4=1)
			gen PSq_16_4 = plb004d
```

```
gen PSq_16_5 = plb004e
gen PSq_16_6 = plb004f
gen PSq_16_7 = plb004g

egen PSq_16_sum = rowtotal(PSq_16_1 PSq_16_2 PSq_16_3 PSq_16_4
PSq_16_5 PSq_16_6 PSq_16_7), missing
egen PSq_16_count = anycount(PSq_16_1 PSq_16_2 PSq_16_3
PSq_16_4 PSq_16_5 PSq_16_6 PSq_16_7), values(1/4)
gen PSq_16 = PSq_16_sum / PSq_16_count

/*Children Relationships (Ch)*/
	/*Children Contact (Chc)*/
	***Three vars in 2010 & 2012. Four vars in 2014-2018***
	***Reverse coded***
		gen Chc_16_1 = plb008a
			recode Chc_16_1 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)
		gen Chc_16_2 = plb008b
			recode Chc_16_2 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)
		gen Chc_16_3 = plb008c
			recode Chc_16_3 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)
		gen Chc_16_4 = plb008d
			recode Chc_16_4 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)


		egen Chc_16_sum = rowtotal(Chc_16_1 Chc_16_2 Chc_16_3 Chc_16_4),
missing
		egen Chc_16_count = anycount(Chc_16_1 Chc_16_2 Chc_16_3
Chc_16_4), values(1/6)
		gen Chc_16 = Chc_16_sum / Chc_16_count

	/*Children Relationship (Chr)*/
	***plb009a-c are reverse coded***
		gen Chr_16_1 = plb007a
			recode Chr_16_1 (1=4)(2=3)(3=2)(4=1)
		gen Chr_16_2 = plb007b
			recode Chr_16_2 (1=4)(2=3)(3=2)(4=1)
		gen Chr_16_3 = plb007c
			recode Chr_16_3 (1=4)(2=3)(3=2)(4=1)
		gen Chr_16_4 = plb007d
		gen Chr_16_5 = plb007e
		gen Chr_16_6 = plb007f
		gen Chr_16_7 = plb007g

		egen Chr_16_sum = rowtotal(Chr_16_1 Chr_16_2 Chr_16_3 Chr_16_4
Chr_16_5 Chr_16_6 Chr_16_7), missing
```

```
			egen Chr_16_count = anycount(Chr_16_1 Chr_16_2 Chr_16_3 Chr_16_4
Chr_16_5 Chr_16_6 Chr_16_7), values(1/4)
			gen Chr_16 = Chr_16_sum / Chr_16_count

	/*Other Family Relationships (OFR)*/
		/*Other Immediate Family Contact (OFRc)*/
		***Three vars in 2010 & 2012. Four vars in 2014-2018***
		***Reverse coded***
			gen OFRc_16_1 = plb012a
				recode OFRc_16_1 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)
			gen OFRc_16_2 = plb012b
				recode OFRc_16_2 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)
			gen OFRc_16_3 = plb012c
				recode OFRc_16_3 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)
			gen OFRc_16_4 = plb012d
				recode OFRc_16_4 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)


			egen OFRc_16_sum = rowtotal(OFRc_16_1 OFRc_16_2 OFRc_16_3
OFRc_16_4), missing
			egen OFRc_16_count = anycount(OFRc_16_1 OFRc_16_2 OFRc_16_3
OFRc_16_4), values(1/6)
			gen OFRc_16 = OFRc_16_sum / OFRc_16_count

		/*Other Immediate Family Relationship Quality (OFRq)*/
		***plb012a-c are reverse coded***
			gen OFRq_16_1 = plb011a
				recode OFRq_16_1 (1=4)(2=3)(3=2)(4=1)
			gen OFRq_16_2 = plb011b
				recode OFRq_16_2 (1=4)(2=3)(3=2)(4=1)
			gen OFRq_16_3 = plb011c
				recode OFRq_16_3 (1=4)(2=3)(3=2)(4=1)
			gen OFRq_16_4 = plb011d
			gen OFRq_16_5 = plb011e
			gen OFRq_16_6 = plb011f
			gen OFRq_16_7 = plb011g

			egen OFRq_16_sum = rowtotal(OFRq_16_1 OFRq_16_2 OFRq_16_3
OFRq_16_4 OFRq_16_5 OFRq_16_6 OFRq_16_7), missing
			egen OFRq_16_count = anycount(OFRq_16_1 OFRq_16_2 OFRq_16_3
OFRq_16_4 OFRq_16_5 OFRq_16_6 OFRq_16_7), values(1/4)
			gen OFRq_16 = OFRq_16_sum / OFRq_16_count

	/*Friend Relationships (FR)*/
		/*Friend Contact (FRc)*/
		***Three vars in 2010 & 2012. Four vars in 2014-2018***
```

```
***Reverse coded***
        gen FRc_16_1 = plb016a
                recode FRc_16_1 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)
        gen FRc_16_2 = plb016b
                recode FRc_16_2 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)
        gen FRc_16_3 = plb016c
                recode FRc_16_3 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)
        gen FRc_16_4 = plb016d
                recode FRc_16_4 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)


        egen FRc_16_sum = rowtotal(FRc_16_1 FRc_16_2 FRc_16_3
FRc_16_4), missing
        egen FRc_16_count = anycount(FRc_16_1 FRc_16_2 FRc_16_3
FRc_16_4), values(1/6)
        gen FRc_16 = FRc_16_sum / FRc_16_count

/*Friend Relationship Quality (FRq)*/
***plb012a-c are reverse coded***
        gen FRq_16_1 = plb015a
                recode FRq_16_1 (1=4)(2=3)(3=2)(4=1)
        gen FRq_16_2 = plb015b
                recode FRq_16_2 (1=4)(2=3)(3=2)(4=1)
        gen FRq_16_3 = plb015c
                recode FRq_16_3 (1=4)(2=3)(3=2)(4=1)
        gen FRq_16_4 = plb015d
        gen FRq_16_5 = plb015e
        gen FRq_16_6 = plb015f
        gen FRq_16_7 = plb015g

        egen FRq_16_sum = rowtotal(FRq_16_1 FRq_16_2 FRq_16_3 FRq_16_4
FRq_16_5 FRq_16_6 FRq_16_7), missing
        egen FRq_16_count = anycount(FRq_16_1 FRq_16_2 FRq_16_3
FRq_16_4 FRq_16_5 FRq_16_6 FRq_16_7), values(1/4)
        gen FRq_16 = FRq_16_sum / FRq_16_count

/*Closeness of Relationships (CoR)*/
        /*Partner/Spouse Closeness (CoRPS)*/
        ***Only one var in 2010 & 2012. Three in 2014-2018***
        ***Reverse coded***
                gen CoRPS_16_1 = plb005
                        recode PSc_16_1 (1=4)(2=3)(3=2)(4=1)
                gen CoRPS_16_2 = plb005a
                        recode PSc_16_1 (1=4)(2=3)(3=2)(4=1)
                gen CoRPS_16_3 = plb005b
                        recode PSc_16_3 (1=3)(3=1)
```

```
			egen CoRPS_16_sum = rowtotal(CoRPS_16_1 CoRPS_16_2
CoRPS_16_3), missing
			egen CoRPS_16_count = anycount(CoRPS_16_1 CoRPS_16_2
CoRPS_16_3), values(0/5)
			gen CoRPS_16 = CoRPS_16_sum / CoRPS_16_count


		/*Number of Close Relationships (CoRn)*/
		***These are continuous but have wide range***
		***Will need to do some sort of transformation. Starting by doing categorical
vars***
			gen CoRn_16_1 = plb009
				replace CoRn_16_1 = 1 if inrange(plb009,1,2)
				replace CoRn_16_1 = 2 if inrange(plb009,3,4)
				replace CoRn_16_1 = 3 if inrange(plb009,5,9)
				replace CoRn_16_1 = 4 if inrange(plb009,10,14)
				replace CoRn_16_1 = 5 if plb009 > 14
				replace CoRn_16_1 = . if plb009 == .
					label variable CoRn_16_1 "n Close Children
Relationships"
					label define CoRn_16_1 0 "0" 1 "1-2" 2 "3-4" 3 "5-9" 4
"10-14" 5 "15+"
					label values CoRn_16_1 CoRn_16_1
			gen CoRn_16_2 = plb013
				replace CoRn_16_2 = 1 if inrange(plb013,1,2)
				replace CoRn_16_2 = 2 if inrange(plb013,3,4)
				replace CoRn_16_2 = 3 if inrange(plb013,5,9)
				replace CoRn_16_2 = 4 if inrange(plb013,10,14)
				replace CoRn_16_2 = 5 if plb013 > 14
				replace CoRn_16_2 = . if plb013 == .
					label variable CoRn_16_2 "n Close Family Relationships"
					label define CoRn_16_2 0 "0" 1 "1-2" 2 "3-4" 3 "5-9" 4
"10-14" 5 "15+"
					label values CoRn_16_2 CoRn_16_2
			gen CoRn_16_3 = plb017
				replace CoRn_16_3 = 0 if plb017 == -2
				replace CoRn_16_3 = 1 if inrange(plb017,1,2)
				replace CoRn_16_3 = 2 if inrange(plb017,3,4)
				replace CoRn_16_3 = 3 if inrange(plb017,5,9)
				replace CoRn_16_3 = 4 if inrange(plb017,10,14)
				replace CoRn_16_3 = 5 if plb017 > 14
				replace CoRn_16_3 = . if plb017 == .
					label variable CoRn_16_3 "n Close Family Relationships"
					label define CoRn_16_3 0 "0" 1 "1-2" 2 "3-4" 3 "5-9" 4
"10-14" 5 "15+"
```

```
label values CoRn_16_3 CoRn_16_3

egen CoRn_16_sum = rowtotal(CoRn_16_1 CoRn_16_2 CoRn_16_3),
missing
egen CoRn_16_count = anycount(CoRn_16_1 CoRn_16_2 CoRn_16_3),
values(0/5)
gen CoRn_16 = CoRn_16_sum / CoRn_16_count


gen year = 2016
gen hhidpn_year = string(hhidpn,"%09.0f") + "_" + string(year,"%04.0f")

merge 1:1 hhidpn using "${data_ed}\rand.2.dta"

/*Depressive Symptoms*/
	***"the higher the score, the more negative the Respondent's feelings in the past
week"***
	***as a result...have to reverse code
	gen temp = r13cesd + 1
	gen r_r13cesd = 10 - temp
	drop temp

keep if !missing(hhidpn_year)

keep /*RAND Vars*/ hhid hhidpn* year hhidpn_year pn ragender raracem rahispan ravetrn
raedyrs raedegrm raeduc educ r13* r16* h13* h16* Ch*_16* FL_16* LS_16* DS_16* z_h16*
l_h16* /*Core Vars*/ p* sFWB* AS* PS* OFR* FR* Co* r_*

	save "${data_ed}\fat16.2.dta", replace

*2018 (q)

	use hhid hhidpn pn /*Control Variable*/ qa019 qb014 /*Subjective FWB*/ qlb035
qlb034e /*Functinal Limitation*/ qg014 qg016 qg021 qg023 qg025 qg030 /*Life Satisfaction*/
qlb002a qlb002b qlb002c qlb002d qlb002e /*Depressive Symptoms*/ qd110 qd111 qd117 qd115
qd113 qd114 qd112 qd116 /*Anxiety Symptoms*/ qlb035c1 qlb035c2 qlb035c3 qlb035c4
qlb035c5 /*Partner/Spouse Closeness*/ qlb005 qlb005a qlb005b /*Partner/Spouse Relationship
Quality*/ qlb004a qlb004b qlb004c qlb004d qlb004e qlb004f qlb004g /*Children Contact*/
qlb008a qlb008b qlb008c qlb008d /*Children Relationship*/ qlb007a qlb007b qlb007c qlb007d
qlb007e qlb007f qlb007g /*Other Immediate Family Contact*/  qlb012a qlb012b qlb012c
qlb012d /*Other Immediate Family Relationship Quality*/ qlb011a qlb011b qlb011c qlb011d
qlb011e qlb011f qlb011g /*Friend Contact*/ qlb016a qlb016b qlb016c qlb016d /*Friend
Relationship Quality*/ qlb015a qlb015b qlb015c qlb015d qlb015e qlb015f qlb015g
/*Partner/Spouse Closeness*/ qlb005 qlb005a qlb005b /*Number of Close Relationships*/
qlb009 qlb013 qlb017 using "${data_raw}\h18f", clear
```

```
/*Financial Wellbeing*/
	/*Subjective FWB (sFWB)*/
		***reverse coding so that higher scores indicate a better situation
		gen sFWB_18_1 = 6 - qlb034e
		gen sFWB_18_2 = 6 - qlb035

		*generating composite score for msFWB
		egen sFWB_18 = rowmean(sFWB_18_1 sFWB_18_2)

/*Psychological*/
	/*Life Satisfaction (LS)*/
		***From RAND-r`i'lbsatwlf = "the higher the score, the higher the Respondent's
self-assessed quality of life"***
		***wlb003 in 2010 & 2012 and then wlb002 in 2014-2018***
		rename qlb002a LS_18_1
		rename qlb002b LS_18_2
		rename qlb002c LS_18_3
		rename qlb002d LS_18_4
		rename qlb002e LS_18_5

		egen LS_18_sum = rowtotal(LS_18_1 LS_18_2 LS_18_3 LS_18_4 LS_18_5),
missing
		egen LS_18_count = anycount(LS_18_1 LS_18_2 LS_18_3 LS_18_4 LS_18_5),
values(1/7)
		gen LS_18 = LS_18_sum / LS_18_count

	/*Anxiety Symptoms (AS)*/
	***Vars in years 2010, 2012, 2018***
		***Reverse coding so higher scores indicate lower anxiety***
		gen AS_18_1 = qlb035c1
			recode AS_18_1 (1=4)(2=3)(3=2)(4=1)
		gen AS_18_2 = qlb035c2
			recode AS_18_2 (1=4)(2=3)(3=2)(4=1)
		gen AS_18_3 = qlb035c3
			recode AS_18_3 (1=4)(2=3)(3=2)(4=1)
		gen AS_18_4 = qlb035c4
			recode AS_18_4 (1=4)(2=3)(3=2)(4=1)
		gen AS_18_5 = qlb035c5
			recode AS_18_5 (1=4)(2=3)(3=2)(4=1)

		egen AS_18_sum = rowtotal(AS_18_1 AS_18_2 AS_18_3 AS_18_4 AS_18_5),
missing
		egen AS_18_count = anycount(AS_18_1 AS_18_2 AS_18_3 AS_18_4
AS_18_5), values(1/4)
		gen AS_18 = AS_18_sum / AS_18_count
```

```
/*Sociological (Social Connection) (SC)*/
***Higher scores indicate higher levels of social connection***

	/*Partner/Spouse Closeness (PS)*/
		/*Partner/Spouse Closeness (PSc)*/
		***Only one var in 2010 & 2012. Three in 2014-2018***
		***Reverse coded***
			gen PSc_18_1 = qlb005
				recode PSc_18_1 (1=4)(2=3)(3=2)(4=1)
			gen PSc_18_2 = qlb005a
				recode PSc_18_2 (1=4)(2=3)(3=2)(4=1)
			gen PSc_18_3 = qlb005b
				recode PSc_18_3 (1=3)(3=1)

			egen PSc_18_sum = rowtotal(PSc_18_1 PSc_18_2 PSc_18_3), missing
			egen PSc_18_count = anycount(PSc_18_1 PSc_18_2 PSc_18_3),
values(1/4)
			gen PSc_18 = PSc_18_sum / PSc_18_count

		/*Partner/Spouse Relationship Quality (PSq)*/
		***qlb005a-c are reverse coded***
			gen PSq_18_1 = qlb004a
				recode PSq_18_1 (1=4)(2=3)(3=2)(4=1)
			gen PSq_18_2 = qlb004b
				recode PSq_18_2 (1=4)(2=3)(3=2)(4=1)
			gen PSq_18_3 = qlb004c
				recode PSq_18_3 (1=4)(2=3)(3=2)(4=1)
			gen PSq_18_4 = qlb004d
			gen PSq_18_5 = qlb004e
			gen PSq_18_6 = qlb004f
			gen PSq_18_7 = qlb004g

			egen PSq_18_sum = rowtotal(PSq_18_1 PSq_18_2 PSq_18_3 PSq_18_4
PSq_18_5 PSq_18_6 PSq_18_7), missing
			egen PSq_18_count = anycount(PSq_18_1 PSq_18_2 PSq_18_3
PSq_18_4 PSq_18_5 PSq_18_6 PSq_18_7), values(1/4)
			gen PSq_18 = PSq_18_sum / PSq_18_count

	/*Children Relationships (Ch)*/
		/*Children Contact (Chc)*/
		***Three vars in 2010 & 2012. Four vars in 2014-2018***
		***Reverse coded***
			gen Chc_18_1 = qlb008a
				recode Chc_18_1 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)
			gen Chc_18_2 = qlb008b
				recode Chc_18_2 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)
```

```
				gen Chc_18_3 = qlb008c
					recode Chc_18_3 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)
				gen Chc_18_4 = qlb008d
					recode Chc_18_4 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)


				egen Chc_18_sum = rowtotal(Chc_18_1 Chc_18_2 Chc_18_3 Chc_18_4), 
missing
				egen Chc_18_count = anycount(Chc_18_1 Chc_18_2 Chc_18_3 
Chc_18_4), values(1/6)
				gen Chc_18 = Chc_18_sum / Chc_18_count

			/*Children Relationship (Chr)*/
			***qlb009a-c are reverse coded***
				gen Chr_18_1 = qlb007a
					recode Chr_18_1 (1=4)(2=3)(3=2)(4=1)
				gen Chr_18_2 = qlb007b
					recode Chr_18_2 (1=4)(2=3)(3=2)(4=1)
				gen Chr_18_3 = qlb007c
					recode Chr_18_3 (1=4)(2=3)(3=2)(4=1)
				gen Chr_18_4 = qlb007d
				gen Chr_18_5 = qlb007e
				gen Chr_18_6 = qlb007f
				gen Chr_18_7 = qlb007g

				egen Chr_18_sum = rowtotal(Chr_18_1 Chr_18_2 Chr_18_3 Chr_18_4 
Chr_18_5 Chr_18_6 Chr_18_7), missing
				egen Chr_18_count = anycount(Chr_18_1 Chr_18_2 Chr_18_3 Chr_18_4 
Chr_18_5 Chr_18_6 Chr_18_7), values(1/4)
				gen Chr_18 = Chr_18_sum / Chr_18_count

		/*Other Family Relationships (OFR)*/
			/*Other Immediate Family Contact (OFRc)*/
			***Three vars in 2010 & 2012. Four vars in 2014-2018***
			***Reverse coded***
				gen OFRc_18_1 = qlb012a
					recode OFRc_18_1 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)
				gen OFRc_18_2 = qlb012b
					recode OFRc_18_2 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)
				gen OFRc_18_3 = qlb012c
					recode OFRc_18_3 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)
				gen OFRc_18_4 = qlb012d
					recode OFRc_18_4 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)
```

```
                egen OFRc_18_sum = rowtotal(OFRc_18_1 OFRc_18_2 OFRc_18_3
OFRc_18_4), missing
                egen OFRc_18_count = anycount(OFRc_18_1 OFRc_18_2 OFRc_18_3
OFRc_18_4), values(1/6)
                gen OFRc_18 = OFRc_18_sum / OFRc_18_count

            /*Other Immediate Family Relationship Quality (OFRq)*/
            ***qlb012a-c are reverse coded***
                gen OFRq_18_1 = qlb011a
                    recode OFRq_18_1 (1=4)(2=3)(3=2)(4=1)
                gen OFRq_18_2 = qlb011b
                    recode OFRq_18_2 (1=4)(2=3)(3=2)(4=1)
                gen OFRq_18_3 = qlb011c
                    recode OFRq_18_3 (1=4)(2=3)(3=2)(4=1)
                gen OFRq_18_4 = qlb011d
                gen OFRq_18_5 = qlb011e
                gen OFRq_18_6 = qlb011f
                gen OFRq_18_7 = qlb011g

                egen OFRq_18_sum = rowtotal(OFRq_18_1 OFRq_18_2 OFRq_18_3
OFRq_18_4 OFRq_18_5 OFRq_18_6 OFRq_18_7), missing
                egen OFRq_18_count = anycount(OFRq_18_1 OFRq_18_2 OFRq_18_3
OFRq_18_4 OFRq_18_5 OFRq_18_6 OFRq_18_7), values(1/4)
                gen OFRq_18 = OFRq_18_sum / OFRq_18_count

        /*Friend Relationships (FR)*/
            /*Friend Contact (FRc)*/
            ***Three vars in 2010 & 2012. Four vars in 2014-2018***
            ***Reverse coded***
                gen FRc_18_1 = qlb016a
                    recode FRc_18_1 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)
                gen FRc_18_2 = qlb016b
                    recode FRc_18_2 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)
                gen FRc_18_3 = qlb016c
                    recode FRc_18_3 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)
                gen FRc_18_4 = qlb016d
                    recode FRc_18_4 (1=6)(2=5)(3=4)(4=3)(5=2)(6=1)


                egen FRc_18_sum = rowtotal(FRc_18_1 FRc_18_2 FRc_18_3
FRc_18_4), missing
                egen FRc_18_count = anycount(FRc_18_1 FRc_18_2 FRc_18_3
FRc_18_4), values(1/6)
                gen FRc_18 = FRc_18_sum / FRc_18_count

            /*Friend Relationship Quality (FRq)*/
```

```
		***qlb012a-c are reverse coded***
			gen FRq_18_1 = qlb015a
				recode FRq_18_1 (1=4)(2=3)(3=2)(4=1)
			gen FRq_18_2 = qlb015b
				recode FRq_18_2 (1=4)(2=3)(3=2)(4=1)
			gen FRq_18_3 = qlb015c
				recode FRq_18_3 (1=4)(2=3)(3=2)(4=1)
			gen FRq_18_4 = qlb015d
			gen FRq_18_5 = qlb015e
			gen FRq_18_6 = qlb015f
			gen FRq_18_7 = qlb015g

			egen FRq_18_sum = rowtotal(FRq_18_1 FRq_18_2 FRq_18_3 FRq_18_4
FRq_18_5 FRq_18_6 FRq_18_7), missing
			egen FRq_18_count = anycount(FRq_18_1 FRq_18_2 FRq_18_3
FRq_18_4 FRq_18_5 FRq_18_6 FRq_18_7), values(1/4)
			gen FRq_18 = FRq_18_sum / FRq_18_count

	/*Closeness of Relationships (CoR)*/
		/*Partner/Spouse Closeness (CoRPS)*/
		***Only one var in 2010 & 2012. Three in 2014-2018***
		***Reverse coded***
			gen CoRPS_18_1 = qlb005
				recode PSc_18_1 (1=4)(2=3)(3=2)(4=1)
			gen CoRPS_18_2 = qlb005a
				recode PSc_18_1 (1=4)(2=3)(3=2)(4=1)
			gen CoRPS_18_3 = qlb005b
				recode PSc_18_3 (1=3)(3=1)

			egen CoRPS_18_sum = rowtotal(CoRPS_18_1 CoRPS_18_2
CoRPS_18_3), missing
			egen CoRPS_18_count = anycount(CoRPS_18_1 CoRPS_18_2
CoRPS_18_3), values(0/5)
			gen CoRPS_18 = CoRPS_18_sum / CoRPS_18_count


		/*Number of Close Relationships (CoRn)*/
		***These are continuous but have wide range***
		***Will need to do some sort of transformation. Starting by doing categorical
vars***
			gen CoRn_18_1 = qlb009
				replace CoRn_18_1 = 1 if inrange(qlb009,1,2)
				replace CoRn_18_1 = 2 if inrange(qlb009,3,4)
				replace CoRn_18_1 = 3 if inrange(qlb009,5,9)
				replace CoRn_18_1 = 4 if inrange(qlb009,10,14)
				replace CoRn_18_1 = 5 if qlb009 > 14
```

```
                        replace CoRn_18_1 = . if qlb009 == .
                                label variable CoRn_18_1 "n Close Children
Relationships"
                                label define CoRn_18_1 0 "0" 1 "1-2" 2 "3-4" 3 "5-9" 4
"10-14" 5 "15+"
                                label values CoRn_18_1 CoRn_18_1
                gen CoRn_18_2 = qlb013
                        replace CoRn_18_2 = 1 if inrange(qlb013,1,2)
                        replace CoRn_18_2 = 2 if inrange(qlb013,3,4)
                        replace CoRn_18_2 = 3 if inrange(qlb013,5,9)
                        replace CoRn_18_2 = 4 if inrange(qlb013,10,14)
                        replace CoRn_18_2 = 5 if qlb013 > 14
                        replace CoRn_18_2 = . if qlb013 == .
                                label variable CoRn_18_2 "n Close Family Relationships"
                                label define CoRn_18_2 0 "0" 1 "1-2" 2 "3-4" 3 "5-9" 4
"10-14" 5 "15+"
                                label values CoRn_18_2 CoRn_18_2
                gen CoRn_18_3 = qlb017
                        replace CoRn_18_3 = 1 if inrange(qlb017,1,2)
                        replace CoRn_18_3 = 2 if inrange(qlb017,3,4)
                        replace CoRn_18_3 = 3 if inrange(qlb017,5,9)
                        replace CoRn_18_3 = 4 if inrange(qlb017,10,14)
                        replace CoRn_18_3 = 5 if qlb017 > 14
                        replace CoRn_18_3 = . if qlb017 == .
                                label variable CoRn_18_3 "n Close Family Relationships"
                                label define CoRn_18_3 0 "0" 1 "1-2" 2 "3-4" 3 "5-9" 4
"10-14" 5 "15+"
                                label values CoRn_18_3 CoRn_18_3

                egen CoRn_18_sum = rowtotal(CoRn_18_1 CoRn_18_2 CoRn_18_3),
missing
                egen CoRn_18_count = anycount(CoRn_18_1 CoRn_18_2 CoRn_18_3),
values(0/5)
                gen CoRn_18 = CoRn_18_sum / CoRn_18_count


gen year = 2018
gen hhidpn_year = string(hhidpn,"%09.0f") + "_" + string(year,"%04.0f")

merge 1:1 hhidpn using "${data_ed}\rand.2.dta"

/*Depressive Symptoms*/
        ***"the higher the score, the more negative the Respondent's feelings in the past
week"***
        ***as a result...have to reverse code
        gen temp = r14cesd + 1
```

```
	gen r_r14cesd = 10 - temp
	drop temp

keep if !missing(hhidpn_year)

keep /*RAND Vars*/ hhid hhidpn* year hhidpn_year pn ragender raracem rahispan ravetrn
raedyrs raedegrm raeduc educ r14* r18* h14* h18* Ch*_18* FL*_18* LS_18* DS_18* z_h18*
l_h18* /*Core Vars*/ q* sFWB* AS* PS* OFR* FR* Co* r_*

	save "${data_ed}\fat18.2.dta", replace

*=====================================================================
==========
*Combine fat file data to create large 5-wave set
*=====================================================================
==========

use "${data_ed}\fat18.2.dta", clear
	merge 1:1 hhidpn_year using "${data_ed}\fat16.2.dta", nogen
	merge 1:1 hhidpn_year using "${data_ed}\fat14.2.dta", nogen
	merge 1:1 hhidpn_year using "${data_ed}\fat12.2.dta", nogen
	merge 1:1 hhidpn_year using "${data_ed}\fat10.2.dta", nogen

/*Creating all DV, IV, and CV from all waves.*/

	/*Financial Wellbeing*/
		/*Subjective FWB (sFWB)*/
			***reverse coding so that higher scores indicate a better situation
			egen sFWB_1 = rowmax(sFWB_*_1)
			egen sFWB_2 = rowmax(sFWB_*_2)

			*generating composite score for msFWB
			egen sFWB = rowmax(sFWB*)
				label variable sFWB "Subjective Financial Wellbeing"

		/*Objective FWB*/
			***Income and Assets***
				***Creating sum of household pension/annuities
				egen ipena = rowmax(h*ipena)
					label variable ipena "Income from ER Pension or Annuity"

				***Creating bianary var of pension/annuities
				egen ipena_b = rowmax(h*ipena_b)
					label variable ipena_b "Has an ER Pension or Annuity"

				***Creating z-score normalization of income and assets***
```

```
egen z_HInc = rowmax(z_h*HInc)
egen z_HAss = rowmax(z_h*HAss)
egen z_HNhAss = rowmax(z_h*HNhAss)
egen z_HNW = rowmax(z_h*HNW )
egen z_HNHoEq = rowmax(z_h*HNHoEq)

***Creating log of income and assets***
egen l_HInc = rowmax(l_h*HInc)
egen l_HAss = rowmax(l_h*HAss)
egen l_HNhAss = rowmax(l_h*HNhAss)
egen l_HNW = rowmax(l_h*HNW)
egen l_HNHoEq = rowmax(l_h*HNHoEq)

***generating debt-to-asset ratio***
egen hd2a = rowmax(h*d2a)

/*Control Variables*/
***Age***
egen age = rowmax(r*age)
***Education***
*Carried from RAND

***Gender***
*Carried from RAND

***Marital Status***
egen mstat = rowmax(r*mstat)

egen marstat = rowmax(r*mstat)
replace marstat = 1 if mstat < 3 /*Married*/
replace marstat = 2 if mstat == 3 /*Partnered*/
replace marstat = 3 if inrange(mstat,4,6) /*Separated/Divorced*/
replace marstat = 4 if mstat == 7 /*Widowed*/
replace marstat = 5 if mstat == 8 /*Never Married*/
label variable marstat "Marital Status"
label define marstat 1 "Married" 2 "Partnered" 3 "Separated/Divorced" 4
"Widowed" 5 "Never Married"
label values marstat marstat

***Employment Status***
gen empl_10 = .
replace empl_10 = 0 if year == 2010 & r10work == 0
replace empl_10 = 1 if year == 2010 & r10work == 1
label variable empl_10 "Employment Status"
label define empl_10 0 "Not working for pay" 1 "Working for pay"
label values empl_10 empl_10
```

```
gen empl_12 = .
	replace empl_12 = 0 if year == 2012 & r11work == 0
	replace empl_12 = 1 if year == 2012 & r11work == 1
	label variable empl_12 "Employment Status"
	label define empl_12 0 "Not working for pay" 1 "Working for pay"
	label values empl_12 empl_12
gen empl_14 = .
	replace empl_14 = 0 if year == 2014 & r12work == 0
	replace empl_14 = 1 if year == 2014 & r12work == 1
	label variable empl_14 "Employment Status"
	label define empl_14 0 "Not working for pay" 1 "Working for pay"
	label values empl_14 empl_14
gen empl_16 = .
	replace empl_16 = 0 if year == 2016 & r13work == 0
	replace empl_16 = 1 if year == 2016 & r13work == 1
	label variable empl_16 "Employment Status"
	label define empl_16 0 "Not working for pay" 1 "Working for pay"
	label values empl_16 empl_16
gen empl_18 = .
	replace empl_18 = 0 if year == 2018 & r14work == 0
	replace empl_18 = 1 if year == 2018 & r14work == 1
	label variable empl_18 "Employment Status"
	label define empl_18 0 "Not working for pay" 1 "Working for pay"
	label values empl_18 empl_18

egen empl = rowmax(empl_*)
	label variable empl "Employment Status"
	label define empl 0 "Not working for pay" 1 "Working for pay"
	label values empl empl

***Race***
	*Carried from RAND

***Ethnicity***
	*Carried from RAND

***Race/Eth***
	*Carried from RAND

***Veteran Status***
	*Carried from RAND

/*Biological [All vars...lower are better]*/
	***Self-Reported Health Status (r`i'SRH)***
	egen SRH = rowmax(r*SRH)
		label variable SRH "Self-Reported Health"
```

```
		label define SRH 1 "Excellent" 2 "Very Good" 3 "Good" 4 "Fair" 5 "Poor"
		label values SRH SRH

	***BMI***
	egen bmi = rowmax(r*bmi)

	***BMI Categories***
		*From CDC:
		*BMI			Weight Status
		*Below 18.5		Underweight
		*18.5 – 24.9	Healthy Weight
		*25.0 – 29.9	Overweight
		*30.0 +				Obesity
	egen BMI_cat = rowmax(r*BMI_cat)
		label variable BMI_cat "BMI Categories"
		label define BMI_cat 1 "Underweight" 2 "Healthy Weight" 3
"Overweight" 4 "Obese"
		label values BMI_cat BMI_cat

	***Chronic Illness (ChIL)***
	egen ChIl_1 = rowmax(ChIl_*_1)
	egen ChIl_2 = rowmax(ChIl_*_2)
	egen ChIl_3 = rowmax(ChIl_*_3)
	egen ChIl_4 = rowmax(ChIl_*_4)
	egen ChIl_5 = rowmax(ChIl_*_5)
	egen ChIl_6 = rowmax(ChIl_*_6)
	egen ChIl_7 = rowmax(ChIl_*_7)
	egen ChIl_8 = rowmax(ChIl_*_8)

	***Composite of ChIl***
	*Unlike funcitonal limitation (below), ChIl has composite already built in
RAND*
	egen ChIl_r = rowmax(ChIl_*_r)
		label variable ChIl_r "# of Chronic Illnesses(RAND)"

	*Built composite for robustness check*
	*First step gives the number of missing values in varlist for each observation
	egen ChIl_miss = rowmiss(ChIl_1 ChIl_2 ChIl_3 ChIl_4 ChIl_5 ChIl_6 ChIl_7
ChIl_8)
	*Second step creates 'sum' var as long at not all vals are missing
	egen ChIl = rowtotal(ChIl_1 ChIl_2 ChIl_3 ChIl_4 ChIl_5 ChIl_6 ChIl_7 ChIl_8)
if ChIl_miss != 8
		label variable ChIl "# of Chronic Illnesses"

	***Functional Limitation (FL)***
	egen FL_1 = rowmax(FL_*_1)
```

```
egen FL_2 = rowmax(FL_*_2)
egen FL_3 = rowmax(FL_*_3)
egen FL_4 = rowmax(FL_*_4)
egen FL_5 = rowmax(FL_*_5)
egen FL_6 = rowmax(FL_*_6)

***Composite of FL***
*First step gives the number of missing values in varlist for each observation
egen FL_miss = rowmiss(FL_1 FL_2 FL_3 FL_4 FL_5 FL_6)
*Second step creates 'sum' var as long at not all vals are missing
egen FL = rowtotal(FL_1 FL_2 FL_3 FL_4 FL_5 FL_6) if FL_miss != 6
	label variable FL "# of Functional Limitations"

/*Psychological*/
	***Life Satisfaction (LS - RAND)***
	*The RAND var is different than the Core vars*
	egen LS = rowmax(LS_*_r)
		label variable LS "Life Satisfaction (RAND)"

	***Depressive Symptoms (DS)***
	egen DS_1 = rowmax(DS_*_1)
	egen DS_2 = rowmax(DS_*_2)
	egen DS_3 = rowmax(DS_*_3)
	egen DS_4 = rowmax(DS_*_4)
	egen DS_5 = rowmax(DS_*_5)
	egen DS_6 = rowmax(DS_*_6)
	egen DS_7 = rowmax(DS_*_7)
	egen DS_8 = rowmax(DS_*_8)

	***Composite of DS***
	*First step gives the number of missing values in varlist for each observation
	egen DS_miss = rowmiss(DS_1 DS_2 DS_3 DS_4 DS_5 DS_6 DS_7 DS_8)
	*Second step creates 'sum' var as long at not all vals are missing
	egen DS = rowtotal(DS_1 DS_2 DS_3 DS_4 DS_5 DS_6 DS_7 DS_8) if 
DS_miss != 8
		label variable DS "# of Depressive Symptoms"

	***Anxiety Symptoms (AS)***
	***Vars in years 2010, 2012, 2018***
	***Reverse coding so higher scores indicate lower anxiety***
	egen AS_1 = rowmax(AS_*_1)
	egen AS_2 = rowmax(AS_*_2)
	egen AS_3 = rowmax(AS_*_3)
	egen AS_4 = rowmax(AS_*_4)
	egen AS_5 = rowmax(AS_*_5)
```

```
		egen AS_sum = rowtotal(AS_1 AS_2 AS_3 AS_4 AS_5), missing
		egen AS_count = anycount(AS_1 AS_2 AS_3 AS_4 AS_5), values(1/4)
		gen AS = AS_sum / AS_count

	/*Sociological (Social Connection) (SC)*/
	***Higher scores indicate higher levels of social connection***

		***Partner/Spouse Relationship (PS)***
			***Partner/Spouse Closeness (PSc)***
			*Only one var in 2010 & 2012. Three in 2014-2018*
			***Reverse coded***
			egen PSc_1 = rowmax(PSc_*_1)
			egen PSc_2 = rowmax(PSc_*_2)
			egen PSc_3 = rowmax(PSc_*_3)

			egen PSc_sum = rowtotal(PSc_1 PSc_2 PSc_3), missing
			egen PSc_count = anycount(PSc_1 PSc_2 PSc_3), values(1/4)
			gen PSc = PSc_sum / PSc_count

			/*Partner/Spouse Relationship Quality (PSq)*/
			***mlb005a-c are reverse coded***
			egen PSq_1 = rowmax(PSq_*_1)
			egen PSq_2 = rowmax(PSq_*_2)
			egen PSq_3 = rowmax(PSq_*_3)
			egen PSq_4 = rowmax(PSq_*_4)
			egen PSq_5 = rowmax(PSq_*_5)
			egen PSq_6 = rowmax(PSq_*_6)
			egen PSq_7 = rowmax(PSq_*_7)

			egen PSq_sum = rowtotal(PSq_1 PSq_2 PSq_3 PSq_4 PSq_5 PSq_6
PSq_7), missing
			egen PSq_count = anycount(PSq_1 PSq_2 PSq_3 PSq_4 PSq_5 PSq_6
PSq_7), values(1/4)
			gen PSq = PSq_sum / PSq_count

		***Children Relationships (Ch)***
			/*Children Contact (Chc)*/
			***Three vars in 2010 & 2012. Four vars in 2014-2018***
			***Reverse coded***
			egen Chc_1 = rowmax(Chc_*_1)
			egen Chc_2 = rowmax(Chc_*_2)
			egen Chc_3 = rowmax(Chc_*_3)
			egen Chc_4 = rowmax(Chc_*_4)

			egen Chc_sum = rowtotal(Chc_1 Chc_2 Chc_3 Chc_4), missing
			egen Chc_count = anycount(Chc_1 Chc_2 Chc_3 Chc_4), values(1/6)
```

```
			gen Chc = Chc_sum / Chc_count

			/*Children Relationship (Chr)*/
			***mlb009a-c are reverse coded***
			egen Chr_1 = rowmax(Chr_*_1)
			egen Chr_2 = rowmax(Chr_*_2)
			egen Chr_3 = rowmax(Chr_*_3)
			egen Chr_4 = rowmax(Chr_*_4)
			egen Chr_5 = rowmax(Chr_*_5)
			egen Chr_6 = rowmax(Chr_*_6)
			egen Chr_7 = rowmax(Chr_*_7)

			egen Chr_sum = rowtotal(Chr_1 Chr_2 Chr_3 Chr_4 Chr_5 Chr_6
Chr_7), missing
			egen Chr_count = anycount(Chr_1 Chr_2 Chr_3 Chr_4 Chr_5 Chr_6
Chr_7), values(1/4)
			gen Chr = Chr_sum / Chr_count

		***Other Family Relationships (OFR)***
			/*Other Immediate Family Contact (OFRc)*/
			***Three vars in 2010 & 2012. Four vars in 2014-2018***
			***Reverse coded***
			egen OFRc_1 = rowmax(OFRc_*_1)
			egen OFRc_2 = rowmax(OFRc_*_2)
			egen OFRc_3 = rowmax(OFRc_*_3)
			egen OFRc_4 = rowmax(OFRc_*_4)

			egen OFRc_sum = rowtotal(OFRc_1 OFRc_2 OFRc_3 OFRc_4), missing
			egen OFRc_count = anycount(OFRc_1 OFRc_2 OFRc_3 OFRc_4),
values(1/6)
			gen OFRc = OFRc_sum / OFRc_count

			/*Other Immediate Family Relationship Quality (OFRq)*/
			***mlb012a-c are reverse coded***
			egen OFRq_1 = rowmax(OFRq_*_1)
			egen OFRq_2 = rowmax(OFRq_*_2)
			egen OFRq_3 = rowmax(OFRq_*_3)
			egen OFRq_4 = rowmax(OFRq_*_4)
			egen OFRq_5 = rowmax(OFRq_*_5)
			egen OFRq_6 = rowmax(OFRq_*_6)
			egen OFRq_7 = rowmax(OFRq_*_7)

			egen OFRq_sum = rowtotal(OFRq_1 OFRq_2 OFRq_3 OFRq_4 OFRq_5
OFRq_6 OFRq_7), missing
			egen OFRq_count = anycount(OFRq_1 OFRq_2 OFRq_3 OFRq_4
OFRq_5 OFRq_6 OFRq_7), values(1/4)
```

```
gen OFRq = OFRq_sum / OFRq_count

***Friend Relationships (FR)***
	/*Friend Contact (FRc)*/
	***Three vars in 2010 & 2012. Four vars in 2014-2018***
	***Reverse coded***
	egen FRc_1 = rowmax(FRc_*_1)
	egen FRc_2 = rowmax(FRc_*_2)
	egen FRc_3 = rowmax(FRc_*_3)
	egen FRc_4 = rowmax(FRc_*_4)

	egen FRc_sum = rowtotal(FRc_1 FRc_2 FRc_3 FRc_4), missing
	egen FRc_count = anycount(FRc_1 FRc_2 FRc_3 FRc_4), values(1/6)
	gen FRc = FRc_sum / FRc_count


	/*Friend Relationship Quality (FRq)*/
	***mlb012a-c are reverse coded***
	egen FRq_1 = rowmax(FRq_*_1)
	egen FRq_2 = rowmax(FRq_*_2)
	egen FRq_3 = rowmax(FRq_*_3)
	egen FRq_4 = rowmax(FRq_*_4)
	egen FRq_5 = rowmax(FRq_*_5)
	egen FRq_6 = rowmax(FRq_*_6)
	egen FRq_7 = rowmax(FRq_*_7)

	egen FRq_sum = rowtotal(FRq_1 FRq_2 FRq_3 FRq_4 FRq_5 FRq_6
FRq_7), missing
	egen FRq_count = anycount(FRq_1 FRq_2 FRq_3 FRq_4 FRq_5 FRq_6
FRq_7), values(1/4)
	gen FRq = FRq_sum / FRq_count

	/*Closeness of Relationships (CoR)*/
	/*Partner/Spouse Closeness (CoRPS)*/
	***Only one var in 2010 & 2012. Three in 2014-2018***
	***Reverse coded***
	egen CoRPS_1 = rowmax(CoRPS_*_1)
	egen CoRPS_2 = rowmax(CoRPS_*_2)
	egen CoRPS_3 = rowmax(CoRPS_*_3)

	egen CoRPS_sum = rowtotal(CoRPS_1 CoRPS_2 CoRPS_3), missing
	egen CoRPS_count = anycount(CoRPS_1 CoRPS_2 CoRPS_3),
values(1/6)
	gen CoRPS = CoRPS_sum / CoRPS_count

	/*Number of Close Relationships (CoRn)*/
```

```
        ***These are continuous but have wide range***
        ***Will need to do some sort of transformation***
        egen CoRn_1 = rowmax(CoRn_*_1)
        egen CoRn_2 = rowmax(CoRn_*_2)
        egen CoRn_3 = rowmax(CoRn_*_3)

        egen CoRn_sum = rowtotal(CoRn_1 CoRn_2 CoRn_3), missing
        egen CoRn_count = anycount(CoRn_1 CoRn_2 CoRn_3), values(1/6)
        gen CoRn = CoRn_sum / CoRn_count

save "${data_ed}\dissertation.2.dta", replace
```

Variable Analysis

```
/***************************************************************************
*Title: dissertation_analysis.do
*Created by: Chet Bennetts
*Created on: 12/21/2023
*Last modified on: 03/23/2024
*Last modified by: Chet Bennetts
*Purpose: Creates .docs for cleaned variables from HRS (2010-2020). Docs include sum,
pwcorr, alpha, and factor commands
***************************************************************************/

clear all

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

global projdir "C:\Users\crben\Dropbox\Grad\KSU\0-Dissertation\data"
	cd "$projdir"
global data_ed "${projdir}\edited"
global data_raw "${projdir}\raw"

*==========================================================================
*"Use" files for all waves - Data importation only
*==========================================================================

/*Primary DTA File*/
use "${data_ed}\dissertation.2.dta", clear

/*Looping routine for 'asdoc' reports*/

local years "2010 2012 2014 2016 2018"
	local i = 8			/*Variation to account for wave/year in Core*/
	local w = 9			/*Variation to account for wave/year in RAND*/
	foreach y in `years' {
		local i = `i' + 2
		local w = `w' + 1

	/*Define save path for each years results*/
	local `i'savePath "${projdir}\Stats\20`i'"

/*Financial Wellbeing*/
	/*Subjective Financial Wellbeing (sFWB)*/
	asdoc sum sFWB_`i'_1 sFWB_`i'_2 sFWB_`i', save(${projdir}\Stats\20`i'\sFWB_`i'.doc)
title(Summary of sFWB - 20`i') replace label
```

```
	asdoc pwcorr sFWB_`i'_1 sFWB_`i'_2, star(0.05) bonferroni title(Correlation of sFWB - 20`i') label
	asdoc alpha sFWB_`i'_1 sFWB_`i'_2, title(Alpha of sFWB - 20`i') label
	asdoc factor sFWB_`i'_1 sFWB_`i'_2, title(Factor of sFWB - 20`i') label

	/*Objective Financial Wellbeing (oFWB)*/
		***Income and Assets***
		asdoc summarize h`i'HInc l_h`i'HInc, save(${projdir}\Stats\20`i'\oFWB_`i'.doc) title(Summary of Income - 20`i') replace label
		asdoc summarize h`i'HAss l_h`i'HAss, title(Summary of Total Assets - 20`i') label

		asdoc summarize h`i'HNhAss l_h`i'HNhAss, title(Summary of Total Non-Housing Assets - 20`i') label
		asdoc summarize h`i'HNW l_h`i'HNW, title(Summary of Total Net Worth - 20`i') label
		asdoc summarize h`i'HNHoEq l_h`i'HNHoEq, title(Summary of Net Value of House - 20`i') label

/*Biological - Physical Health (PH)*/
asdoc sum r`i'SRH r`i'BMI i.r`i'BMI_cat ChIl_`i' ChIl_`i'_r FL_`i', save(${projdir}\Stats\20`i'\PH_`i'.doc) title(Summary of PH - 20`i') replace label
asdoc pwcorr r`i'SRH r`i'BMI r`i'BMI_cat ChIl_`i' ChIl_`i'_r FL_`i', star(0.05) bonferroni title(Correlation of PH - 20`i') label
asdoc alpha r`i'SRH r`i'BMI r`i'BMI_cat ChIl_`i' ChIl_`i'_r FL_`i', title(Alpha of PH - 20`i') label
asdoc factor r`i'SRH r`i'BMI r`i'BMI_cat ChIl_`i' ChIl_`i'_r FL_`i', title(Factor of PH - 20`i') label

	/*Chronic Illness (ChIl)*/
	asdoc sum ChIl_`i'_1 ChIl_`i'_2 ChIl_`i'_3 ChIl_`i'_4 ChIl_`i'_5 ChIl_`i'_6 ChIl_`i'_7 ChIl_`i'_8 ChIl_`i' ChIl_`i'_r, save(${projdir}\Stats\20`i'\ChIl_`i'.doc) title(Summary of ChIl - 20`i') replace label
	asdoc pwcorr ChIl_`i'_1 ChIl_`i'_2 ChIl_`i'_3 ChIl_`i'_4 ChIl_`i'_5 ChIl_`i'_6 ChIl_`i'_7 ChIl_`i'_8, star(0.05) bonferroni title(Correlation of ChIl - 20`i') label
	asdoc alpha ChIl_`i'_1 ChIl_`i'_2 ChIl_`i'_3 ChIl_`i'_4 ChIl_`i'_5 ChIl_`i'_6 ChIl_`i'_7 ChIl_`i'_8, title(Alpha of ChIl - 20`i') label
	asdoc factor ChIl_`i'_1 ChIl_`i'_2 ChIl_`i'_3 ChIl_`i'_4 ChIl_`i'_5 ChIl_`i'_6 ChIl_`i'_7 ChIl_`i'_8, title(Factor of ChIl - 20`i') label

	/*Functional Limitation (FL)*/
	asdoc sum FL_`i'_1 FL_`i'_2 FL_`i'_3 FL_`i'_4 FL_`i'_5 FL_`i'_6 FL_`i', save(${projdir}\Stats\20`i'\FL_`i'.doc) title(Summary of FL - 20`i') replace label
	asdoc pwcorr FL_`i'_1 FL_`i'_2 FL_`i'_3 FL_`i'_4 FL_`i'_5 FL_`i'_6, star(0.05) bonferroni title(Correlation of FL - 20`i') label
	asdoc alpha FL_`i'_1 FL_`i'_2 FL_`i'_3 FL_`i'_4 FL_`i'_5 FL_`i'_6, title(Alpha of FL - 20`i') label
```

```
	asdoc factor FL_`i'_1 FL_`i'_2 FL_`i'_3 FL_`i'_4 FL_`i'_5 FL_`i'_6, title(Factor of FL - 20`i') label

/*Psychological - Mental Health (MH)*/
asdoc sum LS_`i' DS_`i' AS_`i', save(${projdir}\Stats\20`i'\MH_`i'.doc) title(Summary of MH - 20`i') replace label
asdoc pwcorr LS_`i' DS_`i' AS_`i', star(0.05) bonferroni title(Correlation of MH - 20`i') label
asdoc alpha LS_`i' DS_`i' AS_`i', title(Alpha of MH - 20`i') label
asdoc factor LS_`i' DS_`i' AS_`i', title(Factor of MH - 20`i') label

	/*Life Satisfaction (LS)*/
	asdoc sum LS_`i'_1 LS_`i'_2 LS_`i'_3 LS_`i'_4 LS_`i'_5 LS_`i' LS_`i'_r, save(${projdir}\Stats\20`i'\LS_`i'.doc) title(Summary of LS - 20`i') replace label
	asdoc pwcorr LS_`i'_1 LS_`i'_2 LS_`i'_3 LS_`i'_4 LS_`i'_5, star(0.05) bonferroni title(Correlation of LS - 20`i') label
	asdoc alpha LS_`i'_1 LS_`i'_2 LS_`i'_3 LS_`i'_4 LS_`i'_5, title(Alpha of LS - 20`i') label
	asdoc factor LS_`i'_1 LS_`i'_2 LS_`i'_3 LS_`i'_4 LS_`i'_5, title(Factor of LS - 20`i') label

	/*Depressive Symptoms (DS)*/
	asdoc sum DS_`i'_1 DS_`i'_2 DS_`i'_3 DS_`i'_4 DS_`i'_5 DS_`i'_6 DS_`i'_7 DS_`i'_8 DS_`i', save(${projdir}\Stats\20`i'\DS_`i'.doc) title(Summary of DS - 20`i') replace label
	asdoc pwcorr DS_`i'_1 DS_`i'_2 DS_`i'_3 DS_`i'_4 DS_`i'_5 DS_`i'_6 DS_`i'_7 DS_`i'_8, star(0.05) bonferroni title(Correlation of DS - 20`i') label
	asdoc alpha DS_`i'_1 DS_`i'_2 DS_`i'_3 DS_`i'_4 DS_`i'_5 DS_`i'_6 DS_`i'_7 DS_`i'_8, title(Alpha of DS - 20`i') label
	asdoc factor DS_`i'_1 DS_`i'_2 DS_`i'_3 DS_`i'_4 DS_`i'_5 DS_`i'_6 DS_`i'_7 DS_`i'_8, title(Factor of DS - 20`i') label

	/*Anxiety Symptoms (AS)*/
	if `i' == 10 | `i' == 12 | `i' == 18 {
		asdoc sum AS_`i'_1 AS_`i'_2 AS_`i'_3 AS_`i'_4 AS_`i'_5 AS_`i', save(${projdir}\Stats\20`i'\AS_`i'.doc) title(Summary of AS - 20`i') replace label
		asdoc pwcorr AS_`i'_1 AS_`i'_2 AS_`i'_3 AS_`i'_4 AS_`i'_5, star(0.05) bonferroni title(Correlation of AS - 20`i') label
		asdoc alpha AS_`i'_1 AS_`i'_2 AS_`i'_3 AS_`i'_4 AS_`i'_5, title(Alpha of AS - 20`i') label
		asdoc factor AS_`i'_1 AS_`i'_2 AS_`i'_3 AS_`i'_4 AS_`i'_5, title(Factor of AS - 20`i') label
	}
	if `i' == 14 | `i' == 16 {
		*asdoc sum AS_`i'_2 , save(${projdir}\Stats\20`i'\AS_`i'.doc) title(Summary of AS - 20`i') replace label
	}

/*Sociological (Social Connection) (SC)*/
	/*Partner/Spouse Relationship (PS)*/
```

```
	if `i' == 10 | `i' == 12 {
		asdoc sum PSc_`i'_1 PSq_`i', save(${projdir}\Stats\20`i'\MH_`i'.doc)
title(Summary of PS - 20`i') replace label
		asdoc pwcorr PSc_`i'_1 PSq_`i', star(0.05) bonferroni title(Correlation of PS -
20`i') label
		asdoc alpha PSc_`i'_1 PSq_`i', title(Alpha of PS - 20`i') label
		asdoc factor PSc_`i'_1 PSq_`i', title(Factor of PS - 20`i') label
	}
	if `i' == 14 | `i' == 16 | `i' == 18 {
		asdoc sum PSc_`i' PSq_`i', save(${projdir}\Stats\20`i'\MH_`i'.doc) title(Summary
of PS - 20`i') replace label
		asdoc pwcorr PSc_`i' PSq_`i', star(0.05) bonferroni title(Correlation of PS - 20`i')
label
		asdoc alpha PSc_`i' PSq_`i', title(Alpha of PS - 20`i') label
		asdoc factor PSc_`i' PSq_`i', title(Factor of PS - 20`i') label
	}
		/*Partner/Spouse Closeness (PSc)*/
		if `i' == 10 | `i' == 12 {
			asdoc sum PSc_`i'_1 , save(${projdir}\Stats\20`i'\PSc_`i'.doc)
title(Summary of PSc - 20`i') replace label
		}
		if `i' == 14 | `i' == 16 | `i' == 18 {
			asdoc sum PSc_`i'_1 PSc_`i'_2 PSc_`i'_3 PSc_`i',
save(${projdir}\Stats\20`i'\PSc_`i'.doc) title(Summary of PSc - 20`i') replace label
			asdoc pwcorr PSc_`i'_1 PSc_`i'_2 PSc_`i'_3, star(0.05) bonferroni
title(Correlation of PSc - 20`i') label
			asdoc alpha PSc_`i'_1 PSc_`i'_2 PSc_`i'_3, title(Alpha of PSc - 20`i') labe
			asdoc factor PSc_`i'_1 PSc_`i'_2 PSc_`i'_3, title(Factor of PSc - 20`i')
label
		}
		/*Partner/Spouse Relationship Quality (PSq)*/
		asdoc sum PSq_`i'_1 PSq_`i'_2 PSq_`i'_3 PSq_`i'_4 PSq_`i'_5 PSq_`i'_6
PSq_`i'_7, save(${projdir}\Stats\20`i'\PSq_`i'.doc) title(Summary of PSq - 20`i') replace label

		asdoc pwcorr PSq_`i'_1 PSq_`i'_2 PSq_`i'_3 PSq_`i'_4 PSq_`i'_5 PSq_`i'_6
PSq_`i'_7, star(0.05) bonferroni title(Correlation of PSq - 20`i') label
		asdoc alpha PSq_`i'_1 PSq_`i'_2 PSq_`i'_3 PSq_`i'_4 PSq_`i'_5 PSq_`i'_6
PSq_`i'_7, title(Alpha of PSq - 20`i') label
		asdoc factor PSq_`i'_1 PSq_`i'_2 PSq_`i'_3 PSq_`i'_4 PSq_`i'_5 PSq_`i'_6
PSq_`i'_7, title(Factor of PSq - 20`i') label

	/*Children Relationship (Ch)*/
	if `i' == 10 | `i' == 12 {
		asdoc sum Chc_`i'_1 Chr_`i', save(${projdir}\Stats\20`i'\MH_`i'.doc)
title(Summary of Ch - 20`i') replace label
```

```
		asdoc pwcorr Chc_`i'_1 Chr_`i', star(0.05) bonferroni title(Correlation of Ch - 20`i') label
		asdoc alpha Chc_`i'_1 Chr_`i', title(Alpha of Ch - 20`i') label
		asdoc factor Chc_`i'_1 Chr_`i', title(Factor of Ch - 20`i') label
	}
	if `i' == 14 | `i' == 16 | `i' == 18 {
		asdoc sum Chc_`i' Chr_`i', save(${projdir}\Stats\20`i'\MH_`i'.doc) title(Summary of Ch - 20`i') replace label
		asdoc pwcorr Chc_`i' Chr_`i', star(0.05) bonferroni title(Correlation of Ch - 20`i') label
		asdoc alpha Chc_`i' Chr_`i', title(Alpha of Ch - 20`i') label
		asdoc factor Chc_`i' Chr_`i', title(Factor of Ch - 20`i') label
	}
		/*Children Closeness (Chc)*/
		if `i' == 10 | `i' == 12 {
			asdoc sum Chc_`i'_1 Chc_`i'_2 Chc_`i'_3 Chc_`i', save(${projdir}\Stats\20`i'\Chc_`i'.doc) title(Summary of Chc - 20`i') replace label
			asdoc pwcorr Chc_`i'_1 Chc_`i'_2 Chc_`i'_3, star(0.05) bonferroni title(Correlation of Chc - 20`i') label
			asdoc alpha Chc_`i'_1 Chc_`i'_2 Chc_`i'_3, title(Alpha of Chc - 20`i') label
			asdoc factor Chc_`i'_1 Chc_`i'_2 Chc_`i'_3, title(Factor of Chc - 20`i') label
		}
		if `i' == 14 | `i' == 16 | `i' == 18 {
			asdoc sum Chc_`i'_1 Chc_`i'_2 Chc_`i'_3 Chc_`i'_4 Chc_`i', save(${projdir}\Stats\20`i'\Chc_`i'.doc) title(Summary of Chc - 20`i') replace label
			asdoc pwcorr Chc_`i'_1 Chc_`i'_2 Chc_`i'_3 Chc_`i'_4, star(0.05) bonferroni title(Correlation of Chc - 20`i') label
			asdoc alpha Chc_`i'_1 Chc_`i'_2 Chc_`i'_3 Chc_`i'_4, title(Alpha of Chc - 20`i') label
			asdoc factor Chc_`i'_1 Chc_`i'_2 Chc_`i'_3 Chc_`i'_4, title(Factor of Chc - 20`i') label
		}
		/*Children Relationship Quality (Chr)*/
		asdoc sum Chr_`i'_1 Chr_`i'_2 Chr_`i'_3 Chr_`i'_4 Chr_`i'_5 Chr_`i'_6 Chr_`i'_7, save(${projdir}\Stats\20`i'\Chr_`i'.doc) title(Summary of Chr - 20`i') replace label
		asdoc pwcorr Chr_`i'_1 Chr_`i'_2 Chr_`i'_3 Chr_`i'_4 Chr_`i'_5 Chr_`i'_6 Chr_`i'_7, star(0.05) bonferroni title(Correlation of Chr - 20`i') label
		asdoc alpha Chr_`i'_1 Chr_`i'_2 Chr_`i'_3 Chr_`i'_4 Chr_`i'_5 Chr_`i'_6 Chr_`i'_7, title(Alpha of Chr - 20`i') label
		asdoc factor Chr_`i'_1 Chr_`i'_2 Chr_`i'_3 Chr_`i'_4 Chr_`i'_5 Chr_`i'_6 Chr_`i'_7, title(Factor of Chr - 20`i') label

	/*Other Family Relationship (OFR)*/
		/*Other Family Closeness (OFRc)*/
```

```
		if `i' == 10 | `i' == 12 {
			asdoc sum OFRc_`i'_1 OFRc_`i'_2 OFRc_`i'_3 OFRc_`i', 
save(${projdir}\Stats\20`i'\OFRc_`i'.doc) title(Summary of OFRc - 20`i') replace label
			asdoc pwcorr OFRc_`i'_1 OFRc_`i'_2 OFRc_`i'_3, star(0.05) bonferroni 
title(Correlation of OFRc - 20`i') label
			asdoc alpha OFRc_`i'_1 OFRc_`i'_2 OFRc_`i'_3, title(Alpha of OFRc - 
20`i') label
			asdoc factor OFRc_`i'_1 OFRc_`i'_2 OFRc_`i'_3, title(Factor of OFRc - 
20`i') label
		}
		if `i' == 14 | `i' == 16 | `i' == 18 {
			asdoc sum OFRc_`i'_1 OFRc_`i'_2 OFRc_`i'_3 OFRc_`i'_4 OFRc_`i', 
save(${projdir}\Stats\20`i'\OFRc_`i'.doc) title(Summary of OFRc - 20`i') replace label
			asdoc pwcorr OFRc_`i'_1 OFRc_`i'_2 OFRc_`i'_3 OFRc_`i'_4, star(0.05) 
bonferroni title(Correlation of OFRc - 20`i') label
			asdoc alpha OFRc_`i'_1 OFRc_`i'_2 OFRc_`i'_3 OFRc_`i'_4, title(Alpha 
of OFRc - 20`i') label
			asdoc factor OFRc_`i'_1 OFRc_`i'_2 OFRc_`i'_3 OFRc_`i'_4, title(Factor 
of OFRc - 20`i') label
		}
		/*Other Family Relationship Quality (OFRq)*/
		asdoc sum OFRq_`i'_1 OFRq_`i'_2 OFRq_`i'_3 OFRq_`i'_4 OFRq_`i'_5 
OFRq_`i'_6 OFRq_`i'_7, save(${projdir}\Stats\20`i'\OFRq_`i'.doc) title(Summary of OFRq - 
20`i') replace label
		asdoc pwcorr OFRq_`i'_1 OFRq_`i'_2 OFRq_`i'_3 OFRq_`i'_4 OFRq_`i'_5 
OFRq_`i'_6 OFRq_`i'_7, star(0.05) bonferroni title(Correlation of OFRq - 20`i') label
		asdoc alpha OFRq_`i'_1 OFRq_`i'_2 OFRq_`i'_3 OFRq_`i'_4 OFRq_`i'_5 
OFRq_`i'_6 OFRq_`i'_7, title(Alpha of OFRq - 20`i') label
		asdoc factor OFRq_`i'_1 OFRq_`i'_2 OFRq_`i'_3 OFRq_`i'_4 OFRq_`i'_5 
OFRq_`i'_6 OFRq_`i'_7, title(Factor of OFRq - 20`i') label

	/*Friend Relationship (FR)*/
		/*Friend Closeness (FRc)*/
		if `i' == 10 | `i' == 12 {
			asdoc sum FRc_`i'_1 FRc_`i'_2 FRc_`i'_3 FRc_`i', 
save(${projdir}\Stats\20`i'\FRc_`i'.doc) title(Summary of FRc - 20`i') replace label
			asdoc pwcorr FRc_`i'_1 FRc_`i'_2 FRc_`i'_3, star(0.05) bonferroni 
title(Correlation of FRc - 20`i') label
			asdoc alpha FRc_`i'_1 FRc_`i'_2 FRc_`i'_3, title(Alpha of FRc - 20`i') 
label
			asdoc factor FRc_`i'_1 FRc_`i'_2 FRc_`i'_3, title(Factor of FRc - 20`i') 
label
		}
		if `i' == 14 | `i' == 16 | `i' == 18 {
			asdoc sum FRc_`i'_1 FRc_`i'_2 FRc_`i'_3 FRc_`i'_4 FRc_`i', 
save(${projdir}\Stats\20`i'\FRc_`i'.doc) title(Summary of FRc - 20`i') replace label
```

```
				asdoc pwcorr FRc_`i'_1 FRc_`i'_2 FRc_`i'_3 FRc_`i'_4, star(0.05)
bonferroni title(Correlation of FRc - 20`i') label
				asdoc alpha FRc_`i'_1 FRc_`i'_2 FRc_`i'_3 FRc_`i'_4, title(Alpha of FRc -
20`i') label
				asdoc factor FRc_`i'_1 FRc_`i'_2 FRc_`i'_3 FRc_`i'_4, title(Factor of FRc
- 20`i') label
			}
			/*Friend Relationship Quality (FRq)*/
			asdoc sum FRq_`i'_1 FRq_`i'_2 FRq_`i'_3 FRq_`i'_4 FRq_`i'_5 FRq_`i'_6
FRq_`i'_7, save(${projdir}\Stats\20`i'\FRq_`i'.doc) title(Summary of FRq - 20`i') replace label

			asdoc pwcorr FRq_`i'_1 FRq_`i'_2 FRq_`i'_3 FRq_`i'_4 FRq_`i'_5 FRq_`i'_6
FRq_`i'_7, star(0.05) bonferroni title(Correlation of FRq - 20`i') label
			asdoc alpha FRq_`i'_1 FRq_`i'_2 FRq_`i'_3 FRq_`i'_4 FRq_`i'_5 FRq_`i'_6
FRq_`i'_7, title(Alpha of FRq - 20`i') label
			asdoc factor FRq_`i'_1 FRq_`i'_2 FRq_`i'_3 FRq_`i'_4 FRq_`i'_5 FRq_`i'_6
FRq_`i'_7, title(Factor of FRq - 20`i') label

		/*Closeness of Relationships (CoR)*/
			/*Partner/Spouse Closeness (CoRPS)*/
			if `i' == 10 | `i' == 12 {
				asdoc sum CoRPS_`i'_1 , save(${projdir}\Stats\20`i'\CoRPS_`i'.doc)
title(Summary of CoRPS - 20`i') replace label
			}
			if `i' == 14 | `i' == 16 | `i' == 18 {
				asdoc sum CoRPS_`i'_1 CoRPS_`i'_2 CoRPS_`i'_3 CoRPS_`i',
save(${projdir}\Stats\20`i'\CoRPS_`i'.doc) title(Summary of CoRPS - 20`i') replace label
				asdoc pwcorr CoRPS_`i'_1 CoRPS_`i'_2 CoRPS_`i'_3, star(0.05)
bonferroni title(Correlation of CoRPS - 20`i') label
				asdoc alpha CoRPS_`i'_1 CoRPS_`i'_2 CoRPS_`i'_3, title(Alpha of
CoRPS - 20`i') label
				asdoc factor CoRPS_`i'_1 CoRPS_`i'_2 CoRPS_`i'_3, title(Factor of PSc -
20`i') label
			}
			/*Number of Close Relationships (CoRn)*/
			asdoc sum CoRn_`i'_1 CoRn_`i'_2 CoRn_`i'_3 CoRn_`i',
save(${projdir}\Stats\20`i'\CoRn_`i'.doc) title(Summary of CoRn - 20`i') replace label
			asdoc pwcorr CoRn_`i'_1 CoRn_`i'_2 CoRn_`i'_3, star(0.05) bonferroni
title(Correlation of CoRn - 20`i') label
			asdoc alpha CoRn_`i'_1 CoRn_`i'_2 CoRn_`i'_3, title(Alpha of CoRn - 20`i') label
			asdoc factor CoRn_`i'_1 CoRn_`i'_2 CoRn_`i'_3, title(Factor of PSc - 20`i') label
		}
```

Appendix B: Summary and CFA Tables

2010 Wave

Summary of AS - 2010

Variable	Obs	Mean	Std. Dev.	Min	Max
AS 10 1	8167	3.242	.881	1	4
AS 10 2	8152	3.076	.892	1	4
AS 10 3	8149	3.574	.758	1	4
AS 10 4	8147	3.601	.726	1	4
AS 10 5	8144	3.656	.656	1	4
AS 10	8187	3.427	.606	1	4

Correlation of AS - 2010

Variables	(1)	(2)	(3)	(4)	(5)
(1) AS_10_1	1.000				
(2) AS_10_2	0.648*	1.000			
(3) AS_10_3	0.447*	0.522*	1.000		
(4) AS_10_4	0.496*	0.459*	0.482*	1.000	
(5) AS_10_5	0.403*	0.410*	0.500*	0.450*	1.000

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Alpha of AS - 2010

Test scale = mean(unstandardized items)
Average interitem covariance: .2970001
Number of items in the scale: 5
Scale reliability coefficient: 0.8211

Factor of AS - 2010

(obs=8,076)
Factor analysis/correlation — Number of obs = 8,076
Method: principal factors — Retained factors = 2
Rotation: (unrotated) — Number of params = 9

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	2.352	2.236	1.136	1.136
Factor2	0.116	0.182	0.056	1.192
Factor3	-0.066	0.069	-0.032	1.161
Factor4	-0.135	0.062	-0.065	1.095
Factor5	-0.197	.	-0.095	1.000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
AS_10_1	0.725	-0.182	0.441
AS_10_2	0.742	-0.163	0.422
AS_10_3	0.684	0.134	0.514
AS_10_4	0.659	0.080	0.559
AS_10_5	0.610	0.178	0.596

Summary of Chc - 2010

Variable	Obs	Mean	Std. Dev.	Min	Max
Chc 10 1	7044	3.968	1.495	1	6
Chc 10 2	7135	5.067	1.181	1	6
Chc 10 3	6779	2.847	1.854	1	6
Chc 10	7161	4.001	1.103	1	6

Correlation of Chc - 2010

Variables	(1)	(2)	(3)
(1) Chc_10_1	1.000		
(2) Chc_10_2	0.537*	1.000	
(3) Chc_10_3	0.094*	0.213*	1.000

*** *p<0.01*, ** *p<0.05*, * *p<0.1*

Alpha of Chc - 2010
Test scale = mean(unstandardized items)
Average interitem covariance: .5669685
Number of items in the scale: 3
Scale reliability coefficient: 0.4898

Factor of Chc - 2010
(obs=6,695)

Factor analysis/correlation		Number of obs =	6,695
Method: principal factors		Retained factors =	2
Rotation: (unrotated)		Number of params =	3

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	0.902	0.886	1.373	1.373
Factor2	0.016	0.277	0.024	1.397
Factor3	-0.261	.	-0.397	1.000

LR test: independent vs. saturated: chi2(3) = 2625.02 Prob>chi2 = 0.0000
Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
Chc_10_1	0.629	-0.049	0.602
Chc_10_2	0.670	0.005	0.551
Chc_10_3	0.239	0.116	0.929

Summary of Chr - 2010

Variable	Obs	Mean	Std. Dev.	Min	Max
Chr 10 1	7321	3.171	.823	1	4
Chr 10 2	7332	3.413	.867	1	4
Chr 10 3	7321	3.098	.91	1	4
Chr 10 4	7321	3.234	.902	1	4
Chr 10 5	7296	3.315	.804	1	4
Chr 10 6	7312	3.303	.851	1	4
Chr 10 7	7323	3.214	.824	1	4

Correlation of Chr - 2010

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Chr_10_1	1.000						
(2) Chr_10_2	0.554*	1.000					
(3) Chr_10_3	0.608*	0.641*	1.000				
(4) Chr_10_4	0.169*	0.210*	0.156*	1.000			
(5) Chr_10_5	0.230*	0.203*	0.175*	0.398*	1.000		
(6) Chr_10_6	0.344*	0.386*	0.315*	0.456*	0.447*	1.000	
(7) Chr_10_7	0.302*	0.275*	0.264*	0.488*	0.476*	0.530*	1.000

*** *p<0.01, *** *p<0.05, * *p<0.1*

Alpha of Chr - 2010

Test scale = mean(unstandardized items)
Average interitem covariance: .2643732
Number of items in the scale: 7
Scale reliability coefficient: 0.7985

Factor of Chr - 2010

(obs=7,192)

Factor analysis/correlation		Number of obs =	7,192
Method: principal factors		Retained factors =	2
Rotation: (unrotated)		Number of params =	13

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	2.618	1.756	0.913	0.913
Factor2	0.862	0.910	0.301	1.213
Factor3	-0.048	0.058	-0.017	1.197
Factor4	-0.106	0.022	-0.037	1.160
Factor5	-0.128	0.025	-0.044	1.115
Factor6	-0.152	0.026	-0.053	1.062
Factor7	-0.179	.	-0.062	1.000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
Chr_10_1	0.635	-0.340	0.482
Chr_10_2	0.658	-0.362	0.436
Chr_10_3	0.642	-0.439	0.396
Chr_10_4	0.506	0.376	0.603
Chr_10_5	0.517	0.335	0.621
Chr_10_6	0.669	0.236	0.496
Chr_10_7	0.632	0.338	0.486

Summary of CoRn - 2010

Variable	Obs	Mean	Std. Dev.	Min	Max
n Close Children Relationships	7303	1.439	.748	0	5
n Close Family Relationships	7668	1.756	1.129	0	5
n Close Family Relationships	7485	1.971	1.154	0	5
CoRn 10	8269	1.724	.773	0	5

Correlation of CoRn - 2010

Variables	(1)	(2)	(3)
(1) n Close Childr~i	1.000		
(2) n Close Family~s	0.310*	1.000	
(3) n Close Family~s	0.157*	0.311*	1.000

*** *p<0.01*, ** *p<0.05*, * *p<0.1*

Alpha of CoRn - 2010

Test scale = mean(unstandardized items)
Average interitem covariance: .2680117
Number of items in the scale: 3
Scale reliability coefficient: 0.5034

Factor of PSc - 2010

(obs=6,200)
Factor analysis/correlation   Number of obs = 6,200
Method: principal factors   Retained factors = 1
Rotation: (unrotated)   Number of params = 3

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	0.648	0.709	1.796	1.796
Factor2	-0.061	0.165	-0.169	1.626
Factor3	-0.226	.	-0.626	1.000

LR test: independent vs. saturated: chi2(3) = 1261.40 Prob>chi2 = 0.0000
Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Uniqueness
CoRn_10_1	0.415	0.828
CoRn_10_2	0.537	0.712
CoRn_10_3	0.433	0.812

Summary of DS - 2010

Variable	Obs	Mean	Std. Dev.	Min	Max
DS 10 1	20633	.137	.344	0	1
DS 10 2	20616	.274	.446	0	1
DS 10 3	20576	.209	.406	0	1
DS 10 4	20617	.907	.291	0	1
DS 10 5	20594	.851	.356	0	1
DS 10 6	20631	.171	.376	0	1
DS 10 7	20626	.31	.462	0	1
DS 10 8	20628	.192	.394	0	1
# of Depressive Symptoms	20647	3.045	1.395	0	8

Correlation of DS - 2010

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) DS_10_1	1.000							
(2) DS_10_2	0.388*	1.000						
(3) DS_10_3	0.322*	0.377*	1.000					
(4) DS_10_4	-0.435*	-0.278*	-0.266*	1.000				
(5) DS_10_5	-0.508*	-0.303*	-0.273*	0.594*	1.000			
(6) DS_10_6	0.451*	0.285*	0.279*	-0.366*	-0.401*	1.000		
(7) DS_10_7	0.330*	0.296*	0.292*	-0.249*	-0.280*	0.263*	1.000	
(8) DS_10_8	0.581*	0.331*	0.322*	-0.439*	-0.491*	0.539*	0.334*	1.000

**** $p<0.01$, ** $p<0.05$, * $p<0.1$*

Alpha of DS - 2010

Test scale = mean(unstandardized items)
Reversed items: DS_10_4 DS_10_5
Average interitem covariance: .0528137
Number of items in the scale: 8
Scale reliability coefficient: 0.8122

Factor of DS - 2010

(obs=20,442)

Factor analysis/correlation Number of obs = 20,442
Method: principal factors Retained factors = 3
Rotation: (unrotated) Number of params = 21

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	2.997	2.732	1.078	1.078
Factor2	0.265	0.141	0.095	1.173
Factor3	0.124	0.178	0.045	1.218
Factor4	-0.054	0.013	-0.019	1.199
Factor5	-0.067	0.075	-0.024	1.175
Factor6	-0.142	0.025	-0.051	1.124
Factor7	-0.167	0.009	-0.060	1.063
Factor8	-0.176	.	-0.064	1.000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Factor3	Uniqueness
DS_10_1	0.718	0.007	0.070	0.479
DS_10_2	0.508	0.247	-0.098	0.671
DS_10_3	0.475	0.251	-0.095	0.702
DS_10_4	-0.634	0.230	0.148	0.523
DS_10_5	-0.691	0.232	0.120	0.454
DS_10_6	0.613	-0.016	0.178	0.593
DS_10_7	0.457	0.183	-0.038	0.756
DS_10_8	0.731	-0.025	0.177	0.433

Summary of FRc - 2010

Variable	Obs	Mean	Std. Dev.	Min	Max
FRc 10 1	7585	4.091	1.347	1	6
FRc 10 2	7612	4.512	1.268	1	6
FRc 10 3	7264	2.734	1.849	1	6
FRc 10	7653	3.808	1.103	1	6

Correlation of FRc - 2010

Variables	(1)	(2)	(3)
(1) FRc_10_1	1.000		
(2) FRc_10_2	0.507*	1.000	
(3) FRc_10_3	0.209*	0.216*	1.000

*** *p<0.01,* ** *p<0.05,* * *p<0.1*

Alpha of FRc - 2010

Test scale = mean(unstandardized items)
Average interitem covariance: .6344262
Number of items in the scale: 3
Scale reliability coefficient: 0.5389

Factor of FRc - 2010

(obs=7,222)
Factor analysis/correlation Number of obs = 7,222
Method: principal factors Retained factors = 1
Rotation: (unrotated) Number of params = 3

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	0.890	0.940	1.477	1.477
Factor2	-0.049	0.189	-0.082	1.396
Factor3	-0.239	.	-0.396	1.000

LR test: independent vs. saturated: chi2(3) = 2620.58 Prob>chi2 = 0.0000
Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Uniqueness
FRc_10_1	0.625	0.609
FRc_10_2	0.629	0.604
FRc_10_3	0.322	0.896

Summary of FRq - 2010

Variable	Obs	Mean	Std. Dev.	Min	Max
FRq 10 1	7599	3.069	.812	1	4
FRq 10 2	7604	3.083	.879	1	4
FRq 10 3	7594	2.993	.916	1	4
FRq 10 4	7585	3.661	.62	1	4
FRq 10 5	7505	3.608	.623	1	4
FRq 10 6	7549	3.525	.716	1	4
FRq 10 7	7574	3.456	.677	1	4

Correlation of FRq - 2010

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) FRq_10_1	1.000						
(2) FRq_10_2	0.602*	1.000					
(3) FRq_10_3	0.661*	0.669*	1.000				
(4) FRq_10_4	-0.052*	-0.028*	-0.051*	1.000			
(5) FRq_10_5	0.033*	0.042*	0.029*	0.437*	1.000		
(6) FRq_10_6	0.127*	0.160*	0.121*	0.405*	0.434*	1.000	
(7) FRq_10_7	0.100*	0.091*	0.084*	0.418*	0.472*	0.487*	1.000

*** *p<0.01*, ** *p<0.05*, * *p<0.1*

Alpha of FRq - 2010

Test scale = mean(unstandardized items)
Average interitem covariance: .1434211
Number of items in the scale: 7
Scale reliability coefficient: 0.6998

Factor of FRq - 2010

(obs=7,422)

Factor analysis/correlation		Number of obs =	7,422
Method: principal factors		Retained factors =	2
Rotation: (unrotated)		Number of params =	13

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.949	0.425	0.691	0.691
Factor2	1.524	1.617	0.540	1.231
Factor3	-0.093	0.007	-0.033	1.198
Factor4	-0.100	0.038	-0.035	1.163
Factor5	-0.137	0.018	-0.049	1.114
Factor6	-0.155	0.012	-0.055	1.059
Factor7	-0.167	.	-0.059	1.000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
FRq_10_1	0.655	-0.375	0.430
FRq_10_2	0.674	-0.357	0.418
FRq_10_3	0.693	-0.411	0.351
FRq_10_4	0.261	0.558	0.621
FRq_10_5	0.356	0.537	0.585
FRq_10_6	0.459	0.467	0.572
FRq_10_7	0.424	0.519	0.551

Summary of LS - 2010

Variable	Obs	Mean	Std. Dev.	Min	Max
q03a. life is close to ideal	8197	4.654	1.885	1	7
q03b. conditions of life are excellen	8186	4.661	1.901	1	7
q03c. satisfied with life	8227	5.221	1.834	1	7
q03d. have important things in life	8227	5.313	1.76	1	7
q03e. change nothing if lived life ov	8234	4.349	2.076	1	7
LS 10	8280	4.836	1.576	1	7
r10lbsatwlf:w10 life satisfactio	8254	4.839	1.572	1	7

Correlation of LS - 2010

Variables	(1)	(2)	(3)	(4)	(5)
(1) q03a. life is ~l	1.000				
(2) q03b. conditio~n	0.762*	1.000			
(3) q03c. satisfie~e	0.698*	0.758*	1.000		
(4) q03d. have imp~e	0.577*	0.610*	0.692*	1.000	
(5) q03e. change n~v	0.488*	0.508*	0.524*	0.550*	1.000

*** *p<0.01*, ** *p<0.05*, * *p<0.1*

Alpha of LS - 2010

Test scale = mean(unstandardized items)
Average interitem covariance: 2.184291
Number of items in the scale: 5
Scale reliability coefficient: 0.8861

Factor of LS - 2010

(obs=8,058)

Factor analysis/correlation		Number of obs =	8,058
Method: principal factors		Retained factors =	2
Rotation: (unrotated)		Number of params =	9

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	3.093	2.998	1.067	1.067
Factor2	0.096	0.141	0.033	1.101
Factor3	-0.045	0.065	-0.016	1.085
Factor4	-0.110	0.025	-0.038	1.047
Factor5	-0.135	.	-0.047	1.000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
LS_10_1	0.811	-0.145	0.321
LS_10_2	0.856	-0.141	0.247
LS_10_3	0.857	0.010	0.265
LS_10_4	0.758	0.173	0.396
LS_10_5	0.627	0.158	0.582

Summary of Ch - 2010

Variable	Obs	Mean	Std. Dev.	Min	Max
Chc 10 1	7044	3.968	1.495	1	6
Chr 10	7360	3.249	.578	1	4

Correlation of Ch - 2010

Variables	(1)	(2)
(1) Chc_10_1	1.000	
(2) Chr_10	0.198*	1.000

*** *p<0.01,* ** *p<0.05,* * *p<0.1*

Alpha of Ch - 2010

Test scale = mean(unstandardized items)
Average interitem covariance: .1697022
Number of items in the scale: 2
Scale reliability coefficient: 0.2368

Factor of Ch - 2010

(obs=7,000)
Factor analysis/correlation Number of obs = 7,000
Method: principal factors Retained factors = 1
Rotation: (unrotated) Number of params = 1

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	0.237	0.396	3.027	3.027
Factor2	-0.159	.	-2.027	1.000

LR test: independent vs. saturated: chi2(1) = 279.39 Prob>chi2 = 0.0000
Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Uniqueness
Chc_10_1	0.344	0.881
Chr_10	0.344	0.881

Summary of OFRc - 2010

Variable	Obs	Mean	Std. Dev.	Min	Max
OFRc 10 1	7729	3.303	1.51	1	6
OFRc 10 2	7792	4.411	1.36	1	6
OFRc 10 3	7448	2.503	1.689	1	6
OFRc 10	7810	3.441	1.119	1	6

Correlation of OFRc - 2010

Variables	(1)	(2)	(3)
(1) OFRc_10_1	1.000		
(2) OFRc_10_2	0.581*	1.000	
(3) OFRc_10_3	0.080*	0.194*	1.000

*** *p<0.01,* ** *p<0.05,* * *p<0.1*

Alpha of OFRc - 2010
Test scale = mean(unstandardized items)
Average interitem covariance: .6219055
Number of items in the scale: 3
Scale reliability coefficient: 0.5236

Factor of OFRc - 2010
(obs=7,401)
Factor analysis/correlation Number of obs = 7,401
Method: principal factors Retained factors = 2
Rotation: (unrotated) Number of params = 3

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	0.969	0.948	1.319	1.319
Factor2	0.021	0.277	0.029	1.347
Factor3	-0.255	.	-0.347	1.000

LR test: independent vs. saturated: chi2(3) = 3332.40 Prob>chi2 = 0.0000
Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
OFRc_10_1	0.666	-0.050	0.554
OFRc_10_2	0.697	0.009	0.515
OFRc_10_3	0.202	0.137	0.941

Summary of OFRq - 2010

Variable	Obs	Mean	Std. Dev.	Min	Max
OFRq 10 1	7793	2.851	.908	1	4
OFRq 10 2	7808	3.012	1.027	1	4
OFRq 10 3	7803	2.825	1.02	1	4
OFRq 10 4	7776	3.533	.756	1	4
OFRq 10 5	7717	3.413	.803	1	4
OFRq 10 6	7733	3.399	.847	1	4
OFRq 10 7	7764	3.236	.856	1	4

Correlation of OFRq - 2010

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) OFRq_10_1	1.000						
(2) OFRq_10_2	0.618*	1.000					
(3) OFRq_10_3	0.686*	0.716*	1.000				
(4) OFRq_10_4	0.037*	0.028*	0.031*	1.000			
(5) OFRq_10_5	0.150*	0.107*	0.125*	0.428*	1.000		
(6) OFRq_10_6	0.221*	0.250*	0.213*	0.423*	0.519*	1.000	
(7) OFRq_10_7	0.221*	0.186*	0.203*	0.450*	0.533*	0.550*	1.000

*** *p<0.01*, ** *p<0.05*, * *p<0.1*

Alpha of OFRq - 2010
Test scale = mean(unstandardized items)
Average interitem covariance: .2551776
Number of items in the scale: 7
Scale reliability coefficient: 0.7666

Factor of OFRq - 2010
(obs=7,579)

Factor analysis/correlation	Number of obs =	7,579
Method: principal factors	Retained factors =	2
Rotation: (unrotated)	Number of params =	13

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	2.407	1.047	0.759	0.759
Factor2	1.360	1.425	0.429	1.188
Factor3	-0.065	0.028	-0.020	1.168
Factor4	-0.093	0.039	-0.029	1.138
Factor5	-0.132	0.009	-0.042	1.097
Factor6	-0.141	0.024	-0.044	1.052
Factor7	-0.165	.	-0.052	1.000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
OFRq_10_1	0.639	-0.412	0.422
OFRq_10_2	0.647	-0.453	0.376
OFRq_10_3	0.680	-0.488	0.299
OFRq_10_4	0.381	0.465	0.638
OFRq_10_5	0.513	0.458	0.527
OFRq_10_6	0.601	0.379	0.495
OFRq_10_7	0.589	0.421	0.475

Summary of Income - 2010

Variable	Obs	Mean	Std. Dev.	Min	Max
h10itot:w10 income: total hhold	22034	62948.286	97743.431	0	5438860
l h10itot	22034	10.369	1.725	0	15.509

Summary of Total Assets - 2010

Variable	Obs	Mean	Std. Dev.	Min	Max
h10atotb:w10 total of all assets	22034	394142.74	993803.02	-2760000	50900000
l h10atotb	20206	11.082	3.388	0	17.745

Summary of Total Non-Housing Assets - 2010

Variable	Obs	Mean	Std. Dev.	Min	Max
h10atotn:w10 total non-housing a	22034	256633.36	840073.68	-943500	46900000
l h10atotn	19671	9.9	3.798	0	17.664

Summary of Total Net Worth - 2010

Variable	Obs	Mean	Std. Dev.	Min	Max
h10atotf:w10 non-housing financi	22034	106691.96	442027.5	-1250000	21200000
l h10atotf	17533	8.072	4.573	0	16.87

Summary of Net Value of House - 2010

Variable	Obs	Mean	Std. Dev.	Min	Max
h10atoth:w10 net value of house	22034	117693.08	223701.8	-2750000	10000000
l h10atoth	21193	8.366	5.248	0	16.118

Summary of PSq - 2010

Variable	Obs	Mean	Std. Dev.	Min	Max
PSq 10 1	5648	3.293	.82	1	4
PSq 10 2	5650	3.7	.688	1	4
PSq 10 3	5644	3.394	.839	1	4
PSq 10 4	5637	2.972	.922	1	4
PSq 10 5	5629	2.949	.897	1	4
PSq 10 6	5629	3.341	.859	1	4
PSq 10 7	5639	2.947	.842	1	4

Correlation of PSq - 2010

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) PSq_10_1	1.000						
(2) PSq_10_2	0.533*	1.000					
(3) PSq_10_3	0.646*	0.618*	1.000				
(4) PSq_10_4	0.281*	0.246*	0.252*	1.000			
(5) PSq_10_5	0.327*	0.217*	0.312*	0.508*	1.000		
(6) PSq_10_6	0.428*	0.437*	0.427*	0.437*	0.436*	1.000	
(7) PSq_10_7	0.427*	0.313*	0.399*	0.459*	0.513*	0.529*	1.000

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Alpha of PSq - 2010

Test scale = mean(unstandardized items)
Average interitem covariance: .2911883
Number of items in the scale: 7
Scale reliability coefficient: 0.8306

Factor of PSq - 2010

(obs=5,532)

Factor analysis/correlation		Number of obs =	5,532
Method: principal factors		Retained factors =	2
Rotation: (unrotated)		Number of params =	13

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	2.965	2.354	0.980	0.980
Factor2	0.611	0.619	0.202	1.182
Factor3	-0.008	0.051	-0.003	1.179
Factor4	-0.059	0.075	-0.020	1.159
Factor5	-0.134	0.026	-0.044	1.115
Factor6	-0.161	0.027	-0.053	1.062
Factor7	-0.188	.	-0.062	1.000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
PSq_10_1	0.697	-0.260	0.447
PSq_10_2	0.632	-0.333	0.489
PSq_10_3	0.712	-0.347	0.372
PSq_10_4	0.551	0.342	0.579
PSq_10_5	0.588	0.351	0.530

PSq_10_6	0.684	0.121	0.517
PSq_10_7	0.674	0.239	0.489

Summary of sFWB - 2010

Variable	Obs	Mean	Std. Dev.	Min	Max
sFWB 10 1	8170	3.279	1.163	1	5
sFWB 10 2	8171	3.914	1.076	1	5
sFWB 10	8221	3.597	1.028	1	5

Correlation of sFWB - 2010

Variables	(1)	(2)
(1) sFWB_10_1	1.000	
(2) sFWB_10_2	0.678*	1.000

*** *p<0.01,* ** *p<0.05,* * *p<0.1*

Alpha of sFWB - 2010

Test scale = mean(unstandardized items)
Average interitem covariance: .8478999
Number of items in the scale: 2
Scale reliability coefficient: 0.8062

Factor of sFWB - 2010

(obs=8,120)

Factor analysis/correlation Number of obs = 8,120
Method: principal factors Retained factors = 1
Rotation: (unrotated) Number of params = 1

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.137	1.355	1.238	1.238
Factor2	-0.218	.	-0.238	1.000

LR test: independent vs. saturated: chi2(1) = 4988.57 Prob>chi2 = 0.0000
Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Uniqueness
sFWB_10_1	0.754	0.432
sFWB_10_2	0.754	0.432

2012 Wave

Summary of AS - 2012

Variable	Obs	Mean	Std. Dev.	Min	Max
AS 12 1	7187	3.24	.878	1	4
AS 12 2	7179	3.078	.901	1	4
AS 12 3	7176	3.567	.771	1	4
AS 12 4	7185	3.599	.733	1	4
AS 12 5	7187	3.627	.685	1	4
AS 12	7210	3.42	.614	1	4

Correlation of AS - 2012

Variables	(1)	(2)	(3)	(4)	(5)
(1) AS_12_1	1.000				
(2) AS_12_2	0.656*	1.000			
(3) AS_12_3	0.439*	0.512*	1.000		
(4) AS_12_4	0.488*	0.465*	0.474*	1.000	
(5) AS_12_5	0.399*	0.419*	0.519*	0.478*	1.000

*** *p<0.01,* ** *p<0.05,* * *p<0.1*

Alpha of AS - 2012
Test scale = mean(unstandardized items)
Average interitem covariance: .3062874
Number of items in the scale: 5
Scale reliability coefficient: 0.8226

Factor of AS - 2012
(obs=7,112)
Factor analysis/correlation Number of obs = 7,112
Method: principal factors Retained factors = 2
Rotation: (unrotated) Number of params = 9

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	2.364	2.216	1.125	1.125
Factor2	0.148	0.215	0.070	1.195
Factor3	-0.067	0.084	-0.032	1.163
Factor4	-0.151	0.040	-0.072	1.091
Factor5	-0.192	.	-0.091	1.000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
AS_12_1	0.719	-0.209	0.440
AS_12_2	0.744	-0.182	0.413
AS_12_3	0.679	0.148	0.517
AS_12_4	0.663	0.087	0.553
AS_12_5	0.628	0.204	0.564

Summary of Chc - 2012

Variable	Obs	Mean	Std. Dev.	Min	Max
Chc 12 1	6333	3.951	1.507	1	6
Chc 12 2	6412	5.037	1.198	1	6
Chc 12 3	6210	2.905	1.891	1	6
Chc 12	6450	3.989	1.124	1	6

Correlation of Chc - 2012

Variables	(1)	(2)	(3)
(1) Chc_12_1	1.000		
(2) Chc_12_2	0.532*	1.000	
(3) Chc_12_3	0.134*	0.215*	1.000

**** p<0.01, ** p<0.05, * p<0.1*

Alpha of Chc - 2012

Test scale = mean(unstandardized items)
Average interitem covariance: .6139138
Number of items in the scale: 3
Scale reliability coefficient: 0.5054

Factor of Chc - 2012

(obs=6,113)

Factor analysis/correlation Number of obs = 6,113
Method: principal factors Retained factors = 1
Rotation: (unrotated) Number of params = 3

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	0.897	0.910	1.417	1.417
Factor2	-0.013	0.238	-0.020	1.397
Factor3	-0.251	.	-0.397	1.000

LR test: independent vs. saturated: chi2(3) = 2320.36 Prob>chi2 = 0.0000
Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Uniqueness
Chc_12_1	0.627	0.607
Chc_12_2	0.658	0.567
Chc_12_3	0.266	0.929

Summary of Chr - 2012

Variable	Obs	Mean	Std. Dev.	Min	Max
Chr 12 1	6546	3.174	.825	1	4
Chr 12 2	6538	3.427	.852	1	4
Chr 12 3	6534	3.126	.924	1	4
Chr 12 4	6537	3.261	.888	1	4
Chr 12 5	6505	3.324	.808	1	4
Chr 12 6	6519	3.318	.856	1	4
Chr 12 7	6536	3.225	.829	1	4

Correlation of Chr - 2012

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Chr_12_1	1.000						
(2) Chr_12_2	0.564*	1.000					
(3) Chr_12_3	0.608*	0.655*	1.000				
(4) Chr_12_4	0.165*	0.203*	0.163*	1.000			
(5) Chr_12_5	0.246*	0.209*	0.205*	0.412*	1.000		
(6) Chr_12_6	0.352*	0.411*	0.363*	0.461*	0.477*	1.000	
(7) Chr_12_7	0.284*	0.282*	0.272*	0.493*	0.492*	0.555*	1.000

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Alpha of Chr - 2012

Test scale = mean(unstandardized items)
Average interitem covariance: .2732928
Number of items in the scale: 7
Scale reliability coefficient: 0.8066

Factor of Chr - 2012

(obs=6,376)

Factor analysis/correlation	Number of obs	=	6,376
Method: principal factors	Retained factors	=	2
Rotation: (unrotated)	Number of params	=	13

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	2.715	1.853	0.913	0.913
Factor2	0.862	0.913	0.290	1.204
Factor3	-0.051	0.052	-0.017	1.186
Factor4	-0.103	0.031	-0.035	1.151
Factor5	-0.135	0.014	-0.045	1.106
Factor6	-0.149	0.018	-0.050	1.056
Factor7	-0.167	.	-0.056	1.000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
Chr_12_1	0.624	-0.348	0.489
Chr_12_2	0.663	-0.375	0.419
Chr_12_3	0.654	-0.429	0.387
Chr_12_4	0.513	0.370	0.600
Chr_12_5	0.543	0.333	0.594
Chr_12_6	0.700	0.225	0.459
Chr_12_7	0.639	0.342	0.474

Summary of CoRn - 2012

Variable	Obs	Mean	Std. Dev.	Min	Max
n Close Children Relationships	6512	1.448	.789	0	5
n Close Family Relationships	6771	1.787	1.17	0	5
n Close Family Relationships	6529	1.986	1.16	0	5
CoRn 12	7351	1.739	.805	0	5

Correlation of CoRn - 2012

Variables	(1)	(2)	(3)
(1) n Close Childr~i	1.000		
(2) n Close Family~s	0.348*	1.000	
(3) n Close Family~s	0.182*	0.329*	1.000

*** *p<0.01,* ** *p<0.05,* * *p<0.1*

Alpha of CoRn - 2012
Test scale = mean(unstandardized items)
Average interitem covariance: .3128564
Number of items in the scale: 3
Scale reliability coefficient: 0.5389

Factor of PSc - 2012
(obs=5,440)

Factor analysis/correlation	Number of obs = 5,440
Method: principal factors	Retained factors = 1
Rotation: (unrotated)	Number of params = 3

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	0.731	0.791	1.676	1.676
Factor2	-0.059	0.177	-0.136	1.540
Factor3	-0.236	.	-0.540	1.000

LR test: independent vs. saturated: chi2(3) = 1364.66 Prob>chi2 = 0.0000
Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Uniqueness
CoRn_12_1	0.453	0.795
CoRn_12_2	0.572	0.673
CoRn_12_3	0.447	0.800

Summary of CoRPS - 2012

Variable	Obs	Mean	Std. Dev.	Min	Max
CoRPS 12 1	4845	3.453	.766	1	4

Summary of DS - 2012

Variable	Obs	Mean	Std. Dev.	Min	Max
DS 12 1	17688	.134	.341	0	1
DS 12 2	17660	.269	.444	0	1
DS 12 3	17627	.205	.404	0	1
DS 12 4	17669	.904	.294	0	1
DS 12 5	17645	.856	.351	0	1
DS 12 6	17677	.172	.378	0	1
DS 12 7	17671	.313	.464	0	1
DS 12 8	17664	.192	.394	0	1
# of Depressive Symptoms	17696	3.04	1.405	0	8

Correlation of DS - 2012

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) DS_12_1	1.000							
(2) DS_12_2	0.412*	1.000						
(3) DS_12_3	0.328*	0.382*	1.000					
(4) DS_12_4	-0.440*	-0.287*	-0.264*	1.000				
(5) DS_12_5	-0.504*	-0.323*	-0.292*	0.593*	1.000			
(6) DS_12_6	0.463*	0.322*	0.288*	-0.370*	-0.403*	1.000		
(7) DS_12_7	0.335*	0.305*	0.297*	-0.237*	-0.283*	0.279*	1.000	
(8) DS_12_8	0.586*	0.353*	0.326*	-0.441*	-0.504*	0.553*	0.335*	1.000

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Alpha of DS - 2012

Test scale = mean(unstandardized items)
Reversed items: DS_12_4 DS_12_5
Average interitem covariance: .0538332
Number of items in the scale: 8
Scale reliability coefficient: 0.8178

Factor of DS - 2012

(obs=17,490)

Factor analysis/correlation   Number of obs = 17,490
Method: principal factors   Retained factors = 3
Rotation: (unrotated)   Number of params = 21

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	3.063	2.802	1.078	1.078
Factor2	0.261	0.144	0.092	1.169
Factor3	0.117	0.173	0.041	1.211
Factor4	-0.056	0.011	-0.020	1.191
Factor5	-0.068	0.066	-0.024	1.167
Factor6	-0.134	0.034	-0.047	1.120
Factor7	-0.168	0.006	-0.059	1.061
Factor8	-0.174	.	-0.061	1.000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Factor3	Uniqueness
DS_12_1	0.723	0.011	0.065	0.473
DS_12_2	0.533	0.231	-0.097	0.653
DS_12_3	0.482	0.231	-0.114	0.701
DS_12_4	-0.631	0.253	0.125	0.522
DS_12_5	-0.695	0.233	0.111	0.451
DS_12_6	0.626	0.015	0.173	0.578
DS_12_7	0.457	0.187	-0.045	0.754
DS_12_8	0.737	-0.022	0.174	0.426

Summary of FRc - 2012

Variable	Obs	Mean	Std. Dev.	Min	Max
FRc 12 1	6613	4.059	1.379	1	6
FRc 12 2	6641	4.518	1.274	1	6
FRc 12 3	6466	2.77	1.863	1	6
FRc 12	6681	3.796	1.106	1	6

Correlation of FRc - 2012

Variables	(1)	(2)	(3)
(1) FRc_12_1	1.000		
(2) FRc_12_2	0.475*	1.000	
(3) FRc_12_3	0.210*	0.214*	1.000

*** *p<0.01, *** *p<0.05, ** *p<0.1*

Alpha of FRc - 2012

Test scale = mean(unstandardized items)
Average interitem covariance: .6284686
Number of items in the scale: 3
Scale reliability coefficient: 0.5267

Factor of FRc - 2012

(obs=6,405)
Factor analysis/correlation Number of obs = 6,405
Method: principal factors Retained factors = 1
Rotation: (unrotated) Number of params = 3

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	0.836	0.891	1.538	1.538
Factor2	-0.056	0.181	-0.102	1.435
Factor3	-0.237	.	-0.435	1.000

LR test: independent vs. saturated: chi2(3) = 2062.70 Prob>chi2 = 0.0000
Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Uniqueness
FRc_12_1	0.601	0.639
FRc_12_2	0.604	0.635
FRc_12_3	0.332	0.890

Summary of FRq - 2012

Variable	Obs	Mean	Std. Dev.	Min	Max
FRq 12 1	6637	3.095	.803	1	4
FRq 12 2	6633	3.103	.874	1	4
FRq 12 3	6615	3.031	.91	1	4
FRq 12 4	6614	3.657	.632	1	4
FRq 12 5	6585	3.603	.631	1	4
FRq 12 6	6608	3.528	.715	1	4
FRq 12 7	6622	3.455	.695	1	4

Correlation of FRq - 2012

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) FRq_12_1	1.000						
(2) FRq_12_2	0.590*	1.000					
(3) FRq_12_3	0.655*	0.669*	1.000				
(4) FRq_12_4	0.012	-0.004	-0.027*	1.000			
(5) FRq_12_5	0.046*	0.061*	0.026*	0.460*	1.000		
(6) FRq_12_6	0.121*	0.163*	0.099*	0.423*	0.477*	1.000	
(7) FRq_12_7	0.109*	0.109*	0.084*	0.426*	0.502*	0.503*	1.000

**** p<0.01, ** p<0.05, * p<0.1*

Alpha of FRq - 2012

Test scale = mean(unstandardized items)
Average interitem covariance: .1497534
Number of items in the scale: 7
Scale reliability coefficient: 0.7111

Factor of FRq - 2012

(obs=6,480)

Factor analysis/correlation — Number of obs = 6,480
Method: principal factors — Retained factors = 2
Rotation: (unrotated) — Number of params = 13

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	2.015	0.472	0.691	0.691
Factor2	1.543	1.621	0.529	1.220
Factor3	-0.078	0.033	-0.027	1.193
Factor4	-0.112	0.012	-0.038	1.155
Factor5	-0.124	0.032	-0.043	1.112
Factor6	-0.155	0.017	-0.053	1.059
Factor7	-0.172	.	-0.059	1.000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
FRq_12_1	0.589	-0.456	0.446
FRq_12_2	0.611	-0.454	0.420
FRq_12_3	0.613	-0.527	0.346
FRq_12_4	0.386	0.485	0.616
FRq_12_5	0.466	0.496	0.537
FRq_12_6	0.533	0.413	0.544
FRq_12_7	0.518	0.445	0.534

Summary of LS - 2012

Variable	Obs	Mean	Std. Dev.	Min	Max
q03a. life is close to ideal	7193	4.523	1.889	1	7
q03b. conditions of life are excellen	7197	4.532	1.923	1	7
q03c. satisfied with life	7217	5.168	1.857	1	7
q03d. have important things in life	7227	5.264	1.777	1	7
q03e. change nothing if lived life ov	7238	4.283	2.082	1	7
LS 12	7282	4.749	1.575	1	7
r12lbsatwlf:w12 life satisfactio	7276	4.968	1.527	1	7

Correlation of LS - 2012

Variables	(1)	(2)	(3)	(4)	(5)
(1) q03a. life is ~l	1.000				
(2) q03b. conditio~n	0.751*	1.000			
(3) q03c. satisfie~e	0.687*	0.744*	1.000		
(4) q03d. have imp~e	0.553*	0.587*	0.686*	1.000	
(5) q03e. change n~v	0.467*	0.489*	0.507*	0.547*	1.000

*** *p<0.01,* ** *p<0.05,* * *p<0.1*

Alpha of LS - 2012

Test scale = mean(unstandardized items)
Average interitem covariance: 2.164616
Number of items in the scale: 5
Scale reliability coefficient: 0.8799

Factor of LS - 2012

(obs=7,052)

Factor analysis/correlation	Number of obs	=	7,052
Method: principal factors	Retained factors =		2
Rotation: (unrotated)	Number of params =		9

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	3.021	2.903	1.065	1.065
Factor2	0.118	0.161	0.042	1.107
Factor3	-0.043	0.071	-0.015	1.092
Factor4	-0.114	0.033	-0.040	1.052
Factor5	-0.147	.	-0.052	1.000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
LS_12_1	0.800	-0.161	0.334
LS_12_2	0.844	-0.157	0.263
LS_12_3	0.855	0.010	0.269
LS_12_4	0.750	0.195	0.400
LS_12_5	0.613	0.172	0.595

Summary of MH - 2012

Variable	Obs	Mean	Std. Dev.	Min	Max
LS 12	7282	4.749	1.575	1	7
# of Depressive Symptoms	17696	3.04	1.405	0	8
AS 12	7210	3.42	.614	1	4

Correlation of MH - 2012

Variables	(1)	(2)	(3)
(1) LS_12	1.000		
(2) # of Depressiv~s		1.000	
(3) AS_12	0.352*		1.000

*** *p<0.01,* ** *p<0.05,* * *p<0.1*

Summary of OFRc - 2012

Variable	Obs	Mean	Std. Dev.	Min	Max
OFRc 12 1	6784	3.287	1.53	1	6
OFRc 12 2	6840	4.401	1.363	1	6
OFRc 12 3	6671	2.498	1.677	1	6
OFRc 12	6869	3.416	1.126	1	6

Correlation of OFRc - 2012

Variables	(1)	(2)	(3)
(1) OFRc_12_1	1.000		
(2) OFRc_12_2	0.562*	1.000	
(3) OFRc_12_3	0.120*	0.204*	1.000

*** *p<0.01,* ** *p<0.05,* * *p<0.1*

Alpha of OFRc - 2012

Test scale = mean(unstandardized items)
Average interitem covariance: .65214
Number of items in the scale: 3
Scale reliability coefficient: 0.5378

Factor of OFRc - 2012

(obs=6,602)
Factor analysis/correlation Number of obs = 6,602
Method: principal factors Retained factors = 1
Rotation: (unrotated) Number of params = 3

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	0.945	0.949	1.367	1.367
Factor2	-0.004	0.247	-0.005	1.362
Factor3	-0.250	.	-0.362	1.000

LR test: independent vs. saturated: chi2(3) = 2780.75 Prob>chi2 = 0.0000
Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Uniqueness
OFRc_12_1	0.652	0.575
OFRc_12_2	0.680	0.538
OFRc_12_3	0.241	0.942

Summary of OFRq - 2012

Variable	Obs	Mean	Std. Dev.	Min	Max
OFRq 12 1	6859	2.862	.911	1	4
OFRq 12 2	6855	3.03	1.017	1	4
OFRq 12 3	6845	2.848	1.022	1	4
OFRq 12 4	6846	3.536	.763	1	4
OFRq 12 5	6806	3.411	.804	1	4
OFRq 12 6	6802	3.397	.85	1	4
OFRq 12 7	6844	3.252	.852	1	4

Correlation of OFRq - 2012

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) OFRq_12_1	1.000						
(2) OFRq_12_2	0.625*	1.000					
(3) OFRq_12_3	0.677*	0.707*	1.000				
(4) OFRq_12_4	0.046*	0.042*	0.037*	1.000			
(5) OFRq_12_5	0.152*	0.117*	0.131*	0.464*	1.000		
(6) OFRq_12_6	0.246*	0.283*	0.248*	0.452*	0.522*	1.000	
(7) OFRq_12_7	0.229*	0.200*	0.209*	0.485*	0.568*	0.572*	1.000

*** *p<0.01,* ** *p<0.05,* * *p<0.1*

Alpha of OFRq - 2012
Test scale = mean(unstandardized items)
Average interitem covariance: .2658808
Number of items in the scale: 7
Scale reliability coefficient: 0.7777

Factor of OFRq - 2012
(obs=6,648)
Factor analysis/correlation Number of obs = 6,648
Method: principal factors Retained factors = 2
Rotation: (unrotated) Number of params = 13

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	2.512	1.143	0.764	0.764
Factor2	1.369	1.434	0.416	1.180
Factor3	-0.065	0.037	-0.020	1.161
Factor4	-0.102	0.029	-0.031	1.130
Factor5	-0.130	0.009	-0.040	1.090
Factor6	-0.139	0.017	-0.042	1.048
Factor7	-0.157	.	-0.048	1.000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
OFRq_12_1	0.621	-0.445	0.417
OFRq_12_2	0.632	-0.477	0.374
OFRq_12_3	0.652	-0.510	0.315
OFRq_12_4	0.431	0.468	0.595
OFRq_12_5	0.547	0.444	0.503
OFRq_12_6	0.646	0.327	0.475
OFRq_12_7	0.631	0.402	0.440

Summary of Income - 2012

Variable	Obs	Mean	Std. Dev.	Min	Max
h11itot:w11 income: total hhold	20554	64840.504	100253.18	0	3663276
l h11itot	20554	10.385	1.702	0	15.114

Summary of Total Assets - 2012

Variable	Obs	Mean	Std. Dev.	Min	Max
h11atotb:w11 total of all assets	20554	392170.8	999580.23	-1495000	43486000
l h11atotb	18914	11.035	3.421	0	17.588

Summary of Total Non-Housing Assets - 2012

Variable	Obs	Mean	Std. Dev.	Min	Max
h11atotn:w11 total non-housing a	20554	259066.71	851631.05	-1510000	43300000
l h11atotn	18490	9.888	3.79	0	17.584

Summary of Total Net Worth - 2012

Variable	Obs	Mean	Std. Dev.	Min	Max
h11atotf:w11 non-housing financi	20554	109157.97	539913.63	-1685000	42300000
l h11atotf	16520	7.908	4.653	0	17.56

Summary of Net Value of House - 2012

Variable	Obs	Mean	Std. Dev.	Min	Max
h11atoth:w11 net value of house	20554	113388.61	204157.91	-495000	9411437
l h11atoth	19754	8.277	5.263	0	16.057

Summary of PSc - 2012

Variable	Obs	Mean	Std. Dev.	Min	Max
PSc 12 1	4845	3.453	.766	1	4

Summary of PSq - 2012

Variable	Obs	Mean	Std. Dev.	Min	Max
PSq 12 1	4888	3.287	.815	1	4
PSq 12 2	4895	3.703	.668	1	4
PSq 12 3	4896	3.389	.824	1	4
PSq 12 4	4870	2.946	.914	1	4
PSq 12 5	4864	2.922	.893	1	4
PSq 12 6	4875	3.324	.858	1	4
PSq 12 7	4881	2.924	.842	1	4

Correlation of PSq - 2012

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) PSq_12_1	1.000						
(2) PSq_12_2	0.499*	1.000					
(3) PSq_12_3	0.619*	0.614*	1.000				
(4) PSq_12_4	0.281*	0.206*	0.240*	1.000			
(5) PSq_12_5	0.342*	0.195*	0.311*	0.530*	1.000		
(6) PSq_12_6	0.414*	0.404*	0.418*	0.430*	0.463*	1.000	
(7) PSq_12_7	0.442*	0.318*	0.409*	0.471*	0.511*	0.553*	1.000

*** *p<0.01*, ** *p<0.05*, * *p<0.1*

Alpha of PSq - 2012

Test scale = mean(unstandardized items)
Average interitem covariance: .2842337
Number of items in the scale: 7
Scale reliability coefficient: 0.8288

Factor of PSq - 2012

(obs=4,751)

Factor analysis/correlation	Number of obs	=	4,751
Method: principal factors	Retained factors	=	2
Rotation: (unrotated)	Number of params	=	13

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	2.939	2.305	0.973	0.973
Factor2	0.635	0.643	0.210	1.183
Factor3	-0.008	0.047	-0.003	1.180
Factor4	-0.055	0.086	-0.018	1.161
Factor5	-0.142	0.007	-0.047	1.115
Factor6	-0.149	0.049	-0.049	1.065
Factor7	-0.198	.	-0.065	1.000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
PSq_12_1	0.682	-0.243	0.476
PSq_12_2	0.597	-0.368	0.508
PSq_12_3	0.698	-0.365	0.380
PSq_12_4	0.556	0.359	0.562
PSq_12_5	0.609	0.342	0.512
PSq_12_6	0.686	0.124	0.514
PSq_12_7	0.693	0.213	0.474

Summary of sFWB - 2012

Variable	Obs	Mean	Std. Dev.	Min	Max
sFWB 12 1	7244	3.316	1.147	1	5
sFWB 12 2	7259	3.931	1.066	1	5
sFWB 12	7299	3.622	1.009	1	5

Correlation of sFWB - 2012

Variables	(1)	(2)
(1) sFWB_12_1	1.000	
(2) sFWB_12_2	0.660*	1.000

**** p<0.01, ** p<0.05, * p<0.1*

Alpha of sFWB - 2012

Test scale = mean(unstandardized items)

Average interitem covariance: .8053801

Number of items in the scale: 2

Scale reliability coefficient: 0.7931

Factor of sFWB - 2012

(obs=7,204)

Factor analysis/correlation		Number of obs =	7,204
Method: principal factors		Retained factors =	1
Rotation: (unrotated)		Number of params =	1

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.095	1.320	1.258	1.258
Factor2	-0.224	.	-0.258	1.000

LR test: independent vs. saturated: chi2(1) = 4116.19 Prob>chi2 = 0.0000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Uniqueness
sFWB_12_1	0.740	0.452
sFWB_12_2	0.740	0.452

2014 Wave

Summary of AS - 2014

Variable	Obs	Mean	Std. Dev.	Min	Max
q26r. nervous	7432	4.103	1.004	1	5

Summary of Chc - 2014

Variable	Obs	Mean	Std. Dev.	Min	Max
Chc 14 1	6436	3.822	1.499	1	6
Chc 14 2	6471	4.986	1.182	1	6
Chc 14 3	6311	2.917	1.878	1	6
Chc 14 4	6296	2.414	1.888	1	6
Chc 14	6534	3.567	1.129	1	6

Correlation of Chc - 2014

Variables	(1)	(2)	(3)	(4)
(1) Chc_14_1	1.000			
(2) Chc_14_2	0.512*	1.000		
(3) Chc_14_3	0.104*	0.190*	1.000	
(4) Chc_14_4	0.098*	0.184*	0.565*	1.000

*** *p<0.01,* ** *p<0.05,* * *p<0.1*

Alpha of Chc - 2014

Test scale = mean(unstandardized items)
Average interitem covariance: .7200027
Number of items in the scale: 4
Scale reliability coefficient: 0.5959

Factor of Chc - 2014

(obs=6,139)

Factor analysis/correlation	Number of obs	=	6,139
Method: principal factors	Retained factors	=	2
Rotation: (unrotated)	Number of params	=	6

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.136	0.586	0.945	0.945
Factor2	0.549	0.788	0.457	1.403
Factor3	-0.239	0.006	-0.199	1.204
Factor4	-0.245	.	-0.204	1.000

LR test: independent vs. saturated: chi2(6) = 4510.83 Prob>chi2 = 0.0000
Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
Chc_14_1	0.439	0.434	0.619
Chc_14_2	0.519	0.375	0.590
Chc_14_3	0.584	-0.328	0.552
Chc_14_4	0.577	-0.336	0.554

Summary of ChIl - 2014

Variable	Obs	Mean	Std. Dev.	Min	Max
r12hibpe:w12 r ever had high blo	18747	.617	.486	0	1
r12diabe:w12 r ever had diabetes	18747	.251	.434	0	1
r12cancre:w12 r ever had cancer	18747	.154	.361	0	1
r12lunge:w12 r ever had lung dis	18747	.103	.305	0	1
r12hearte:w12 r ever had heart p	18747	.249	.432	0	1
r12stroke:w12 r ever had stroke	18747	.094	.292	0	1
r12psyche:w12 r ever had psych p	18747	.199	.399	0	1
r12arthre:w12 r ever had arthrit	18747	.587	.492	0	1
# of Chronic Illnesses	18747	2.253	1.541	0	8
# of Chronic Illnesses(Rand)	18747	2.253	1.541	0	8

Correlation of ChIl - 2014

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) r12hibpe:w12 r~h	1.000							
(2) r12diabe:w12 r~b	0.245*	1.000						
(3) r12cancre:w12 ~n	0.057*	0.024*	1.000					
(4) r12lunge:w12 r~g	0.082*	0.055*	0.056*	1.000				
(5) r12hearte:w12 ~a	0.196*	0.135*	0.074*	0.165*	1.000			
(6) r12stroke:w12 ~r	0.131*	0.087*	0.043*	0.089*	0.189*	1.000		
(7) r12psyche:w12 ~y	0.077*	0.083*	0.030*	0.169*	0.098*	0.103*	1.000	
(8) r12arthre:w12 ~t	0.180*	0.094*	0.099*	0.147*	0.184*	0.100*	0.159*	1.000

**** p<0.01, ** p<0.05, * p<0.1*

Alpha of ChIl - 2014

Test scale = mean(unstandardized items)
Average interitem covariance: .0188305
Number of items in the scale: 8
Scale reliability coefficient: 0.5073

Factor of ChIl - 2014

(obs=18,747)

Factor analysis/correlation Number of obs = 18,747
Method: principal factors Retained factors = 4
Rotation: (unrotated) Number of params = 26

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	0.914	0.770	1.595	1.595
Factor2	0.144	0.127	0.251	1.846
Factor3	0.017	0.012	0.030	1.876
Factor4	0.006	0.081	0.010	1.886
Factor5	-0.076	0.011	-0.132	1.754
Factor6	-0.087	0.071	-0.152	1.602
Factor7	-0.158	0.028	-0.276	1.325
Factor8	-0.186	.	-0.325	1.000

LR test: independent vs. saturated: chi2(28) = 6359.56 Prob>chi2 = 0.0000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Factor3	Factor4	Uniqueness
ChIl_14_1	0.412	-0.187	0.002	0.013	0.795
ChIl_14_2	0.319	-0.204	-0.034	0.019	0.855
ChIl_14_3	0.158	0.055	0.103	0.018	0.961
ChIl_14_4	0.313	0.182	-0.025	0.003	0.868
ChIl_14_5	0.429	-0.002	0.022	-0.032	0.815
ChIl_14_6	0.311	0.000	0.001	-0.053	0.900
ChIl_14_7	0.294	0.158	-0.061	0.017	0.884
ChIl_14_8	0.391	0.079	0.025	0.026	0.840

Summary of Chr - 2014

Variable	Obs	Mean	Std. Dev.	Min	Max
Chr 14 1	6556	3.17	.833	1	4
Chr 14 2	6564	3.424	.859	1	4
Chr 14 3	6560	3.133	.908	1	4
Chr 14 4	6556	3.302	.881	1	4
Chr 14 5	6554	3.333	.812	1	4
Chr 14 6	6620	3.296	.855	1	4
Chr 14 7	6585	3.255	.799	1	4

Correlation of Chr - 2014

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Chr_14_1	1.000						
(2) Chr_14_2	0.570*	1.000					
(3) Chr_14_3	0.637*	0.646*	1.000				
(4) Chr_14_4	0.197*	0.216*	0.183*	1.000			
(5) Chr_14_5	0.268*	0.228*	0.217*	0.445*	1.000		
(6) Chr_14_6	0.387*	0.422*	0.357*	0.434*	0.439*	1.000	
(7) Chr_14_7	0.331*	0.305*	0.298*	0.489*	0.485*	0.563*	1.000

*** *p<0.01*, ** *p<0.05*, * *p<0.1*

Alpha of Chr - 2014

Test scale = mean(unstandardized items)
Average interitem covariance: .278203
Number of items in the scale: 7
Scale reliability coefficient: 0.8141

Factor of Chr - 2014

(obs=6,393)
Factor analysis/correlation Number of obs = 6,393
Method: principal factors Retained factors = 2
Rotation: (unrotated) Number of params = 13

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	2.783	1.995	0.933	0.933
Factor2	0.788	0.836	0.264	1.198
Factor3	-0.049	0.033	-0.016	1.181
Factor4	-0.081	0.042	-0.027	1.154
Factor5	-0.124	0.032	-0.042	1.113
Factor6	-0.155	0.025	-0.052	1.060
Factor7	-0.180	.	-0.060	1.000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
Chr_14_1	0.661	-0.325	0.458
Chr_14_2	0.668	-0.342	0.437
Chr_14_3	0.666	-0.416	0.382
Chr_14_4	0.514	0.368	0.601
Chr_14_5	0.540	0.326	0.602
Chr_14_6	0.688	0.204	0.486
Chr_14_7	0.653	0.330	0.464

Summary of CoRn - 2014

Variable	Obs	Mean	Std. Dev.	Min	Max
n Close Children Relationships	6564	1.436	.769	0	5
n Close Family Relationships	6831	1.749	1.152	0	5
n Close Family Relationships	6624	2.003	1.172	0	5
CoRn 14	7464	1.73	.796	0	5

Correlation of CoRn - 2014

Variables	(1)	(2)	(3)
(1) n Close Childr~i	1.000		
(2) n Close Family~s	0.327*	1.000	
(3) n Close Family~s	0.146*	0.321*	1.000

*** *p<0.01,* ** *p<0.05,* * *p<0.1*

Alpha of CoRn - 2014
Test scale = mean(unstandardized items)
Average interitem covariance: .2858902
Number of items in the scale: 3
Scale reliability coefficient: 0.5126

Factor of PSc - 2014
(obs=5,415)
Factor analysis/correlation Number of obs = 5,415
Method: principal factors Retained factors = 1
Rotation: (unrotated) Number of params = 3

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	0.675	0.713	1.709	1.709
Factor2	-0.038	0.204	-0.097	1.612
Factor3	-0.242	.	-0.612	1.000

LR test: independent vs. saturated: chi2(3) = 1204.25 Prob>chi2 = 0.0000
Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Uniqueness
CoRn_14_1	0.425	0.820
CoRn_14_2	0.559	0.688
CoRn_14_3	0.427	0.818

Summary of CoRPS - 2014

Variable	Obs	Mean	Std. Dev.	Min	Max
CoRPS 14 1	4955	1.557	.774	1	4
CoRPS 14 2	4976	2.047	.806	1	4
CoRPS 14 3	4974	1.729	.6	1	3
CoRPS 14	5071	1.786	.627	1	4

Correlation of CoRPS - 2014

Variables	(1)	(2)	(3)
(1) CoRPS_14_1	1.000		
(2) CoRPS_14_2	0.670*	1.000	
(3) CoRPS_14_3	0.459*	0.485*	1.000

**** p<0.01, ** p<0.05, * p<0.1*

Alpha of CoRPS - 2014

Test scale = mean(unstandardized items)
Average interitem covariance: .2825771
Number of items in the scale: 3
Scale reliability coefficient: 0.7700

Factor of PSc - 2014

(obs=4,849)
Factor analysis/correlation Number of obs = 4,849
Method: principal factors Retained factors = 1
Rotation: (unrotated) Number of params = 3

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.504	1.594	1.230	1.230
Factor2	-0.090	0.102	-0.074	1.157
Factor3	-0.192	.	-0.157	1.000

LR test: independent vs. saturated: chi2(3) = 4365.53 Prob>chi2 = 0.0000
Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Uniqueness
CoRPS_14_1	0.756	0.428
CoRPS_14_2	0.771	0.405
CoRPS_14_3	0.581	0.663

Summary of DS - 2014

Variable	Obs	Mean	Std. Dev.	Min	Max
DS 14 1	17688	.134	.341	0	1
DS 14 2	17660	.269	.444	0	1
DS 14 3	17627	.205	.404	0	1
DS 14 4	17669	.904	.294	0	1
DS 14 5	17645	.856	.351	0	1
DS 14 6	17677	.172	.378	0	1
DS 14 7	17671	.313	.464	0	1
DS 14 8	17664	.192	.394	0	1
# of Depressive Symptoms	17696	3.04	1.405	0	8

Correlation of DS - 2014

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) DS_14_1	1.000							
(2) DS_14_2	0.412*	1.000						
(3) DS_14_3	0.328*	0.382*	1.000					
(4) DS_14_4	-0.440*	-0.287*	-0.264*	1.000				
(5) DS_14_5	-0.504*	-0.323*	-0.292*	0.593*	1.000			
(6) DS_14_6	0.463*	0.322*	0.288*	-0.370*	-0.403*	1.000		
(7) DS_14_7	0.335*	0.305*	0.297*	-0.237*	-0.283*	0.279*	1.000	
(8) DS_14_8	0.586*	0.353*	0.326*	-0.441*	-0.504*	0.553*	0.335*	1.000

*** *p<0.01,* ** *p<0.05,* * *p<0.1*

Alpha of DS - 2014

Test scale = mean(unstandardized items)
Reversed items: DS_14_4 DS_14_5
Average interitem covariance: .0538332
Number of items in the scale: 8
Scale reliability coefficient: 0.8178

Factor of DS - 2014

(obs=17,490)

Factor analysis/correlation   Number of obs = 17,490
Method: principal factors   Retained factors = 3
Rotation: (unrotated)   Number of params = 21

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	3.063	2.802	1.078	1.078
Factor2	0.261	0.144	0.092	1.169
Factor3	0.117	0.173	0.041	1.211
Factor4	-0.056	0.011	-0.020	1.191
Factor5	-0.068	0.066	-0.024	1.167
Factor6	-0.134	0.034	-0.047	1.120
Factor7	-0.168	0.006	-0.059	1.061
Factor8	-0.174	.	-0.061	1.000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Factor3	Uniqueness
DS_14_1	0.723	0.011	0.065	0.473
DS_14_2	0.533	0.231	-0.097	0.653
DS_14_3	0.482	0.231	-0.114	0.701
DS_14_4	-0.631	0.253	0.125	0.522
DS_14_5	-0.695	0.233	0.111	0.451
DS_14_6	0.626	0.015	0.173	0.578
DS_14_7	0.457	0.187	-0.045	0.754
DS_14_8	0.737	-0.022	0.174	0.426

Summary of FL - 2014

Variable	Obs	Mean	Std. Dev.	Min	Max
FL 14 1	18722	.123	.329	0	1
FL 14 2	18721	.087	.282	0	1
FL 14 3	18725	.092	.289	0	1
FL 14 4	18723	.047	.212	0	1
FL 14 5	18719	.083	.276	0	1
FL 14 6	18718	.074	.263	0	1
# of Functional Limitations	18731	.507	1.249	0	6

Correlation of FL - 2014

Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) FL_14_1	1.000					
(2) FL_14_2	0.509*	1.000				
(3) FL_14_3	0.555*	0.546*	1.000			
(4) FL_14_4	0.415*	0.420*	0.477*	1.000		
(5) FL_14_5	0.518*	0.494*	0.501*	0.420*	1.000	
(6) FL_14_6	0.470*	0.484*	0.500*	0.406*	0.493*	1.000

*** *p<0.01,* ** *p<0.05,* * *p<0.1*

Alpha of FL - 2014

Test scale = mean(unstandardized items)
Average interitem covariance: .0366554
Number of items in the scale: 6
Scale reliability coefficient: 0.8455

Factor of FL - 2014

(obs=18,685)

Factor analysis/correlation Number of obs = 18,685
Method: principal factors Retained factors = 1
Rotation: (unrotated) Number of params = 6

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	2.820	2.856	1.166	1.166
Factor2	-0.035	0.017	-0.015	1.152
Factor3	-0.052	0.022	-0.021	1.130
Factor4	-0.074	0.030	-0.030	1.100
Factor5	-0.104	0.034	-0.043	1.057
Factor6	-0.138	.	-0.057	1.000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Uniqueness
FL_14_1	0.707	0.501
FL_14_2	0.701	0.509
FL_14_3	0.741	0.451
FL_14_4	0.599	0.641
FL_14_5	0.691	0.523
FL_14_6	0.667	0.556

Summary of FRc - 2014

Variable	Obs	Mean	Std. Dev.	Min	Max
FRc 14 1	6686	4.032	1.342	1	6
FRc 14 2	6711	4.461	1.286	1	6
FRc 14 3	6528	2.666	1.797	1	6
FRc 14 4	6553	2.054	1.717	1	6
FRc 14	6757	3.328	1.074	1	6

Correlation of FRc - 2014

Variables	(1)	(2)	(3)	(4)
(1) FRc_14_1	1.000			
(2) FRc_14_2	0.474*	1.000		
(3) FRc_14_3	0.222*	0.203*	1.000	
(4) FRc_14_4	0.145*	0.149*	0.514*	1.000

*** *p<0.01*, ** *p<0.05*, * *p<0.1*

Alpha of FRc - 2014

Test scale = mean(unstandardized items)
Average interitem covariance: .6790329
Number of items in the scale: 4
Scale reliability coefficient: 0.6121

Factor of FRc - 2014

(obs=6,398)

Factor analysis/correlation Number of obs = 6,398
Method: principal factors Retained factors = 2
Rotation: (unrotated) Number of params = 6

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.114	0.720	1.079	1.079
Factor2	0.394	0.619	0.382	1.460
Factor3	-0.225	0.025	-0.218	1.242
Factor4	-0.250	.	-0.242	1.000

LR test: independent vs. saturated: chi2(6) = 4007.71 Prob>chi2 = 0.0000
Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
FRc_14_1	0.502	0.328	0.640
FRc_14_2	0.495	0.330	0.646
FRc_14_3	0.584	-0.269	0.587
FRc_14_4	0.525	-0.326	0.618

Summary of FRq - 2014

Variable	Obs	Mean	Std. Dev.	Min	Max
FRq 14 1	6699	3.055	.804	1	4
FRq 14 2	6701	3.07	.88	1	4
FRq 14 3	6696	2.975	.903	1	4
FRq 14 4	6696	3.683	.602	1	4
FRq 14 5	6661	3.637	.611	1	4
FRq 14 6	6665	3.56	.694	1	4
FRq 14 7	6691	3.477	.678	1	4

Correlation of FRq - 2014

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) FRq_14_1	1.000						
(2) FRq_14_2	0.582*	1.000					
(3) FRq_14_3	0.658*	0.676*	1.000				
(4) FRq_14_4	-0.030*	-0.019	-0.024*	1.000			
(5) FRq_14_5	0.017	0.051*	0.027*	0.476*	1.000		
(6) FRq_14_6	0.114*	0.162*	0.120*	0.404*	0.464*	1.000	
(7) FRq_14_7	0.080*	0.079*	0.089*	0.441*	0.473*	0.495*	1.000

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Alpha of FRq - 2014

Test scale = mean(unstandardized items)
Average interitem covariance: .1414243
Number of items in the scale: 7
Scale reliability coefficient: 0.7032

Factor of FRq - 2014

(obs=6,551)
Factor analysis/correlation Number of obs = 6,551
Method: principal factors Retained factors = 2
Rotation: (unrotated) Number of params = 13

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.973	0.410	0.680	0.680
Factor2	1.563	1.638	0.539	1.219
Factor3	-0.075	0.012	-0.026	1.193
Factor4	-0.088	0.052	-0.030	1.163
Factor5	-0.139	0.016	-0.048	1.115
Factor6	-0.155	0.023	-0.054	1.062
Factor7	-0.178	.	-0.061	1.000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
FRq_14_1	0.599	-0.434	0.453
FRq_14_2	0.635	-0.422	0.418
FRq_14_3	0.661	-0.478	0.334
FRq_14_4	0.344	0.529	0.601
FRq_14_5	0.420	0.525	0.547
FRq_14_6	0.507	0.425	0.563
FRq_14_7	0.470	0.481	0.548

Summary of LS - 2014

Variable	Obs	Mean	Std. Dev.	Min	Max
q02a. life is close to ideal	7404	4.846	1.814	1	7
q02b. conditions of life are excellen	7412	4.85	1.822	1	7
q02c. satisfied with life	7432	5.334	1.768	1	7
q02d. have important things in life	7441	5.38	1.715	1	7
q02e. change nothing if lived life ov	7454	4.427	2.03	1	7
LS 14	7478	4.964	1.528	1	7
r12lbsatwlf:w12 life satisfactio	7465	4.966	1.526	1	7

Correlation of LS - 2014

Variables	(1)	(2)	(3)	(4)	(5)
(1) q02a. life is ~l	1.000				
(2) q02b. conditio~n	0.765*	1.000			
(3) q02c. satisfie~e	0.701*	0.765*	1.000		
(4) q02d. have imp~e	0.588*	0.618*	0.684*	1.000	
(5) q02e. change n~v	0.500*	0.518*	0.534*	0.559*	1.000

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Alpha of LS - 2014

Test scale = mean(unstandardized items)
Average interitem covariance: 2.066018
Number of items in the scale: 5
Scale reliability coefficient: 0.8887

Factor of LS - 2014

(obs=7,291)
Factor analysis/correlation Number of obs = 7,291
Method: principal factors Retained factors = 2
Rotation: (unrotated) Number of params = 9

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	3.123	3.036	1.069	1.069
Factor2	0.087	0.136	0.030	1.099
Factor3	-0.049	0.061	-0.017	1.082
Factor4	-0.110	0.020	-0.037	1.044
Factor5	-0.130	.	-0.044	1.000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
LS_14_1	0.817	-0.129	0.316
LS_14_2	0.861	-0.137	0.240
LS_14_3	0.858	-0.002	0.264
LS_14_4	0.759	0.161	0.398
LS_14_5	0.635	0.161	0.571

Summary of Ch - 2014

Variable	Obs	Mean	Std. Dev.	Min	Max
Chc 14	6534	3.567	1.129	1	6
Chr 14	6684	3.273	.588	1	4

Correlation of Ch - 2014

Variables	(1)	(2)
(1) Chc_14	1.000	
(2) Chr_14	0.220*	1.000

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Alpha of Ch - 2014

Test scale = mean(unstandardized items)
Average interitem covariance: .1454044
Number of items in the scale: 2
Scale reliability coefficient: 0.3060

Factor of Ch - 2014
(obs=6,521)

Factor analysis/correlation		Number of obs =	6,521
Method: principal factors		Retained factors =	1
Rotation: (unrotated)		Number of params =	1

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	0.269	0.441	2.768	2.768
Factor2	-0.172	.	-1.768	1.000

LR test: independent vs. saturated: chi2(1) = 324.87 Prob>chi2 = 0.0000
Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Uniqueness
Chc_14	0.367	0.866
Chr_14	0.367	0.866

Summary of OFRc - 2014

Variable	Obs	Mean	Std. Dev.	Min	Max
OFRc 14 1	6892	3.221	1.508	1	6
OFRc 14 2	6939	4.375	1.385	1	6
OFRc 14 3	6792	2.446	1.658	1	6
OFRc 14 4	6783	1.978	1.62	1	6
OFRc 14	6968	3.031	1.072	1	6

Correlation of OFRc - 2014

Variables	(1)	(2)	(3)	(4)
(1) OFRc_14_1	1.000			
(2) OFRc_14_2	0.565*	1.000		
(3) OFRc_14_3	0.096*	0.166*	1.000	
(4) OFRc_14_4	0.127*	0.164*	0.532*	1.000

*** *p<0.01,* ** *p<0.05,* * *p<0.1*

Alpha of OFRc - 2014
Test scale = mean(unstandardized items)
Average interitem covariance: .6514325
Number of items in the scale: 4
Scale reliability coefficient: 0.6000

Factor of OFRc - 2014
(obs=6,681)

Factor analysis/correlation		Number of obs =	6,681
Method: principal factors		Retained factors =	2
Rotation: (unrotated)		Number of params =	6

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.135	0.556	0.921	0.921
Factor2	0.580	0.804	0.470	1.392
Factor3	-0.225	0.033	-0.182	1.209
Factor4	-0.258	.	-0.209	1.000

LR test: independent vs. saturated: chi2(6) = 5036.42 Prob>chi2 = 0.0000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
OFRc_14_1	0.543	-0.380	0.561
OFRc_14_2	0.588	-0.332	0.545
OFRc_14_3	0.492	0.410	0.590
OFRc_14_4	0.503	0.397	0.589

Summary of OFRq - 2014

Variable	Obs	Mean	Std. Dev.	Min	Max
OFRq 14 1	6946	2.841	.918	1	4
OFRq 14 2	6959	2.992	1.022	1	4
OFRq 14 3	6951	2.812	1.019	1	4
OFRq 14 4	6955	3.566	.736	1	4
OFRq 14 5	6914	3.45	.791	1	4
OFRq 14 6	6919	3.429	.824	1	4
OFRq 14 7	6957	3.287	.824	1	4

Correlation of OFRq - 2014

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) OFRq_14_1	1.000						
(2) OFRq_14_2	0.633*	1.000					
(3) OFRq_14_3	0.700*	0.733*	1.000				
(4) OFRq_14_4	0.029*	0.031*	0.015	1.000			
(5) OFRq_14_5	0.145*	0.125*	0.128*	0.465*	1.000		
(6) OFRq_14_6	0.227*	0.245*	0.220*	0.431*	0.540*	1.000	
(7) OFRq_14_7	0.195*	0.176*	0.194*	0.462*	0.556*	0.572*	1.000

**** p<0.01, ** p<0.05, * p<0.1*

Alpha of OFRq - 2014

Test scale = mean(unstandardized items)
Average interitem covariance: .2525014
Number of items in the scale: 7
Scale reliability coefficient: 0.7706

Factor of OFRq - 2014

(obs=6,758)

Factor analysis/correlation		Number of obs =	6,758
Method: principal factors		Retained factors =	2
Rotation: (unrotated)		Number of params =	13

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	2.459	1.014	0.741	0.741
Factor2	1.445	1.523	0.435	1.176
Factor3	-0.079	0.010	-0.024	1.152
Factor4	-0.089	0.037	-0.027	1.125
Factor5	-0.126	0.005	-0.038	1.088
Factor6	-0.131	0.029	-0.040	1.048
Factor7	-0.160	.	-0.048	1.000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
OFRq_14_1	0.635	-0.436	0.406
OFRq_14_2	0.648	-0.468	0.360
OFRq_14_3	0.678	-0.511	0.279
OFRq_14_4	0.391	0.479	0.618
OFRq_14_5	0.539	0.464	0.494
OFRq_14_6	0.614	0.379	0.479
OFRq_14_7	0.596	0.431	0.459

Summary of Income - 2014

Variable	Obs	Mean	Std. Dev.	Min	Max
h14HInc	31744	69739.47	133139.65	0	10938250
l h14HInc	18747	10.423	1.696	0	16.208

Summary of Total Assets - 2014

Variable	Obs	Mean	Std. Dev.	Min	Max
h14HAss	31744	446346.08	1998718.2	-2729000	3.089e+08
l h14HAss	17537	11.085	3.433	0	19.549

Summary of Total Non-Housing Assets - 2014

Variable	Obs	Mean	Std. Dev.	Min	Max
h14HNhAss	31744	295982.56	1603016	-1294500	2.457e+08
l h14HNhAss	17020	9.919	3.825	0	19.32

Summary of Total Net Worth - 2014

Variable	Obs	Mean	Std. Dev.	Min	Max
h14HNW	31744	125823.33	1215968.7	-1499500	2.020e+08
l h14HNW	15267	7.947	4.668	0	19.124

Summary of Net Value of House - 2014

Variable	Obs	Mean	Std. Dev.	Min	Max
h14HNHoEq	31744	125850.61	210246.98	-3860000	5000000
l h14HNHoEq	18301	8.307	5.309	0	15.425

Summary of PH - 2014

Variable	Obs	Mean	Std. Dev.	Min	Max
Self-Reported Health	31722	2.908	1.054	1	5
r14BMI	31244	28.728	6.185	11	76.6
r14BMI cat	.	.	.	.	.
Underweight	35626	.013	.114	0	1
Healthy Weight	35626	.229	.42	0	1
Overweight	35626	.321	.467	0	1
Obese	35626	.437	.496	0	1
# of Chronic Illnesses	18747	2.253	1.541	0	8
# of Chronic Illnesses(Rand)	18747	2.253	1.541	0	8
# of Functional Limitations	18731	.507	1.249	0	6

Correlation of PH - 2014

Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) Self-Reported ~h	1.000					
(2) r14BMI	0.158*	1.000				
(3) BMI Categories	0.121*	0.844*	1.000			
(4) # of Chronic I~s	0.452*	0.163*	0.124*	1.000		
(5) # of Chronic I~)	0.452*	0.163*	0.124*	1.000*	1.000	
(6) # of Functiona~s	0.388*	0.034*	-0.005	0.334*	0.334*	1.000

*** *p<0.01,* ** *p<0.05,* * *p<0.1*

Alpha of PH - 2014

Test scale = mean(unstandardized items)
Average interitem covariance: 1.08129
Number of items in the scale: 6
Scale reliability coefficient: 0.4545

Factor of PH - 2014

(obs=18,259)
(collinear variables specified)
Factor analysis/correlation Number of obs = 18,259
Method: principal factors Retained factors = 3
Rotation: (unrotated) Number of params = 15
Warning: Solution is a Heywood case; that is, invalid or boundary values of uniqueness.

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	2.486	1.031	0.637	0.637
Factor2	1.455	1.195	0.373	1.009
Factor3	0.260	0.260	0.067	1.076
Factor4	0.000	0.129	0.000	1.076
Factor5	-0.129	0.039	-0.033	1.043
Factor6	-0.168	.	-0.043	1.000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Factor3	Uniqueness
r14SRH	0.498	-0.096	0.319	0.641
r14BMI	0.395	0.794	0.025	0.213
r14BMI_cat	0.357	0.810	-0.021	0.216
ChIl_14	0.954	-0.262	-0.149	-0.000
ChIl_14_r	0.954	-0.262	-0.149	-0.000
FL_14	0.368	-0.152	0.335	0.729

Summary of PSc - 2014

Variable	Obs	Mean	Std. Dev.	Min	Max
PSc 14 1	4955	3.443	.774	1	4
PSc 14 2	4976	2.953	.806	1	4
PSc 14 3	4974	1.729	.6	1	3
PSc 14	5071	2.882	.624	1	4

Correlation of PSc - 2014

Variables	(1)	(2)	(3)
(1) PSc_14_1	1.000		
(2) PSc_14_2	0.670*	1.000	
(3) PSc_14_3	-0.459*	-0.485*	1.000

*** *p<0.01,* ** *p<0.05,* * *p<0.1*

Alpha of PSc - 2014
Test scale = mean(unstandardized items)
Reversed item: PSc_14_3
Average interitem covariance: .2825771
Number of items in the scale: 3
Scale reliability coefficient: 0.7700

Factor of PSc - 2014
(obs=4,849)
Factor analysis/correlation Number of obs = 4,849
Method: principal factors Retained factors = 1
Rotation: (unrotated) Number of params = 3

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.504	1.594	1.230	1.230
Factor2	-0.090	0.102	-0.074	1.157
Factor3	-0.192	.	-0.157	1.000

LR test: independent vs. saturated: chi2(3) = 4365.53 Prob>chi2 = 0.0000
Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Uniqueness
PSc_14_1	0.756	0.428
PSc_14_2	0.771	0.405
PSc_14_3	-0.581	0.663

Summary of PSq - 2014

Variable	Obs	Mean	Std. Dev.	Min	Max
PSq 14 1	5027	3.267	.825	1	4
PSq 14 2	5003	3.685	.688	1	4
PSq 14 3	4993	3.386	.834	1	4
PSq 14 4	4986	2.985	.901	1	4
PSq 14 5	4977	2.969	.883	1	4
PSq 14 6	4979	3.322	.865	1	4
PSq 14 7	4986	2.946	.837	1	4

Correlation of PSq - 2014

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) PSq_14_1	1.000						
(2) PSq_14_2	0.530*	1.000					
(3) PSq_14_3	0.647*	0.625*	1.000				
(4) PSq_14_4	0.260*	0.218*	0.249*	1.000			
(5) PSq_14_5	0.296*	0.186*	0.307*	0.507*	1.000		
(6) PSq_14_6	0.409*	0.391*	0.402*	0.438*	0.446*	1.000	
(7) PSq_14_7	0.413*	0.303*	0.397*	0.467*	0.501*	0.550*	1.000

*** *p<0.01,* ** *p<0.05,* * *p<0.1*

Alpha of PSq - 2014
Test scale = mean(unstandardized items)
Average interitem covariance: .2812525
Number of items in the scale: 7
Scale reliability coefficient: 0.8253

Factor of PSq - 2014
(obs=4,875)

Factor analysis/correlation	Number of obs =	4,875
Method: principal factors	Retained factors =	2
Rotation: (unrotated)	Number of params =	13

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	2.910	2.233	0.960	0.960
Factor2	0.677	0.697	0.223	1.183
Factor3	-0.021	0.032	-0.007	1.176
Factor4	-0.053	0.078	-0.018	1.159
Factor5	-0.131	0.022	-0.043	1.116
Factor6	-0.153	0.045	-0.050	1.065
Factor7	-0.198	.	-0.065	1.000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
PSq_14_1	0.682	-0.282	0.456
PSq_14_2	0.613	-0.363	0.492
PSq_14_3	0.713	-0.363	0.360
PSq_14_4	0.553	0.350	0.572
PSq_14_5	0.577	0.354	0.542
PSq_14_6	0.678	0.162	0.514
PSq_14_7	0.680	0.244	0.478

Summary of sFWB - 2014

Variable	Obs	Mean	Std. Dev.	Min	Max
sFWB 14 1	7365	3.326	1.14	1	5
sFWB 14 2	7367	4.013	1.02	1	5
sFWB 14	7439	3.668	.981	1	5

Correlation of sFWB - 2014

Variables	(1)	(2)
(1) sFWB_14_1	1.000	
(2) sFWB_14_2	0.634*	1.000

*** *p<0.01,* ** *p<0.05,* * *p<0.1*

Alpha of sFWB - 2014
Test scale = mean(unstandardized items)
Average interitem covariance: .7368013
Number of items in the scale: 2
Scale reliability coefficient: 0.7725

Factor of sFWB - 2014
(obs=7,293)

Factor analysis/correlation	Number of obs	=	7,293
Method: principal factors	Retained factors	=	1
Rotation: (unrotated)	Number of params	=	1

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.037	1.269	1.288	1.288
Factor2	-0.232	.	-0.288	1.000

LR test: independent vs. saturated: chi2(1) = 3753.40 Prob>chi2 = 0.0000
Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Uniqueness
sFWB_14_1	0.720	0.482
sFWB_14_2	0.720	0.482

2016 Wave

Summary of Chc - 2016

Variable	Obs	Mean	Std. Dev.	Min	Max
Chc 16 1	5282	3.816	1.479	1	6
Chc 16 2	5350	4.945	1.262	1	6
Chc 16 3	5218	3.043	1.913	1	6
Chc 16 4	5239	2.837	2.021	1	6
Chc 16	5396	3.681	1.186	1	6

Correlation of Chc - 2016

Variables	(1)	(2)	(3)	(4)
(1) Chc_16_1	1.000			
(2) Chc_16_2	0.547*	1.000		
(3) Chc_16_3	0.170*	0.228*	1.000	
(4) Chc_16_4	0.173*	0.237*	0.505*	1.000

*** *p<0.01,* ** *p<0.05,* * *p<0.1*

Alpha of Chc - 2016
Test scale = mean(unstandardized items)
Average interitem covariance: .8555213
Number of items in the scale: 4
Scale reliability coefficient: 0.6293

Factor of Chc - 2016
(obs=5,069)
Factor analysis/correlation Number of obs = 5,069
Method: principal factors Retained factors = 2
Rotation: (unrotated) Number of params = 6

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.230	0.818	1.051	1.051
Factor2	0.412	0.644	0.352	1.403
Factor3	-0.232	0.008	-0.198	1.205
Factor4	-0.240	.	-0.205	1.000

LR test: independent vs. saturated: chi2(6) = 3701.70 Prob>chi2 = 0.0000
Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
Chc_16_1	0.555	-0.331	0.583
Chc_16_2	0.609	-0.278	0.552
Chc_16_3	0.521	0.338	0.614
Chc_16_4	0.529	0.333	0.609

Summary of ChIl - 2016

Variable	Obs	Mean	Std. Dev.	Min	Max
r13hibpe:w13 r ever had high blo	20912	.598	.49	0	1
r13diabe:w13 r ever had diabetes	20912	.262	.44	0	1
r13cancre:w13 r ever had cancer	20912	.141	.349	0	1
r13lunge:w13 r ever had lung dis	20912	.104	.305	0	1
r13hearte:w13 r ever had heart p	20912	.229	.42	0	1
r13stroke:w13 r ever had stroke	20912	.088	.283	0	1
r13psyche:w13 r ever had psych p	20912	.209	.407	0	1
r13arthre:w13 r ever had arthrit	20912	.547	.498	0	1
# of Chronic Illnesses	20912	2.178	1.566	0	8
# of Chronic Illnesses(Rand)	20912	2.178	1.566	0	8

Correlation of ChIl - 2016

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) r13hibpe:w13 r~h	1.000							
(2) r13diabe:w13 r~b	0.253*	1.000						
(3) r13cancre:w13 ~n	0.068*	0.029*	1.000					
(4) r13lunge:w13 r~g	0.091*	0.062*	0.063*	1.000				
(5) r13hearte:w13 ~a	0.207*	0.136*	0.094*	0.173*	1.000			
(6) r13stroke:w13 ~r	0.141*	0.090*	0.050*	0.117*	0.206*	1.000		
(7) r13psyche:w13 ~y	0.072*	0.075*	0.036*	0.172*	0.098*	0.103*	1.000	
(8) r13arthre:w13 ~t	0.199*	0.108*	0.113*	0.153*	0.202*	0.110*	0.184*	1.000

*** *p<0.01, *** *p<0.05, ** *p<0.1*

Alpha of ChIl - 2016

Test scale = mean(unstandardized items)
Average interitem covariance: .0202304
Number of items in the scale: 8
Scale reliability coefficient: 0.5282

Factor of ChIl - 2016

(obs=20,912)

Factor analysis/correlation		Number of obs =	20,912
Method: principal factors		Retained factors =	4
Rotation: (unrotated)		Number of params =	26

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	0.987	0.835	1.535	1.535
Factor2	0.152	0.131	0.237	1.772
Factor3	0.022	0.007	0.034	1.806
Factor4	0.014	0.102	0.022	1.828
Factor5	-0.087	0.007	-0.136	1.692
Factor6	-0.094	0.065	-0.146	1.546
Factor7	-0.159	0.034	-0.247	1.299
Factor8	-0.192	.	-0.299	1.000

LR test: independent vs. saturated: chi2(28) = 8065.39 Prob>chi2 = 0.0000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Factor3	Factor4	Uniqueness
ChIl_16_1	0.422	-0.197	-0.015	0.012	0.782
ChIl_16_2	0.319	-0.210	-0.051	-0.003	0.852
ChIl_16_3	0.181	0.048	0.068	0.082	0.954
ChIl_16_4	0.327	0.174	-0.014	-0.020	0.862
ChIl_16_5	0.444	-0.005	0.062	-0.022	0.798
ChIl_16_6	0.329	0.015	0.059	-0.064	0.884
ChIl_16_7	0.294	0.177	-0.077	-0.007	0.876
ChIl_16_8	0.419	0.072	-0.023	0.049	0.816

Summary of Chr - 2016

Variable	Obs	Mean	Std. Dev.	Min	Max
Chr 16 1	5465	3.168	.834	1	4
Chr 16 2	5470	3.407	.861	1	4
Chr 16 3	5463	3.135	.924	1	4
Chr 16 4	5456	3.266	.881	1	4
Chr 16 5	5455	3.329	.818	1	4
Chr 16 6	5526	3.244	.878	1	4
Chr 16 7	5501	3.214	.822	1	4

Correlation of Chr - 2016

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Chr_16_1	1.000						
(2) Chr_16_2	0.571*	1.000					
(3) Chr_16_3	0.615*	0.662*	1.000				
(4) Chr_16_4	0.149*	0.196*	0.157*	1.000			
(5) Chr_16_5	0.249*	0.231*	0.236*	0.417*	1.000		
(6) Chr_16_6	0.372*	0.434*	0.367*	0.403*	0.418*	1.000	
(7) Chr_16_7	0.307*	0.312*	0.302*	0.454*	0.456*	0.552*	1.000

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Alpha of Chr - 2016

Test scale = mean(unstandardized items)
Average interitem covariance: .2761621
Number of items in the scale: 7
Scale reliability coefficient: 0.8064

Factor of Chr - 2016

(obs=5,294)

Factor analysis/correlation	Number of obs	=	5,294
Method: principal factors	Retained factors	=	2
Rotation: (unrotated)	Number of params	=	13

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	2.702	1.938	0.941	0.941
Factor2	0.763	0.810	0.266	1.207
Factor3	-0.046	0.033	-0.016	1.191
Factor4	-0.079	0.055	-0.028	1.163
Factor5	-0.135	0.016	-0.047	1.116
Factor6	-0.151	0.033	-0.052	1.064
Factor7	-0.184	.	-0.064	1.000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
Chr_16_1	0.642	-0.318	0.486
Chr_16_2	0.693	-0.330	0.411
Chr_16_3	0.682	-0.386	0.386
Chr_16_4	0.467	0.389	0.631
Chr_16_5	0.519	0.321	0.628
Chr_16_6	0.677	0.205	0.500
Chr_16_7	0.631	0.330	0.493

Summary of CoRn - 2016

Variable	Obs	Mean	Std. Dev.	Min	Max
n Close Children Relationships	5467	1.414	.762	0	5
n Close Family Relationships	5772	1.777	1.16	0	5
n Close Family Relationships	5593	1.954	1.139	0	5
CoRn 16	6292	1.716	.78	0	5

Correlation of CoRn - 2016

Variables	(1)	(2)	(3)
(1) n Close Childr~i	1.000		
(2) n Close Family~s	0.308*	1.000	
(3) n Close Family~s	0.118*	0.305*	1.000

*** *p<0.01,* ** *p<0.05,* * *p<0.1*

Alpha of CoRn - 2016
Test scale = mean(unstandardized items)
Average interitem covariance: .2607592
Number of items in the scale: 3
Scale reliability coefficient: 0.4881

Factor of PSc - 2016
(obs=4,540)
Factor analysis/correlation Number of obs = 4,540
Method: principal factors Retained factors = 1
Rotation: (unrotated) Number of params = 3

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	0.616	0.637	1.756	1.756
Factor2	-0.022	0.222	-0.061	1.695
Factor3	-0.244	.	-0.695	1.000

LR test: independent vs. saturated: chi2(3) = 880.14 Prob>chi2 = 0.0000
Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Uniqueness
CoRn_16_1	0.396	0.843
CoRn_16_2	0.541	0.707
CoRn_16_3	0.407	0.834

Summary of CoRPS - 2016

Variable	Obs	Mean	Std. Dev.	Min	Max
CoRPS 16 1	4139	1.55	.768	1	4
CoRPS 16 2	4113	2.025	.79	1	4
CoRPS 16 3	4114	1.75	.585	1	3
CoRPS 16	4220	1.787	.618	1	4

Correlation of CoRPS - 2016

Variables	(1)	(2)	(3)
(1) CoRPS_16_1	1.000		
(2) CoRPS_16_2	0.648*	1.000	
(3) CoRPS_16_3	0.427*	0.465*	1.000

*** *p<0.01,* ** *p<0.05,* * *p<0.1*

Alpha of CoRPS - 2016

Test scale = mean(unstandardized items)
Average interitem covariance: .2586895
Number of items in the scale: 3
Scale reliability coefficient: 0.7492

Factor of PSc - 2016

(obs=4,014)

Factor analysis/correlation Number of obs = 4,014
Method: principal factors Retained factors = 1
Rotation: (unrotated) Number of params = 3

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.431	1.519	1.253	1.253
Factor2	-0.089	0.112	-0.077	1.175
Factor3	-0.200	.	-0.175	1.000

LR test: independent vs. saturated: chi2(3) = 3285.64 Prob>chi2 = 0.0000
Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Uniqueness
CoRPS_16_1	0.734	0.461
CoRPS_16_2	0.759	0.424
CoRPS_16_3	0.562	0.684

Summary of DS - 2016

Variable	Obs	Mean	Std. Dev.	Min	Max
DS 16 1	19947	.135	.342	0	1
DS 16 2	19933	.279	.449	0	1
DS 16 3	19889	.195	.396	0	1
DS 16 4	19927	.907	.291	0	1
DS 16 5	19902	.857	.35	0	1
DS 16 6	19944	.174	.379	0	1
DS 16 7	19927	.318	.466	0	1
DS 16 8	19937	.202	.401	0	1
# of Depressive Symptoms	19965	3.061	1.391	0	8

Correlation of DS - 2016

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) DS_16_1	1.000							
(2) DS_16_2	0.381*	1.000						
(3) DS_16_3	0.324*	0.340*	1.000					
(4) DS_16_4	-0.431*	-0.269*	-0.272*	1.000				
(5) DS_16_5	-0.498*	-0.293*	-0.274*	0.589*	1.000			
(6) DS_16_6	0.444*	0.294*	0.291*	-0.365*	-0.400*	1.000		
(7) DS_16_7	0.318*	0.289*	0.279*	-0.233*	-0.285*	0.263*	1.000	
(8) DS_16_8	0.581*	0.327*	0.311*	-0.429*	-0.495*	0.528*	0.329*	1.000

**** p<0.01, ** p<0.05, * p<0.1*

Alpha of DS - 2016
Test scale = mean(unstandardized items)
Reversed items: DS_16_4 DS_16_5
Average interitem covariance: .0520076
Number of items in the scale: 8
Scale reliability coefficient: 0.8086

Factor of DS - 2016
(obs=19,713)
Factor analysis/correlation Number of obs = 19,713
Method: principal factors Retained factors = 3
Rotation: (unrotated) Number of params = 21

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	2.963	2.720	1.090	1.090
Factor2	0.243	0.141	0.089	1.179
Factor3	0.102	0.152	0.037	1.217
Factor4	-0.050	0.015	-0.018	1.198
Factor5	-0.065	0.065	-0.024	1.174
Factor6	-0.131	0.034	-0.048	1.126
Factor7	-0.164	0.014	-0.060	1.066
Factor8	-0.179	.	-0.066	1.000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Factor3	Uniqueness
DS_16_1	0.715	0.026	0.073	0.483
DS_16_2	0.496	0.219	-0.099	0.696
DS_16_3	0.469	0.206	-0.112	0.725
DS_16_4	-0.631	0.246	0.119	0.527
DS_16_5	-0.692	0.241	0.085	0.455
DS_16_6	0.615	0.028	0.144	0.600
DS_16_7	0.450	0.177	-0.063	0.763
DS_16_8	0.727	0.002	0.169	0.443

Summary of FL - 2016

Variable	Obs	Mean	Std. Dev.	Min	Max
FL 16 1	20868	.116	.32	0	1
FL 16 2	20869	.081	.273	0	1
FL 16 3	20872	.083	.276	0	1
FL 16 4	20872	.041	.198	0	1
FL 16 5	20864	.081	.273	0	1
FL 16 6	20868	.067	.25	0	1
# of Functional Limitations	20876	.469	1.197	0	6

Correlation of FL - 2016

Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) FL_16_1	1.000					
(2) FL_16_2	0.495*	1.000				
(3) FL_16_3	0.541*	0.536*	1.000			
(4) FL_16_4	0.393*	0.390*	0.459*	1.000		
(5) FL_16_5	0.524*	0.481*	0.491*	0.385*	1.000	
(6) FL_16_6	0.476*	0.493*	0.512*	0.383*	0.507*	1.000

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Alpha of FL - 2016

Test scale = mean(unstandardized items)
Average interitem covariance: .0334965
Number of items in the scale: 6
Scale reliability coefficient: 0.8407

Factor of FL - 2016

(obs=20,840)

Factor analysis/correlation	Number of obs = 20,840
Method: principal factors	Retained factors = 1
Rotation: (unrotated)	Number of params = 6

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	2.769	2.780	1.168	1.168
Factor2	-0.011	0.049	-0.005	1.163
Factor3	-0.061	0.009	-0.026	1.137
Factor4	-0.070	0.041	-0.030	1.108
Factor5	-0.111	0.034	-0.047	1.061
Factor6	-0.145	.	-0.061	1.000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Uniqueness
FL_16_1	0.703	0.506
FL_16_2	0.690	0.525
FL_16_3	0.735	0.459
FL_16_4	0.566	0.679
FL_16_5	0.688	0.527
FL_16_6	0.682	0.535

Summary of FRc - 2016

Variable	Obs	Mean	Std. Dev.	Min	Max
FRc 16 1	5625	3.983	1.338	1	6
FRc 16 2	5650	4.45	1.251	1	6
FRc 16 3	5543	2.811	1.831	1	6
FRc 16 4	5553	2.57	1.938	1	6
FRc 16	5685	3.467	1.1	1	6

Correlation of FRc - 2016

Variables	(1)	(2)	(3)	(4)
(1) FRc_16_1	1.000			
(2) FRc_16_2	0.447*	1.000		
(3) FRc_16_3	0.228*	0.200*	1.000	
(4) FRc_16_4	0.138*	0.150*	0.494*	1.000

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Alpha of FRc - 2016

Test scale = mean(unstandardized items)
Average interitem covariance: .7060123
Number of items in the scale: 4
Scale reliability coefficient: 0.5976

Factor of FRc - 2016

(obs=5,431)

Factor analysis/correlation Number of obs = 5,431
Method: principal factors Retained factors = 2
Rotation: (unrotated) Number of params = 6

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.074	0.723	1.124	1.124
Factor2	0.351	0.565	0.368	1.492
Factor3	-0.214	0.042	-0.224	1.268
Factor4	-0.256	.	-0.268	1.000

LR test: independent vs. saturated: chi2(6) = 3117.14 Prob>chi2 = 0.0000
Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
FRc_16_1	0.489	0.312	0.663
FRc_16_2	0.480	0.312	0.672
FRc_16_3	0.581	-0.246	0.602
FRc_16_4	0.516	-0.309	0.638

Summary of FRq - 2016

Variable	Obs	Mean	Std. Dev.	Min	Max
FRq 16 1	5646	3.081	.813	1	4
FRq 16 2	5632	3.089	.869	1	4
FRq 16 3	5636	3.036	.902	1	4
FRq 16 4	5639	3.681	.614	1	4
FRq 16 5	5602	3.597	.65	1	4
FRq 16 6	5623	3.526	.727	1	4
FRq 16 7	5631	3.45	.696	1	4

Correlation of FRq - 2016

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) FRq_16_1	1.000						
(2) FRq_16_2	0.592*	1.000					
(3) FRq_16_3	0.655*	0.678*	1.000				
(4) FRq_16_4	-0.019	0.015	-0.025	1.000			
(5) FRq_16_5	0.022	0.059*	0.034*	0.453*	1.000		
(6) FRq_16_6	0.099*	0.157*	0.097*	0.433*	0.483*	1.000	
(7) FRq_16_7	0.086*	0.113*	0.090*	0.427*	0.490*	0.521*	1.000

*** *p<0.01,* ** *p<0.05,* * *p<0.1*

Alpha of FRq - 2016

Test scale = mean(unstandardized items)
Average interitem covariance: .149653
Number of items in the scale: 7
Scale reliability coefficient: 0.7098

Factor of FRq - 2016

(obs=5,513)

Factor analysis/correlation		Number of obs =	5,513
Method: principal factors		Retained factors =	2
Rotation: (unrotated)		Number of params =	13

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	2.001	0.436	0.684	0.684
Factor2	1.565	1.661	0.535	1.219
Factor3	-0.095	0.005	-0.033	1.187
Factor4	-0.101	0.026	-0.034	1.153
Factor5	-0.127	0.023	-0.043	1.109
Factor6	-0.149	0.021	-0.051	1.058
Factor7	-0.170	.	-0.058	1.000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
FRq_16_1	0.580	-0.465	0.447
FRq_16_2	0.630	-0.439	0.410
FRq_16_3	0.631	-0.512	0.341
FRq_16_4	0.372	0.492	0.619
FRq_16_5	0.447	0.499	0.551
FRq_16_6	0.525	0.443	0.528
FRq_16_7	0.505	0.456	0.537

Summary of LS - 2016

Variable	Obs	Mean	Std. Dev.	Min	Max
q02a. life is close to ideal	6262	4.875	1.805	1	7
q02b. conditions of life are excellen	6262	4.84	1.827	1	7
q02c. satisfied with life	6280	5.355	1.767	1	7
q02d. have important things in life	6290	5.403	1.697	1	7
q02e. change nothing if lived life ov	6295	4.406	2.053	1	7
LS 16	6326	4.972	1.516	1	7
r13lbsatwlf:w13 life satisfactio	6306	4.974	1.513	1	7

Correlation of LS - 2016

Variables	(1)	(2)	(3)	(4)	(5)
(1) q02a. life is ~l	1.000				
(2) q02b. conditio~n	0.744*	1.000			
(3) q02c. satisfie~e	0.689*	0.771*	1.000		
(4) q02d. have imp~e	0.566*	0.615*	0.692*	1.000	
(5) q02e. change n~v	0.473*	0.500*	0.509*	0.546*	1.000

*** *p<0.01,* ** *p<0.05,* * *p<0.1*

Alpha of LS - 2016

Test scale = mean(unstandardized items)
Average interitem covariance: 2.018642
Number of items in the scale: 5
Scale reliability coefficient: 0.8825

Factor of LS - 2016

(obs=6,154)
Factor analysis/correlation Number of obs = 6,154
Method: principal factors Retained factors = 2
Rotation: (unrotated) Number of params = 9

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	3.073	2.983	1.069	1.069
Factor2	0.089	0.128	0.031	1.100
Factor3	-0.039	0.071	-0.013	1.086
Factor4	-0.110	0.029	-0.038	1.048
Factor5	-0.138	.	-0.048	1.000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
LS_16_1	0.794	-0.130	0.353
LS_16_2	0.858	-0.133	0.247
LS_16_3	0.864	-0.012	0.254
LS_16_4	0.761	0.168	0.393
LS_16_5	0.618	0.162	0.592

Summary of Ch - 2016

Variable	Obs	Mean	Std. Dev.	Min	Max
Chc 16	5396	3.681	1.186	1	6
Chr 16	5604	3.251	.593	1	4

Correlation of Ch - 2016

Variables	(1)	(2)
(1) Chc_16	1.000	
(2) Chr_16	0.259*	1.000

*** *p<0.01,* ** *p<0.05,* * *p<0.1*

Alpha of Ch - 2016

Test scale = mean(unstandardized items)
Average interitem covariance: .1813021
Number of items in the scale: 2
Scale reliability coefficient: 0.3454

Factor of Ch - 2016
(obs=5,386)

Factor analysis/correlation	Number of obs = 5,386
Method: principal factors	Retained factors = 1
Rotation: (unrotated)	Number of params = 1

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	0.326	0.517	2.433	2.433
Factor2	-0.192	.	-1.433	1.000

LR test: independent vs. saturated: chi2(1) = 373.06 Prob>chi2 = 0.0000
Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Uniqueness
Chc_16	0.404	0.837
Chr_16	0.404	0.837

Summary of OFRc - 2016

Variable	Obs	Mean	Std. Dev.	Min	Max
OFRc 16 1	5809	3.22	1.502	1	6
OFRc 16 2	5847	4.349	1.396	1	6
OFRc 16 3	5755	2.582	1.7	1	6
OFRc 16 4	5756	2.43	1.841	1	6
OFRc 16	5873	3.163	1.139	1	6

Correlation of OFRc - 2016

Variables	(1)	(2)	(3)	(4)
(1) OFRc_16_1	1.000			
(2) OFRc_16_2	0.566*	1.000		
(3) OFRc_16_3	0.178*	0.223*	1.000	
(4) OFRc_16_4	0.170*	0.223*	0.516*	1.000

*** *p<0.01*, ** *p<0.05*, * *p<0.1*

Alpha of OFRc - 2016
Test scale = mean(unstandardized items)
Average interitem covariance: .8049178
Number of items in the scale: 4
Scale reliability coefficient: 0.6398

Factor of OFRc - 2016
(obs=5,655)

Factor analysis/correlation	Number of obs = 5,655
Method: principal factors	Retained factors = 2
Rotation: (unrotated)	Number of params = 6

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.251	0.803	1.019	1.019
Factor2	0.449	0.681	0.365	1.385
Factor3	-0.232	0.008	-0.189	1.196
Factor4	-0.240	.	-0.196	1.000

LR test: independent vs. saturated: chi2(6) = 4360.49 Prob>chi2 = 0.0000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
OFRc_16_1	0.570	-0.337	0.562
OFRc_16_2	0.614	-0.292	0.538
OFRc_16_3	0.526	0.352	0.599
OFRc_16_4	0.522	0.356	0.601

Summary of OFRq - 2016

Variable	Obs	Mean	Std. Dev.	Min	Max
OFRq 16 1	5869	2.815	.922	1	4
OFRq 16 2	5866	3.004	1.031	1	4
OFRq 16 3	5869	2.831	1.019	1	4
OFRq 16 4	5862	3.532	.778	1	4
OFRq 16 5	5839	3.395	.817	1	4
OFRq 16 6	5838	3.361	.883	1	4
OFRq 16 7	5856	3.223	.869	1	4

Correlation of OFRq - 2016

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) OFRq_16_1	1.000						
(2) OFRq_16_2	0.625*	1.000					
(3) OFRq_16_3	0.669*	0.722*	1.000				
(4) OFRq_16_4	0.063*	0.070*	0.063*	1.000			
(5) OFRq_16_5	0.153*	0.169*	0.168*	0.473*	1.000		
(6) OFRq_16_6	0.269*	0.318*	0.279*	0.455*	0.545*	1.000	
(7) OFRq_16_7	0.234*	0.222*	0.235*	0.464*	0.575*	0.580*	1.000

*** *p<0.01,* ** *p<0.05,* * *p<0.1*

Alpha of OFRq - 2016

Test scale = mean(unstandardized items)
Average interitem covariance: .2883162
Number of items in the scale: 7
Scale reliability coefficient: 0.7906

Factor of OFRq - 2016

(obs=5,716)

Factor analysis/correlation — Number of obs = 5,716
Method: principal factors — Retained factors = 2
Rotation: (unrotated) — Number of params = 13

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	2.617	1.329	0.788	0.788
Factor2	1.287	1.365	0.388	1.176
Factor3	-0.078	0.017	-0.023	1.152
Factor4	-0.094	0.014	-0.028	1.124
Factor5	-0.108	0.035	-0.033	1.091
Factor6	-0.143	0.018	-0.043	1.048
Factor7	-0.161	.	-0.048	1.000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
OFRq_16_1	0.615	-0.434	0.434
OFRq_16_2	0.656	-0.464	0.355
OFRq_16_3	0.667	-0.494	0.310
OFRq_16_4	0.438	0.444	0.612
OFRq_16_5	0.571	0.439	0.481
OFRq_16_6	0.667	0.315	0.455
OFRq_16_7	0.633	0.388	0.448

Summary of Income - 2016

Variable	Obs	Mean	Std. Dev.	Min	Max
h16HInc	20912	74204.541	159343.19	0	10036000
l h16HInc	20912	10.4	1.933	0	16.122

Summary of Total Assets - 2016

Variable	Obs	Mean	Std. Dev.	Min	Max
h16HAss	20912	438146.34	1171675.1	-1098000	34149000
l h16HAss	19451	10.861	3.719	0	17.346

Summary of Total Non-Housing Assets - 2016

Variable	Obs	Mean	Std. Dev.	Min	Max
h16HNhAss	20912	287545.86	1017307.8	-1115000	31410000
l h16HNhAss	18675	9.609	4.116	0	17.263

Summary of Total Net Worth - 2016

Variable	Obs	Mean	Std. Dev.	Min	Max
h16HNW	20912	109570.16	473339.4	-1800000	16150000
l h16HNW	16540	7.492	4.861	0	16.597

Summary of Net Value of House - 2016

Variable	Obs	Mean	Std. Dev.	Min	Max
h16HNHoEq	20912	130135.28	232613.78	-500000	6000000
l h16HNHoEq	20557	8.031	5.474	0	15.607

Summary of PH - 2016

Variable	Obs	Mean	Std. Dev.	Min	Max
Self-Reported Health	20888	2.952	1.066	1	5
r16BMI	20578	28.958	6.358	10.3	92.8
r16BMI cat	.	.	.	.	.
Underweight	20718	.016	.126	0	1
Healthy Weight	20718	.248	.432	0	1
Overweight	20718	.36	.48	0	1
Obese	20718	.376	.484	0	1
# of Chronic Illnesses	20912	2.178	1.566	0	8
# of Chronic Illnesses(Rand)	20912	2.178	1.566	0	8
# of Functional Limitations	20876	.469	1.197	0	6

Correlation of PH - 2016

Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) Self-Reported ~h	1.000					
(2) r16BMI	0.155*	1.000				
(3) BMI Categories	0.114*	0.841*	1.000			
(4) # of Chronic I~s	0.453*	0.150*	0.117*	1.000		
(5) # of Chronic I~)	0.453*	0.150*	0.117*	1.000*	1.000	
(6) # of Functiona~s	0.382*	0.060*	0.013	0.343*	0.343*	1.000

*** *p<0.01,* ** *p<0.05,* * *p<0.1*

Alpha of PH - 2016

Test scale = mean(unstandardized items)
Average interitem covariance: .9998555
Number of items in the scale: 6
Scale reliability coefficient: 0.4607

Factor of PH - 2016

(obs=20,333)
(collinear variables specified)
Factor analysis/correlation Number of obs = 20,333
Method: principal factors Retained factors = 3
Rotation: (unrotated) Number of params = 15
Warning: Solution is a Heywood case; that is, invalid or boundary values of uniqueness.

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	2.482	1.036	0.640	0.640
Factor2	1.446	1.196	0.372	1.012
Factor3	0.249	0.249	0.064	1.076
Factor4	0.000	0.133	0.000	1.076
Factor5	-0.133	0.030	-0.034	1.042
Factor6	-0.163	.	-0.042	1.000

LR test: independent vs. saturated: chi2(15) = . Prob>chi2 = .
Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Factor3	Uniqueness
r16SRH	0.504	-0.063	0.312	0.645
r16BMI	0.383	0.795	0.019	0.221
r16BMI_cat	0.346	0.809	-0.040	0.225
ChIl_16	0.953	-0.266	-0.145	-0.000
ChIl_16_r	0.953	-0.266	-0.145	-0.000
FL_16	0.381	-0.120	0.329	0.732

Summary of PSc - 2016

Variable	Obs	Mean	Std. Dev.	Min	Max
PSc 16 1	4139	3.45	.768	1	4
PSc 16 2	4113	2.975	.79	1	4
PSc 16 3	4114	1.75	.585	1	3
PSc 16	4220	2.884	.613	1	4

Correlation of PSc - 2016

Variables	(1)	(2)	(3)
(1) PSc_16_1	1.000		
(2) PSc_16_2	0.648*	1.000	
(3) PSc_16_3	-0.427*	-0.465*	1.000

*** *p<0.01, ** p<0.05, * p<0.1*

Alpha of PSc - 2016

Test scale = mean(unstandardized items)
Reversed item: PSc_16_3
Average interitem covariance: .2586895
Number of items in the scale: 3
Scale reliability coefficient: 0.7492

Factor of PSc - 2016

(obs=4,014)

Factor analysis/correlation Number of obs = 4,014
Method: principal factors Retained factors = 1
Rotation: (unrotated) Number of params = 3

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.431	1.519	1.253	1.253
Factor2	-0.089	0.112	-0.077	1.175
Factor3	-0.200	.	-0.175	1.000

LR test: independent vs. saturated: chi2(3) = 3285.64 Prob>chi2 = 0.0000
Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Uniqueness
PSc_16_1	0.734	0.461
PSc_16_2	0.759	0.424
PSc_16_3	-0.562	0.684

Summary of PSq - 2016

Variable	Obs	Mean	Std. Dev.	Min	Max
PSq 16 1	4183	3.307	.799	1	4
PSq 16 2	4163	3.692	.681	1	4
PSq 16 3	4161	3.411	.815	1	4
PSq 16 4	4157	2.964	.927	1	4
PSq 16 5	4153	2.966	.892	1	4
PSq 16 6	4146	3.31	.879	1	4
PSq 16 7	4158	2.921	.843	1	4

Correlation of PSq - 2016

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) PSq_16_1	1.000						
(2) PSq_16_2	0.507*	1.000					
(3) PSq_16_3	0.640*	0.605*	1.000				
(4) PSq_16_4	0.283*	0.235*	0.263*	1.000			
(5) PSq_16_5	0.314*	0.184*	0.307*	0.537*	1.000		
(6) PSq_16_6	0.403*	0.386*	0.408*	0.439*	0.439*	1.000	
(7) PSq_16_7	0.421*	0.279*	0.398*	0.473*	0.515*	0.536*	1.000

*** *p<0.01, ** p<0.05, * p<0.1*

Alpha of PSq - 2016
Test scale = mean(unstandardized items)
Average interitem covariance: .2828072
Number of items in the scale: 7
Scale reliability coefficient: 0.8258

Factor of PSq - 2016
(obs=4,059)
Factor analysis/correlation Number of obs = 4,059
Method: principal factors Retained factors = 2
Rotation: (unrotated) Number of params = 13

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	2.908	2.252	0.965	0.965
Factor2	0.656	0.677	0.218	1.183
Factor3	-0.021	0.013	-0.007	1.176
Factor4	-0.034	0.105	-0.011	1.165
Factor5	-0.138	0.021	-0.046	1.119
Factor6	-0.159	0.040	-0.053	1.066
Factor7	-0.199	.	-0.066	1.000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
PSq_16_1	0.684	-0.274	0.456
PSq_16_2	0.587	-0.369	0.519
PSq_16_3	0.708	-0.358	0.371
PSq_16_4	0.575	0.339	0.554
PSq_16_5	0.598	0.358	0.514
PSq_16_6	0.666	0.133	0.539
PSq_16_7	0.679	0.235	0.483

Summary of sFWB - 2016

Variable	Obs	Mean	Std. Dev.	Min	Max
sFWB 16 1	6199	3.231	1.139	1	5
sFWB 16 2	6136	3.96	1.029	1	5
sFWB 16	6260	3.59	.985	1	5

Correlation of sFWB - 2016

Variables	(1)	(2)
(1) sFWB_16_1	1.000	
(2) sFWB_16_2	0.626*	1.000

*** *p<0.01*, ** *p<0.05*, * *p<0.1*

Alpha of sFWB - 2016
Test scale = mean(unstandardized items)
Average interitem covariance: .731061
Number of items in the scale: 2
Scale reliability coefficient: 0.7653

Factor of sFWB - 2016
(obs=6,075)

Factor analysis/correlation	Number of obs	=	6,075
Method: principal factors	Retained factors	=	1
Rotation: (unrotated)	Number of params	=	1

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.017	1.252	1.299	1.299
Factor2	-0.234	.	-0.299	1.000

LR test: independent vs. saturated: chi2(1) = 3017.99 Prob>chi2 = 0.0000
Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Uniqueness
sFWB_16_1	0.713	0.491
sFWB_16_2	0.713	0.491

2018 Wave

Summary of AS - 2018

Variable	Obs	Mean	Std. Dev.	Min	Max
AS 18 1	5591	3.291	.85	1	4
AS 18 2	5577	3.073	.882	1	4
AS 18 3	5576	3.562	.762	1	4
AS 18 4	5589	3.609	.716	1	4
AS 18 5	5587	3.606	.71	1	4
AS 18	5605	3.426	.598	1	4

Correlation of AS - 2018

Variables	(1)	(2)	(3)	(4)	(5)
(1) AS_18_1	1.000				
(2) AS_18_2	0.649*	1.000			
(3) AS_18_3	0.427*	0.485*	1.000		
(4) AS_18_4	0.487*	0.426*	0.453*	1.000	
(5) AS_18_5	0.385*	0.394*	0.508*	0.483*	1.000

**** p<0.01, ** p<0.05, * p<0.1*

Alpha of AS - 2018
Test scale = mean(unstandardized items)
Average interitem covariance: .2892788
Number of items in the scale: 5
Scale reliability coefficient: 0.8143

Factor of AS - 2018
(obs=5,538)
Factor analysis/correlation Number of obs = 5,538
Method: principal factors Retained factors = 2
Rotation: (unrotated) Number of params = 9

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	2.296	2.123	1.118	1.118
Factor2	0.173	0.224	0.084	1.202
Factor3	-0.051	0.115	-0.025	1.178
Factor4	-0.166	0.033	-0.081	1.097
Factor5	-0.199	.	-0.097	1.000

LR test: independent vs. saturated: chi2(10) = 9138.15 Prob>chi2 = 0.0000
Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
AS_18_1	0.721	-0.218	0.433
AS_18_2	0.723	-0.207	0.435
AS_18_3	0.663	0.143	0.541
AS_18_4	0.652	0.111	0.563
AS_18_5	0.625	0.224	0.560

Summary of Chc - 2018

Variable	Obs	Mean	Std. Dev.	Min	Max
Chc 18 1	4777	3.816	1.5	1	6
Chc 18 2	4818	4.907	1.256	1	6
Chc 18 3	4726	3.125	1.931	1	6
Chc 18 4	4735	2.973	2.025	1	6
Chc 18	4856	3.726	1.178	1	6

Correlation of Chc - 2018

Variables	(1)	(2)	(3)	(4)
(1) Chc_18_1	1.000			
(2) Chc_18_2	0.532*	1.000		
(3) Chc_18_3	0.149*	0.229*	1.000	
(4) Chc_18_4	0.160*	0.257*	0.451*	1.000

**** p<0.01, ** p<0.05, * p<0.1*

Alpha of Chc - 2018

Test scale = mean(unstandardized items)
Average interitem covariance: .8158208
Number of items in the scale: 4
Scale reliability coefficient: 0.6094

Factor of Chc - 2018

(obs=4,615)

Factor analysis/correlation		Number of obs =	4,615
Method: principal factors		Retained factors =	2
Rotation: (unrotated)		Number of params =	6

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.165	0.812	1.109	1.109
Factor2	0.353	0.578	0.336	1.444
Factor3	-0.225	0.017	-0.214	1.230
Factor4	-0.242	.	-0.231	1.000

LR test: independent vs. saturated: chi2(6) = 2987.60 Prob>chi2 = 0.0000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
Chc_18_1	0.550	-0.308	0.603
Chc_18_2	0.629	-0.225	0.554
Chc_18_3	0.474	0.327	0.669
Chc_18_4	0.492	0.317	0.657

Summary of ChIl - 2018

Variable	Obs	Mean	Std. Dev.	Min	Max
r14hibpe:w14 r ever had high blo	17146	.624	.484	0	1
r14diabe:w14 r ever had diabetes	17146	.287	.452	0	1
r14cancre:w14 r ever had cancer	17146	.152	.359	0	1
r14lunge:w14 r ever had lung dis	17146	.113	.317	0	1
r14hearte:w14 r ever had heart p	17146	.246	.431	0	1
r14stroke:w14 r ever had stroke	17146	.091	.288	0	1
r14psyche:w14 r ever had psych p	17146	.224	.417	0	1
r14arthre:w14 r ever had arthrit	17146	.587	.492	0	1
# of Chronic Illnesses	17146	2.325	1.568	0	8
# of Chronic Illnesses(Rand)	17146	2.325	1.568	0	8

Correlation of ChIl - 2018

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) r14hibpe:w14 r~h	1.000							
(2) r14diabe:w14 r~b	0.244*	1.000						
(3) r14cancre:w14 ~n	0.058*	0.022*	1.000					
(4) r14lunge:w14 r~g	0.088*	0.060*	0.060*	1.000				
(5) r14hearte:w14 ~a	0.204*	0.123*	0.097*	0.161*	1.000			
(6) r14stroke:w14 ~r	0.137*	0.085*	0.048*	0.100*	0.202*	1.000		
(7) r14psyche:w14 ~y	0.072*	0.078*	0.024*	0.170*	0.098*	0.102*	1.000	
(8) r14arthre:w14 ~t	0.190*	0.099*	0.099*	0.158*	0.188*	0.103*	0.173*	1.000

*** *p<0.01,* ** *p<0.05,* * *p<0.1*

Alpha of ChIl - 2018

Test scale = mean(unstandardized items)
Average interitem covariance: .019765
Number of items in the scale: 8
Scale reliability coefficient: 0.5142

Factor of ChIl - 2018

(obs=17,146)

Factor analysis/correlation	Number of obs =	17,146
Method: principal factors	Retained factors =	4
Rotation: (unrotated)	Number of params =	26

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	0.942	0.797	1.565	1.565
Factor2	0.145	0.107	0.240	1.806
Factor3	0.038	0.034	0.063	1.869
Factor4	0.004	0.093	0.007	1.876
Factor5	-0.088	0.005	-0.147	1.730
Factor6	-0.093	0.065	-0.154	1.575
Factor7	-0.158	0.030	-0.263	1.312
Factor8	-0.188	.	-0.312	1.000

LR test: independent vs. saturated: chi2(28) = 6134.92 Prob>chi2 = 0.0000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Factor3	Factor4	Uniqueness
ChIl_18_1	0.416	-0.192	-0.016	0.009	0.789
ChIl_18_2	0.308	-0.204	-0.068	0.006	0.859
ChIl_18_3	0.167	0.050	0.116	0.037	0.955
ChIl_18_4	0.321	0.174	-0.030	-0.003	0.866
ChIl_18_5	0.434	-0.005	0.077	-0.016	0.805
ChIl_18_6	0.321	0.002	0.059	-0.044	0.891
ChIl_18_7	0.293	0.166	-0.097	-0.004	0.877
ChIl_18_8	0.406	0.078	-0.015	0.027	0.828

Summary of Chr - 2018

Variable	Obs	Mean	Std. Dev.	Min	Max
Chr 18 1	4690	3.165	.82	1	4
Chr 18 2	4699	3.407	.864	1	4
Chr 18 3	4688	3.087	.932	1	4
Chr 18 4	4695	3.321	.863	1	4
Chr 18 5	4678	3.347	.8	1	4
Chr 18 6	4965	3.3	.857	1	4
Chr 18 7	4939	3.258	.803	1	4

Correlation of Chr - 2018

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Chr_18_1	1.000						
(2) Chr_18_2	0.568*	1.000					
(3) Chr_18_3	0.630*	0.666*	1.000				
(4) Chr_18_4	0.146*	0.192*	0.154*	1.000			
(5) Chr_18_5	0.234*	0.195*	0.198*	0.429*	1.000		
(6) Chr_18_6	0.334*	0.408*	0.352*	0.410*	0.408*	1.000	
(7) Chr_18_7	0.276*	0.294*	0.288*	0.454*	0.473*	0.554*	1.000

*** *p<0.01,* ** *p<0.05,* * *p<0.1*

Alpha of Chr - 2018
Test scale = mean(unstandardized items)
Average interitem covariance: .2632256
Number of items in the scale: 7
Scale reliability coefficient: 0.8008

Factor of Chr - 2018
(obs=4,588)

Factor analysis/correlation		Number of obs =	4,588
Method: principal factors		Retained factors =	2
Rotation: (unrotated)		Number of params =	13

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	2.650	1.801	0.911	0.911
Factor2	0.850	0.877	0.292	1.204
Factor3	-0.027	0.057	-0.009	1.194
Factor4	-0.085	0.055	-0.029	1.165
Factor5	-0.140	0.022	-0.048	1.117
Factor6	-0.162	0.017	-0.056	1.062
Factor7	-0.179	.	-0.061	1.000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
Chr_18_1	0.639	-0.337	0.478
Chr_18_2	0.684	-0.345	0.413
Chr_18_3	0.684	-0.407	0.366
Chr_18_4	0.470	0.392	0.626
Chr_18_5	0.505	0.356	0.618
Chr_18_6	0.663	0.223	0.510
Chr_18_7	0.625	0.349	0.488

Factor of Ch - 2010

(obs=6,534)

Factor analysis/correlation	Number of obs	=	6,534
Method: principal factors	Retained factors	=	4
Rotation: (unrotated)	Number of params	=	34

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	2.865	1.597	0.780	0.780
Factor2	1.268	0.943	0.345	1.125
Factor3	0.325	0.294	0.088	1.213
Factor4	0.031	0.068	0.008	1.222
Factor5	-0.037	0.069	-0.010	1.212
Factor6	-0.106	0.017	-0.029	1.183
Factor7	-0.124	0.022	-0.034	1.149
Factor8	-0.146	0.020	-0.040	1.109
Factor9	-0.165	0.071	-0.045	1.064
Factor10	-0.236	.	-0.064	1.000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Factor3	Factor4	Uniqueness
Chc_10_1	0.352	0.448	0.277	-0.070	0.594
Chc_10_2	0.433	0.482	0.265	0.007	0.510
Chc_10_3	0.162	0.119	0.135	0.151	0.919
Chr_10_1	0.679	0.180	-0.173	0.030	0.476
Chr_10_2	0.714	0.211	-0.159	-0.029	0.420
Chr_10_3	0.690	0.243	-0.266	0.008	0.394
Chr_10_4	0.407	-0.489	0.042	-0.026	0.592
Chr_10_5	0.456	-0.392	0.122	0.001	0.623
Chr_10_6	0.625	-0.332	0.078	-0.013	0.493
Chr_10_7	0.563	-0.426	0.105	0.018	0.490

Summary of CoRPS - 2018

Variable	Obs	Mean	Std. Dev.	Min	Max
CoRPS 18 1	3768	1.524	.754	1	4
CoRPS 18 2	3750	2.03	.802	1	4
CoRPS 18 3	3742	1.727	.586	1	3
CoRPS 18	3829	1.772	.622	1	4

Correlation of CoRPS - 2018

Variables	(1)	(2)	(3)
(1) CoRPS_18_1	1.000		
(2) CoRPS_18_2	0.677*	1.000	
(3) CoRPS_18_3	0.461*	0.458*	1.000

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Alpha of CoRPS - 2018

Test scale = mean(unstandardized items)
Average interitem covariance: .2678456
Number of items in the scale: 3
Scale reliability coefficient: 0.7621

Factor of PSc - 2018

(obs=3,678)

Factor analysis/correlation Number of obs = 3,678
Method: principal factors Retained factors = 1
Rotation: (unrotated) Number of params = 3

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.494	1.581	1.228	1.228
Factor2	-0.086	0.105	-0.071	1.157
Factor3	-0.191	.	-0.157	1.000

LR test: independent vs. saturated: chi2(3) = 3289.68 Prob>chi2 = 0.0000
Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Uniqueness
CoRPS_18_1	0.767	0.412
CoRPS_18_2	0.767	0.412
CoRPS_18_3	0.564	0.682

Summary of DS - 2018

Variable	Obs	Mean	Std. Dev.	Min	Max
DS 18 1	16459	.13	.336	0	1
DS 18 2	16447	.277	.448	0	1
DS 18 3	16404	.197	.398	0	1
DS 18 4	16430	.906	.291	0	1
DS 18 5	16423	.861	.346	0	1
DS 18 6	16457	.164	.371	0	1
DS 18 7	16452	.319	.466	0	1
DS 18 8	16436	.187	.39	0	1
# of Depressive Symptoms	16479	3.033	1.384	0	8

Correlation of DS - 2018

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) DS_18_1	1.000							
(2) DS_18_2	0.380*	1.000						
(3) DS_18_3	0.334*	0.361*	1.000					
(4) DS_18_4	-0.420*	-0.283*	-0.292*	1.000				
(5) DS_18_5	-0.502*	-0.305*	-0.289*	0.594*	1.000			
(6) DS_18_6	0.465*	0.304*	0.289*	-0.372*	-0.411*	1.000		
(7) DS_18_7	0.312*	0.284*	0.277*	-0.232*	-0.263*	0.269*	1.000	
(8) DS_18_8	0.585*	0.332*	0.320*	-0.424*	-0.492*	0.540*	0.326*	1.000

*** *p<0.01,* ** *p<0.05,* * *p<0.1*

Alpha of DS - 2018

Test scale = mean(unstandardized items)
Reversed items: DS_18_4 DS_18_5
Average interitem covariance: .0515066
Number of items in the scale: 8
Scale reliability coefficient: 0.8105

Factor of DS - 2018

(obs=16,226)

Factor analysis/correlation   Number of obs = 16,226
Method: principal factors   Retained factors = 3
Rotation: (unrotated)   Number of params = 21

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	2.992	2.754	1.084	1.084
Factor2	0.238	0.107	0.086	1.170
Factor3	0.131	0.193	0.048	1.218
Factor4	-0.062	0.005	-0.022	1.195
Factor5	-0.067	0.064	-0.024	1.171
Factor6	-0.130	0.031	-0.047	1.124
Factor7	-0.162	0.019	-0.059	1.065
Factor8	-0.180	.	-0.065	1.000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Factor3	Uniqueness
DS_18_1	0.716	0.031	0.094	0.477
DS_18_2	0.505	0.209	-0.125	0.686
DS_18_3	0.483	0.192	-0.147	0.708
DS_18_4	-0.630	0.245	0.136	0.525
DS_18_5	-0.692	0.249	0.083	0.452
DS_18_6	0.627	0.025	0.156	0.583
DS_18_7	0.440	0.182	-0.048	0.771
DS_18_8	0.727	0.013	0.183	0.437

Summary of FL - 2018

Variable	Obs	Mean	Std. Dev.	Min	Max
FL 18 1	17116	.11	.313	0	1
FL 18 2	17118	.084	.277	0	1
FL 18 3	17115	.081	.272	0	1
FL 18 4	17119	.04	.196	0	1
FL 18 5	17117	.082	.274	0	1
FL 18 6	17112	.066	.248	0	1
# of Functional Limitations	17120	.463	1.177	0	6

Correlation of FL - 2018

Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) FL_18_1	1.000					
(2) FL_18_2	0.490*	1.000				
(3) FL_18_3	0.535*	0.540*	1.000			
(4) FL_18_4	0.385*	0.397*	0.450*	1.000		
(5) FL_18_5	0.509*	0.473*	0.469*	0.367*	1.000	
(6) FL_18_6	0.446*	0.463*	0.474*	0.347*	0.479*	1.000

*** *p<0.01*, ** *p<0.05*, * *p<0.1*

Alpha of FL - 2018

Test scale = mean(unstandardized items)
Average interitem covariance: .0320262
Number of items in the scale: 6
Scale reliability coefficient: 0.8324

Factor of FL - 2018

(obs=17,099)

Factor analysis/correlation	Number of obs =	17,099
Method: principal factors	Retained factors =	2
Rotation: (unrotated)	Number of params =	11

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	2.675	2.672	1.175	1.175
Factor2	0.003	0.067	0.002	1.177
Factor3	-0.063	0.014	-0.028	1.149
Factor4	-0.077	0.033	-0.034	1.115
Factor5	-0.111	0.041	-0.049	1.067
Factor6	-0.151	.	-0.067	1.000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
FL_18_1	0.697	-0.008	0.514
FL_18_2	0.694	0.007	0.518
FL_18_3	0.729	0.025	0.468
FL_18_4	0.557	0.035	0.688
FL_18_5	0.672	-0.031	0.547
FL_18_6	0.643	-0.024	0.585

Summary of FRc - 2018

Variable	Obs	Mean	Std. Dev.	Min	Max
FRc 18 1	5041	3.964	1.387	1	6
FRc 18 2	5057	4.394	1.32	1	6
FRc 18 3	4948	2.841	1.828	1	6
FRc 18 4	4982	2.633	1.924	1	6
FRc 18	5096	3.471	1.126	1	6

Correlation of FRc - 2018

Variables	(1)	(2)	(3)	(4)
(1) FRc_18_1	1.000			
(2) FRc_18_2	0.476*	1.000		
(3) FRc_18_3	0.277*	0.210*	1.000	
(4) FRc_18_4	0.162*	0.171*	0.459*	1.000

*** *p<0.01,* ** *p<0.05,* * *p<0.1*

Alpha of FRc - 2018

Test scale = mean(unstandardized items)
Average interitem covariance: .759947
Number of items in the scale: 4
Scale reliability coefficient: 0.6139

Factor of FRc - 2018

(obs=4,860)

Factor analysis/correlation Number of obs = 4,860
Method: principal factors Retained factors = 2
Rotation: (unrotated) Number of params = 6

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.131	0.823	1.156	1.156
Factor2	0.307	0.503	0.314	1.470
Factor3	-0.196	0.068	-0.201	1.270
Factor4	-0.264	.	-0.270	1.000

LR test: independent vs. saturated: chi2(6) = 2897.08 Prob>chi2 = 0.0000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
FRc_18_1	0.562	-0.259	0.617
FRc_18_2	0.527	-0.277	0.645
FRc_18_3	0.556	0.256	0.626
FRc_18_4	0.477	0.313	0.675

Summary of FRq - 2018

Variable	Obs	Mean	Std. Dev.	Min	Max
FRq 18 1	5072	3.067	.811	1	4
FRq 18 2	5070	3.093	.873	1	4
FRq 18 3	5063	3.012	.892	1	4
FRq 18 4	5063	3.678	.613	1	4
FRq 18 5	5027	3.614	.625	1	4
FRq 18 6	5054	3.543	.706	1	4
FRq 18 7	5062	3.46	.678	1	4

Correlation of FRq - 2018

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) FRq_18_1	1.000						
(2) FRq_18_2	0.596*	1.000					
(3) FRq_18_3	0.651*	0.667*	1.000				
(4) FRq_18_4	-0.013	-0.003	-0.029*	1.000			
(5) FRq_18_5	0.059*	0.067*	0.062*	0.455*	1.000		
(6) FRq_18_6	0.147*	0.193*	0.150*	0.384*	0.456*	1.000	
(7) FRq_18_7	0.090*	0.092*	0.090*	0.424*	0.496*	0.488*	1.000

*** *p<0.01, ** p<0.05, * p<0.1*

Alpha of FRq - 2018
Test scale = mean(unstandardized items)
Average interitem covariance: .1478887
Number of items in the scale: 7
Scale reliability coefficient: 0.7137

Factor of FRq - 2018
(obs=4,962)

Factor analysis/correlation	Number of obs = 4,962
Method: principal factors	Retained factors = 2
Rotation: (unrotated)	Number of params = 13

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	2.018	0.539	0.708	0.708
Factor2	1.479	1.556	0.519	1.227
Factor3	-0.077	0.031	-0.027	1.200
Factor4	-0.108	0.029	-0.038	1.162
Factor5	-0.137	0.017	-0.048	1.114
Factor6	-0.154	0.016	-0.054	1.060
Factor7	-0.170	.	-0.060	1.000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
FRq_18_1	0.614	-0.423	0.443
FRq_18_2	0.643	-0.414	0.415
FRq_18_3	0.656	-0.464	0.355
FRq_18_4	0.334	0.509	0.629
FRq_18_5	0.443	0.508	0.546
FRq_18_6	0.517	0.398	0.574
FRq_18_7	0.471	0.487	0.540

Summary of LS - 2018

Variable	Obs	Mean	Std. Dev.	Min	Max
q02a. life is close to ideal	5629	4.918	1.796	1	7
q02b. life conditions are excellent	5629	4.934	1.81	1	7
q02c. satisfied with life	5644	5.41	1.728	1	7
q02d. have important things in life	5654	5.435	1.703	1	7
q02e. change none if lived life over	5667	4.465	2.034	1	7
LS 18	5685	5.03	1.511	1	7
r14lbsatwlf:w14 life satisfactio	5674	5.029	1.511	1	7

Correlation of LS - 2018

Variables	(1)	(2)	(3)	(4)	(5)
(1) q02a. life is ~l	1.000				
(2) q02b. life con~t	0.747*	1.000			
(3) q02c. satisfie~e	0.692*	0.765*	1.000		
(4) q02d. have imp~e	0.589*	0.629*	0.698*	1.000	
(5) q02e. change n~r	0.487*	0.513*	0.530*	0.545*	1.000

**** p<0.01, ** p<0.05, * p<0.1*

Alpha of LS - 2018

Test scale = mean(unstandardized items)
Average interitem covariance: 2.012723
Number of items in the scale: 5
Scale reliability coefficient: 0.8861

Factor of LS - 2018

(obs=5,531)

Factor analysis/correlation   Number of obs = 5,531
Method: principal factors   Retained factors = 2
Rotation: (unrotated)   Number of params = 9

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	3.098	3.030	1.075	1.075
Factor2	0.067	0.114	0.023	1.098
Factor3	-0.047	0.061	-0.016	1.082
Factor4	-0.107	0.022	-0.037	1.045
Factor5	-0.129	.	-0.045	1.000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
LS_18_1	0.802	-0.117	0.343
LS_18_2	0.856	-0.120	0.254
LS_18_3	0.861	0.001	0.259
LS_18_4	0.767	0.142	0.391
LS_18_5	0.627	0.138	0.588

Summary of Ch - 2018

Variable	Obs	Mean	Std. Dev.	Min	Max
Chc 18	4856	3.726	1.178	1	6
Chr 18	4995	3.269	.587	1	4

Correlation of Ch - 2018

Variables	(1)	(2)
(1) Chc_18	1.000	
(2) Chr_18	0.247*	1.000

**** p<0.01, ** p<0.05, * p<0.1*

Alpha of Ch - 2018

Test scale = mean(unstandardized items)
Average interitem covariance: .1699875
Number of items in the scale: 2
Scale reliability coefficient: 0.3305

Factor of Ch - 2018

(obs=4,851)

Factor analysis/correlation	Number of obs	=	4,851
Method: principal factors	Retained factors	=	1
Rotation: (unrotated)	Number of params	=	1

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	0.308	0.494	2.525	2.525
Factor2	-0.186	.	-1.525	1.000

LR test: independent vs. saturated: chi2(1) = 305.18 Prob>chi2 = 0.0000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Uniqueness
Chc_18	0.392	0.846
Chr_18	0.392	0.846

Summary of OFRc - 2018

Variable	Obs	Mean	Std. Dev.	Min	Max
OFRc 18 1	5263	3.158	1.498	1	6
OFRc 18 2	5286	4.312	1.406	1	6
OFRc 18 3	5206	2.623	1.722	1	6
OFRc 18 4	5221	2.501	1.841	1	6
OFRc 18	5326	3.163	1.14	1	6

Correlation of OFRc - 2018

Variables	(1)	(2)	(3)	(4)
(1) OFRc_18_1	1.000			
(2) OFRc_18_2	0.561*	1.000		
(3) OFRc_18_3	0.166*	0.223*	1.000	
(4) OFRc_18_4	0.165*	0.252*	0.470*	1.000

*** *p<0.01,* ** *p<0.05,* * *p<0.1*

Alpha of OFRc - 2018

Test scale = mean(unstandardized items)
Average interitem covariance: .7912162
Number of items in the scale: 4
Scale reliability coefficient: 0.6312

Factor of OFRc - 2018

(obs=5,098)

Factor analysis/correlation	Number of obs	=	5,098
Method: principal factors	Retained factors	=	2
Rotation: (unrotated)	Number of params	=	6

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.213	0.820	1.066	1.066
Factor2	0.393	0.611	0.345	1.411
Factor3	-0.218	0.032	-0.192	1.219
Factor4	-0.250	.	-0.219	1.000

LR test: independent vs. saturated: chi2(6) = 3615.50 Prob>chi2 = 0.0000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
OFRc_18_1	0.574	-0.313	0.573
OFRc_18_2	0.637	-0.244	0.534
OFRc_18_3	0.481	0.345	0.650
OFRc_18_4	0.496	0.341	0.638

Summary of OFRq - 2018

Variable	Obs	Mean	Std. Dev.	Min	Max
OFRq 18 1	5329	2.86	.921	1	4
OFRq 18 2	5323	3.033	1.011	1	4
OFRq 18 3	5313	2.835	1.009	1	4
OFRq 18 4	5308	3.542	.758	1	4
OFRq 18 5	5292	3.408	.814	1	4
OFRq 18 6	5296	3.393	.86	1	4
OFRq 18 7	5320	3.235	.849	1	4

Correlation of OFRq - 2018

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) OFRq_18_1	1.000						
(2) OFRq_18_2	0.640*	1.000					
(3) OFRq_18_3	0.693*	0.727*	1.000				
(4) OFRq_18_4	0.047*	0.053*	0.050*	1.000			
(5) OFRq_18_5	0.183*	0.142*	0.160*	0.444*	1.000		
(6) OFRq_18_6	0.270*	0.304*	0.264*	0.429*	0.519*	1.000	
(7) OFRq_18_7	0.239*	0.224*	0.234*	0.460*	0.560*	0.553*	1.000

*** *p<0.01*, ** *p<0.05*, * *p<0.1*

Alpha of OFRq - 2018

Test scale = mean(unstandardized items)
Average interitem covariance: .2744249
Number of items in the scale: 7
Scale reliability coefficient: 0.7858

Factor of OFRq - 2018

(obs=5,185)
Factor analysis/correlation   Number of obs = 5,185
Method: principal factors   Retained factors = 2
Rotation: (unrotated)   Number of params = 13

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	2.577	1.278	0.782	0.782
Factor2	1.299	1.357	0.394	1.176
Factor3	-0.058	0.037	-0.018	1.158
Factor4	-0.095	0.030	-0.029	1.129
Factor5	-0.126	0.017	-0.038	1.091
Factor6	-0.142	0.017	-0.043	1.048
Factor7	-0.159	.	-0.048	1.000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
OFRq_18_1	0.655	-0.408	0.404
OFRq_18_2	0.674	-0.444	0.349
OFRq_18_3	0.694	-0.474	0.294
OFRq_18_4	0.393	0.468	0.627
OFRq_18_5	0.540	0.451	0.505
OFRq_18_6	0.626	0.343	0.490
OFRq_18_7	0.612	0.414	0.454

Summary of Income - 2018

Variable	Obs	Mean	Std. Dev.	Min	Max
h18HInc	17146	77480.185	167681.82	0	7406316
l h18HInc	17146	10.393	1.994	0	15.818

Summary of Total Assets - 2018

Variable	Obs	Mean	Std. Dev.	Min	Max
h18HAss	17146	522916.99	1888078.2	-1635000	1.172e+08
l h18HAss	15978	10.985	3.735	0	18.579

Summary of Total Non-Housing Assets - 2018

Variable	Obs	Mean	Std. Dev.	Min	Max
h18HNhAss	17146	342954.52	1496670.5	-1985000	1.000e+08
l h18HNhAss	15300	9.671	4.178	0	18.421

Summary of Total Net Worth - 2018

Variable	Obs	Mean	Std. Dev.	Min	Max
h18HNW	17146	131642.82	602822.49	-1985000	21453234
l h18HNW	13599	7.538	4.939	0	16.881

Summary of Net Value of House - 2018

Variable	Obs	Mean	Std. Dev.	Min	Max
h18HNHoEq	17146	158332.78	838820.28	-399200	99110000
l h18HNHoEq	16954	8.193	5.501	0	18.412

Summary of PH - 2018

Variable	Obs	Mean	Std. Dev.	Min	Max
Self-Reported Health	17135	2.933	1.05	1	5
r18BMI	16903	29.061	6.441	10.2	103.6
r18BMI cat	.	.	.	.	.
Underweight	16998	.017	.128	0	1
Healthy Weight	16998	.244	.43	0	1
Overweight	16998	.359	.48	0	1
Obese	16998	.38	.485	0	1
# of Chronic Illnesses	17146	2.325	1.568	0	8
# of Chronic Illnesses(Rand)	17146	2.325	1.568	0	8
# of Functional Limitations	17120	.463	1.177	0	6

Correlation of PH - 2018

Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) Self-Reported ~h	1.000					
(2) r18BMI	0.153*	1.000				
(3) BMI Categories	0.114*	0.835*	1.000			
(4) # of Chronic I~s	0.454*	0.156*	0.125*	1.000		
(5) # of Chronic I~)	0.454*	0.156*	0.125*	1.000*	1.000	
(6) # of Functiona~s	0.383*	0.059*	0.017*	0.335*	0.335*	1.000

*** *p<0.01,* ** *p<0.05,* * *p<0.1*

Alpha of PH - 2018

Test scale = mean(unstandardized items)
Average interitem covariance: 1.009771
Number of items in the scale: 6
Scale reliability coefficient: 0.4574

Factor of PH - 2018

(obs=16,723)
(collinear variables specified)
Factor analysis/correlation Number of obs = 16,723
Method: principal factors Retained factors = 3
Rotation: (unrotated) Number of params = 15
Warning: Solution is a Heywood case; that is, invalid or boundary values of uniqueness.

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	2.483	1.062	0.644	0.644
Factor2	1.421	1.167	0.369	1.012
Factor3	0.255	0.255	0.066	1.079
Factor4	0.000	0.137	0.000	1.079
Factor5	-0.137	0.029	-0.036	1.043
Factor6	-0.166	.	-0.043	1.000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Factor3	Uniqueness
r18SRH	0.502	-0.069	0.316	0.643
r18BMI	0.391	0.786	0.014	0.229
r18BMI_cat	0.355	0.800	-0.035	0.233
ChIl_18	0.952	-0.269	-0.145	-0.000
ChIl_18_r	0.952	-0.269	-0.145	-0.000
FL_18	0.373	-0.118	0.334	0.736

Summary of PSc - 2018

Variable	Obs	Mean	Std. Dev.	Min	Max
PSc 18 1	3768	3.476	.754	1	4
PSc 18 2	3750	2.97	.802	1	4
PSc 18 3	3742	1.727	.586	1	3
PSc 18	3829	2.899	.618	1	4

Correlation of PSc - 2018

Variables	(1)	(2)	(3)
(1) PSc_18_1	1.000		
(2) PSc_18_2	0.677*	1.000	
(3) PSc_18_3	-0.461*	-0.458*	1.000

*** *p<0.01*, ** *p<0.05*, * *p<0.1*

Alpha of PSc - 2018

Test scale = mean(unstandardized items)
Reversed item: PSc_18_3
Average interitem covariance: .2678456
Number of items in the scale: 3
Scale reliability coefficient: 0.7621

Factor of PSc - 2018

(obs=3,678)

Factor analysis/correlation	Number of obs = 3,678
Method: principal factors	Retained factors = 1
Rotation: (unrotated)	Number of params = 3

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.494	1.581	1.228	1.228
Factor2	-0.086	0.105	-0.071	1.157
Factor3	-0.191	.	-0.157	1.000

LR test: independent vs. saturated: chi2(3) = 3289.68 Prob>chi2 = 0.0000
Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Uniqueness
PSc_18_1	0.767	0.412
PSc_18_2	0.767	0.412
PSc_18_3	-0.564	0.682

Summary of PSq - 2018

Variable	Obs	Mean	Std. Dev.	Min	Max
PSq 18 1	3784	3.287	.83	1	4
PSq 18 2	3772	3.686	.683	1	4
PSq 18 3	3769	3.399	.832	1	4
PSq 18 4	3761	2.994	.909	1	4
PSq 18 5	3750	2.993	.887	1	4
PSq 18 6	3753	3.336	.846	1	4
PSq 18 7	3765	2.937	.832	1	4

Correlation of PSq - 2018

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) PSq_18_1	1.000						
(2) PSq_18_2	0.564*	1.000					
(3) PSq_18_3	0.659*	0.635*	1.000				
(4) PSq_18_4	0.281*	0.216*	0.231*	1.000			
(5) PSq_18_5	0.312*	0.176*	0.282*	0.512*	1.000		
(6) PSq_18_6	0.429*	0.407*	0.398*	0.448*	0.428*	1.000	
(7) PSq_18_7	0.431*	0.289*	0.383*	0.451*	0.492*	0.533*	1.000

*** *p<0.01*, ** *p<0.05*, * *p<0.1*

Alpha of PSq - 2018
Test scale = mean(unstandardized items)
Average interitem covariance: .2794887
Number of items in the scale: 7
Scale reliability coefficient: 0.8246

Factor of PSq - 2018
(obs=3,674)
Factor analysis/correlation Number of obs = 3,674
Method: principal factors Retained factors = 2
Rotation: (unrotated) Number of params = 13

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	2.911	2.197	0.947	0.947
Factor2	0.714	0.727	0.232	1.179
Factor3	-0.013	0.035	-0.004	1.174
Factor4	-0.048	0.080	-0.016	1.159
Factor5	-0.129	0.037	-0.042	1.117
Factor6	-0.166	0.028	-0.054	1.063
Factor7	-0.194	.	-0.063	1.000

LR test: independent vs. saturated: chi2(21) = 9548.15 Prob>chi2 = 0.0000
Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
PSq_18_1	0.719	-0.258	0.417
PSq_18_2	0.632	-0.377	0.458
PSq_18_3	0.713	-0.368	0.356
PSq_18_4	0.542	0.372	0.567
PSq_18_5	0.560	0.376	0.545
PSq_18_6	0.670	0.162	0.525
PSq_18_7	0.655	0.252	0.507

Summary of sFWB - 2018

Variable	Obs	Mean	Std. Dev.	Min	Max
sFWB 18 1	5608	3.339	1.145	1	5
sFWB 18 2	5574	4.093	1	1	5
sFWB 18	5697	3.711	.975	1	5

Correlation of sFWB - 2018

Variables	(1)	(2)
(1) sFWB_18_1	1.000	
(2) sFWB_18_2	0.628*	1.000

*** *p<0.01*, ** *p<0.05*, * *p<0.1*

Alpha of sFWB - 2018
Test scale = mean(unstandardized items)
Average interitem covariance: .7176292
Number of items in the scale: 2
Scale reliability coefficient: 0.7662

Factor of sFWB - 2018

(obs=5,485)

Factor analysis/correlation		Number of obs =	5,485
Method: principal factors		Retained factors =	1
Rotation: (unrotated)		Number of params =	1

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.022	1.256	1.296	1.296
Factor2	-0.234	.	-0.296	1.000

LR test: independent vs. saturated: chi2(1) = 2749.34 Prob>chi2 = 0.0000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Uniqueness
sFWB_18_1	0.715	0.489
sFWB_18_2	0.715	0.489