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Trajectories and Patterns of Wealth in Later Life: Implications for Physical, Mental, and Cognitive Health

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by
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ABSTRACT OF THE DISSERTATION

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This study aims to contribute to our understanding of the longitudinal link between wealth and health in later life. Prior research on the wealth-health relationship has focused on general households, with little consideration for older adults. Further, several gaps are identified in the literature. For example, studies often utilize a shorter window of observation and treat wealth as a static measure without considering the trajectory and the heterogeneity of wealth over time. In addition, prior studies often explore the impact of wealth on a single aspect of health, ignoring the "codependent" nature of health at older ages. Further, the impacts of life course factors on the development of wealth are not often tested, and such effects are not accounted for when examining the "wealth-health" nexus, creating issues of endogeneity. Using life-cycle hypothesis, cumulative dis/advantage model, and asset-based welfare theory, this study addresses these issues by exploring how life course factors relate to wealth trajectory in later life, and investigating the longitudinal relationship between wealth and multidimensional health when life course factors are simultaneously modeled.

Using latent growth curve modeling (LGCM) and latent growth mixture modeling (LGMM) via the structural equation modeling approach and generalized propensity score analysis, this study analyzes data from six biennial waves of the Health and Retirement Study (HRS), a national representative panel study of Americans aged 51 and older. This study has three research aims. It first explores the trajectory of wealth of older Americans between 2004 and 2014, and examines how life course factors correlate with wealth trajectory. Models of quadratic function and piece-wise function that allow the testing of the spline in the wealth trajectory are used as additional tests to examine the impact of the 2008 economic recession on the wealth trajectory. Second, physical, mental, and cognitive health are entered in the model to examine how health outcomes individually and jointly respond to the wealth trajectory. Finally, it uses LGMM to identify heterogeneous patterns in both wealth and health, and employs generalized propensity score analysis to explore the longitudinal associations between wealth patterns and health patterns when the effect of life course factors on wealth were modeled.

This study contributes to the field methodologically and substantively. It uses novel methods to explore the trajectory and patterns of wealth in later life and examines the longitudinal wealth-health nexus by accounting for endogeneity. It offers strong evidence about the relationship between wealth and health, and provides policy and research implications for strengthening economic security and positive health at older ages.

Chapter 1: Introduction

Wealth—an important aspect of the three-legged stool of retirement security in later life (defined as Social Security, assets and wealth, and employer-sponsored pension programs such as defined-benefit pension and defined-contribution pension)—has received increased attention in recent years as our society ages rapidly. For example, the 2015 White House Conference on Aging had one panel discussion focusing on financial security (U.S. Department of Human & Health Services, 2016). In this panel a wide array of actions and discussions in both public and private sectors had been made, including strengthening Social Security, promoting availability of lifetime income options (e.g., provision of defined-benefit pension programs or annuities), increasing financial capability (e.g., access, knowledge, and decision), and most important of all, ensuring economic opportunities to save and build a sound financial cushion at old age. Further, the United States Senate Special Committee on Aging has held at least seven hearings within a decade regarding strengthening economic security and financial health of older Americans. These important meetings provide critical implications in that strengthening older adults' economic well-being has great potential to promote healthy aging and increase quality of life (Huang & Greenfield, 2015).

Recent scholarship, however, suggest that older adults are more vulnerable to the risks of wealth inequality (Crystal, 2016), as many of them are financially ill-prepared. For example, the 2017 Retirement Confidence Survey (Employee Benefit Research Institute, 2017) found that approximately one in five (18%) American workers aged 55 and older had less than $1,000 in savings and retirement, with about another 20% having between $1,000 and less than $50,000, and about another quarter (26%) reporting savings between $50,000 and less than $250,000.

Studies further show that these older workers, compared to other ages, had more concerns regarding health and health-related expenditures, such as worries about not having enough money to pay for long-term care and other care-related expenses. This problem may be further exacerbated by the extended life expectancy in the United States. Americans are living longer than ever before. In 2016, life expectancy at birth in the U.S. was 78.6 years. When Americans reach age 65, they are expected to live an additional 20 years (Center for Disease Control & Prevention, 2017). This trend suggests that, although older Americans may have more time to help grow and continue contributing to the economy, longer lives can also increase the risk of outliving personal wealth. Accordingly, older adults may have compromised living standards, poor quality of life, or negative well-being outcomes as their wealth depletes over time.

The aforementioned evidence and trends suggest that studying the impacts of wealth on outcomes in later life is warranted (Huang & Greenfield, 2015). Looking at the impacts of wealth on well-being outcomes in later life, compared to the effects of income, draws out further implications because wealth is a much more meaningful measure of economic and financial security (Sherraden, 1991), especially in later life (Brown, 2012; Morrow-Howell & Sherraden, 2015). A recent synthesized study showed that the explorations on health outcomes in later life is promising (C. E. Pollack et al., 2007) because health research often ignores the impact of wealth and asset-related measures on health outcomes (Baum, 2005), and these studies are often based on cross-sectional design or employ shorter windows of observation. In addition, compared to studies on the aging population, a large body of studies that explore the impacts of wealth on well-being-related outcomes concentrates on the child and youth population (e.g., Chowa, Ansong, & Masa, 2010; Shanks, Kim, Loke, & Destin, 2010). As Sherraden (1991) notes, assets could produce positive effects, including long-term planning, higher personal efficacy, and increased social engagement. In addition, assets can generate more assets if individuals take proper financial actions, which may lead to favorable economic, psychological, social, health, and intergenerational outcomes (Lerman & McKernan, 2008; Paxton, 2001). However, little research focuses on the effects of the wealth-health relationship in later life, which creates a window of opportunity for this dissertation to test the longitudinal wealth-health relationship among older persons.

Guided by life-cycle hypothesis, life course/cumulative disadvantage perspective, and asset-based welfare theory, this dissertation aims to explore the longitudinal link between wealth and well-being outcomes (i.e., the asset-effect) among older adults, with special attention paid to health outcomes in later life. Using latent growth curve modeling (LGCM) and latent growth mixture modeling (LGMM) within the structural equation modeling (SEM) approach, this dissertation seeks to: (1) explore the trajectory of wealth in later life, and then investigate how life course factors associate with wealth trajectory; (2) examine how wealth trajectory is associated with physical, mental, and cognitive health outcomes longitudinally given the fact that health in later life is often co-dependent and comorbid (Haas, 2008; Kwon & Park, 2017; Wickrama, Mancini, Kwag, & Kwon, 2013); and (3) investigate the heterogeneous patterns both in the trajectory of wealth and health, and examine the longitudinal association between wealth patterns and health patterns at old age.

1.1 Definitions of Key Concepts

1.1.1 Wealth

This study defines wealth as net worth, representing the *tangible* aspect of assets. In this dissertation, these two terms (i.e., wealth and assets) are used interchangeably. Briefly speaking, assets can be defined as tangible and intangible properties (Sherraden, 1991). However, studying tangible assets, such as savings, financial assets, or home, vehicle, or business ownership, have considerable advantages. First, tangible assets can be measured with economic values and second, tangible assets are more associated with human lives and social policies. Many studies recognize these merits and therefore use tangible assets as a proxy to represent overall assets. Following the work of Nam, Huang, and Sherraden (2008), this dissertation focuses on the tangible part of assets and more specifically, uses wealth as a general term for assets.

Using the guidelines developed by Chang (2010), Nam et al. (2008) and Sherraden (1991), wealth in later life may include the following types: (1) savings and transaction accounts (e.g., checking, savings, or individual retirement accounts (IRAs) such as 401(k), 403(b), or Keoghs accounts); (2) stocks, bonds, mutual funds, and other financial securities such as life insurance; (3) real properties such as house, building, or land; (4) fixed capitals (e.g., machines and/or equipment); (5) business properties; (6) employer-sponsored pension programs, either in defined-benefit (DB) or defined-contribution (DC) programs; and (7) other assets such as art collections, jewelry, and collectibles. These types of wealth require a life-long accumulation, and studies have showed that they are highly influenced by life course factors (Rank, 2008).

To draw a clear picture of wealth, this study operationalizes wealth as the total values of assets minus debts, that is, the net worth. This approach is consistent with several theoretical and empirical works focusing on wealth issues in general or older households (Chang, 2010; Greenfield, 2013; C. E. Pollack et al., 2007). The measurement section provides more details on the construction of wealth in this study.

1.1.2 Older Adult and Later Life

The terms "older adult" and "later life" may include different age ranges, as the definition for these terms varies by cultures and societies (Chen et al., 2018). However, most works on wealth in later life generally include individuals aged 50 and older (e.g., Barrett & O'Sullivan, 2014; Bearden & Wilder, 2007; Bonke & Browning, 2009; Geyer, Spreckelsen, & von dem Knesebeck, 2014; Hochman & Skopek, 2013; Kim & Richardson, 2012). Further, the data set used in this study, the Health and Retirement Study, collects information from older adults aged 50 and above. Therefore, this study defines both older adult and later life as individuals aged 50 and older.

1.1.3 Trajectory and Patterns

Using the SEM approach, both the trajectory and patterns were modeled as latent factors and represented the longitudinal changes for any given construct, in this dissertation, wealth and health. However, these two terms are defined differently in this study.

The term "trajectory" refers to the average changes at the *population* level, assuming that individuals from a targeted population share a homogeneous trajectory (Kline, 2015; Wang & Wang, 2012) for both wealth and health longitudinally. The identification of the mean trajectory in SEM involves the use of latent growth curve modeling (LGCM). This mean trajectory, or so called *latent growth curve* using the SEM language, describes the *inter-individual* changes in wealth and health across time (Wickrama, Lee, O'Neal, & Lorenz, 2016). The trajectory can be broken down into two pieces: the intercept and slope, and these two components are explored in both wealth and health. Using wealth as an example, the intercept of wealth indicates the average initial values of net worth at the baseline. The slope represents the average rates of change in wealth across time, and the identifications of the slope requires differential model specifications, such as the linear function (i.e., a linear trend indicating increases or declines over time) or the polynomial function (i.e., quadratic or cubic). For example, if the slope of wealth is a linear function, and it is observed to decrease over time, this means that all individuals in a target population have the same levels of decline in wealth. Note that since different functions for slope could be specified, the best model of slope can be selected using model comparisons (Wang & Wang, 2012). The Method section provides more details on the selection process.

In contrast, the term "patterns" represents the *heterogeneity* within the mean trajectory, meaning that different *subpopulations* can be identified through the relaxations of the mean assumption in the overall population trajectory (Grimm, Ram, & Estabrook, 2017; Wickrama et al., 2016). The patterns describe the *intra-individual* changes within the mean population trajectory, indicating that the mean trajectory can be broken down into several heterogeneous and distinct *trajectory groups*; these different trajectory groups or subpopulations are called *latent trajectory classes* using SEM language (Wang & Wang, 2012). Explorations of the heterogeneity involve the use of both latent growth curve modeling (LGMM) and latent growth mixture modeling (LGMM). The model begins with explorations of the mean trajectory for both wealth and health using LGCM, and then identifies the subgroups within the mean wealth and health trajectory using LGMM. For example, if the LGCM identifies that wealth has a linear decline over time, the LGMM may identify distinct subgroups (i.e., latent classes) based on this linear function of wealth, where one group has a faster decline in wealth and another group experiences a slower decline in wealth. It should be noted that the identification of patterns requires an exploratory approach to determine the best SEM model with appropriate latent trajectory classes using both objective and subjective selection. See method section for the process of model selection.

In sum, these two terms—trajectory and patterns—are used in this dissertation to describe the longitudinal changes of wealth and health, but they represent different ideas of change, with the trajectory describing the changes as a mean populational estimate, whereas the patterns represent the changes as subpopulation estimates.

1.2 Purpose of Dissertation

The purpose of this dissertation is to advance knowledge in the longitudinal wealth-health relationship in later life by understanding: (1) the longitudinal changes (i.e., the trajectory and the patterns) in both wealth and health, (2) the associations of life course factors and longitudinal changes in wealth, and (3) the effects of wealth trajectory and patterns on longitudinal changes of health in later life. Using rigorous methodologies and theoretical models, this study uses six waves of nationally representative data—the Health and Retirement Study—to achieve these aims.

1.3 Organization of Dissertation

This dissertation is organized as follows: Chapter 2 presents the background and significance of the topic of wealth in later life. It includes information on how life course factors influence wealth, how wealth affects health in later life, and a review of research gaps in the current literature. The applications of two theories—cumulative disadvantage model and the asset-based welfare theory—are also discussed. Chapter 2 concludes with the research questions and hypotheses proposed by this study. Chapter 3 discusses the methods of this study, including data and sample selection, measurement, and analytical approaches. Chapter 4 presents the detailed findings of this dissertation, with each section tied to the proposed research questions. Chapter 5 discusses the study results in relation to current literature and the implications from the findings.

Chapter 2: Background and Significance

This chapter presents theoretical and empirical scholarship relevant to the topic of wealth in later life. It begins with the evidence of how life course factors influence wealth in later life, followed by a review section of the effects of wealth on health outcomes of older adults. This chapter then discusses the research gaps in current literature, the theoretical perspectives, and the proposed conceptual model used in this dissertation. This chapter concludes with the dissertation's research questions and hypotheses.

2.1 Factors Associated with Wealth in Later Life

Wealth in later life is the product of long-term accumulation; it is the outcome of lifelong and financial experiences accumulated throughout a life course (Sherraden & Morrow-Howell, 2015). As wealth is a product that requires a lifetime accumulation, research has shown that it is influenced by a series of social, economic, and financial factors over the life course (Rank, 2008). Using life course perspective, this section reviews key life course factors that are highly associated with wealth accumulation and development over time. Different types of life course factors, including the ascribed factors (gender, race, and cohort) and the socioeconomic status (SES) both in childhood and adulthood (income, education, marital status, and work status), are discussed here. It should be noted that the findings for the relationships between the life course factors and wealth presented in this section are mostly descriptive in nature or simply a bivariate association, and little is known about the net effect in a multivariate setting.

2.1.1 Gender

Economic inequality in terms of economic security and mobility between males and females is well-documented in the literature. In general, women earn 78% of income compared to their male counterparts, but they only own 36% as much in wealth (Chang, 2010). However, such attention has been paid to income rather than wealth, and therefore little is known about the effect of gender on wealth (Brown, 2012). The major reason for this absence is that the wealth data are often collected at the household level whereas gender is an individual-level characteristic, and how to attribute household wealth by gender remains a debate in the current literature (Brown, 2012; Chang, 2010). Therefore, research often uses non-married samples (e.g., widowed, divorced, or never married) when studying the gender difference in wealth.

Using the 2004 Survey of Consumer Finance (SCF), Chang (2010) found that the median wealth for single men ($28,610) is 2.75 times that of single women ($10,400). This difference further varies by single status (widowed, divorced, and never married). Using a dollar-to-cent ratio of median wealth as an indicator, women who were widowed, divorced, and never married earn 60%, 45%, and 6% of wealth compared to men. Among respondents aged 60 and older, single women only own 53% of wealth compared to single men. Using the "wealth poor" (defined as having zero or negative wealth) as an assessment, 31% of women are defined as wealth poor but for single men, the rate is 22%. These results suggest that gender difference exists in wealth, with females have lower levels of wealth compared to males.

2.1.2 Education

Education is a powerful predictor of wealth across the life course (Emmons & Noeth, 2015). Individuals with higher levels of education often have more opportunities to get a well-paying job and tend to work longer, even past retirement age, which ensures higher levels of economic security in later life (Murphy, Johnson, & Mermin, 2013).

Using the SCF between 1995 and 2004, Carasso and McKernan (2008) found that wealth varies greatly by levels of education. In terms of *wealth ownership*, for example, almost 90% of households with a high school degree or above owned a transaction account, whereas 30% of unbanked households are not highly educated (having some high school education). The shares of owning retirement accounts increase with educational increases. About 70% of household heads who were college graduates had a retirement account. For those who had a high school education, only 15% had a retirement account. Owning assets only tells part of the story: households with higher education also have more opportunities to have higher values in financial assets such as saving accounts, bonds, or stocks. Using values in the retirement account as an example, Carasso and McKernan (2008) found that the median values of retirement accounts are similar between the people (i.e., household heads) with a high school education and with some college experience. However, the median value of retirement accounts of households with a college degree or above is 3.5–4 times higher than other types of households. This result showed that wealth is unevenly distributed across levels of education; individuals with a college degree, compared to other education levels, had higher levels of wealth in terms of values and ownerships.

2.1.3 Income Levels

The role of income in wealth has been examined in a number of studies (Butrica, 2008; Butrica, Murphy, & Zedlewski, 2010; Carasso & McKernan, 2008). Using the 2004 HRS, Butrica et al. (2010) examined the sources of income among older persons by income status (poor, near poor, low-income, and middle or high-income). The results indicate that Social Security is a major source of income for poor (83%), near-poor (87%), and low-income (75%) older adults. In contrast, sources of income are more diversified among older persons with higher income. For example, Social Security only accounts for 24% of their income; other sources of income including defined-benefit (DB) pension plans (22%), earnings (22%), and assets (24%).

Carasso and McKernan (2008) also supported this finding. Dividing household income into quintiles, they found that both the shares and values of wealth are unevenly distributed across income quintiles. For example, among the households at the top income quintile (top 20% of income), about 40% of them report owning stocks. This value, compared to households at the bottom quintile, is four times larger. Further, the values of wealth significantly vary across income quintiles. The median value of wealth in retirement accounts for the top 20% of households is approximately $130,000. The value is four times higher compared to the fourth quintile, 13 times larger than the second quintile, and 26 times higher than the bottom quintile.

2.1.4 Race

Race is often suggested by the literature as a proxy of socioeconomic status and social resources (Rank, 2008). Research has shown that people of color are more likely to have lower life earnings and experience discrimination both in life and work, which leads to economic instability in later life (Hudson, 2015; Hudson, 2016). Findings from these studies suggested that the process of wealth development is significantly influenced by race (McKernan, Ratcliffe, Steuerle, & Zhang, 2013, 2014b). Further, studies also showed that the wealth gaps by race remain significant even when the socioeconomic differences were controlled for in the model (Hudson, 2015).

Using the 2010 HRS, findings from Angel and Mudrazija (2015) provide ample evidence on how wealth, including sizes and types, differs by race. Using the sources of income as an example, older Americans who identified themselves as white or Caucasian have higher retirement income ($35,000). However, the average retirement income for non-Hispanic blacks is $22,500, and is only $17,000 for Mexican-origin older adults. They also found that older adults of color (i.e., blacks or Hispanics) are more likely to rely on public benefits (e.g., Social Security) and continue to work even past retirement age. Further, wealth ownerships significantly vary across race. They found that only 10% of income is from assets among black and Hispanic older adults, compared to 31% for older whites. Pension ownership, especially employer-sponsored pensions, also varies greatly by race. Approximately 50% of older whites have pensions, compared to approximately 10% for both older blacks and Hispanics. This result may partially reflect employment discrimination against the people of color, as minorities are more likely to have work with lower pay and fewer benefits (Shanks & Leigh, 2015).

2.1.5 Cohort

A cohort refers to the time that individuals live at a specific chronological, political, social, or economic context or the time of a defined event (Hutchison, 2005).These contextual effects of time may have a lifelong impact on individuals' thinking, perceptions, behaviors, and life chances and opportunities (Dannefer, 2003; Hatch, 2005), which in turn, influence their wealth accumulation over time (Rank, 2008). The difference across cohorts—including age, birth, and sociohistorical cohorts—is called "cohort effect" (Hutchison, 2010).

In the current literature, there are only a few studies that empirically examine how the cohort effect—especially on the effect of birth cohort—influences the process of wealth accumulation. McKernan et al. (2014b), for example, found that the wealth of succeeding cohorts is often more than their preceding cohorts. However, they found that such a cohort effect is not constant across time. Their study found that those born after 1960 did not have a positive accumulation in wealth compared to the individuals born in an earlier cohort. Further, little is known about what makes the difference and why. It is noteworthy that not many studies are aware of the cohort effect (Rank, 2008), but the cohort effect indeed may play a critical role in influencing wealth accumulation across cohorts (Emmons & Noeth, 2015). The relationship between the cohort effect and assets among older persons warrants special attention.

2.1.6 Marital Status

Research has shown that marital status strongly influences the accumulation of assets (Rank, 2008). Single households, compared to their married equivalents, are more likely to be economically disadvantaged. Carasso and McKernan (2008), for example, used the 1995–2004 SCF to explore how wealth varies by marital status. They found that single-headed families were less likely to have retirement accounts, savings, bonds, and stocks compared to their married or cohabited counterparts. In addition, married and cohabited households had 2.5 times more wealth than the single-headed families. Another analysis using the 1992 HRS conducted by Wilmoth and Koso (2002) also found similar results. They found that marital status predicted wealth among preretirement adults: wealth among individuals who were not continuously married (e.g., divorced, separated, or widowed) was significantly lower than those who were married. In addition, remarriage could offset the negative effects due to marriage disruption. Those who remarried suffered less wealth loss compared to those who were not in a marriage. Lastly, in an analysis exploring how gendered wealth is, Chang (2010) found that there is a consistent pattern in the differences of wealth across marital status: married households have the highest wealth levels, followed by those who were widowed, divorced, and never-married households, and such a pattern holds across gender.

2.1.7 Work

Little research focuses on how wealth in later life is distributed by working status (e.g., full-time work, part-time work, or self-employment), which is possibly due to issues of sample selection and research focus. For example, research may focus more on the younger working population (e.g., Chang, 2010) and others may simply focus on older adults with an assumption that they gradually left the labor market or retired (Denton & Boos, 2007). In addition, among these studies, most of them are descriptive in nature, and we know very little about how wealth differs across work.

Only one study that was done by Denton and Boos (2007) could possibly answer this question. However, in their work they focus on occupation (e.g., different types of industry) rather than the types of work. They explored how the impact of different occupations (e.g., sales [reference group], management, agriculture, science, and not in labor force) may have on wealth (defined by net worth), and how such an impact is moderated by gender. Results showed that not working has a negative impact on wealth for men, but this effect was not found among women.

2.1.8 Childhood Socioeconomic Factors

Studies have showed that childhood socioeconomic factors, such as parents' education, family economic status, and parents' employment status, are critical in influencing individuals' life chances and human capital in adulthood (Currie, 2009; Duncan & Brooks-Gunn, 1997; Duncan, Yeung, Brooks-Gunn, & Smith, 1998). Using Panel Study of Income Dynamics between 1967 and 1973, Duncan et al. (1998) found that family economic status (measured by family income) at children's age 0 to 5 is positively associated with higher education outcomes (measured by the numbers of schooling year and high school completion rates), controlling for the effects of gender, race, marital status, maternal employment, and other residential mobility. As discussed in the earlier section where education is one of the major drivers that influence wealth development over time, evidence suggests that childhood SES factors may have a long-term effect on wealth and these effects need to be considered in the model (Currie, 2009).

2.2 Impacts of Wealth on Health Outcomes

2.2.1 Directionality in Wealth-Health Relationship

When examining the relationship between economic resources (including income and wealth) and health outcomes in later life, the direction between wealth and health should be addressed. That is, is wealth influencing health in later life, or vice versa? Some studies (Adams, Hurd, McFadden, Merrill, & Ribeiro, 2003; Lee & Kim, 2003) find evidence that health is the "cause" for wealth. However, these studies focus on how an occurrence of a new health event (e.g., chronic diseases, cancer, or surgery) is associated with wealth depletion or decumulation. In contrast, a strong body of literature (Bloom & Canning, 2000; Deaton, 2002), including a systematic review study (C. E. Pollack et al., 2007), generally supports the notion that wealth is a determinant of health. Further, evidence from the economic literature shows that more wealth is associated with better health outcomes, and this is especially true in later life (Deaton, 2002).

It should be noted again that wealth is not always the study focus when examining its impact on health outcomes (Baum, 2005). Therefore, the evidence presented in this section is drawing from the studies focusing on the effects of socioeconomic status (SES) on health outcomes of interest, including physical, mental, and cognitive health, as these studies often treat wealth as one of the SES indicators.

2.2.2 Physical and Self-Reported Health

Physical health can be defined both objectively and subjectively. The definition for subjective health is consistent, as studies often use a single question to evaluate respondents' subjective feelings toward their overall physical health (i.e., self-rated health). For objective physical health, research often uses the numbers of limitation related to activities of daily living (Sloan & Wang, 2005) or mobility functions such as carrying objects, moving, or standing (von dem Knesebeck, Lüschen, Cockerham, & Siegrist, 2003).

In terms of association between wealth and objective physical health, the cross-sectional research generally supports a positive relationship between wealth and objective physical health (or a negative relationship with functional limitations). For example, Sloan and Wang (2005) explored how wealth (measured by net worth) was associated with personal tasks and instrumental activities of daily living (e.g., preparing meals, grocery shopping, and driving), with the wealth measures categorizing positive and negative values. Results showed that positive net worth was not associated with mobility (except for driving), but negative net worth showed a strong association: older adults with more negative net worth had poor physical health, including lower scores in meal preparation, shopping, and driving. Another example using a sample of 3,617 respondents from the first wave of the Americans' Changing Lives (ACL), Robert (1998) examined how SES indicators, including income and assets, influence functional limitations when controlling for community SES. Results showed that both income and assets were significant in predicting functional limitations, and those with higher assets (> $10,000) had fewer functional limitations.

Research also shows that wealth is associated with physical health longitudinally. Using five waves of the Health and Retirement Study (HRS) from 1994 to 2002, Haas (2008) examined how the baseline (i.e., year 1994) socioeconomic status (SES) in childhood and adulthood were associated with the trajectory of functional ability (measured by number of limitations). This study further tested how income and wealth were associated with changes of functional ability. Results showed that functional limitations increased over time, and both income and wealth were associated with the intercept (i.e., initial levels of functional limitations) but not the slope (i.e., increases in limitations). Findings suggested that higher values in the baseline income and wealth were associated with lower initial levels of functional limitations, but they were not associated with the increases of functional limitations over time.

Other studies provide more details by testing whether the association between wealth and physical health varies by country context and race. von dem Knesebeck et al. (2003), for example, used two national telephone surveys in Germany (N = 682) and the US (N = 608) among people aged 60 and older to study how SES indicators, including income, education, occupation, home ownership, and asset ownership (real estate, stocks, or both) influence functional limitations. Results showed that lower income and no assets were associated with higher levels of functional limitations, but the significant effect was only observed among older Americans. This insignificant result is also replicated by Geyer et al. (2014), in the study they examined how SES indicators (including wealth) influence health among older Germans, and the results showed that wealth was not associated with health. Findings suggested that the insignificant effect of wealth should be attributed to the differences in welfare systems, as Germany has a universal pension system to economically support older adults, and therefore wealth, compared to other SES indicators, may have less impacts on health in later life. Lastly, using a sample of 6,962 respondents aged 70 and older, Schoenbaum and Waidmann (1997) examined how SES indicators, including education, income, occupation, and assets, could influence the disparity in self-rated health and functional limitations by race. Results showed that the black/white disparity in health was reduced when SES variables were controlled for. Further, assets had a larger positive effect on health status especially for older blacks.

Regarding the relationship between wealth and subjective physical health, a large body of literature supports the connection that wealth is positively associated with self-rated health in later life (Deaton & Paxson, 1998), although these findings are primarily based on cross-sectional designs. For example, Aittomäki, Martikainen, Laaksonen, Lahelma, and Rahkonen (2010) used a sample of 6,509 middle-aged individuals to examine the association between wealth (net worth) and self-reported health (good vs. less than good). Findings revealed that wealth, compared to income, was a stronger predictor of health. Those with higher levels of wealth were more likely to report having good health. Another study using two cross-sectional data from the 2002 and 2007 German Socio-Economic Panel, Geyer et al. (2014) examined the association between multiple wealth indicators (financial assets, home ownership, life insurance, and debts) and health, and how the associations vary by retired status. Results showed that the associations between wealth and health were much stronger in the non-retired middle-aged sample. However, for the retired sample, they found that home ownership was the only significant factor that was associated with health.

There are also several works focusing on variations in the relationship between wealth and self-rated health. For example, Kim, Sargent-Cox, French, Kendig, and Anstey (2011) examined how wealth (net worth, in decile) was associated with health across Australia, the US, and South Korea. Results showed that the wealth-health relationship was much stronger in the US than in Australia and South Korea. They conclude that such variations may be attributed to the differences in the welfare programs across countries. Another study using 26,615 respondents aged 18 to 95 from five waves of the Panel Study of Income Dynamics (PSID), Hajat, Kaufman, Rose, Siddiqi, and Thomas (2011) explored whether the relationship between wealth (in quintiles) and self-rated health (poor vs. good health) varied by race and gender. Results showed that, compared to the wealthiest quintile (top 20%), those with lower wealth had 16% to 44% higher chances to report having poor health. Further, older women, especially with lower wealth, had higher odds to report poor health compared to their wealthier male counterparts.

2.2.3 Mental Health

Mental health captures the psychological expression of an individual's perceptions to overall health. Current scholarship often uses depressive symptoms (e.g., Bearden & Wilder, 2007; Chiao, Weng, & Botticello, 2011; Hamoudi & Dowd, 2014) or psychological distress (e.g., Carter, Blakely, Collings, Gunasekara, & Richardson, 2009) to measure mental health of older people. However, not many studies explore the association between wealth and mental health in later life.

For the associations between wealth and mental health, the current evidence shows a mixed result. A few studies found that wealth was not associated with mental health in later life. Using the 2006 HRS, Hamoudi and Dowd (2014) examined how wealth was associated with later-life psychological well-being, including depression and anxiety (both were dichotomized by median values), positive and negative affect, and life satisfaction. They found that wealth was negatively associated with anxiety, depression, and negative affect but was positively associated with life satisfaction. However, only the effect on anxiety was significant. Another study using five waves of the Taiwan Longitudinal Study on Aging from 1989 to 2007, Chiao et al. (2011) examined how income, economic strain, wealth (measured by home ownership), and other SES indicators were associated with depression and self-rated health. Results showed that the effects of income and wealth on health were not significant, but economic strain showed a stronger association with depression and self-rated health.

In contrast, some studies show a significant association between wealth and mental health. Carter et al. (2009), for example, used three waves of the Survey of Families, Income, and Employment in New Zealand to investigate how wealth (in quintile) was associated with psychological distress. Results showed that, compared to the highest wealth quintile, respondents in the lower wealth quintile had higher levels of psychological distress when controlling for ethnicity, family structure, and other SES indicators such as employment status and income. Bearden and Wilder (2007) also supported this finding. Using five waves of HRS from 1992 to

2000, they examined the association between wealth (net financial, housing, and pension wealth) and psychological well-being (reversed-coded depression) among retired older adults when controlling for life course factors such as race and marital status. Results showed that wealth was positively associated with psychological well-being, and this effect remained significant when the life course factors were controlled in the model. In sum, the current scholarship shows that the relationship between wealth and mental health remains inconclusive, in part because each study defines wealth differently. Therefore, more studies are required to test the link between wealth and mental health in later life.

2.2.4 Cognitive Health

Results from the current research generally support the notion that wealth is positively associated with cognitive function in later life, although variations exist in these studies, such as differences in operationalization, sample selection, and country contexts. For example, using a sample of 2,574 older adults aged 70 to 79 from the cities of Pittsburgh and Memphis, Koster et al. (2005) examined the relationship between three SES indicators (education, income levels, and types of asset ownership) and cognitive impairment (measured by a modified mini-mental state examination, MMSE) over four years, controlling for baseline chronic health factors, such as heart diseases, diabetes, hypertension, and other diseases. Results showed that those with lower income levels, no assets, and no college degree had cognitive decline over time. Using the 2006 HRS, Hamoudi and Dowd (2014) examined how housing wealth was associated with multiple cognition measures (Series 7s, short-term recall memory, long-term recall memory, 3 of 3 numeracy questions, Wechsler adults intelligence scale-revised, and dementia risks) among 4,207 older adults aged 65 and older. Results showed that, controlling for the baseline covariates, housing wealth was positively associated with cognition, with significant results shown on the long-term memory recall and numeracy questions.

Several cross-national studies also document the positive effect of wealth on cognition in later life. For example, using 10,985 respondents aged 50 to 90 from four waves of the English Longitudinal Study on Ageing (2002–2008), Allerhand, Gale, and Deary (2014) examined how education, wealth (in quintile), and health-related variables (e.g., depression, smoking, exercise) affected cognition longitudinally. Results showed that, controlling for health variables, older adults with more wealth had higher levels of cognition, including general cognition, executive function, memory, and processing speed. In a cross-national comparison study, Lyu, Lee, and Dugan (2014) used a sample of respondents aged 65 and older from 2008 HRS (n = 10,175) and the Korean Longitudinal Study on Aging (KLoSA, n = 3,550) to investigate the relationships between socioeconomic factors (e.g., education, income quartiles, and wealth quartiles) and cognition (measured by orientation, numeric ability, and language), controlling for health (e.g., self-rated health, depression, and sensory problems) and health behaviors (e.g., smoking and drinking). They further examined whether these associations vary between countries. Results showed that wealth, compared to income, was a stronger predictor for better cognition. Older adults with less wealth, compared to their wealthier counterparts, had a lower level of cognition, and such an effect was observed in both older Americans and Koreans.

There are a few studies that investigated variations in the association between wealth and cognition by key demographic variables, such as gender and race. Cagney and Lauderdale (2002), for example, explored the relationship between net worth (categorized into five ordinal groups) and cognition (recall memory, working memory, and knowledge, language, and orientation) among older adults. They further examined whether the associations varied by race (white, black, and Latino). Results showed that wealth was negatively associated with cognition, but this effect was only observed among older whites. In terms of gender differences, using a sample of 4,155 Koreans aged 65 years and older from the 2006 KLoSA, Lee, Back, Kim, and Byeon (2010) studied how multiple SES risks (e.g., low education, lowest income quartile, lowest wealth quartile, and unemployment) were associated with cognitive impairment between men and women. Findings revealed that lower levels of wealth were associated with cognitive impairment in both men and women, however, this effect was much stronger in women.

2.3 Research Gaps

The findings and evidence in research generally support a positive link between wealth and health, indicating that more wealth is associated with better physical, mental, and cognitive health in later life. However, several methodological gaps in research are identified in the current literature.

First, most studies use a cross-sectional design to examine the relationship between wealth and health, thus limiting the conclusions to approach a causal argument. As discussed earlier, wealth is not always the focus in the health-related studies (Baum, 2005). Among the studies that examine the relationship between wealth and health, although a positive link is observed, these findings are primarily based on a cross-sectional design. For example, in research that examines the association of wealth on physical health, many studies only use a single time point to test the wealth-health relationship (see Robert, 1998; Schoenbaum & Waidmann, 1997; Sloan & Wang, 2005; von dem Knesebeck et al., 2003). Similar scenarios are found in the studies on mental health (see Aittomäki et al., 2010; Geyer et al., 2014; Hamoudi & Dowd, 2014; Kim et al., 2011) and cognitive health (see Cagney & Lauderdale, 2002; Hamoudi & Dowd, 2014; Lee et al., 2010; Lyu et al., 2014; Sloan & Wang, 2005). Empirical works that investigate the longitudinal link between wealth and physical, mental, and cognitive health in later life are scant, and whether wealth has a positive effect on health in a longitudinal setting remains unclear.

Second, when examining the influences of wealth on health outcomes, studies tend to treat wealth as a static measure without considering the dynamics in wealth development over time (i.e., accumulation or decumulation). Little is known about the impacts of longitudinal changes in wealth on health; only a few studies examined the trajectory and the heterogeneity of wealth. For example, Rauscher and Elliott (2016) explored income and wealth (operationalized by net worth) trajectories using four waves (1989–2011) of PSID among 3,189 young adults. They further examined how the wealth trajectory is associated with the income trajectory, with comparisons made between the high- and low-income households. Findings suggested that the initial wealth helped to stabilize income and wealth changes among the high-income households, but such effects were not observed among low-income households. Other studies focus on identifying distinct wealth patterns across time. Friedline, Nam, and Loke (2014), for example, examined the wealth (measured by net worth) trajectory classes among 435 households using six waves of PSID (1999–2009). Results showed that two patterns of wealth could be identified: the high and stable group, and the declining group. Loke (2013) used the 1986–2000 National Longitudinal Survey of Youth (NLSY79) to explore the wealth trajectory patterns among young adults. The results showed that four distinct wealth patterns—low and stable, low but accumulating, high and stable, and high and accumulating—can be identified.

Although the studies that exploring the wealth trajectory and patterns are centered on the younger population, the implications from these studies suggest that explorations on the wealth trajectory and patterns using an older sample are promising. In fact, a few studies have examined the wealth trajectory among older adults. For example, using the HRS from 1998 to 2008 HRS, Greenfield (2013) examined the wealth trajectory among 3107 older adults, with a focus on how caregiving experience may impact the wealth trajectory among older caregivers. Another study using HRS from 1998 to 2006, Love, Palumbo, and Smith (2009) examined the trajectory of annualized comprehensive wealth that was constructed by the financial, housing, and annuity wealth among 4630 retirees. However, none of these studies examine how the longitudinal changes in wealth—including the wealth trajectory and patterns—may affect health outcomes in later life.

Third, when research explores the association between wealth and health, most studies only examine one single health outcome at a time. Although some studies explore one or more health outcomes (e.g., Chiao et al., 2011; Sloan & Wang, 2005), these studies mainly explore how wealth influences health *individually*. Such an approach, however, ignores the fact that health in later life is usually codependent or comorbid (Kwon & Park, 2017; Wickrama et al., 2013), and how these health outcomes *jointly* respond to wealth in later life remains unknown. Further, like wealth, health could also change over time. However, among the studies examining the impacts of wealth on health, only one study (Haas, 2008) examined the health trajectory longitudinally, and this study only focuses on changes of physical health over time; none of these studies examined the heterogeneity (i.e., the patterns) of health over time.

Recent evidence has shown that the longitudinal patterns of health can be identified across time. Park, Kwon, and Lee (2017), for example, used the 1998–2010 HRS to identify the longitudinal patterns of cognitive functioning. Results showed that cognitive functioning could be grouped into five categories: stable high, stable low, stable moderate, high-to-moderate (decline), and moderate-to-high (increase). Also, using the 2006–2012 KLoSA, Lee, Park, Kwon, and Cho (2017) examined whether the longitudinal patterns of depressive symptoms varied across poor status, and they found that five distinct patterns (stable high, stable low, high-to-moderate, slight increasing, and steeply increasing) can be identified among poor older adults, and three patterns (high-to-moderate, steeply increasing, and stable low) can be found in non-poor older adults. Lastly, there are some empirical studies examining the "joint health trajectories" by using multiple health outcomes. For example, Kwon and Park (2017) examined the joint trajectory of physical and mental health using 1998–2010 HRS, and Wickrama et al. (2013) used the 1998–2006 HRS to explore joint health trajectories using activities of daily living (ADL), number of chronic illness, depressive symptoms, and memory problems. These empirical works suggest that it is feasible to explore multidimensional health trajectories using multiple health outcomes, and such an exploration could further our understanding on the dynamics between different longitudinal health outcomes (Kwon & Park, 2017).

Lastly, there are several methodological issues that should be considered in the estimates between life course factors, wealth, and health found in the current literature. The first issue is a lack of the use of the multivariate approach in examining the relationship between life course factors and wealth. As Rank (2008) suggested, wealth is highly influenced by the life course factors, including race, gender, employment, marital status, income, education, cohort, and childhood SES factors. Although several descriptive works that describe the bivariate association between some of the life course factors and wealth do exist in the literature, there are very limited studies that focus on how life course factors influence wealth using a multivariate approach. Specifically, we know very little about the "net effect" of each life course factor on wealth, that is, what is the effect of a specific life course factor on wealth, when other life course factors were modeled.

The second issue involves additional tests on the wealth trajectory. Although several studies have examined the longitudinal changes and the patterns of wealth (e.g., Greenfield, 2013; Love et al., 2009), these studies generally do not consider how the wealth trajectory may be influenced by structural influences such as an economic downturn. However, empirical evidence has shown that significant sociohistorical events, such as financial crises (McKernan, Ratcliffe, Steuerle, & Zhang, 2014a; Ruhm, 2015), may substantially impact the development of wealth over time. For instance, using four waves of PSID from 1989 to 2011, Rauscher and Elliott (2016) showed that both the trajectory of income and wealth were influenced by the 2008 financial recession. Specifically, they found that both income and wealth peaked at 2007 and then decreased in 2011, indicating the financial crisis in 2008 altered the wealth trajectory of individuals in a 20-year span. These findings suggest that the role of significant sociohistorical events should be considered in examining the wealth trajectory and patterns, but such investigations have not been fully examined at older ages.

The last issue is the most critical: many of the wealth-health estimates suffer from the endogeneity problem. There are two major reasons can cause endogeneity, with one on the omitted-variable bias and the other on the lack of strict exogeneity in the explanatory variable (Abdallah, Goergen, & O'Sullivan, 2015). The endogeneity problem in the wealth-health estimates is due to a lack of strict exogeneity in the explanatory variable, in this study, the wealth. As previously discussed, life course factors are highly associated with wealth in later life. Although many of the studies examining the wealth-health relationship among older adults do consider the effects of life course factors, these studies only model life course factors on health rather than the wealth indicators. This creates a serious endogenous issue in estimating the relationship between wealth and health (Sherraden & McKernan, 2008), as research has shown that wealth is influence by a series of life course factors (Rank, 2008). To ensure an unbiased estimate between wealth and health, the effect of life course factors on wealth should be modeled.

In sum, several major gaps in the current research that examine the relationship between wealth in later life that should be addressed, including: (1) the use of cross-sectional design; (2) a lack of investigation of the changes—the trajectory and patterns—in wealth and health; and (3) the endogeneity concern in the wealth-health estimates due to life course factors. To address these research gaps, this study uses rigorous analyses to examine the longitudinal relationship between life course factors and the trajectory and patterns of wealth and health in later life.

2.4 Theoretical Perspective

This dissertation seeks to explore how wealth is longitudinally associated with health outcomes in later life, and specifically, how the trajectory and patterns of wealth influence health trajectories and patterns at old age. Further, given the endogenous nature of wealth (Sherraden & McKernan, 2008), the effect of life course factors should be considered when investigating the longitudinal wealth-health association. Three relevant theories—the life-cycle hypothesis, the cumulative advantage/disadvantage model, and the asset-based welfare theory—are used in this study to address the issues on longitudinal changes in wealth and the links between life course factors, wealth, and health.

2.4.1 Life-Cycle Hypothesis

The concept of wealth trajectory is based on the life-cycle hypothesis (Ando & Modigliani, 1963). Life-cycle hypothesis (LCH) posits that saving (i.e., wealth trajectory) in a lifespan is an inverted bell curve, with wealth starting at zero in childhood, increasing in early adulthood as individuals enter the labor market. Wealth reaches its peak at retirement, followed by decumulation, with the expectation that wealth gradually depletes until death (Ando & Modigliani, 1963; Deaton, 2005). LCH is one of the widely-used economic theories that explains how an individuals' wealth accumulation is based on the balance between saving and consumption over a lifespan (Browning & Crossley, 2001). Although several revisions have been made to improve the theoretical interpretability, such as adding the components of precautionary saving (Hubbard, Skinner, & Zeldes, 1994) or bequest motive (Carroll, 1997) to address the non-dissaving issue at the very old age, LCH remains an applicable and testable economic model in explaining the trajectory of wealth across the life course (Deaton, 2005; Hubbard et al., 1994).

LCH has two important features in describing the wealth trajectory in later life. First, LCH suggests that saving is a result of consumption smoothing. LCH assumes that individuals want to maximize their well-being through maintaining a higher standard of living. Because consumption determines individual living standards, in order to achieve utility maximization, individuals will consume as much as their financial resources permit (Nam et al., 2008). LCH further assumes that the relationship between consumption and financial resources will be balanced in the long-run, indicating that standards of living are relatively stable across a lifespan. However, financial resources are not equally distributed across time. Thus, individuals tend to save in order to achieve relatively smooth consumption given the fluctuations of financial resources over time (Ando & Modigliani, 1963; Deaton, 2005).

Further, LCH assumes that variations in wealth can be observed due to individuals' choices and preference. Even when individuals have similar socioeconomic characteristics, differences in wealth across subgroups remain. As Bernheim, Skinner, and Weinberg (2001) suggested, factors related to time preference (i.e., individuals' delayed their consumption), tolerance to financial risks or exposure to uncertainty (i.e., risk averse), preference (e.g., choose to work or retire at old age), and other factors (e.g., gender or race), all play a role in shaping one's wealth trajectory.

LCH informs this study in two ways. First, as the theory suggests that wealth across a life course is an inverted U-shape, it assumes that both the wealth accumulation and decumulation can be observed in one's wealth trajectory across a lifespan, with a decumulation in wealth seen at old age. Second, it suggests that wealth trajectories varied by subgroups, such as gender or race. However, this economic model does not provide theoretical explanations on the variations of wealth trajectory across subgroups and the association between wealth and health, as this study focuses on wealth-health relationship. Therefore, adding the cumulative advantage/disadvantage model and the asset-based welfare theory in this study can better clarify how wealth varies by subgroups and why wealth affects health.

2.4.2 Cumulative Advantage/Disadvantage Model

Cumulative advantage/disadvantage model (CAD) has paid attention to economic inequality, with a focus on how the inequality accumulates throughout a lifespan and how the heterogeneity and trajectory of certain characteristics can be influenced by exposure to early-life adversities or advantages (Dannefer, 2003; O'Rand, 1996). This theory suggests that the accumulation of advantages over time leads to later success, while the accumulation of disadvantages produces unfavorable outcomes. Inequalities between the groups with and without advantages will be revealed at old age (O'Rand, 1996). As this theory is fully influenced by the life course perspective (Ferraro & Shippee, 2009), the CAD model assumes that the accumulation process (for either advantages or disadvantages) is shaped by a series of personal, structural, or environmental factors. Yet, individual choices, such as human agency and individuals' resilience, may also play a major role in shaping one's economic inequality in later life.

Since the CAD model assumes that inequality requires a life-long process of accumulation, inequality can be defined broadly to any characteristic that needs time to develop, such as wealth, health, or socioeconomic status (Dannefer, 2003). Further, as informed by the life course perspective, the CAD model focuses on how earlier life influences, including personal, family, community, social structure, and time/historical, may play a role in affecting a diverse trajectory and producing heterogeneity in later life (Crystal, 2016; Crystal & Shea, 1990; Ferraro & Shippee, 2009; O'Rand, 1996). As such, the CAD model can be used in this study to explain variations in wealth in later life, specifically, how the trajectory and patterns of wealth vary by life course factors that including gender, race, education, income, employment, marital status, historical cohort, and childhood SES factors.

2.4.3 Asset-Based Welfare Theory

Unlike the CAD which focuses on how and what life course factors influence the process of wealth accumulation, the asset-based welfare theory emphasizes the impacts of assets on well-being outcomes (Sherraden, 1991). As Sherraden (1991) and Paxton (2001) note, owning assets will produce psychological, social, and economic benefits because individuals think and act differently when they accumulate assets, and the world responds to them differently as well. Therefore, Sherraden (1991) developed the asset-based welfare theory to illustrate the effects of assets on well-being outcomes, or the so called “asset-effect.”

Two important features are discussed in this theory. The first is the asset-effect. As Sherraden (1991, p. 148) suggested, assets can produce positive influences on individuals’ outcomes, including: (1) improving household stability; (2) strengthening future orientation; (3) promoting human capital; (4) enabling focus and specialization; (5) providing a foundation for risk-taking; (6) increasing personal efficacy; (7) enhancing social influence; (8) increasing civic and political participation; and (9) increasing the welfare of offspring. Paxton (2001) revisited the asset-based welfare theory by summarizing these positive asset effects into three types:

economic, social, and psychological. Specifically, he further stated that asset effects should be examined by investigating the asset-experience, including accumulating assets (ways of asset accumulation), possessing assets (values and types), and spending assets (spending behavior). This theory is further extended by Lerman and McKernan (2008) to cover a wide array of well-being outcomes, including: (1) economic well-being (measured objectively and subjectively), (2) social and civic engagement (e.g., pro-social behavioral outcomes in individual, family, and community levels), (3) health and psychological well-being (e.g., physical, mental, and cognitive health), and (4) intergenerational well-being (e.g., welfare of children, more life chances for children).

Second, the asset-based welfare theory assumes that differential asset trajectories and patterns across individuals can be identified. As Sherraden (1991) suggested, there are many paths of asset accumulation for each individual. For example, individuals with a better socioeconomic standing (e.g., wealthy families) can leverage the assets they have to generate more assets, placing them on a trajectory of upward social and economic mobility. In contrast, people with socioeconomic disadvantages (e.g., poor families) often lack such an opportunity or are prevented from doing so due to the limits set by welfare programs. Because each individual has a different asset trajectory, it is expected that variations in economic, social, health and psychological outcomes can be observed, as the asset-based welfare theory suggests that individuals' well-being outcomes are highly shaped by wealth.

2.4.4 Proposed Theoretical Model

The life-cycle hypothesis, the cumulative advantage/disadvantage (CAD) model, and the asset-based welfare theory can be integrated together, as each theory has the utility to address different research gaps, such as the longitudinal changes in wealth (i.e., trajectory and patterns), the endogeneity of wealth, and the links between life course factors, wealth, and health.

The life-cycle hypothesis suggests that the development of wealth in a life course includes both accumulation and decumulation. However, wealth in later life diminishes steadily, indicating that a decreasing trend in wealth can be observed across all older individuals. Therefore, the life-cycle hypothesis can be used as a base model to describe the longitudinal changes in wealth, with the assumption that, on average, all older adults have a decline trajectory of wealth in later life.

Both CAD and asset-based welfare theory address different aspects of wealth and health in later life, and these two theories can be closely connected. Informed by the life course perspective, the CAD model stresses the importance of early-life influences, assuming the process of accumulation in wealth is influenced by a series of life course factors. Further, it also provides theoretical explanations on variations in wealth by subgroups. Thus, the CAD model can be used to explain the association between wealth and life course factors that include ascribed factors, childhood SES, and adulthood SES variables.

The asset-based welfare theory emphasizes the impacts of wealth on a series of economic, social, and health well-being outcomes, with assumptions that individuals may have differential development in wealth and can be classified into varied trajectory patterns of wealth. Therefore, the use of asset-based welfare theory provides a theoretical foundation for exploring differential wealth patterns in later life; it also provides explanations on the link between wealth and health, in that it assumes more wealth is positively associated with physical, mental, and cognitive health in later life.

Lastly, the connection between the CAD model and the asset-based welfare theory can address the endogeneity issue in wealth. As the CAD model assumes that life course factors are critical predictors for wealth, and the asset-based welfare theory suggests that wealth is closely related to health, the simultaneous use of both theories implies that explorations of the wealth-health link should consider the influences of life course factors on wealth. Such a combination provides a useful theoretical framework to examine the relationship between life course factors, wealth, and health in later life, thus, minimizing the endogeneity problem in wealth when estimating the association between wealth and health.

Combined with the life-cycle hypothesis, the CAD model, and the asset-based welfare theory, Figure 1 lists several key life course factors that have been identified as critical to the development of wealth. Figure 1 further indicates that wealth (e.g., values and types of wealth) may lead to various well-being outcomes, such as economic, social, intergenerational, and health and psychological well-being. This study focuses on the health outcomes, as this study aims to understand how physical, mental, and cognitive health individually and jointly relate to wealth in later life.

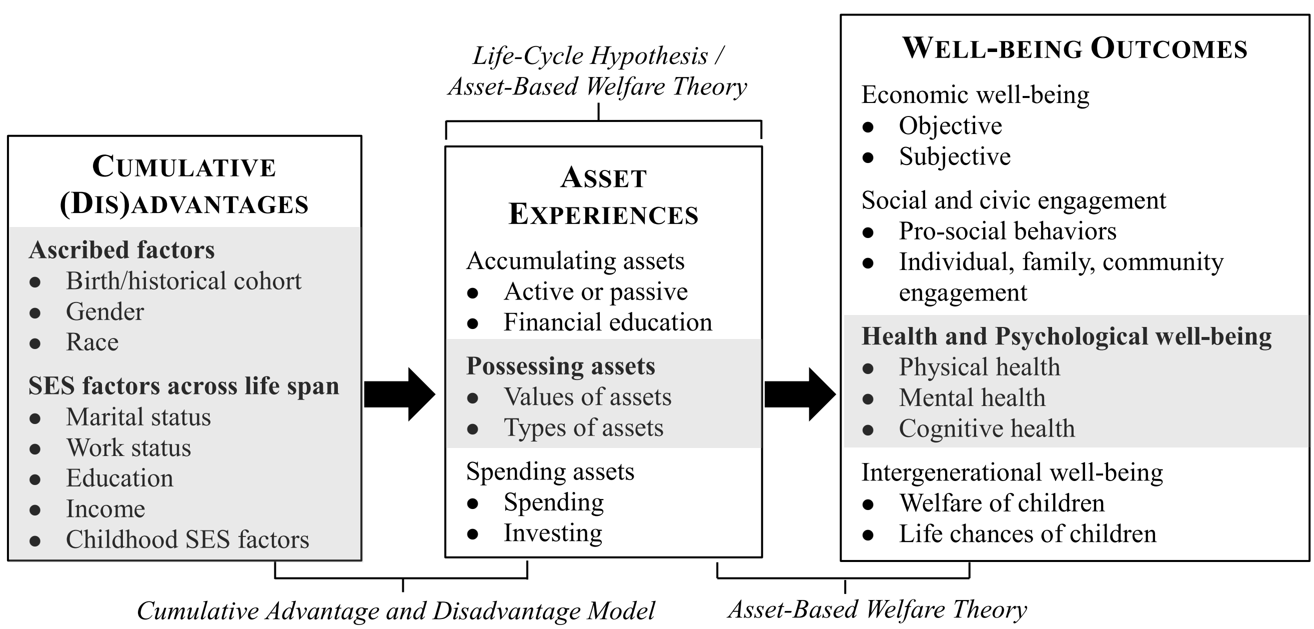

Figure 1. Proposed Theoretical Model

2.5 Research Questions and Hypotheses

To address the research gaps, this study uses a longitudinal data set—the Health and Retirement Study (HRS) from 2004–2014—to investigate the trajectory and patterns of wealth of older Americans. Further, this study examines how multiple health outcomes (i.e., physical, mental, and cognitive health) individually and jointly respond to the wealth trajectory. Finally, this study explores the heterogeneous patterns for both wealth and health trajectories, and examines the longitudinal association between wealth patterns and health patterns in later life. Three research questions (RQ) and hypotheses in this study are listed below.

RQ 1: Does wealth trajectory in later life (i.e., intercept and slope of wealth) vary by cumulative disadvantages (i.e., life course factors)?

H1: Older adults' wealth declines over time (i.e., the slope of wealth is negative).

H2: Older adults with cumulative disadvantages (e.g., older adults who are female, non-white, not married, unemployed, low education, low-income, born in later cohorts, and with lower childhood socioeconomic status) have lower levels of initial wealth (i.e., the intercept).

H3: Older adults with cumulative disadvantages (e.g., older adults who are female, non-white, not married, unemployed, low education, low-income, born in later cohorts, and with lower childhood socioeconomic status) have a slower rate of decline in wealth, partly because they have lower levels of wealth to deplete across time.

RQ 2: How does wealth trajectory (i.e., intercept and slope of wealth) relate to health trajectory (i.e., intercept and slope of health), including physical, mental, and cognitive health, in later life?

H4: Older adults' overall health, assessed by physical mobility limitations, depressive symptoms, cognition and self-rated health, declines over time (i.e., the slope of overall health is negative).

H5: Older adults with higher initial wealth have better initial health and have a slower rate of decline in health over time; that is, the intercept of wealth trajectory (i.e., initial levels of wealth) has a positive effect on both the intercept (i.e., initial levels) and slope (i.e., rates of change) of health.

H6: Older adults with declines in wealth have a faster rate of decline in health; that is, the slope of wealth has a positive effect on the slope of health.

RQ 3: What are the patterns of wealth and multidimensional health in later life, and how do these patterns relate to each other longitudinally?

H7: Older adults with wealth patterns that are either maintained at the higher level or increasing over time have health patterns that indicate a maintenance or improving health status.

Chapter 3: Methods

This chapter outlines the methods used in this dissertation, including the data source, sample selection, measurements for the variables of interest, and analytical approach.

3.1 Data and Sampling Strategy

3.1.1 Data Source

Six waves of the publicly-available Health and Retirement Study (HRS), from 2004 to 2014, were used in this study. Although 2016 data are currently available (Early Version 2, released in July 2018), it only provides partial information and notable errors may exist. Therefore, the 2016 data are not used in this dissertation but will be included for future publication. Beginning in 1992 and funded by the U.S. National Institute on Aging and the Social Security Administration, the HRS has become a leading source for researchers to study wealth, life course, and health of older Americans. The HRS collects data from a national representative sample of community-dwelling Americans aged 51 and older and their spouses every two years, resulting in a sample with approximately 20,000 respondents in every wave.

The HRS uses multi-stage probability design with considerations of geographic stratification and clustering with oversampling for African Americans, Hispanics, and residents of Florida (Sonnega et al., 2014). To address the sample attrition issue over time, the HRS has refreshed its sample every sixth year since 1998 to ensure the representativeness of the US population; each newly refreshed sample represents a birth cohort in the HRS. See Figure 2 for more details.

Several data sources associated with HRS were used in this study. First, this study uses the *RAND HRS Longitudinal File 2014* (v.3) created by the RAND Corporation, a cleaned, organized, and imputed version of all waves of HRS data (since 1992) that includes important wealth and health measures. Using the HRS has several advantages. First, the HRS provides rich data on economic and health variables among nationally-representative older Americans. Most importantly, as HRS surveys individuals from middle-age, this design allows explorations of the dynamics and transitions in wealth and health longitudinally, which is critical to this study, as this dissertation seeks to understand the longitudinal association between wealth and health in later life.

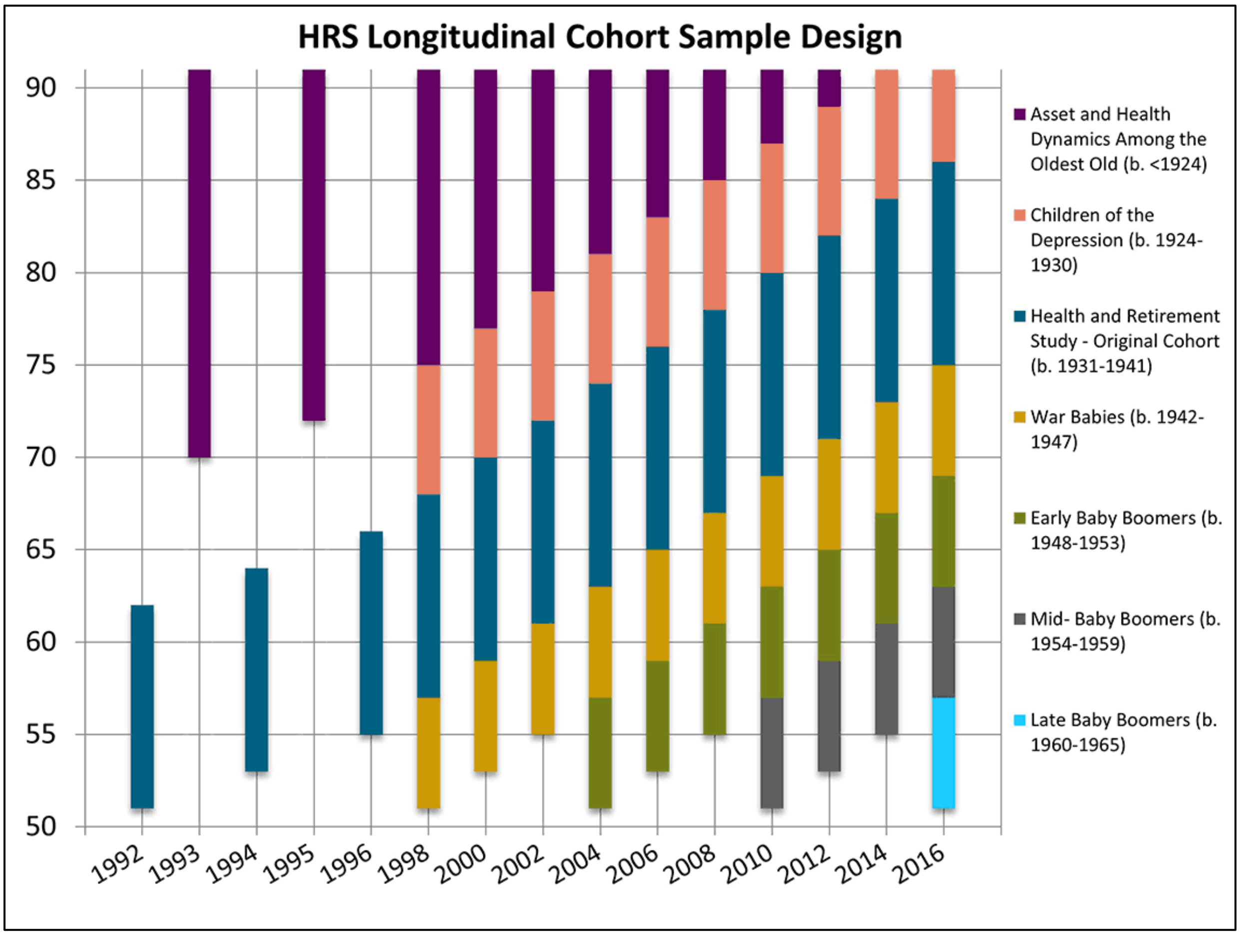

Figure 2. HRS Longitudinal Cohort Sample Design. Source: (Health and Retirement Study, n.d.)

Second, to systematically collect all life course variables—especially the childhood SES variables—that are examined in this dissertation, this study used nine waves of the *RAND HRS*

Fat File from 1998 to 2014, as childhood SES variables were collected since 1998. Third, the variables related to survey analyses, including clusters, stratum, and person-level analysis weights, were extracted from the *Tracker File 2016* (v.1.0) to address the complex survey design in the HRS. Lastly, the rural/urban status was selected from the *Census Region/Division and Mobility File* (v.6.1). All these cross-wave data sets were merged with the *RAND HRS Longitudinal File* based on the personal and household identifiers.

3.1.2 Sample Selection

Respondents aged 51 and above at the baseline (2004) were selected from the *RAND HRS Longitudinal File*. As the RAND HRS contains survey respondents from 1992 and onward, sample attrition due to death, loss of contact, or refusal to participate in HRS may occur prior to the proposed study timeframe (2004–2014). This study therefore excluded the attrited sample before the year 2004, indicating that all selected respondents were alive in 2004. Further, this study excluded respondents aged below 51 at the baseline, as the respondents aged 51 and older were representative to the national profile in the US, if sampling weights were utilized.

The attrition issues and other sample criteria are also considered in the following sample selections. First, as this study used six time points of data from 2004–2014 HRS, this study excluded respondents if they were missing more than three times (i.e., 50% of the study period) due to death, loss of contact, or refusal to participate. It should be noted that this selection criterion also excludes the respondents who joined in the 2010 HRS (i.e., Mid-baby boomers, see Figure 2.) as they did not have any information between 2004 and 2008. Further, although the HRS collects data from a community-dwelling sample, respondents living in nursing homes could be followed up with in later waves, but their health and wealth information are not collected. This study removed these nursing home samples to ensure all respondents were community-dwelling older adults. Lastly, the preliminary result for the race distribution showed that there was a small group of respondents who identified themselves as other races (less than 3%). Therefore, this study further removed respondents who reported themselves as other races to better reflect how race may influence both wealth trajectory and patterns in later life. The final sample in this dissertation includes 16,189 unique individuals across six time points; see Figure 3 for details.

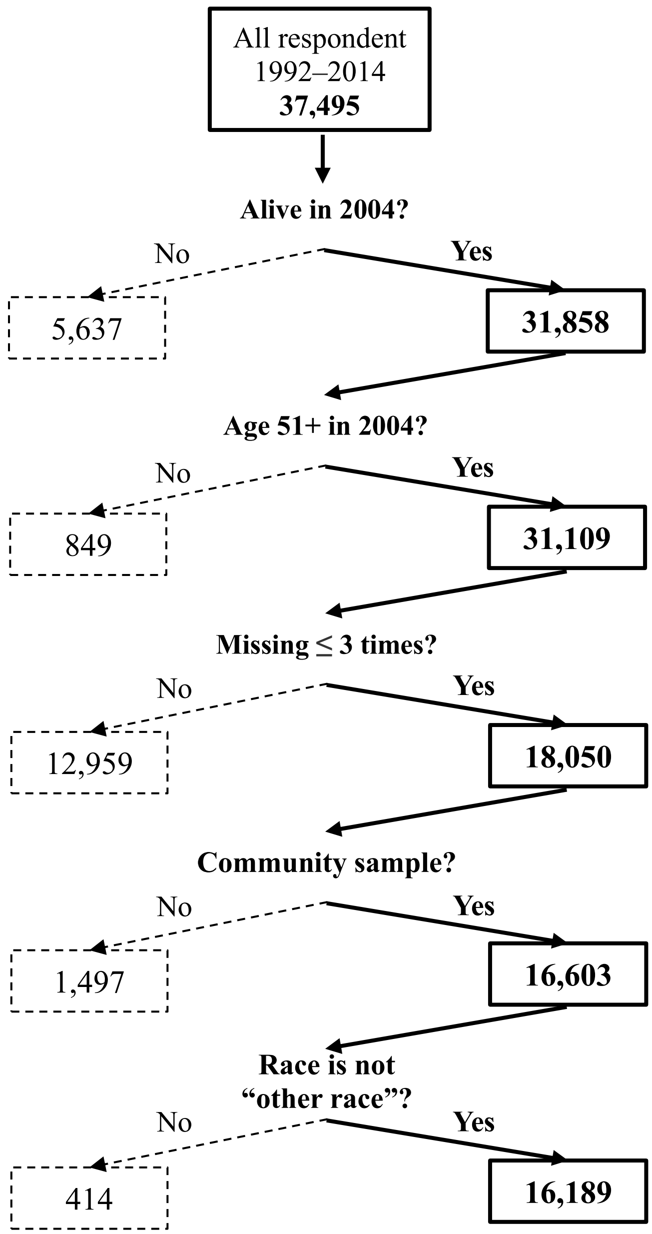

Figure 3. Sample Selection Flow-chart

3.1.3 Protection of Human Subjects

As this dissertation uses de-identified, publicly-available data, with no access to any identifiable information, this study is not considered a human subject study. The Washington University in St. Louis Institutional Review Board (IRB), the Human Research Protection Office (HRPO), approves this study (IRB ID No. 201803015).

3.1.4 Treatment for Missing Data and Attrition

Missing values should be considered in the longitudinal studies because exclusion of these missing values may bias the estimates and the standard errors. Missing values in longitudinal data include death of a respondent, non-response, or loss of contact. This study uses two approaches to address the missing values and attrition. For **RQ1** and **RQ2**, because of the use of SEM via M*plus*, it allows full information maximum likelihood (FIML) estimation to impute the missing values. The FIML imputation is a model-based approach to handle missing data (Little, 2013), indicating that the parameters of a SEM model are estimated when missing values are presented, and every piece of information in the variables is used to model for both parameter estimates and standard errors (Little, 2013; Wang & Wang, 2012). As Wickrama et al. (2013) indicated, the FIML used limited data from the respondents and calculated respondents' contribution in each time point, and the information could be used to estimate the portion of the trajectory for both wealth and health. The FIML was used to impute the missing values for **RQ1** and **RQ2** when the six waves of wide-form HRS data were used.

The second approach is multivariate imputation with chained equations (MICE) using Stata, a data-based approach to handle missing values when the patterns of wealth and health in **RQ3** were identified. Because the wealth and health patterns address the longitudinal changes from six waves of HRS data, each individual is grouped into a distinct trajectory pattern based on their performance in wealth and health longitudinally, which results in a wide-form data with one variable indicating wealth patterns and another representing health patterns. To estimate the relationship between patterns of wealth and health while correcting the endogeneity of wealth due to life course factors, this study uses MICE to impute missing values. The MICE is a flexible method to impute missing values and it has advantages to impute both categorical and continuous variables using different link functions (e.g., logit for binary variable, multinomial for categorical variables, and linear for continuous variables) (White, Royston, & Wood, 2011). Further, the MICE uses multiple data sets to address the statistical uncertainty across imputed data sets (Royston & White, 2011), and therefore it obtains less biased parameter estimates and standard errors when compared to traditional methods such as listwise deletion, pairwise deletion, or dummy variables adjustment of missing values.

There is no consensus on how many imputed data sets should be produced, with possible numbers range from at least 5 to 100 or more. Graham, Olchowski, and Gilreath (2007) suggested that 20 imputed data sets may be sufficient, as simulation results showed that 20 imputed data sets demonstrate a similar efficiency in addressing missing values when compared the results based on 100 imputed data sets (Graham et al., 2007). Therefore, a total of 20 imputed data set are created, and the results were combined using Rubin’s rule (Rubin, 1987). The preliminary analyses in this study using 20 imputed data sets showed that the relative efficiency was close to an average value of 0.99 (max = 1.00), indicating the multiple imputation technique provides good estimates for estimating variance in regression-type models.

Both FIML and MICE are used in this study to handle missing values in the longitudinal data sets. However, it should be noted that the attrition or missing cases due to death may also be imputed through these imputation methods. This study uses two ways to increase the precision in model estimation. First, a time-invariant attrition variable that captures the death of respondents and other missing reasons over the six time points is created and being controlled for in the model. Second, the study employs a person-level analysis weight from the *Tracker File*. The use of personal weight in the analyses not only makes the analyses representative of the national profiles, but accounts for both missing and attrition due to death, as a dead respondent is assigned 0 in the personal weight. Using estimates of wealth-health patterns as an example, this study conducts sensitivity tests to compare the results across three models: (1) imputation with only personal weight applied; (2) imputation with attrition variable controlled; and (3) imputation with consideration for both personal weight and attrition variable. Results showed that the estimates do not differ across models, but the combined use of imputation, personal weight, and attrition may produce a much more conservative result (see Appendix A). Therefore, this study uses imputation (both FIML and MICE), personal weight, and attrition variables throughout to address missing values in six waves of the HRS.

3.1.5 Cluster, Data Collection Effect, and Complex Survey Design

Based on Sonnega et al. (2014), the HRS uses a multi-stage area probability design, with consideration for geographic stratification and clustering, to sample respondents aged 51 and older. In the sample selection process, HRS has always oversampled African Americans, Hispanics, and respondents residing in Florida. If the respondent is coupled, then his/her spouse or partners are also included in the HRS, regardless of their age. Respondents from the single household answered all questions. For the coupled household, each respondent is either assigned as a financial respondent or a family respondent, with financial respondents answering questions related to income, housing, and wealth, and family respondents answering questions associated with family composition and transfer. Both financial respondent and family respondents share exact the same information in questions related to wealth and family, indicating a clustering nature in these variables. Further, the mode of interview may differ across respondents in the process of data collection. Prior to 2004, most baseline interviews were conducted face-to-face (FTF), with phone interviews used in the follow-up waves. However, respondents aged 80 and older are offered FTF interviews. Beginning in 2006, the HRS used mix-method design for data collection, with half of the sample assigned to FTF interview and the other half assigned to phone interview. The mode of interview alternates every two years, indicating that a respondent will use the same interview method (either FTF or phone interview) every four years. These data collection designs may create methodological issues when conducting data analyses; below lists how this study addresses these analysis issues.

The first issue is the clustered nature of wealth. Wealth is the main variable of interest because this study aims to identify both the trajectories and patterns of wealth for older adults, but the data collection procedure introduces a clustered effect in wealth, as wealth is measured at the household level with answers provided by one of the respondents (i.e., financial respondent). To correct the clustered nature in wealth, this study considers the cluster effect by using the household identifier as a clustering variable when exploring both the trajectory (using latent growth curve modeling) and patterns (using latent growth mixture modeling) of wealth. See section 3.3.2 for details of these methods.

The second is the potential “method effect” in influencing both wealth and health. Because the HRS uses different interview methods, including the FTF and phone interview, these data collection methods may affect the quality of wealth and health. The sensitivity test in Appendix B showed that respondents using FTF interview method had a higher score in depressive symptoms and lower score of cognition compared to respondents using phone interview.

However, there was no statistical difference in wealth. This is probably due to respondents who use FTF are much older, as respondents aged 80 and older are offered this method. Therefore, this study controls for the type of interview method when estimating the health outcomes but not for wealth, as wealth does not differ across interview methods.

Lastly, because the HRS uses multi-stage design to collect data, this study uses sampling weights to account for differential probabilities of selection, with consideration for geographic stratification and clustering, to make the estimates reflect the national profiles and close to the population inference (Sonnega et al., 2014).

3.2 Measurement

3.2.1 Wealth Measure: Net Worth

The HRS collects varied types of wealth measures of older Americans, including (1) home (primary residence); (2) other real assets; (3) vehicle; (4) business; (5) retirement account (e.g., individual retirement accounts, IRA; Keogh accounts); (6) stocks, mutual funds, and investment trusts; (7) checking, savings, and money market accounts; (8) certificates of deposit (CDs); (9) government saving bonds and treasury bills; (10) other types of assets; and (11) secured and unsecured debts such as mortgages, loans, and other types of debts.

Construction of a wealth measure in later life remains inconclusive in the literature because inclusion or exclusion of certain types of wealth may significantly alter the study findings (Greenfield, 2013; Smith, 2002). To address this issue, a systematic review of the types of wealth holdings in later life (C. E. Pollack et al., 2007) showed that the most common wealth holdings of older adults include savings (e.g., checking, savings, & CDs), investments (e.g., stocks, mutual funds, and bonds), retirement accounts and pensions (e.g., IRAs), home ownership (primary residence and/or other real assets), and business/vehicle equity. To draw a clear trajectory of wealth in later life, the effect of debts should be considered in the construction of wealth measure. Therefore, this study operationalizes wealth as the sum of all types of wealth net of debts reported by the respondents; in other words—the net worth. Evidence suggests that this measure has been widely used in the current scholarship (Friedline et al., 2014; Greenfield, 2013; C. E. Pollack et al., 2007; Rauscher & Elliott, 2016). This measure was used to construct the wealth trajectory and patterns, with one serving as an outcome in **RQ1** and the others serving as a predictor for **RQ2** and **RQ3**.

This study uses dollars of net worth instead of changes, because using total value adds clarity to interpretation (Greenfield, 2013). This study does not consider income as a part of wealth measure due to the fact that income has little variation and only addresses in part the economic resources in later life. It should be noted that, although wealth may be dependent in part on income, adding income into the wealth measure may confound the findings, as these two constructs (i.e., wealth vs. income) are distinct in nature (Sherraden, 1991). Further, this study aims to test the asset-effect using wealth measure, that is, examine the effect of net-worth which is independent from income. Therefore, this study treats income as part of life course correlates and is modeled throughout analyses.

In addition, wealth is notoriously skewed, and the inclusion of skewed variables in the model may bias the results. Because wealth measure can have negative values, this study chooses inverse hyperbolic sine (IHS) transformation (Friedline, Masa, & Chowa, 2015; Pence, 2006) over the traditional transformation method (e.g., logarithm transformation) to correct the wealth measure, as the IHS transformation has the ability to keep the negative values while simultaneously correcting the serious skewness. Further, the IHS transformation demonstrates a better ability to correct the skewness of wealth compared to other methods; Appendix C presents these findings. The values of wealth and income in each wave were adjusted to the 2014 level using the CPI inflation calculator (https://data.bls.gov/cgi-bin/cpicalc.pl) to ensure the values were comparable across waves.

3.2.2 Health Measures: Physical, Mental, and Cognitive Health

Three types of health outcomes that capture physical, mental, and cognitive health were used in this study. Physical health is measured objectively and subjectively. For the objective physical health, an index combining 11 binary items (1 = *yes*, 0 = *no*) of physical mobility was used (*range*: 0–11) (Haas, 2008; Kwon & Park, 2017). This measure captures the "mobility function" of physical health, providing sufficient variances, and is suitable for use if a sample involves a middle-aged population (Kwon & Park, 2017). These 11 items included: (1) walking one block; (2) walking several blocks; (3) sitting for two hours; (4) getting up from a chair; (5) climbing one stair; (6) climbing several stairs; (7) keeling, kneeling, or crouching; (8) lifting or carrying weight over ten pounds; (9) picking up a dime from a table; (10) reaching one's arm over the shoulder; and (11) pulling or pushing large objects. This measure has been validated as a reliable measure for assessing physical health in later life (Haas, 2008; Kwon & Park, 2017). In addition to the use of objective health measure, a reverse-coded single item of self-reported health status (1 = *poor*, 5 = *excellent*) was used to capture the subjective aspect of physical health. Both measures capture the objective and subjective aspect of physical health.

Mental health was assessed by eight binary measures (1 = *yes*, 0 = *no*) of the modified version of the Center for Epidemiological Studies-Depression (CES-D) scale. The items of CES-D include: (1) felt depressed; (2) felt everything respondents did was an effort; (3) sleep was restless; (4) felt happy; (5) felt lonely; (6) felt sad; (7) could not get going; and (8) enjoyed life. Two positive-worded items (i.e., felt happy and enjoyed life) were reverse coded and then combined with the other six measures (*range*: 0–8), with a higher score indicating more depressive symptoms. This measure has been evaluated as a reliable and valid measure in assessing mental health of older Americans (Wickrama et al., 2013).

Cognitive health (*range*: 0–27) was measured by the sum scores of the number of words recalled immediately and with a delay, Series 7s, and the ability to count backwards from 20. These three measures are a subset of the telephone interview of cognitive status (TICs) in the HRS, as the full TICs is only assessed among respondents aged 65 and older. Although this study used a subset of TICs, these three measures have been widely used as a valid measure for cognition (see Cagney & Lauderdale, 2002; Hamoudi & Dowd, 2014; Sloan & Wang, 2005).

3.2.3 Adulthood Life Course and Ascribed Factors

From a life course perspective (Hutchison, 2005; Rank, 2008; Sullivan & Meschede, 2016) and cumulative disadvantage model (Crystal, 2016; Crystal & Shea, 1990; Dannefer, 2003), wealth is highly influenced by life course factors, and therefore when testing the association between wealth and health, the effect of life course on wealth should be controlled in order to correct for endogeneity issues (Sherraden & McKernan, 2008). This study controls both time-varying and time invariant life course factors (Kwon & Park, 2017; Rank, 2008), including ascribed factors and socioeconomic status (SES) across life course in the model.

Ascribed factors are time-invariant factors, including: gender (1 = *female*, 0 = *male*), race (1 = *white* [reference group], 2 = *black*, and 3 = *Hispanic*), and a cohort variable constructed by the RAND HRS based on respondents' birth year (1 = *AHEAD cohort* [reference group], born prior to 1923; 2 = *CODA cohort [Children of Depression Era]*, born 1924–1930; 3 = *HRS cohort*, born 1931–1941; 4 = *WB cohor*t [War Baby], born 1942–1947, and 5 = *EBB cohort* [Early Baby Boomer], born 1948–1953).

SES variables include a time-invariant education level (in years, up to 17 years) and a time-varying income level (in dollars) that is constructed by RAND HRS by combining all sources of income, including earned income and income from pensions, capitals, and other sources. Education was dichotomized as a binary measure indicating whether a respondent has a college degree or not (1 = *No college degree*, 0 = *College degree*) (Kwon & Park, 2017; Lyu & Burr, 2016). Following the method proposed by Turrell et al. (2002) and Luo and Waite (2005), the income was dichotomized as a binary measure indicating whether a respondent's income was below the median values in each wave (1 = *Below median income*; 0 = *Above median income*).

Marital status and working status could be changed over time, but previous studies showed that these two constructs may have few variations across time (Kwon & Park, 2017; Park et al., 2017). However, to capture the changes over time, this study creates the proportion of time for these two variables, indicating the numbers of time points that respondents remained married or working across time.

3.2.4 Childhood Life Course Factors

Four life course measures related to socioeconomic status (SES) in childhood were used: Parents' education (for both father's and mother's education), father's occupation, and family economic status in childhood. Although there are other childhood SES indicators in the HRS, this study chooses these four variables to be consistent with the current literature when discussing the effect of childhood SES measures on both wealth and health (see Kwon, Kim, Lee, & Park, 2018; Luo & Waite, 2005; Lyu & Burr, 2016). All these time-invariant variables are firstly being surveyed in 1998 HRS, with additional samples answering the exact same set of questions in follow-up waves. The childhood SES variables between 1998 and 2014 were merged together in this study.

Parents' education was measured by the respondents' report of their father's and mother's highest education level (in years, up to 17 years). Following previous studies (Brown, 2010; Kwon & Park, 2017; Luo & Waite, 2005; Lyu & Burr, 2016), this study dichotomized parents' education using eight years as a cut-off (1 = *Low education [less than 8 years]*; 0 = *Higher education [more than 8 years]*). Father's occupation—a categorical variable indicating the types of industry—is reported by the respondents about their father's occupation when they were age 16; detailed information of occupation categories are presented in Appendix D. Following the methods described by Lyu and Burr (2016) and Luo and Waite (2005), this study dichotomized the father's occupation into two levels: white-collar occupation (including management, professional position, sales, clerical, and service) and blue-collar occupation (all other positions), with white-collar occupation serving as a reference group (1 = *Blue-collar*; 0 = *White-collar*). Lastly, the family economic status was measured by a single item "*Now think about your family when you were growing up, from birth to age 16. Would you say your family during that time was pretty well off financially, about average, or poor?*" Followed studies of Kwon and Park (2017) and Kwon et al. (2018), a binary measure was created to capture whether respondents were poor in childhood (1 = *Poor*; 0 = *Average/Well off*).

It is possible that respondents may not have had either a father or a mother growing up, resulting in missingness or non-responsive values in the childhood SES variables. In this study, there are 15.8% and 9.9% missing in father's education and mother's education, respectively. These missing proportions are similar to what Lyu and Burr (2016) had found in a sample of respondents aged 65 and older using 1998 to 2010 HRS, in that they found about 15.4% of the father's education and 12.4% of the mother's education were missing. Currently, there are three approaches in dealing with missing values in the childhood SES variables, including: (1)

combining the missing group with the group with lower values (i.e., low parents' education and blue-collar job) (Brown, 2010; Luo & Waite, 2005); (2) controlling for missing indicators (Lyu & Burr, 2016); and (3) keeping the missing values but using multiple imputation (Kwon et al., 2018; Kwon & Park, 2017) to address missingness. This study chooses the third approach, as it is much more conservative and robust in dealing with missing values in childhood SES variables.

3.2.5 Covariates and Control Variables

Covariates for wealth and health measures were also controlled in this study, including: age (continuous), rural/urban status (1 = *Urban*; 0 = *Rural*), childhood self-rated health status (1 = *Poor*; 0 = *Average/Good*), numbers of chronic diseases (continuous); all four were from the baseline. Further, a time-invariant attrition variable (1 = *Attrition due to death or non-response*; 0 = *Not attrition*) and a time-varying method of interview (1 = *Face-to-face interview*; 0 = *Phone interview*) were also controlled in the model, as previous discussions show that these two measures may influence the quality and estimates for wealth and health outcomes.

3.2.6 Descriptive Statistics

Appendix E presents the descriptive statistics of the study variables by each wave. The average age for the respondents were 65.45 years old, and approximately three in five (57.06%) were females. Overall, about seven in ten (71.85%) respondents identified as white or Caucasian, followed by black or African Americans (16.76%) and Hispanics (11.39%). In terms of education and income, about four in five (78.23%) of respondents did not have a college degree, and about one half of respondents reported their income below median values across time. About half of the respondents (48.08%) lived in urban area. In terms of proportion of time that a respondent stayed married and remained at work, about 33% and 64% of the time respondents were still at work and stayed married.

Overall, the health status of respondents declines over time, with mobility limitations and depressive symptoms increasing as well as self-rated health and cognition decreasing as respondents age. The descriptive statistics of health generally support a linear decline in health, but such a statement needs to be confirmed by the analysis discussed in the next section. In terms of wealth, the trend supports a decline in wealth over time, but such a decline is not as clear as health outcomes that were shown in the Appendix.

3.3 Analyses

3.3.1 Overview of the Analytical Approaches

In this dissertation, three questions are proposed to examine the relationship between life course factors and the trajectory and patterns of wealth and health in later life. **RQ1** examines how life course factors influence wealth trajectory, and **RQ2** investigates how wealth trajectory influences health trajectory when the life course factors were modeled. Both questions were answered using latent growth curve modeling (LCGM) via SEM approach. To address **RQ3** in exploring the heterogeneity for wealth and health, latent growth mixture modeling (LGMM) was used to identify the trajectory patterns for both wealth and health, followed by a generalized propensity score analysis to assess the longitudinal relationship between the patterns of wealth and health, with considerations for the influences of life course factors on wealth patterns.

The contents of the analytical approach are organized as follows. Sections 3.3.2 to 3.3.4 introduce the methodological concepts for both LGCM and LGMM, followed by section 3.3.5 which describes the evaluation methods using model fit indices for these two types of analyses in the SEM framework. It concludes with section 3.3.6, which provides details of the generalized propensity score procedures on how such a method can be used to account for endogeneity due to life course factors when estimating the relationship between wealth patterns and health patterns in later life.

3.3.2 Latent Growth Curve Modeling and Latent Growth Mixture Modeling

Using SEM built within Mplus 7.4, this study used latent growth curve modeling (LGCM) and latent growth mixture modeling (LGMM) (Grimm et al., 2017; Wickrama et al., 2016) to explore trajectory and patterns for both wealth and health. The benefit of using SEM to handle longitudinal data rather than the use of the multilevel analysis is that SEM provides indices to evaluate the model fit (e.g., root mean square error of approximation, RMSEA; comparative fit index, CFI; and Tucker-Lewis index, TLI) based on how well the model captures the observed data (Grimm et al., 2017).

LGCM is a SEM approach in which the growth curves are estimated from fixed paths in the measurement model. The growth curves describe the *inter-individual* changes over time by estimating two latent constructs in the SEM: the initial level (the intercept, π_{0i}) and the growth curve (the rate of change over time, $\pi_{1i}t$) (see **Eq. 1**; adapted from Wickrama et al., 2016 , p. 23). Using wealth as an example, the initial level (i.e., latent intercept) indicates the average wealth at the baseline or the starting point of the time. The growth curve (i.e., latent growth factor) describes the change in wealth over time, and is defined as an average trend of wealth. The growth rate could be specified as a linear function (i.e., the change in wealth is a linear function of time) or as a polynomial non-linear function (e.g., quadratic, cubic, or higher-order functions of time) (Wang & Wang, 2012). Accordingly, LGCM assumes that individuals are all drawn from a single population with common population parameters, resulting in an estimate for the trajectory as a single mean estimate (Grimm et al., 2017; Wickrama et al., 2016).

$$y_{it} = \pi_{0i} + \pi_{1i}t + \varepsilon_{it}\,,\ \ \varepsilon_{it} \sim NID(0, \sigma_{it}^2) \qquad \textbf{(Eq. 1)}$$

The application of using LGCM in wealth is scant; only one study was identified in the current scholarship. Rauscher and Elliott (2016) explored income and wealth (operationalized by net worth) trajectory using four waves (1989, 2003, 2007, and 2011) of PSID among 3,189 young adults. Specifically, they explored how income and wealth trajectory were influenced by the 2007–2008 financial recession, and examined how income trajectory was associated with wealth trajectory. These findings were further compared between high (income > $50,000) and low-income (< $50,000) households. Results showed that the trajectory of income and wealth was influenced by the financial crisis, with both income and wealth peaking at 2007 and then decreasing in 2011. They further found that initial wealth helped to stabilize income and wealth changes among higher income household, but such effects were not observed among low-income households.

Although empirical study has supported the use of LGCM to explore wealth trajectory, this *homogeneous* assumption may not be accurately specified because there may be *heterogeneous* subgroups or patterns within the population, as the development of wealth is usually heterogeneous across time. For example, if the LGCM identifies the trajectory of wealth as linear on average, distinct patterns of linear change, either a positive (i.e., wealth accumulates over time) or a negative (i.e., wealth declines over time) trend, may still exist in this mean linear trajectory. To address this possible misspecification issue, the LGMM is used. LGMM is an extension of LGCM that relaxes the single population assumption to allow differential parameter estimates across identified subpopulations. This indicates that the mean growth curves from the overall population are broken down into several "homogeneous" distinct patterns or trajectory classes (*k* groups or latent classes *c*) based on the probabilities in differential trajectories (see **Eq. 2** for individual *i* at time *t* in class *k*; Wickrama et al., 2016, p. 201); such a technique enables us to identify information about inter-individual differences in *intra-individual* changes involving unobserved heterogeneity within a large population (Grimm et al., 2017; Wickrama et al., 2016).

$$y_{kti} = \sum_{k=1}^{k} P\,(c = k)(\pi_{k0i} + \pi_{k1i}t + \varepsilon_{kit}),\ \varepsilon_{kit} \sim NID(0, \sigma_{kt}^2) \qquad \textbf{(Eq. 2)}$$

Although the application of using LGMM in wealth in later life is still in its nascent stages, there are a few empirical works that have been done in children and youth populations. Friedline et al. (2014), for example, used LGMM to explore the wealth trajectory classes (measured by net worth) among 435 households using six waves of PSID (1999–2009). Specifically, they examined how households' wealth trajectory classes were associated with youths' savings account ownership and amounts of saving. Results showed that two wealth trajectory patterns (high and stable vs. declining, reference group) were identified. In addition, high and stable wealth trajectory was positively associated with youths' savings amount and savings account ownership, but these effects were not observed in declining group. Another study using the 1986–2000 National Longitudinal Survey of Youth (NLSY79), Loke (2013) explored how the net worth trajectory classes were associated with youths' education attainment (e.g., college attendance and graduation), and how such a relationship was mediated by both mothers' and children's expectations. The study identified four wealth patterns (low and stable [reference group], low but accumulating, high and stable, and high and accumulating). Results showed that, youths born into households with higher wealth patterns were more likely to attend college and graduate from college. Youth in the lower-income households, however, had similar education outcomes as their wealthier counterparts if the households had a low but accumulating pattern in wealth. Results further showed that the effects of assets were either partially or fully mediated by the mother's educational expectations.

Both LGCM and LGMM are necessary to address the study's questions. This study first identified the trajectory of wealth and examined how it relates to life course factors (**RQ1**). Next, this study explored the individual and joint health trajectory when physical, mental, and cognitive health were simultaneously considered, investigating the association between wealth trajectory and health trajectory (**RQ2**). Both questions were answered using LGCM. Additional tests for wealth trajectories using quadratic and piece-wise functions and explorations for the individual- and joint-health trajectories were examined, with details documented below in section 3.3.3 and 3.3.4. To address the heterogeneity in wealth and health (**RQ3**), the LGMM is used to identify the patterns based on the trajectory found previously in wealth and health. After the patterns for both wealth and health were identified, a generalized propensity score analysis was used to address the endogeneity of wealth due to life course factors when estimating the relationship between patterns of wealth and health. Section 3.3.6 describes the procedures.

3.3.3 Additional Test for Wealth Trajectory

For the constructions of wealth trajectory, guided by the CAD model, this study considers the effect of historical events on wealth trajectory. As this study uses the 2004–2014 HRS to model the wealth trajectory of older Americans, the wealth trajectory may be influenced by the 2007–2008 economic recession. For example, the wealth trajectory may be identified as a positive slope between 2000 and 2008. However, due to the economic recession, this increasing trend of wealth trajectory may be reduced to a slightly flat slope or may even be diverted to a negative slope. To address this non-linear form in wealth trajectory, this study uses two approaches to address the "transitions" in wealth trajectory, with one model using a polynomial function of wealth trajectory with *unknown* time point for transition (e.g., quadratic or cubic terms), and another model using a piece-wise LGCM (Kohli & Harring, 2013) that allows the growth curves to vary before and after 2007–2008—a known time point—to account for the impacts of the financial crisis on the wealth trajectory. According to Wang and Wang (2012), both the polynomial function and the piece-wise LGCM are a type of model to re-estimate the growth curve (latent growth factor) by breaking up the growth into separate linear segments or pieces. Each segment represents an individual slope, but these slopes are joined or tied to adjacent segments at fixed time points. The joint points are referred to as knots or splines. Models of the polynomial function of wealth and the piece-wise LGCM are used as additional tests to address the possible “period” effect that causes a non-linear trajectory in wealth change over time.

3.3.4 Individual and Joint Health Trajectory

Another analytical issue is the construction of health trajectory. As one of the purposes of this dissertation is to examine how health individually and jointly respond to the wealth trajectory, this study tested both the parallel process model (PPM) and the curve-of-factor model (CFM) (Wickrama et al., 2016) to model the individual and joint effect of health when physical, mental, and cognitive health are simultaneously considered. Both analyses can model multiple health outcomes simultaneously, but they differ slightly in nature. The PPM treats each health outcome as an individual construct or a subdomain of health. To address the change in each subdomain, a LGCM is fitted to each health outcome. However, changes in one subdomain of health is often associated with changes in another subdomain of health over time, which produces associated *parallel growth curves* across health outcomes (Wickrama et al., 2016). This means that different LGCM models for physical, mental, and cognitive health are combined together to make a single omnibus PPM, allowing researchers to examine how cross-subdomain associations of health are associated with wealth trajectory. In short, the PPM is used to test how each health trajectory *individually* respond to wealth trajectory.

The CFM takes a more sophisticated approach to model the joint effect of health. CFM fits the growth curves (i.e., the intercept and slope) based on a latent factor of “global” health at each time point. First, a confirmatory factor analysis (CFA) was fitted using physical, mental, and cognitive health outcomes to produce the global health at each wave, followed by a series of longitudinal measurement equality tests to examine whether the CFA model in each wave has *configural invariance* (same form), *weak invariance* (same factor loadings), *strong invariance* (same factor loadings and means), and *strict invariance* (same factor loadings, means, and residual variances). The longitudinal CFA invariance was met if the changes of CFI value (i.e., ΔCFI) between the unconstrained and the constrained model less than 0.01 (Cheung & Rensvold, 2002). For example, if the CFI value of the *weak invariance* model (constrained) minus the *configural model* (unconstrained) is less than 0.01, then a weak invariance model is determined; otherwise, an unconstrained model should be accepted. The use of ΔCFI for measurement invariance is recommended, as it is less sensitive to sample size but is more sensitive to a lack of invariance when compared to the traditional χ^2 values (Meade, Johnson, & Braddy, 2008).

As suggested by Wickrama et al. (2016), at least a partial or full *strong invariance* should be established to fit a CFM model. After the longitudinal measurement invariance is established, a CFM model is fitted to estimate the "global" initial health and growth curve using CFA model at each time point. The CFM is used to examine how health trajectory (i.e., global health) *jointly* responds to wealth trajectory.

3.3.5 Model Fits Assessment for SEM Models

To identify the best model for LGCM, an unconditioned LGCM with either linear function, non-linear polynomial function, or piece-wise function was first estimated to determine the shape of the growth curve for both wealth and health. Without an absolute index to determine the model's fit (Bryne, 2012), followed the recommendations made by Kline (2015), this study uses multiple mode fit indexes, including: (1) χ^2 goodness-of-fit statistics, (2) the comparative fit index (CFI), (3) the Tucker-Lewis fit index (TLI), and (4) the root mean square error of approximation (RMSEA) and its 90% confidence interval (CI). Using guidelines suggested by prior researchers, the cutoff for each index is as follows. For CFI and TLI, the values should be equal to or greater than 0.90 (Bryne, 2012; Wang & Wang, 2012) or 0.95 (Hu & Bentler, 1999; Kline, 2015). For RMSEA, a value less than 0.05 indicates a close fit, 0.05–0.08 indicates a fair fit, 0.08–0.10 indicates a mediocre fit, and a value greater than 0.10 suggests poor fit (Wang & Wang, 2012). Further, Kline (2015) suggests that the model has a good fit when the upper bound of CI for RMSEA is not greater than 0.10.

After the shape of the growth curve has been determined, the next step is to use LGMM to identify the number of trajectory classes (i.e., latent class) for both wealth and health in an unconditioned LGMM. In a mixture model, the conventional fit indexes, such as χ^2, CFI, TLI, and RMSEA, are not available and the model selection is based on other fit indexes that are discussed below. However, it remains inconclusive to select the best mixture model as there are varied approaches in terms of model selection (Grimm et al., 2017). The current approach to select the best model include the use of the following indexes: (1) the Lo-Mendell-Rubin likelihood ratio test (LMR test) that compares K-class model to K-1 class mode (Muthén, 2003), (2) the Bootstrap LMR test (BLRT) (Nylund, Asparouhov, & Muthén, 2007), (3) The BIC values (Nylund et al., 2007), and (4) the sample-size adjusted BIC value (SSABIC) (Enders & Tofighi, 2008). A significant LMR and BLRT test indicates a favor of K-class over the K-1 class model, and a model with smaller values in BIC and SSABIC is preferred. Other considerations include successful model convergence (Grimm et al., 2017), a greater Entropy value (range: 0–1, greater if the values > 0.80) that suggests latent classification accuracy (Jung & Wickrama, 2008), and class size greater than 1% of the sample (Jung & Wickrama, 2008). Specifically, model interpretability based on theoretical and empirical evidence should also be considered. Following guidelines set by Grimm et al. (2017), this study considers both objective model fit information and subjective model interpretability to select the best model for LGMM.

3.3.6 Generalized Propensity Score Analysis

Generalized propensity score (GPS) analysis (Imbens, 2000), or so-called dosage analysis (Guo & Fraser, 2015), is a method of statistical adjustment using propensity scores as sampling weights that control for selection bias into the treatment of concern, in this study, the wealth trajectory patterns. Prior research has shown that life course factors across life stages have critical impacts on wealth development over time, with evidence suggesting that older adults with cumulative advantages (e.g., being female, not white, with lower socioeconomic status, etc.) may be placed into a low or flat wealth trajectory pattern with little growth in wealth over time. Therefore, this study uses GPS to address the endogeneity issue on wealth (Sherraden & McKernan, 2008), that is, the selection bias into varied patterns of wealth trajectory due to life course factors. The GPS belongs to a larger family of methods called propensity score analysis, or PSA (Guo & Fraser, 2015). Adapting the definitions made by Rosenbaum and Rubin (1983), propensity scores in this study are defined as the probability of belonging to certain wealth trajectory patterns, conditional on a set of observed life course factors.

The PSA can be treated as a quasi-experimental framework as it balances the differences between the treatment and the control groups based on a selected set of covariates, making the estimation of a treatment effect approach to a randomized-control trial setting. The traditional PSA involves a binary treatment variable, where one group receives treatment and the other serves as a control group. However, such a framework can be extended from a binary treatment condition to multiple treatments, in which the treatments can be a continuous (e.g., treatment takes on a continuum of values) or a categorical (i.e., different types of treatment) variable. This type of PSA with continuous or categorical treatment is called *dosage analysis*, and this method recently has received much attention among social science researchers (Guo & Fraser, 2015).

This study uses GPS because it offers many methodological advantages, as its methodological properties are very similar to the inverse probability of treatment weights (IPTW) estimator. First, it is possible that more than two types of wealth patterns can be identified. These different types of wealth patterns can be regarded as *multiple treatments*, making the GPS an appropriate PSA method in this study. Second, the GPS, like the IPTW, uses propensity scores produced from the treatment variable as sampling weights in the outcome analyses. This approach allows GPS to use most types of multivariate analyses regardless of the measurement of the outcome variables, and keeps most observations in the study (Guo & Fraser, 2015), making this type of method more attractive than other PSA methods like propensity score matching or subclassification. As **RQ3** aims to examine how wealth patterns (a categorical treatment) influence health patterns (a categorical outcome) when considering the impacts of life course factors on wealth, the use of GPS offers solutions on addressing in part the endogeneity issues of wealth, and when the outcome is categorical in nature. Following the procedures described by Guo and Fraser (2015), there are three steps in conducting GPS.

Step 1: Estimate propensity scores. As the treatment variable in this study is categorical in nature, following the method developed by Imbens (2000), this study first uses a multinomial logistic regression to estimate the propensity scores for each level of treatment dosage. The procedure regressed the treatment variable (i.e., wealth patterns) on the 11 life course factors—four childhood SES variables (education of father and mother, father's occupation, and family SES) and seven ascribed/adulthood factors (gender, race, cohort, marital and work status, education, and income)—and then saved the predicted scores. Next, it calculated the inverse of the predicted scores to produce the propensity scores. Noted that, for a single respondent, although multiple propensity scores can be obtained through multinomial logistic regression, only one score—the inverse of the predicted probability for a participant falling into a specific wealth pattern—is used. This procedure created a single weight variable to represent the propensity for each respondent being placed into a specific wealth pattern.

Step 2: Conduct imbalance check. Next, this study used propensity scores as weights to conduct a series of imbalance checks using either OLS regression, logistic regression, or multinomial logistic regression, depending on the measurement types of the life course factors. Results of an imbalance check in Appendix F show that, before applying the propensity scores as weights, the pre-GPS models showed that all 11 life course factors were associated with wealth patterns. However, results from the post-GPS models showed that only three life course factors showed random significance. These findings indicate that, with few exceptions, the use of GPS properly balances the differences of life course covariates across varied treatment groups (i.e., wealth patterns), which increases the confidence for estimating the treatment effects of wealth patterns on health patterns in **RQ3**.

Step 3: Performed outcome analyses. Lastly, as the outcome of **RQ3**—the health patterns—is a categorical variable, a multinomial logistic regression using propensity scores as sampling weights was conducted to examine how wealth patterns influence health patterns in later life. Specifically, a set of d−1 dummy variables of wealth patterns were created, with omission for one wealth pattern serving as a reference group. The control variables for the health patterns include the same set of 11 life course factors that were used in creating propensity scores, as well as other covariates including baseline age, childhood health, rural/urban status, attrition, and mode of interview. Because missing values do exist both in the life course factors and other covariates, a total of 20 imputed data sets using multiple imputation with chained equations (MICE) were created, and the results were combined using Rubin's rule.

There are three methodological issues that should be discussed in the GPS procedures.

Issue 1: Covariates for selection equation and response equation. When using GPS, or PSA in general, there are two equations that need proper model specifications, with one on the *selection equation* (i.e., model that creates propensity scores) indicating the covariates associated with the treatment variable, and the other on the *response equation* (i.e., outcome analyses) representing factors associated with the outcome variable (Austin, 2011). As Austin (2011, p. 414) clearly indicated: "*There is a lack of consensus in the applied literature as to which variables to include in the propensity score model,*" the choices of covariates for both selection and response equations remain an ongoing debate. Typically, there are three types of variables for inclusion in the PSA (Austin, 2011): (1) covariates associated with treatment assignment, (2) factors that affect the outcome variable (i.e., the potential confounders), and (3) variables that influence both treatment assignment and outcome (i.e., the true confounders). A Monte Carlo study done by Austin, Grootendorst, and Anderson (2007) highlighted the use of controlling for the potential confounders (covariates that influence outcome) and the true confounders (covariates that both affect treatment and outcome) in a context of propensity score matching. For the PSA with weighting design, however, Freedman and Berk (2008, p. 10) stated that "*It rarely makes sense to use the same set of covariates in the response and selection equation,*" suggesting that the model specifications for the covariates used in both selection and response equations *cannot* be exactly the same.

Based on the propositions set by these scholars, this study used 11 life course factors for both wealth (selection equation) and health (response equation), as literature and theory suggest that the life course factors are critical in influencing both wealth and health (for the effect of life course factors on health, see Kwon et al. (2018); Luo and Waite (2005); Lyu and Burr (2016) for examples) in later life. However, for the health outcome, this study further controlled five more variables (i.e., baseline age, childhood health, rural/urban status, attrition, and mode of interview) in the response equation. By doing this, the model specifications for covariates used in both selection and response equations are approximately 68% overlapped (11 variables /16 variables), which supports the guideline made by Freedman and Berk (2008).

Issue 2: Propensity scores and multiple imputation. As this study employs multiple imputation to impute missing values, the second methodological issue involves *when* the propensity scores should be created, *before* or *after* the imputation. Following the demonstrations made by Eulenburg et al. (2016), this study created propensity scores *after* the imputation, meaning the propensity scores were produced based on the 20 imputed data sets, followed by an outcome analysis (i.e., multinomial logistic regression).

Issue 3: Propensity score weights and sampling weights of complex survey design. As discussed earlier, this study uses person-level sampling weights to ensure the representativeness of the estimates. However, the GPS also uses propensity scores as sampling weights in order to control for selection bias and minimize endogeneity. To date, the discussions on the simultaneous use of both sampling weights (to correct for the complex survey design) and propensity scores (to correct for sample selection) remain inconclusive (Austin, Jembere, & Chiu, 2018). Following the method suggested by Guo and Fraser (2015), this study created a new "grand" weight by multiplying the propensity scores and the sampling weights, followed by the use of the grand weight in the outcome analysis. Results from a simulation study conducted by DuGoff, Schuler, and Stuart (2014) suggested that the use of grand weight is necessary to obtain unbiased treatment estimates that are generalizable to the survey population.

Chapter 4: Results

Using latent growth curve modeling (LGCM), latent growth mixture modeling (LGMM), and generalized propensity score, this chapter presents the findings for the research questions that were proposed in this study, including: (1) Do life course factors influence wealth trajectory, (2) Does wealth trajectory affect health trajectories longitudinally, and (3) How do wealth patterns relate to health patterns in later life.

4.1 Research Question 1: Effects of Life Course Factors on Wealth Trajectory

RQ1 in this study asked, "Does wealth trajectory in later life vary by cumulative disadvantages?" To answer this question, this study uses latent growth curve modeling (LGCM) to examine how life course factors associate with wealth trajectory. Life course factors were defined as: childhood SES (lower education of parents, father's job is blue-collar, and poor family SES), adulthood SES (no college education and income below median values), and life course covariates that included gender (females vs. males), race (whites [reference group], blacks, and Hispanics), proportions of time remaining at work and in marriage, and birth cohorts. Other control variables included baseline age, health in childhood, urban-rural status, attrition, and the baseline health outcomes included self-rated health, mobility limitations, depressive symptoms, cognition, and numbers of chronic diseases.

The outcome of this study is the trajectory of wealth in later life, including the intercept (initial values) and the slope (changes over time) of wealth. Although this study hypothesizes that the slope of wealth declines over time, such a hypothesis needs to be examined through multiple LGCM models. Further, this study also hypothesizes that life course factors were associated with wealth trajectory, meaning that life course factors were associated with the intercept and slope of wealth. Two parts of the findings are presented here to answer **RQ1**. First, the explorations of different models of wealth trajectory using LGCM are discussed. After the wealth trajectory has been identified, the second part of the findings present how life course factors influence wealth trajectory.

4.1.1 Wealth Trajectory

Table 1 presents the LGCM results for the linear, quadratic, and piece-wise trajectory models of wealth. All the analyses were modeled using maximum likelihood estimation. The linear trajectory model specification assumes that wealth declines over time, in this study, from 2004 to 2014. The quadratic and the piece-wise models were built on the linear trajectory model, assuming that a turning point can be observed in the declining wealth. The difference between these two is that the piece-wise model sets the turning point starting in the year 2008 (i.e., the beginning year of the financial crisis), but for the quadratic model, the turning point of wealth is determined by the SEM models. Both the quadratic and the piece-wise models served as additional tests for the linear trajectory model.

Results from Table 1 showed that these three models fit the data very well. Although the results of model comparisons using chi-square difference tests ($\Delta\chi^2$) showed that the quadratic model and piece-wise model were better, these three models had very similar model fits. However, the linear trajectory model was much simpler and it provided better interpretability. Therefore, this study selects the linear model as the best model to represent wealth trajectory in later life.

The results of the linear trajectory model showed that the initial wealth for older adults was 3.50 (IHS transformed wealth) at the baseline (in this study, the year 2004). The estimated mean of value of −0.07 ($p < .001$) indicates a significant decline in wealth from 2004. This finding supports the hypothesis made in this study, that a declining trajectory of wealth can be identified among older adults. The results further suggest that heterogeneity exists in this decreasing trend of wealth, as the variance components of intercept ($b = 3.24$, $p < .001$) and slope ($b = 0.05$, $p < .001$) were significant. This implies that, across all individuals, variations in wealth exist in both the initial values of wealth and the decline of wealth across time. Therefore, explorations on the variations in wealth across individuals were necessary, as the homogeneous assumption of the linear trajectory in wealth could be relaxed to identify various wealth patterns. These explorations for wealth patterns will be presented in **RQ3**.

Table 1. Results of Latent Growth Curve Models (LGCM) for Wealth Trajectory

	Linear trajectory model	*Quadratic trajectories model*	*Piece-wise trajectories model*
Model fit			
$\chi^2_{(df)}$	$2063.814_{(16)}$***	$1124.353_{(12)}$***	$1113.543_{(12)}$***
CFI	0.978	0.988	0.988
TLI	0.980	0.985	0.985
RMSEA (90% CI)	0.079	0.076	0.075
	(0.076, 0.080)	(0.072, 0.079)	(0.072, 0.079)
Model comparisons		939.46***	950.27***
Model results			
Mean			
Intercept	3.50***	3.49***	3.47***
Slope (linear)	−0.07***	−0.07***	−0.05***
Slope (quadratic)		0.00	
Slope (linear)			−0.08***
Variance			
Intercept	3.24***	3.25***	3.26***
Slope (linear)	0.05***	0.28***	0.18***
Slope (quadratic)		0.01***	
Slope (linear)			0.10***

Note. Skewness of net worth was corrected using inverse hyperbolic sine (IHS) transformation. *df* = degrees of freedom. CFI = Comparative Fit Index. TLI = Tucker-Lewis Index. RMSEA = Root Mean Square Error of Approximation. All the models were based on maximum likelihood estimation.
**p* < .05, ***p* < .01, ****p* < .001, two-tailed test.

4.1.2 Associations of Life Course Factors and Wealth Trajectory

Two hypotheses were made for the associations between life course factors and wealth trajectory. For the *intercept of wealth* (i.e., the initial values of wealth), this study hypothesizes that that older adults with cumulative disadvantages (e.g., older adults who are female, non-whites, or with lower education) have lower levels of initial wealth. For the *slope of wealth* (i.e., the decline in wealth), this study hypothesizes that older adults with cumulative disadvantages have a slower decrease in wealth, partly because they have lower levels of wealth to deplete across time. These results are presented in Table 2.

For the intercept of wealth, results showed that childhood and adulthood SES were significantly associated with the intercept of wealth. Specifically, older adults with lower childhood SES, including mothers with lower education ($b = -0.11$, $p < .05$) and fathers with a blue-collar job ($b = -0.14$, $p < .01$), and older adults with lower adulthood SES, such as those with no college education ($b = -0.51$, $p < .001$) and income below median ($b = -0.96$, $p < .001$), are more likely to have lower levels of initial wealth.

In terms of other life course covariates, results showed that older females ($b = -0.13$, $p < .001$), blacks ($b = -0.92$, $p < .001$) and Hispanics ($b = -0.69$, $p < .01$), compared to their male and white counterparts, had lower levels of initial wealth. For the effect of cohort on wealth intercept, only the comparison between the 1948-1953 cohort and the cohort born prior to 1923 was significant ($b = -0.40$, $p < .001$). This means that respondents born in later cohorts had a lower initial level of wealth. Marriage showed a protective effect on wealth: those who were married were more likely to have a higher level of initial wealth ($b = 0.74$, $p < .001$). Working, however, seems to have a negative effect on wealth. Those who spent more time on work showed a lower level of initial wealth ($b = -0.43$, $p < .001$). These findings, with few exceptions, generally support the hypothesis made in this study that older adults with cumulative disadvantages have a lower level of initial wealth.

However, it seems like life course factors were not associated with the slope of wealth; only income and cohort were associated. In this study, low-income was negatively associated with the decline of wealth ($b = -0.04$, $p < .001$), this means that low-income older adults (i.e., income below median values) had a *faster* decline in their wealth, thus not supporting the hypothesis in this study. The cohort has a positive effect on the decline of wealth slope ($b = 0.06$, $p < .01$), meaning that older adults born in later cohorts (i.e., 1942-1947 and 1948-1953 cohorts), compared to cohorts born prior to 1923, had a *slower* decline in wealth. Such a finding supports the hypothesis in this study, in that it hypothesizes that older adults born in later cohorts experience a slower rate of decline in wealth. These mixed findings suggest that the effect of life course factors on wealth are inconclusive, and therefore the hypotheses made in this study are not fully supported.

Table 2. Estimates of Life Course Factors on Wealth Trajectory

	Wealth Trajectory	
	Intercept (I)	*Slope (S)*
Life course factors		
Childhood SES		
Father's education (low)	−0.04	−0.02
Mother's education (low)	−0.11*	0.01
Father's job (blue-collar)	−0.14**	0.004
Family SES (poor)	−0.03	0.004
Adulthood SES		
Education level (< college)	−0.51***	−0.02
Income (< median)	−0.96***	−0.04***
Life course covariates		
Female	−0.13***	−0.001
Race (*ref*: White)		
Black	−0.92***	0.02
Hispanics	−0.69***	0.02
Working (proportion)	−0.43***	0.01
Married (proportion)	0.74***	0.001
Cohort (*ref*: Born prior to 1923, AHEAD)		
1924-1930 (CoDA)	−0.08	0.02
1931-1941 (HRS)	−0.04	0.03
1942-1947 (WB)	−0.18	0.06**
1948-1953 (EBB)	−0.40***	0.06**
Other covariates		
Age (baseline)	0.03***	−0.001
Poor childhood health	−0.13	0.02
Living in urban area	0.33***	−0.03***
Attrition	0.03	−0.02
Baseline health outcomes		
Mobility limitations	−0.06***	−0.002
Self-rated health	0.17***	−0.01
Depressive symptoms	−0.03**	0.001
Cognition	0.03***	−0.001
Number of chronic diseases	−0.07***	−0.003

Note. Model fit: $\chi^2_{(112)}$ = 1239.595, $p < .001$. CFI = 0.972. TLI = 0.961. RMSEA (90% CI) = 0.025 (0.024, 0.026).
*$p < .05$, **$p < .01$, ***$p < .001$, two-tailed test.

4.2 Research Question 2: Effects of Wealth Trajectory on Health Trajectory

RQ2 in this study asked, "How does wealth trajectory relate to health trajectory, when the effects of life course factors were modeled?" Specifically, this study asked how health trajectory *individually* and *jointly* responds to wealth trajectory in later life, as the health trajectory involves four health outcomes including physical, mental, and cognitive health. This study first hypothesizes that a decline in health can be observed in the health trajectory, and the wealth trajectory is significantly associated with health trajectory. As the aim of this study is to explore the individual and joint health trajectory, although this study hypothesizes that health declines over time, it is not clear whether such a decline can be observed in both individual and joint health trajectories. Therefore, two models—the parallel process model (PPM, for the individual health trajectory) and the curve-of-factor model (CFM, for the joint health trajectory)—were tested in this study using LGCM.

This section is divided into three parts. The first two sections explore the individual and the joint health trajectory using PPM and CFM. The last section presents the estimates of wealth trajectory on individual and joint health trajectories, with discussions on whether these findings were consistent with the hypotheses in this study.

4.2.1 Individual Health Trajectory from Parallel Process Model

The parallel process model (PPM) is a technique that combines different latent growth curve models (LGCM) for each health outcome (i.e., physical mobility limitations, self-rated health, depressive symptoms, and cognition) simultaneously. There are two steps in constructing a PPM, with the first step investigating the individual trajectory for each health outcome, and then combining all four LGCM together into a single model that reflects the trajectory for each health outcome.

Table 3 presents the LGCM results for each health outcome; the linear and quadratic models were tested. Findings suggested that, although the results of model comparisons using chi-square difference tests showed that a quadratic model had a better fit except for the cognitive health, the linear trajectory model had a satisfactory model fit and was a more parsimonious model. Therefore, this study selects the linear trajectory model as the base model for each health outcome, and these models were combined to construct a PPM model.

Table 3. Results of Latent Growth Curve Models (LGCM) for Individual Health Trajectory

	Model fit				
	$\chi^2_{(df)}$	*CFI*	*TLI*	*RMSEA (90% CI)*	$\Delta\chi^2_{(\Delta df)}$
Mobility limitations					
Linear	$814.726_{(16)}$***	0.988	0.989	0.056 (0.052, 0.059)	
Quadratic	$311.864_{(12)}$***	0.995	0.994	0.039 (0.036, 0.043)	$502.86_{(4)}$***
Depressive symptoms					
Linear	$147.677_{(16)}$***	0.996	0.996	0.023 (0.019, 0.026)	
Quadratic	$82.632_{(12)}$***	0.998	0.997	0.019 (0.015, 0.023)	$65.05_{(4)}$***
Cognition					
Linear	$335.346_{(16)}$***	0.993	0.994	0.035 (0.032, 0.039)	
Quadratic	$332.186_{(12)}$***	0.993	0.991	0.041 (0.037, 0.045)	$3.16_{(4)}$
Self-rated health					
Linear	$329.900_{(16)}$***	0.994	0.994	0.035 (0.032, 0.038)	
Quadratic	$128.937_{(12)}$***	0.998	0.997	0.025 (0.021, 0.028)	$200.96_{(4)}$***

Note. df = degrees of freedom. CFI = Comparative Fit Index. TLI = Tucker-Lewis Index. RMSEA = Root Mean Square Error of Approximation. All the models were based on maximum likelihood estimation.
**p* < .05, ***p* < .01, ****p* < .001

Table 4 presents the results of PPM when the physical, mental, and cognitive health outcomes were modeled simultaneously. The PPM model showed a satisfactory model fit ($\chi^2_{(220)} = 1789.927$, $p < .001$; CFI = 0.993; TLI = 0.991; RMSEA = 0.021). Results indicated that, for each health trajectory, mobility limitations ($b = 0.25$, $p < .001$) and depressive symptoms ($b = 0.02$, $p < .001$)

increased over time, whereas cognition (*b* = −0.38, $p < .001$) and self-rated health (*b* = −0.06, p <.001) declined as respondents aged. Further, the variances for both the intercept (*range* = 0.88 to 12.02, all $p < .001$) and the slope (*range* = 0.02 to 0.16, all $p < .001$) were significant, indicating the latent intercept (initial levels of health) and the latent slope (declines in each health status) significantly vary across individuals, and further explorations on health heterogeneity are warranted. To sum up, for the individual health trajectory model, these results confirm that the health status of respondents is decreasing over time.

Table 4 also shows the correlation of the growth factors (i.e., the intercept and slope) across different health outcomes. In terms of the intercept (i.e., the initial level of health), a positive correlation was found between mobility limitations and depressive symptoms ($r = 0.57$, $p < .001$) and between cognition and self-rated health ($r = 0.43$, $p < .001$). These two sets of health measures were negatively associated with each other. For example, higher initial levels of mobility limitations were associated with lower initial levels of cognition ($r = -0.28$, $p < .001$), and higher initial levels of depressive symptoms were associated with lower initial levels of self-rated health ($r = -0.58$, $p < .001$).

For the relationship between the intercept (i.e., the initial levels of health) and the slope (i.e., the changes in health), it was found that respondents with a higher initial level of mobility limitations and depressive symptoms had a *slower* increase in these two health conditions over time. Further, they also have a *slower* decline in self-rated health (r = 0.19 to 0.26, $p < .001$). Respondents with a higher initial level of mobility limitation were found to have a *faster* decline in cognition ($r = -0.10$, $p < .001$). For respondents with higher initial levels of cognition and self-rated health, they had a *slower* increase in mobility limitations (r = −0.08 to −0.15, $p < .001$) and a *slower* decline in cognition (r = 0.16 to 0.17, $p < .001$), but they experienced a *faster* decline in self-rated health ($r = -0.10$ to -0.34, $p < .001$).

For the associations that involve two slopes, respondents with an increase in mobility limitations experienced a *faster* increase in depressive symptoms ($r = 0.41$, $p < .001$), whereas respondents who had cognition decline over time experienced a *faster* decline in self-rated health ($r = 0.10$, $p < .001$). Respondents who experienced increases in both mobility limitations and depressive symptoms had a *faster* rate in the decline of both cognition ($r = -0.24$ to -0.27, $p < .001$) and self-rated health ($r = -0.39$ to -0.53, $p < .001$). See Appendix G for more details on these interpretations.

Table 4. Results of Parallel Process Model (PPM) for Physical, Mental, and Cognitive Health

	Intercept (INT) growth factors		*Slope (SLP) growth factors*		*Correlation among Growth Factors (Standardized)*								
	Mean	*Var*	*Mean*	*Var*		INT_{MOB}	INT_{DEP}	INT_{COG}	INT_{SRH}	SLP_{MOB}	SLP_{DEP}	SLP_{COG}	SLP_{SRH}
Physical mobility limitations (MOB)	2.39***	6.03***	0.25***	0.16***	INT_{MOB}	--							
					INT_{DEP}	0.57***	--						
Depressive symptoms (DEP)	1.41***	2.29***	0.02***	0.05***	INT_{COG}	−0.28***	−0.32***	--					
					INT_{SRH}	−0.68***	−0.58***	0.43***	--				
Cognition (COG)	15.72***	12.02***	−0.38***	0.14***	SLP_{MOB}	−0.08***	−0.01	−0.15***	−0.08***	--			
					SLP_{DEP}	−0.07***	−0.26***	−0.03	0.01	0.41***	--		
Self-rated health (SRH)	3.24***	0.88***	−0.06***	0.02***	SLP_{COG}	−0.10***	−0.04	0.16***	0.17***	−0.27***	−0.24***	--	
					SLP_{SRH}	0.26***	0.19***	−0.10***	−0.34***	−0.53***	−0.39***	0.10**	--

Note. Model fit: $\chi^2_{(220)} = 1789.927$, $p < .001$; CFI = 0.993; TLI = 0.991; RMSEA (90% CI) = 0.021 (0.020, 0.022). *Var* = variance. CFI = Comparative Fit Index. TLI = Tucker-Lewis Index. RMSEA = Root Mean Square Error of Approximation. All the models were based on maximum likelihood estimation.

*$p < .05$, **$p < .01$, ***$p < .001$, two-tailed test.

4.2.2 Joint Health Trajectory from Curve-of-Factor Model

Unlike the PPM which shows the *individual* health trajectory for each health outcome, the curve-of-factor model (CFM) shows the *joint* health trajectory when the global health measure was created to capture physical mobility limitations, self-rated health, depressive symptoms, and cognition at each time point. The tests for the CFM also require two steps. First, a longitudinal confirmatory factor analysis (CFA) that captures four health outcomes in each time point was performed, and a series of measurement invariance tests that constrained the factor loading (weak invariance), the mean (strong invariance), and the variance (strict invariance) of each health indicator across time were examined. The change of CFI values (*ΔCFI*) was used to test the model invariance, with a value less than or equal to 0.01 indicating the model was invariant. The strong invariance model should be established to construct a CFM. Second, based on the strong invariance longitudinal CFA model, a CFM model was created to examine the trajectory of joint health.

Table 5 shows the details of the longitudinal CFA invariance tests. The initial model (M1) indicates a configural invariance, meaning the CFA models had the same form across time, and a global health that captures physical, mental, and cognitive health can be established in each time point. The following tests constrained the factor loading, mean, and variance for testing the longitudinal invariance. The results showed that, the constrained models always demonstrated a better fit than the unconstrained models, as indicated by the model comparisons using chi-square differences test and the ΔCFI values. The final model showed that, the strict measurement invariance—a model that fixed factor loadings, means, and variances of each health indicator the same across time—can be established in this study. The strict invariance model had a satisfactory model fit ($\chi^2_{(227)} = 4532.431$, $p < .001$; CFI = 0.980; TLI = 0.976; RMSEA = 0.034), and the creation of CFM was built on this model to explore the joint health trajectory.

Table 5. Results from Models Testing Measurement Invariance in a Longitudinal CFA Model

	$\chi^2_{(df)}$	*Model comparison*	$\Delta\chi^2_{(\Delta df)}$	*CFI*	*ΔCFI*	*TLI*	*RMSEA (90% CI)*
M1: LCFA with *configural invariance* (same form)	$1154.421_{(177)}$***			0.996		0.993	0.018 (0.017, 0.019)
M2: LCFA with *weak invariance* (same loading)	$1636.666_{(192)}$***	M2 vs. M1	$482.245_{(15)}$***	0.993	0.003	0.991	0.022 (0.021, 0.023)
M3: LCFA with *strong invariance* (same mean)	$3950.789_{(207)}$***	M3 vs. M2	$2314.123_{(15)}$***	0.983	0.010	0.977	0.033 (0.033, 0.034)
M4: LCFA with *strict invariance* (same variance)	$4532.431_{(227)}$***	M4 vs. M3	$581.642_{(20)}$***	0.980	0.003	0.976	0.034 (0.033, 0.035)

Note. CFA = confirmatory factor analysis. *df* = degrees of freedom. CFI = Comparative Fit Index. TLI = Tucker-Lewis Index. RMSEA = Root Mean Square Error of Approximation. All the models were based on maximum likelihood estimation.
*$p < .05$, **$p < .01$, ***$p < .001$

Table 6 presents the results of curve-of-factor model (CFM), and the findings suggested that the model fits the data well ($\chi^2_{(243)} = 4830.318$, $p < .001$; CFI = 0.979; TLI = 0.976; RMSEA = 0.034). Results showed that, overall, the health status of respondents declines as they age ($b = -0.17$, $p < .001$). Further, the significant variance components for both intercept ($b = 2.65$, $p < .001$) and slope ($b = 0.04$, $p < .001$) indicate that heterogeneity exists in the joint health status, and therefore investigation into the subgroup difference in health is needed. Note that it is possible to test the polynomial functions (e.g., quadratic or cubic) for the joint health trajectory. However, convergence issues occurred when these functions were tested in the model. Therefore, for this study, a linear trajectory of global health is selected.

The result of the joint health trajectory is similar to the findings of the PPM model. Both models show that health is decline over time. Therefore, these two models confirm the hypothesis in this study that a decline in health can be observed.

Table 6. Results of Curve-of-Factor (CFM) for Joint Health Trajectory

	Global health trajectory model
Model fit	
χ^2 (df)	$4830.318_{(243)}$***
CFI	0.979
TLI	0.976
RMSEA (90% CI)	0.034 (0.033, 0.035)
Model results	
Mean	
Intercept	15.21***
Slope (linear)	−0.17***
Variance	
Intercept	2.65***
Slope (linear)	0.04***

Note. df = degrees of freedom. CFI = Comparative Fit Index. TLI = Tucker-Lewis Index. RMSEA = Root Mean Square Error of Approximation. All the models were based on maximum likelihood estimation.
**p* < .05, ***p* < .01, ****p* < .001, two-tailed test.

4.2.3 Associations of Wealth Trajectory and the Individual Health Trajectory

Both the wealth and the health trajectory models have intercept (initial level) and slope (changes over time), and in **RQ2** the outcome is the health trajectory. Therefore, this study hypothesizes that the intercept of wealth (i.e., the initial levels of wealth) has a positive effect on the intercept and slope of health. This means that older adults with higher initial levels of wealth have better initial levels of health (wealth intercept → health intercept) and have a slower decline in health over time (wealth intercept → health slope). This study further hypothesizes that the wealth slope has a positive effect on the slope of health, indicating that a decline in wealth is associated with a faster rate of decline in health. These hypotheses were all tested in the individual (i.e., PPM) and joint health trajectory (i.e., CFM) models. Findings are presented below.

Table 7 shows the estimates of wealth trajectory on the individual health trajectory (i.e., PPM) when the life course factors were modeled ($\chi^2_{(826)} = 4781.358$, $p < .001$; CFI = 0.977; TLI = 0.970; RMSEA = 0.017). Both the wealth and the health trajectories were modeled by the same set of covariates—including the life course factors, life course covariates, and other covariates—except for the interview method, as results from the sensitivity test showed that the interview method was not correlated with wealth but was associated with health. Therefore, the interview method was modeled only for health trajectory. Note that this arrangement also addresses the endogeneity in wealth, as the effect of life course factors on wealth trajectory were modeled to estimate the effect of wealth trajectory on health trajectory.

Focusing on the relationships between the wealth trajectory and individual health trajectory, in terms of the wealth intercept on the health intercept, findings suggested that a higher initial level of wealth was positively associated with better initial levels of cognition ($b = 0.26$, $p < .001$) and self-rated health ($b = 0.10$, $p < .001$), but was negatively associated with lower initial levels of mobility limitations ($b = -0.23$, $p < .001$) and depressive symptoms ($b = -0.13$, $p < .001$). In terms of the wealth intercept on the health slope, only the model of mobility limitations was significant ($b = -0.02$, $p < .001$). As the changes of mobility limitation increase over time, this finding suggested that, a higher level of initial wealth is associated with a *slower* increase in mobility limitations. The effect of the wealth intercept on the trajectory of depressive symptoms, cognition, and self-rated health was not significant.

Lastly, the slope of wealth trajectory was found to be significantly associated with every slope of health trajectory. Noting that the slope of wealth is in decline over time ($b = -0.07$, see findings in Table 1), results showed that respondents with a decline in wealth experienced a *faster* rate of decline in cognition ($b = 0.13$, $p < .001$) and self-rated health ($b = 0.06$, $p < .001$) as well as a *faster* rate of increase in mobility limitations ($b = -0.17$, $p < .001$) and depressive symptoms ($b = -0.11$, $p < .001$). Except for the effect of the wealth intercept on the health slope, these findings support the hypotheses that wealth has a positive effect on health, in that a higher level of initial wealth is associated with a higher level of initial health, and a decline in health is associated with a faster rate of decline in health.

Table 7. Estimates of Wealth trajectory on Individual Health Trajectory

	Wealth		*Mobility limitation*		*Depressive symptoms*		*Cognition*		*Self-rated health*	
	I	*S*	*I*	*S*	*I*	*S*	*I*	*S*	*I*	*S*
Wealth trajectory										
Intercept (*I*)			−0.23***	−0.02***	−0.13***	0.002	0.26***	0.01	0.10***	−0.001
Slope (*S*)				−0.17***		−0.11***		0.13**		0.06***
Life course factors										
Childhood SES										
Father's education (low)	−0.11*	−0.02	0.33***	−0.003	0.16**	0.003	−0.33**	−0.03	−0.13***	0.01
Mother's education (low)	−0.14*	0.01	−0.14	0.01	0.19**	−0.03	−0.49***	−0.05	−0.06	0.01
Father's job (blue-collar)	−0.15**	0.01	−0.02	−0.01	−0.05	−0.01	−0.30**	0.01	−0.04	0.001
Family SES (poor)	−0.06	0.01	0.16**	0.000	0.24***	−0.01	0.05	−0.02	−0.08***	0.001
Adulthood SES										
Education (< college)	−0.62***	−0.02	0.13*	0.02	0.03	0.01	−1.41***	−0.001	−0.15***	0.001
Income (< median)	−1.10***	−0.04***	0.40***	−0.03*	0.28***	−0.01	−0.78***	−0.004	−0.19***	0.01**
Life course covariates										
Female	−0.14***	−0.003	0.68***	−0.03**	0.16***	−0.01	1.05***	−0.003	0.06**	0.01
Race (*ref*: White)										
Black	−1.04***	0.03*	−0.17	0.03	−0.12	−0.01	−1.89***	−0.01	−0.08**	0.001
Hispanics	−0.85***	0.02	−0.12	0.004	0.14	0.01	−1.78***	0.10**	−0.34***	0.03**
Working (proportion)	−0.27***	0.01	−1.16***	−0.04*	−0.52***	−0.002	0.84***	0.06*	0.43***	−0.01
Married (proportion)	0.76***	−0.001	0.11	0.01	−0.37***	0.04*	−0.39***	0.03	−0.02	−0.001
Cohort (*ref*: born prior 1923)										
1924-1930	−0.05	0.02	−0.29*	−0.03	−0.11	0.003	0.04	−0.05	0.13*	−0.02
1931-1941	−0.003	0.03	−0.44**	−0.04	−0.44***	0.05*	0.21	−0.02	0.13*	−0.02
1942-1947	−0.18	0.06**	−0.21	−0.04	−0.24	0.02	−0.05	−0.01	0.07	−0.01
1948-1953	−0.46***	0.06**	−0.33	0.03	−0.24	0.06	−0.65*	0.01	0.01	−0.01
Other covariates										
Age (baseline)	0.04***	−0.001	−0.03***	0.01***	−0.05***	0.01***	−0.07***	−0.02***	0.01***	−0.02***
Poor childhood health	−0.28**	0.02	0.62***	0.004	0.62***	−0.03	−0.50**	−0.02	−0.30***	0.01
Living in urban area	0.36***	−0.03***	−0.04	−0.02	0.02	0.01	0.27***	−0.004	−0.01	0.003

	Wealth		*Mobility limitation*		*Depressive symptoms*		*Cognition*		*Self-rated health*	
	I	*S*	*I*	*S*	*I*	*S*	*I*	*S*	*I*	*S*
Chronic diseases (baseline)	−0.19***	−0.002	0.71***	0.01	0.32***	−0.004	−0.14***	0.004	−0.32***	0.02***
Attrition	0.01	−0.02	0.05	0.04	0.14*	−0.003	−0.47**	−0.05	−0.04	−0.01
Interview method			−0.002	0.003	−0.02	0.04	−0.52*	−0.06	0.02	0.01

Note. Model fit: $\chi^2_{(826)} = 4781.358$, $p < .001$; CFI = 0.977; TLI = 0.970; RMSEA (90% *CI*) = 0.017 (0.017, 0.018).
*$p < .05$, **$p < .01$, ***$p < .001$, two-tailed test.

4.2.4 Associations of Wealth Trajectory and the Joint Health Trajectory

Table 8 presents the CFM results on the effect of wealth trajectory on joint health trajectory. Similar to the findings in the individual health trajectory model (i.e., PPM), the results showed that wealth trajectory was associated with the joint health trajectory. Findings suggested that, for the effect of wealth intercept on health intercept, respondents with a higher initial level of wealth were found to have a higher initial level of joint health ($b = 0.22$, $p < .001$), that means, those with higher initial levels of wealth had better self-rated health, higher cognition, and lower mobility limitations and depressive symptoms. However, wealth intercept was not associated with slope of joint health ($b = 0.01$, $p > .05$).

In terms of associations between slopes of wealth and health, findings suggested that the slope of wealth was positively associated with the slope of joint health ($b = 0.14$, $p < .001$). As both the slopes of wealth and health are negative (indicating that wealth and health decline over time), this positive association indicated that a decline in wealth was associated with a *faster* rate of decline in all health outcomes, including mobility limitations, self-rated health, depressive symptoms, and cognition.

Table 8. Estimates of Wealth trajectory on Joint Health Trajectory

	Wealth		*Joint Health*	
	Intercept (I)	*Slope (S)*	*Intercept (I)*	*Slope (S)*
Wealth trajectory				
Intercept (*I*)			0.22***	0.01
Slope (*S*)				0.14***
Life course factors				
Childhood SES				
Father's education (low)	−0.11*	−0.02	−0.29***	0.01
Mother's education (low)	−0.14*	0.01	−0.07	0.01
Father's job (blue-collar)	−0.15**	0.01	−0.03	0.004
Family SES (poor)	−0.05	0.01	−0.18***	−0.001
Adulthood SES				
Education level (< college)	−0.62***	−0.02	−0.27***	−0.01
Income (< median)	−1.11***	−0.04***	−0.42***	0.03**
Life course covariates				
Female	−0.14***	−0.003	−0.12**	0.02*
Race (*ref*: White)				
Black	−1.04***	0.03*	−0.10	−0.01
Hispanics	−0.85***	0.02	−0.43***	0.03*
Working (proportion)	−0.27***	0.01	0.95***	0.01
Married (proportion)	0.76***	−0.001	0.01	−0.01
Cohort (*ref*: born prior 1923)				
1924-1930	−0.05	0.02	0.24*	−0.01
1931-1941	−0.01	0.03	0.35**	−0.01
1942-1947	−0.19	0.06*	0.16	0.01
1948-1953	−0.47***	0.06**	0.11	−0.03
Other covariates				
Age (baseline)	0.04***	−0.001	0.03***	0.010***
Poor childhood health	−0.28**	0.02	−0.67***	0.02
Living in urban area	0.36***	−0.03***	0.02	0.01
Chronic diseases (baseline)	−0.19***	−0.002	0.62***	0.01***
Attrition	0.01	−0.02	0.10	−0.02
Interview method			−0.003	−0.002

Note. Model fit: $\chi^2_{(948)}$ = 8862.414, $p < .001$; CFI = 0.954; TLI = 0.948; RMSEA (90% CI) = 0.023 (0.022, 0.023).
*$p < .05$, **$p < .01$, ***$p < .001$, two-tailed test.

4.3 Research Question 3: Effects of Wealth Patterns on Health Patterns

The final question—**RQ3**—in this study asked, "How do wealth patterns associate with health patterns in later life?" To answer this question, this study first uses latent growth mixture models (LGMM) to explore the heterogeneous patterns in both wealth and health. As findings from the previous LGCM results showed that the variances of intercept and slope for both wealth and health trajectory are significant, it is indicative that subgroup differences in wealth and health trajectory can be identified. After these patterns of wealth and health have had been identified, this study uses generalized propensity score to estimate how wealth patterns influence health patterns, controlling for the effects of life course factors on wealth patterns.

Four sets of findings are presented here. The first two sections describe the constructions of wealth patterns and health patterns. The third section shows the bivariate analyses for the associations between life course factors, wealth patterns, and health patterns. The last section presents the estimates of the generalized propensity score analyses on the effect of wealth patterns on health patterns.

4.3.1 Wealth Patterns

To examine the heterogeneity in wealth, the latent growth mixture model (LGMM) was used to identify the subgroups—or the latent trajectory classes—of wealth using the linear trajectory of wealth as a base model (see Table 1). As discussed in the method section, explorations of latent trajectory classes require both objective and subjective selections. The objective selections involve the use of model fit indexes, in that a smaller value of BIC, a larger value of entropy, a significant LMR test and Bootstrap LMR test, and the size of class proportion (>1%) should be considered. The subjective selections include both the theoretical justifications and the model interpretability using a graphic visualization approach. These criteria were used to select the best latent trajectory class model of wealth, and this process is also called class enumeration.

Table 9 shows the results of class enumeration for wealth patterns using LGMM. A total of five models (from 2-class model to 6-class model) were examined. Overall, the LGMM prefers a model with many latent classes, as a smaller BIC value and a larger entropy value were found in the model with more latent classes. This means that the 3-class model is better than the 2-class model, and the 4-class model is better than the 3-class model, and so on. Further, the significant LMR test and the bootstrap LMR test also suggested that the model with more latent classes had a better fit compared to the model with fewer latent classes, as the tests were significant when the model compared k-class to k-1 class. However, using class proportion as a selection criterion, results suggested that the 4-class model is an appropriate model because the smallest class proportion for this model was 2.38%, compared to that of 0.90% for the 5-class model.

Table 9. Results of Latent Growth Mixture Models (LGMM) for Wealth Patterns

Models	*2-Class*	*3-Class*	*4-Class*	*5-Class*	*6-Class*
Fit indexes					
Log Likelihood	−127085.202	−125833.882	−124971.121	−124500.404	−124285.496
BIC	254306.092	251832.529	250136.084	249204.342	248803.601
SSABIC	254261.601	251778.504	250072.526	249137.605	248727.331
Entropy	0.806	0.838	0.858	0.866	0.874
Adjusted LMRT (*p*)	2255.907 (.000)	2419.430 (.000)	1668.149 (.000)	1001.572 (.000)	415.526 (.048)
BLRT (*p*)	2333.492 (.000)	2502.640 (.000)	1725.521 (.000)	1036.018 (.000)	429.817 (.000)
Class size (*n*, %)					
Class 1	3245 (20.04%)	3346 (20.67%)	385 (2.38%)	11699 (72.27%)	70 (0.43%)
Class 2	12944 (79.96%)	903 (5.58%)	11836 (73.11%)	145 (0.90%)	146 (0.90%)
Class 3		11940 (73.75%)	3025 (18.69%)	2823 (17.44%)	11677 (72.13%)
Class 4			943 (5.83%)	1130 (6.98%)	1137 (7.02%)
Class 5				392 (2.42%)	414 (2.56%)
Class 6					2745 (16.96%)

Note. BIC = Bayesian Information Criteria. SSABIC = Sample size adjusted BIC. LMRT = Lo-Mendell-Rubin Likelihood Ratio Test. BLRT = Bootstrap Likelihood Ratio Test. p = p value. The class results were adjusted for household clustered effect using TYPE = COMPLEX MIXTURE in M*plus*. BLRT was produced using TYPE = MIXTURE.

**p* < .05, ***p* < .01, ****p* < .001

The class enumeration process using objective indexes describes the complexities in the process of model selections. However, it is not uncommon that these model fit indexes may sometimes disagree with each other, and therefore it is also critical to use theoretical justification and graphic approach to select a model. Combined the objective index and the graphical approach as shown in Figure 4, it suggested that the 4-class model may have both theoretical justifications and model interpretability, as it is possible to identify respondents with wealth patterns that were maintained at the higher and the lower levels. It is also possible to identify changes in wealth across time, with one group experiencing wealth accumulation and another group experiencing wealth depletion over time. Based on the objective and subjective indexes, this study selects the 4-class model as the final model to represent the wealth patterns in later life.

Figure 4 presents the wealth patterns—or the trajectory classes—that were identified from the linear wealth trajectory model using LGMM. Note that the vertical bar has negative values of wealth, as the IHS transformation allows negative values in the process of transformation. As shown in the figure, about seven in 10 (73.11%) respondents had a wealth pattern that was maintained at a higher level; this group of respondents (Class 2) was labeled as *Stable High* group. Following this logic, about one in five (18.69%) people (Class 3) were labeled as *Stable Low*, as they had low wealth across time. Approximately five percent of the respondents (5.83%) had a wealth pattern that was higher at the baseline, but they experienced a decline in their wealth. This group of people (Class 4) was further labeled as *High & Decline* group. Lastly, a total of 2.38% respondents (Class 1) were labeled as *Low & Increasing*, because they had a lower level of wealth at the baseline, but their wealth was accumulated across time. See Figure 4 for more information.

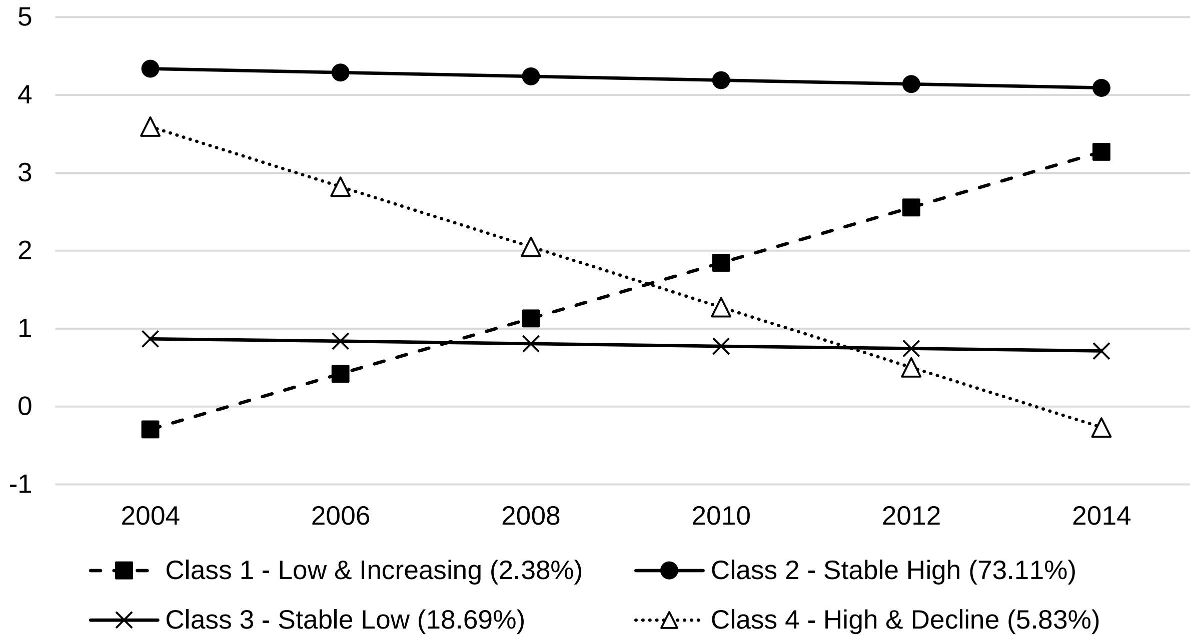

Figure 4. Wealth Patterns in Later Life, 2004 to 2014

4.3.2 Health Patterns

Using both the objective indexes and subjective model selection strategies, Table 10 shows the details of class enumeration for the joint health patterns involving four health trajectory models. A total of five models (from 2-class model to 6-class model) were also examined using LGMM.

Similar to the findings of wealth patterns, the LGMM favors the models with more latent classes for health, as indicated by a smaller BIC value and the significant tests for both LMR test and the bootstrap LMR test. Therefore, a subjective model selection strategy was used to select the best latent class model. After considering the objective indexes and examining the figures for each latent class model, the results showed that the 5-class model is much more meaningful when compared to other models, as it provides a more comprehensive picture to address the changes of health when compared to the 4-class model, but offers simpler information when compared to the 6-class model. Therefore, the 5-class model is selected as the final model for health patterns in this study.

Figure 5 lists the five groups of respondents in terms of their joint health status. The largest group (Class 4, 52.30%) was labeled as *Stable good health*, as this group maintained their health at a higher level, indicating this group of respondents had lower levels of mobility limitations and depressive symptoms, but had a higher level of cognition and better self-rated health. In contrast, there was a group which seemed the most vulnerable (Class 3, 10.92%) because they had the lowest score in each health outcome. This group was therefore labeled as the *Stable poor health*.

There were two groups that experienced declines in their overall health, meaning that their mobility limitations and depressive symptoms increased over time, but their cognition and self-rated health declined as they aged. However, the rates of decline differed a little bit, where one group had a slower rate of decline (Class 2, 16.80%) but another group demonstrated a faster rate of decline in the joint health (Class 1, 9.54%). Based on these findings, the former group was labeled as S*low-decline health*, and the latter was labeled as *Rapid-decline health*. Lastly, results suggested that a group experienced a “recovery” from the poor health status (Class 5, 10.43%), indicating that their mobility limitations and depressive symptoms decreased across time, whereas their cognition and self-rated health improved over time. This group was further labeled as *Improved health* based on this interesting finding.

To get a clearer picture about the health patterns, Figure 6 presents the changes of each health outcome (i.e., mobility limitations, self-rated health, depressive symptoms, and cognition) by each health pattern. See Figure 6 for details.

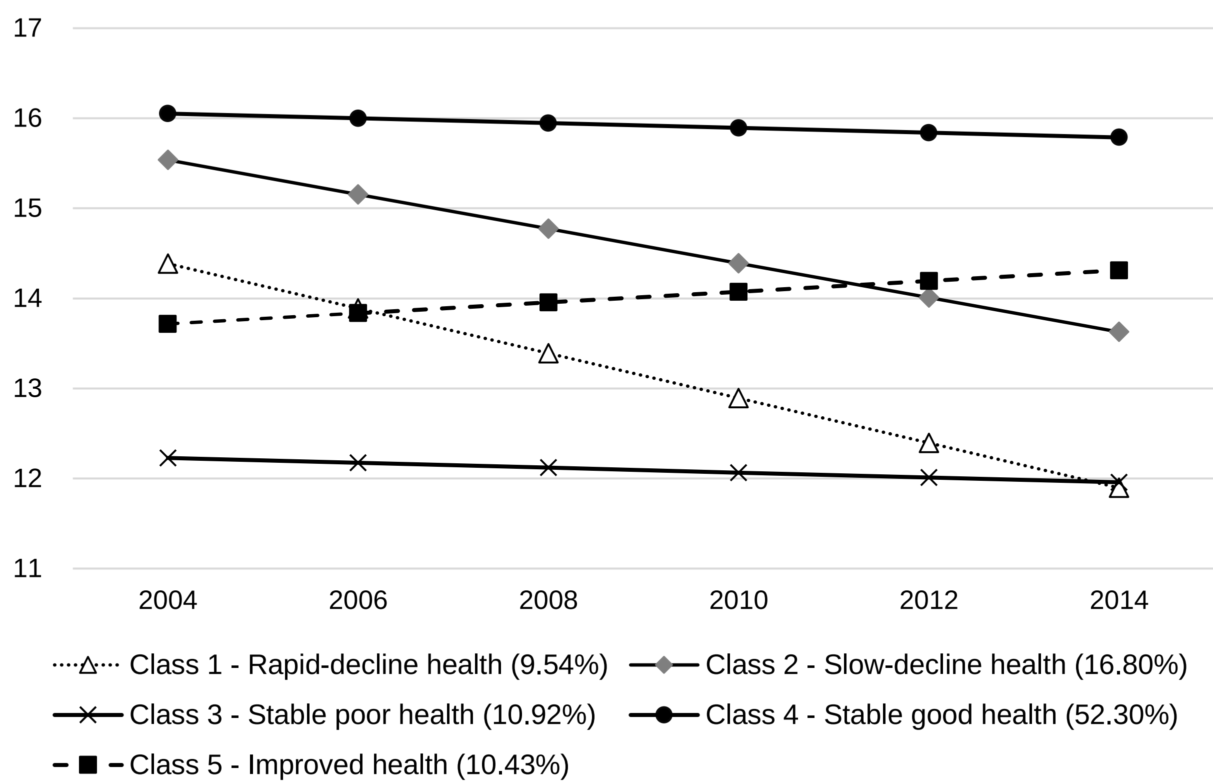

Figure 5. Joint Health Patterns in Later Life, 2004 to 2014

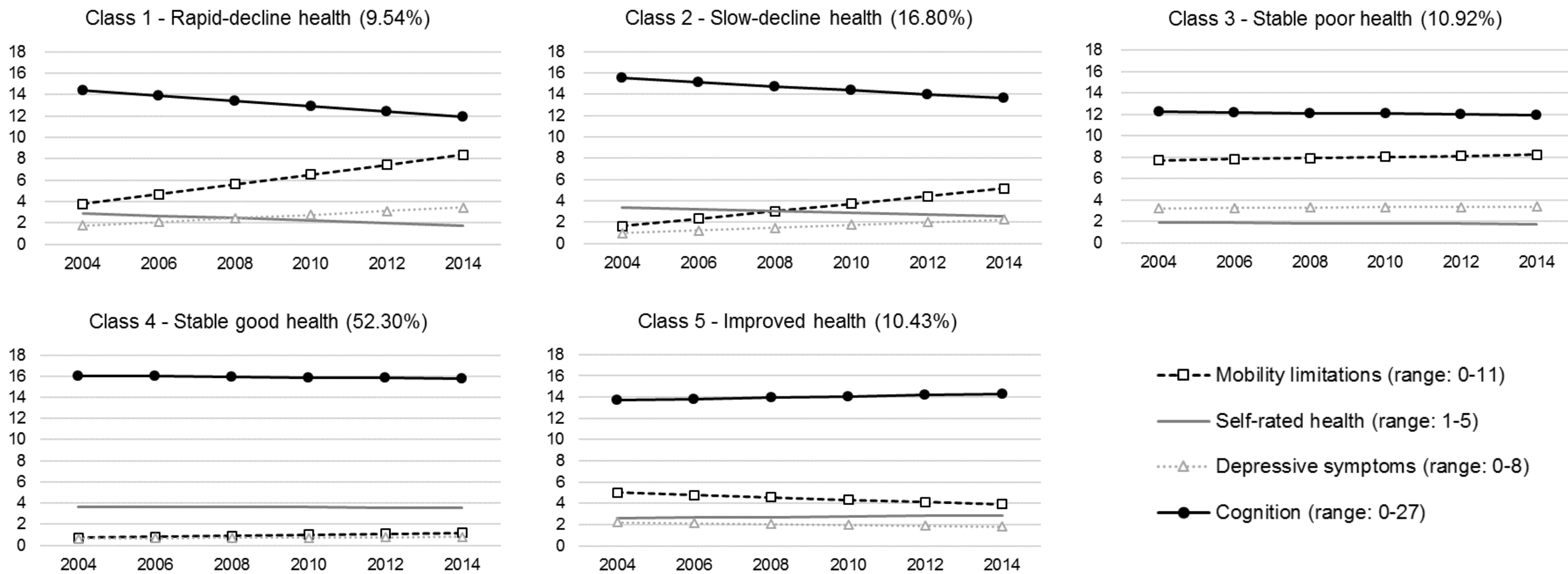

Figure 6. Joint Health Patterns, by Each Health Status, 2004 to 2014

Table 10 Results of Latent Growth Mixture Models (LGMM) for Health Trajectory

Fit statistics	*2-Class*	*3-Class*	*4-Class*	*5-Class*	*6-Class*
GMM					
Log Likelihood	−624827.301	−622757.574	−621723.803	−621200.445	−620761.981
BIC	1250439.661	1246329.282	1244290.818	1243273.178	1242425.325
SSABIC	1250182.248	1246062.336	1244014.338	1242987.165	1242129.778
Entropy	0.842	0.807	0.807	0.796	0.801
Adjusted LMRT (*p*)	17183.246 (.000)	4001.823 (.000)	1998.797 (.000)	1011.915 (.000)	847.772 (.000)
BLRT (*p*)	17774.218 (.000)	4139.455 (.000)	2067.540 (.000)	1046.718 (.000)	876.929 (.000)
Class size (*n*, %)					
Class 1	4994 (30.85%)	2481 (15.33%)	2973 (18.36%)	1545 (9.54%)	3066 (18.94%)
Class 2	11195 (69.15%)	4446 (27.46%)	1840 (11.37%)	2720 (16.80%)	754 (4.65%)
Class 3		9262 (57.21%)	2157 (13.32%)	1768 (10.92%)	1949 (12.04%)
Class 4			9219 (56.95%)	8467 (52.30%)	1317 (8.14%)
Class 5				1689 (10.43%)	8014 (49.50%)
Class 6					1089 (6.73%)

Note. BIC = Bayesian Information Criteria. SSABIC = Sample size adjusted BIC. LMRT = Lo-Mendell-Rubin Likelihood Ratio Test. BLRT = Bootstrap Likelihood Ratio Test. p = p value. The class results were adjusted for household clustered effect using TYPE = COMPLEX MIXTURE in M*plus*. BLRT was produced using TYPE = MIXTURE.
$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

4.3.3 Associations of Wealth Patterns and Health Patterns: Bivariate Analyses

Results of LGMM for wealth and health trajectory models showed that, for the wealth model, four patterns were identified: *Low and increasing* (Class 1, 2.38%), *Stable high* (Class 2, 73.11%), *Stable low* (Class 3, 18.69%), and *High & decline* (Class 4, 5.83%). Results for the health model showed five distinct patterns, including: *Rapid-decline health* (Class 1, 9.54%), *Slow-decline health* (Class 2, 16.80%), *Stable poor health* (Class 3, 10.92%), *Stable good health* (Class 4, 52.30%), and *Improved health* (Class 5, 10.43%). These trajectory patterns represent the longitudinal changes in wealth and health, and these results further confirmed that heterogeneity exists in both of these important constructs.

The final research question in this study examines how the wealth patterns associate with health patterns longitudinally, with considerations of life course factors. The findings presented in this section describe the bivariate associations between life course factors, wealth patterns, and health patterns. These findings were weighted and controlled for complex survey design, including personal sampling weights, strata, and clusters.

Table 11 shows the associations between life course factors and wealth patterns. In terms of sociodemographic factors, the age (measured at the baseline) for older adults with a *Stable high* wealth pattern (*Mean* = 61.88) and a *Stable low* wealth pattern was very similar (*Mean* = 61.75), but those with a *Low but increasing* wealth pattern were much younger (*Mean* = 57.40). However, their health status (measured at the baseline) were very different. Older adults with a *Stable high* wealth pattern had the highest score in each health, as they had fewer chronic diseases ($F = 47.15$, $p < .001$), lower mobility limitations ($F = 88.97$, $p < .001$), and less depressive symptoms ($F = 121.87$, $p < .001$). But they were found to have higher cognition ($F = 62.61$, $p < .001$) and better self-rated health ($F = 129.84$, $p < .001$). In contrast, older adults with wealth patterns other than

Stable high were less healthy, and older adults with a wealth pattern that was *Stable low* had the worst health status, as they had the lowest score in each health outcomes.

In terms of life course factors, results showed that both poor childhood SES and adulthood SES were associated with wealth patterns. Older adults with fathers with low education (χ^2=386.41, p < .001), mother's education (χ^2=513.10, p < .001), fathers with a blue collar job (χ^2=84.22, p < .001), was born in a poor family (χ^2=160.39, p < .001), had no college education (χ^2=591.56, p < .001), and with less income (χ^2=253.21, p < .001) were less likely to have a wealth pattern that was maintained at higher level (i.e., *Stable high*), but were more likely to have a low or decline wealth pattern.

Variations in gender (χ^2=47.43, p < .001) were observed in the wealth patterns. Females were more likely to have a *Stable low* wealth pattern but were less likely to be in the increasing wealth group (i.e., *Low but increasing*). A distinct variation was found in race (χ^2=173.79, p < .001). Older blacks or Hispanics, compared to older whites, were more likely to have a *Stable low* wealth pattern. For the effect of cohort (χ^2=290.41, p < .001), results suggested that respondents born in earlier cohorts were more likely to have a better wealth pattern (e.g., *Stable high* or *High but decline*). For those born into later cohorts, they were more likely to have a wealth pattern that was *Low & increasing*.

Table 11. Life Course Factors and Wealth Patterns: Bivariate Analyses

	(Total sample) M (SD) or %	*Class 1* *Low & Increasing (2.38%)*	*Class 2* *Stable High (73.11%)*	*Class3* *Stable Low (18.69%)*	*Class 4* *High & decline (5.82%)*	*Statistics* χ^2/F
Childhood SES						
Father's education (low) [a]	22.07%	25.17%	18.84%	39.50%	27.51%	χ^2=386.41***
Mother's education (low) [a]	17.22%	17.99%	13.91%	34.50%	21.22%	χ^2=513.10***
Father's job (blue-collar) [a]	65.60%	73.42%	63.71%	74.96%	66.62%	χ^2=84.22***
Family SES (poor)[a]	28.00%	34.84%	25.66%	37.83%	30.91%	χ^2=160.39***
Adulthood SES						
Education level (< college) [a]	71.41%	82.25%	66.82%	89.88%	80.60%	χ^2=591.56***
Income (< median) [a]	36.28%	44.59%	26.56%	79.09%	52.30%	χ^2=253.21***
Life course covariates						
Female [a]	55.45%	47.89%	54.46%	61.18%	57.15%	χ^2=47.43***
Race						
White	81.87%	69.64%	88.31%	53.40%	74.41%	χ^2=173.79***
Black	9.64%	16.24%	6.26%	24.66%	13.38%	
Hispanics	8.49%	14.12%	5.44%	21.95%	12.21%	
Cohort						
Prior 1923 (AHEAD)	4.82%	2.18%	4.78%	4.87%	6.42%	χ^2=290.41***
1924-1930 (CoDA)	5.48%	2.11%	5.56%	5.57%	5.64%	
1931-1941 (HRS)	34.58%	18.27%	36.78%	28.49%	27.75%	
1942-1947 (WB)	25.64%	33.44%	26.20%	21.35%	25.79%	
1948-1953 (EBB)	29.48%	44.00%	26.67%	39.72%	34.41%	
Other covariates						
Age (baseline)	61.70 (8.44)	57.40 (6.05)	61.88 (8.21)	61.75 (9.70)	60.98 (9.21)	F=34.79***
Poor childhood health [a]	5.72%	6.77%	4.68%	10.66%	5.72%	χ^2=134.54***
Living in urban area [a]	49.01%	46.92%	49.83%	43.53%	51.02%	χ^2=28.20*
Chronic diseases	1.44 (1.23)	1.49 (1.30)	1.35 (1.15)	1.90 (1.53)	1.62 (1.31)	F=47.15***
Baseline health outcomes						
Mobility limitations	1.95 (2.48)	2.45 (2.84)	1.65 (2.16)	3.47 (3.53)	2.45 (2.78)	F=88.97***

	(Total sample) M (SD) or %	Class 1 Low & Increasing (2.38%)	Class 2 Stable High (73.11%)	Class3 Stable Low (18.69%)	Class 4 High & decline (5.82%)	Statistics χ^2/F
Self-rated health	3.47 (1.06)	3.08 (1.14)	3.61 (0.98)	2.77 (1.21)	3.23 (1.11)	F=129.84***
Depressive symptoms	1.22 (1.83)	2.01 (2.23)	1.00 (1.58)	2.25 (2.61)	1.64 (2.15)	F=121.87***
Cognition	16.77 (3.86)	16.27 (3.77)	17.16 (3.56)	14.59 (4.88)	16.48 (4.06)	F=62.61***

Note. [a] Report only yes category. Percentage was weighted and controlled for complex survey design.
*p < .05, **p < .01, ***p < .001, two-tailed test.

Table 12 presents the bivariate associations between life course factors, wealth patterns, and health patterns. Results showed that there was a strong association between the wealth patterns and the health patterns (χ^2=1462.66, $p < .001$). Older adults with a *Stable low* wealth pattern were more likely to have a *Stable poor health* or *Rapid-decline health*. In contrast, older adults with a *Stable high* wealth pattern were more likely to be in the *Stable good health* group.

In terms of other characteristics, older adults with cumulative disadvantages, including low childhood SES—low father's education (χ^2=511.40, $p < .001$), low mother's education (χ^2=438.92, $p < .001$), fathers with blue-collar jobs (χ^2=141.77, $p < .001$), and with poor family SES (χ^2=354.92, $p < .001$)—and low adulthood SES—no college education (χ^2=869.15, $p < .001$) and lower income (χ^2=1953.91, $p < .001$)—were more likely to have a health pattern that was either declining (e.g., *Slow-decline* or *Rapid-decline*) or *Stable poor*.

Further, females (χ^2=457.42, $p < .001$), blacks (χ^2=482.98, $p < .001$), or Hispanics (χ^2=802.37, $p < .001$) were more likely to have a *Rapid-decline health* or *Stable poor health*. In terms of the effect of cohort, those born in the earlier cohorts were more likely to have poor or declining health, and those born in the later cohort were more likely to have a *Stable good health* or *Improved health*.

Table 12. Life Course Factors, Wealth Patterns, and Health Patterns: Bivariate Analyses

		Class 1	*Class 2*	*Class3*	*Class 4*	*Class 5*	*Statistics*
	(Total sample) M (SD) or %	*Rapid-decline health (9.54%)*	*Slow-decline health (16.80%)*	*Stable poor health (10.92%)*	*Stable good health (52.30%)*	*Improved health (10.43%)*	χ^2/F
Wealth patterns							
Low & increasing (Class 1)	2.51%	3.57%	2.73%	4.18%	2.12%	2.73%	χ^2=1462.66***
Stable high (Class 2)	77.00%	60.72%	72.60%	45.01%	84.75%	68.10%	
Stable low (Class 3)	14.89%	26.19%	16.66%	43.12%	8.76%	23.25%	
High & decline (Class 4)	5.60%	9.53%	8.01%	7.68%	4.37%	5.92%	
Childhood SES							
Father's education (low) [a]	22.07%	34.34%	27.12%	42.23%	16.63%	31.12%	χ^2=511.40***
Mother's education (low) [a]	17.22%	27.08%	21.55%	34.66%	12.85%	21.58%	χ^2=438.92***
Father's job (blue-collar) [a]	65.60%	74.46%	69.39%	76.45%	61.25%	73.34%	χ^2=141.77***
Family SES (poor) [a]	28.00%	36.14%	31.46%	45.10%	23.38%	34.40%	χ^2=354.92***
Adulthood SES							
Education (< college) [a]	71.41%	86.89%	80.17%	91.32%	63.52%	84.37%	χ^2=869.15***
Income (< median) [a]	36.28%	61.28%	45.72%	75.37%	24.41%	53.31%	χ^2=1953.91***
Life course covariates							
Female [a]	55.45%	65.22%	59.20%	73.13%	49.50%	68.69%	χ^2=457.42***
Race							
White	81.87%	73.90%	79.77%	62.61%	85.94%	78.39%	χ^2=482.98***
Black	9.64%	15.41%	9.99%	19.36%	7.49%	12.02%	
Hispanics	8.49%	10.69%	10.24%	18.04%	6.57%	9.58%	
Cohort							
Prior 1923 (AHEAD)	4.82%	11.00%	10.12%	7.44%	2.64%	5.02%	χ^2=802.37***
1924-1930 (CoDA)	5.48%	11.43%	8.34%	6.32%	3.90%	7.09%	
1931-1941 (HRS)	34.58%	38.13%	41.27%	33.48%	32.48%	36.64%	
1942-1947 (WB)	25.64%	17.88%	20.37%	24.11%	27.11%	30.16%	
1948-1953 (EBB)	29.48%	21.56%	19.90%	28.64%	33.88%	21.10%	

	(Total sample) M (SD) or %	*Class 1* Rapid-decline health (9.54%)	*Class 2* Slow-decline health (16.80%)	*Class3* Stable poor health (10.92%)	*Class 4* Stable good health (52.30%)	*Class 5* Improved health (10.43%)	*Statistics* χ^2/F
Other covariates							
Age (baseline)	61.70 (8.44)	65.54 (10.77)	65.09 (9.74)	62.91 (9.63)	60.35 (7.44)	62.20 (8.40)	F=44.54***
Poor childhood health [a]	5.72%	9.37%	5.59%	16.69%	3.56%	9.19%	χ^2=412.26***
Living in urban area [a]	49.01%	44.79%	47.74%	40.12%	51.45%	44.10%	χ^2=76.60***

Note. [a] Report only yes category. Percentage was weighted and controlled for complex survey design.
*p < .05, **p < .01, ***p < .001, two-tailed test.

4.3.4 Associations of Wealth Patterns and Health Patterns: Multivariate Analyses

Table 13 presents the multivariate results for the effects of wealth patterns on health patterns using multinomial logistic regression. Because life course factors have critical impacts on wealth, the estimates of wealth pattern on health patterns may suffer from the endogeneity issues. Therefore, this study uses generalized propensity score (GPS) analysis to balance the differences of life course factors on wealth patterns by creating propensity score weights, and then performs the multinomial logistic regression with both propensity score weights and sampling weights. Results of the imbalanced check (see Appendix F) showed that, except for some random significances (e.g., gender, working status, and marital status), the use of the grand weight (the multiplication term of propensity score weights and sampling weights, see method section for more details) balanced the differences of life course factors on wealth patterns. This means the GPS analysis has removed the observed endogeneity in wealth, and therefore increases the confidence in the estimations.

Using the largest group for wealth and health patterns as reference groups, results of GPS analysis indicated that wealth patterns (reference group: Class 2-*Stable high*) were significantly associated with the health patterns (reference group: Class 4- *Stable good health*). Compared to those with a *Stable high* wealth pattern, older adults with a *Low & increasing* wealth pattern were more likely to have *Rapid-decline health* ($RRR = 3.01$, $p < .001$) or *Stable-poor health* ($RRR = 3.40$, $p < .001$). In addition, older adults with a declining pattern of wealth (i.e., *High & decline*) were more likely to have a decline pattern (e.g., *Rapid-* or *Slow-decline health*) or *Stable poor health*. The most notable results were for older adults with a *Stable low* wealth pattern: those with a *Stable low wealth* pattern had higher odds to have *Rapid-decline health* ($RRR = 3.55$, $p < .001$) or *Stable-poor health* ($RRR = 5.00$, $p < .001$).

This study further changes the reference groups in order to better clarify the complex relationships between wealth patterns and health patterns; these findings are presented in Table 14 and Appendix H. It is evident that, regardless of what reference groups were used for both wealth and health patterns, older adults with a *Stable high* wealth pattern are more likely to have better health (either *Stable good health* or *Improved health*) or have a slower decline in health (i.e., *Slow-decline health*). They are also less likely to have poor health and be in the *Rapid-decline health* or *Stable poor health* groups. In contrast, older adults with a *Stable low* wealth pattern are observed to have poor health in later life: they are more likely to have *Stable poor rather* than *Stable good health*.

Findings also reveal some positive effects of health for older adults with a *Low & increasing* or a *High & decline* wealth pattern. Generally speaking, older adults with these two types of wealth patterns tend to have poor health only when compared to older adults with the best wealth pattern (i.e., *Stable high*). When compared to the worst wealth pattern (i.e., *Stable low*), older adults with either a *Low & increasing* or a *High & decline* wealth pattern tend to have better health. For example, when compared to older adults with a *Stable low* wealth pattern, older adults with a *Low & increasing* wealth pattern are more likely to have a *Stable good health*. For older adults with a *High & decline* pattern, they are more likely to have *Stable good health* or *Slow-decline health*, and are less likely to have *Stable poor health*.

In terms of life course factors on health patterns, holding all other factors constant, results showed that older adults who were female and had no college degree were more likely to have a poor health status. In contrast, working had a protective effect on health. Older adults who continued to work were less likely to have *Rapid-decline*, *Slow-decline*, or *Stable poor* health. Those who were married, compared to those were not married, were less likely to have *Rapid-*

decline health. Another notable result is the effect of income and wealth patterns on health patterns. This study showed that income was not related to health patterns when the wealth patterns were considered in the model. This finding suggests that wealth plays a more important role in influencing health in later life compared to income.

Table 13. Wealth Patterns and Health Patterns: Generalized Propensity Score Analysis

	Joint-Health Patterns			
	Class 1: Rapid-decline health (9.54%)	*Class 2: Slow-decline health (16.80%)*	*Class 3: Stable poor health (10.92%)*	*Class 5: Improved health (10.43%)*
	RRR	*RRR*	*RRR*	*RRR*
Wealth patterns (*ref*: Stable high, Class 2)				
Low & increasing (Class 1)	3.01**	1.77*	3.40***	1.33
Stable low (Class 3)	3.55***	1.88***	5.00***	2.37*
High & decline (Class 4)	2.53***	1.88***	1.99**	1.33
Life course factors				
Childhood SES				
Father's education (low)	1.84	1.23	1.67	1.73
Mother's education (low)	1.03	1.03	1.28	1.13
Father's job (blue-collar)	0.91	1.08	1.31	0.86
Family SES (poor)	1.26	0.88	1.76	1.08
Adulthood SES				
Education level (< college)	2.27**	1.64	3.04*	3.15**
Income (< median)	0.71	1.21	1.8	1.79
Life course covariates				
Female	1.69*	1.29	2.73***	1.72*
Race (*ref*: White)				
Black	0.53*	0.57*	0.59	0.65
Hispanics	0.59	0.88	0.43	0.37
Working (proportion)	0.09***	0.46**	0.04***	0.43**
Married (proportion)	0.46*	0.90	1.10	0.81
Cohort (*ref*: Born prior 1923, AHEAD)				
1924-1930 (CoDA)	3.89	1.94	1.13	2.51
1931-1941 (HRS)	0.55	0.78	0.35	2.43
1942-1947 (WB)	0.41	0.65	0.26	2.31
1948-1953 (EBB)	1.25	0.90	0.48	2.44

	Joint-Health Patterns			
	Class 1: Rapid-decline health (9.54%)	*Class 2: Slow-decline health (16.80%)*	*Class 3: Stable poor health (10.92%)*	*Class 5: Improved health (10.43%)*
	RRR	*RRR*	*RRR*	*RRR*
Other covariates				
Age (baseline)	0.97	0.99	0.90**	0.97
Poor childhood health	1.83	0.91	2.23*	2.41**
Living in urban area	1.47	1.38	1.55	1.37
Chronic diseases (baseline)	2.26***	1.40**	3.44***	2.19***
Attrition	1.35	1.15	1.07	0.78
Interview method (face-to-face)	0.36	0.64	0.86	1.49
Constant	0.38	0.24	2.20	0.03

Note. ref = reference group. Reference group of joint health patterns: Class 4 (*Stable good health*).
Results were based on 20 imputed data sets with control for complex survey design.
*$p < .05$, **$p < .01$, ***$p < .001$, two-tailed test.

Table 14. Wealth Patterns and Health Patterns: Changes of Reference Groups for Both Wealth and Health Patterns

Wealth patterns (W)	*Health patterns (H)*				
	Stable good (H_{SG})	*Stable poor (H_{SP})*	*Rapid-decline (H_{RD})*	*Slow-decline (H_{SD})*	*Improved (H_{IM})*
Stable high (W_{SH})	$+ (W_{LI}, H_{RD})$ $+ (W_{LI}, H_{SD})$ $+ (W_{LI}, H_{SP})$ $+ (W_{SL}, H_{RD})$ $+ (W_{SL}, H_{RD})$ $+ (W_{SL}, H_{SP})$ $+ (W_{SL}, H_{IM})$ $+ (W_{HD}, H_{RD})$ $+ (W_{HD}, H_{SD})$ $+ (W_{HD}, H_{SP})$	$- (W_{LI}, H_{SD})$ $- (W_{LI}, H_{IM})$ $- (W_{SL}, H_{RD})$ $- (W_{SL}, H_{SG})$ $- (W_{SL}, H_{IM})$ $- (W_{HD}, H_{SG})$	$- (W_{LI}, H_{SG})$ $- (W_{LI}, H_{SG})$ $- (W_{LI}, H_{IM})$ $- (W_{SL}, H_{RD})$ $- (W_{SL}, H_{SG})$ $- (W_{SL}, H_{IM})$ $- (W_{HD}, H_{SG})$ $- (W_{HD}, H_{IM})$	$+ (W_{LI}, H_{SP})$ $+ (W_{SL}, H_{RD})$ $+ (W_{SL}, H_{SP})$ $- (W_{SL}, H_{SG})$ $- (W_{HD}, H_{SG})$	$+ (W_{LI}, H_{RD})$ $+ (W_{LI}, H_{SP})$ $+ (W_{SL}, H_{RD})$ $+ (W_{SL}, H_{SP})$ $- (W_{SL}, H_{SG})$ $+ (W_{HD}, H_{RD})$
Stable low (W_{SL})	$- (W_{LI}, H_{IM})$ $- (W_{SH}, H_{RD})$ $- (W_{SH}, H_{SD})$ $- (W_{SH}, H_{SP})$ $- (W_{SH}, H_{IM})$ $- (W_{HD}, H_{SP})$ $- (W_{HD}, H_{IM})$	$+ (W_{SH}, H_{SD})$ $+ (W_{SH}, H_{SG})$ $+ (W_{SH}, H_{IM})$ $+ (W_{HD}, H_{SD})$ $+ (W_{HD}, H_{SG})$	$+ (W_{SH}, H_{SG})$ $+ (W_{SH}, H_{IM})$	$- (W_{SH}, H_{RD})$ $- (W_{SH}, H_{SP})$ $+ (W_{SH}, H_{SG})$ $- (W_{HD}, H_{SP})$ $- (W_{HD}, H_{IM})$	$+ (W_{LI}, H_{SG})$ $- (W_{SH}, H_{RD})$ $- (W_{SH}, H_{SP})$ $+ (W_{SH}, H_{SG})$ $+ (W_{HD}, H_{SG})$
Low & increasing (W_{LI})	$- (W_{SH}, H_{RD})$ $- (W_{SH}, H_{SD})$ $- (W_{SH}, H_{SP})$ $+ (W_{SL}, H_{IM})$	$+ (W_{SH}, H_{SD})$ $+ (W_{SH}, H_{IM})$	$+ (W_{SH}, H_{SG})$ $+ (W_{SH}, H_{SG})$ $+ (W_{SH}, H_{IM})$	$+ (W_{SH}, H_{SG})$	$- (W_{SH}, H_{RD})$ $- (W_{SH}, H_{SP})$ $- (W_{SL}, H_{SG})$
High & decline (W_{HD})	$- (W_{SH}, H_{RD})$ $- (W_{SH}, H_{SD})$ $- (W_{SH}, H_{SP})$ $+ (W_{SL}, H_{SP})$ $+ (W_{SL}, H_{IM})$	$+ (W_{SH}, H_{SG})$ $- (W_{SL}, H_{RD})$ $- (W_{SL}, H_{SG})$	$+ (W_{SH}, H_{SG})$ $+ (W_{SH}, H_{IM})$	$+ (W_{SH}, H_{SG})$ $+ (W_{SL}, H_{SP})$ $+ (W_{SL}, H_{IM})$	$- (W_{SH}, H_{RD})$ $- (W_{SL}, H_{SG})$

Note. The relationships document here representing the results of multinomial logistic regression models with $p < .05$ from the Appendix H. A + sign indicates the relative risks ratio (RRR) greater than 1 (i.e., more likely), and a – sign indicates the RRR less than 1 (i.e., less likely). The categories in the parentheses indicate the reference groups for both wealth and health patterns.

Chapter 5: Discussion

This chapter summarizes the main findings on the relationships between wealth and health in later life, and then discusses the limitations. This chapter concludes with implications for policy and research based on the findings presented in this study.

5.1 Discussion on Key findings

The focus of this study aims to examine the longitudinal wealth-health nexus in later life with three proposed research questions exploring the links between life course factors, wealth, and physical, mental, and cognitive health.

RQ1 asks how life course factors influence wealth trajectory in later life, with hypotheses suggesting that wealth declines in later life (**H1**), and that life course factors are associated with the initial levels of wealth (**H2**) as well as declines in wealth (**H3**). Results from **RQ1** revealed that wealth declines as older adults age, and older adults with cumulative disadvantage characteristics, such as being female, black, Hispanic, not married (reflecting the proportion of time remaining in marriage), with low childhood and adulthood SES, were more likely to have lower initial levels of wealth. Yet, it is found that older adults have lower levels of initial wealth if they spend more time at work (reflecting the proportion of time remaining at work), and some of the low childhood SES variables (e.g., father with low education and poor family SES) and cohort are not associated with initial levels of wealth. Findings further suggest that, with exceptions for income and cohort, life course factors have little or nothing to do with declines in wealth.

RQ2 tests the longitudinal relationship between wealth and health, with attention paid to how wealth trajectory relates to individual- and joint-health trajectories when the life course factors were modeled. This study hypothesizes that the health of older adults declines over time (**H4**), initial levels of wealth are associated with better initial levels of health and a slower decline in health (**H5**), and the declines in wealth associate with a faster decline in health (**H6**). Results from **RQ2** indicate that health declines as respondents grow old, and older adults with higher initial levels of wealth have better initial levels of overall health, including lower mobility limitations and depressive symptoms, and higher cognition and self-rated health. In terms of initial levels of wealth on declines in health, only the effect on mobility limitations is significant. Older adults with higher initial levels of wealth have slower increases in mobility limitations. Further, older adults with declines in wealth have a faster decline in all health outcomes, including more increases in mobility limitations and depressive symptoms as well as more decreases in cognition and self-rated health.

Using the generalized propensity score—a quasi-experimental design—**RQ3** examines how the longitudinal patterns of wealth associate with health patterns. The hypothesis suggests that older adults with wealth patterns that are either maintained at higher levels or increasing over time have health patterns that indicate a maintenance or improving health status. Results indicated that differential trajectory patterns for wealth (*Stable low*, *Stable high*, *Low & increasing*, *High & decline*) and health (*Rapid-decline*, *Slow-decline*, *Stable good*, *Stable poor*, and *Improved*) can be identified. Regardless of what reference groups were used for wealth patterns, older adults with a wealth pattern that is *Stable high* are more likely to have good health status. In addition, when compared to older adults with a *Stable low* wealth pattern, older adults with *Low & increasing* and *High & decline* are more likely to have better health such as *Stable good health* or *Slow-decline health*. The summaries of each hypothesis, research question, and related findings are presented in Table 15, with explanations on whether the findings support the hypotheses.

Table 15. Summaries of Findings, by Hypothesis

Hypothesis	*Relationship tested*	*Findings*
Research Question 1 (RQ 1)		
H1	Older adults' wealth declines over time.	**Fully supported.** Older adults' wealth decreases 0.07 unit (IHS transformed wealth) by every two years
H2	Older adults with cumulative disadvantages have lower levels of initial wealth.	**Partially supported.** Older adults who are female, black, Hispanic, not married, with low childhood SES (mothers with low education and fathers with blue-collar jobs) and low adulthood SES (no college degree and low-income) have lower levels of initial wealth. However, older adults who keep working have lower levels of initial wealth. Initial levels of wealth do not differ across father's education, family's SES, and cohort
H3	Older adults with cumulative disadvantages have a slower rate of decline in wealth.	**Mixed.** Older adults born in later cohorts have a slower rate of decline in wealth. However, low-income older adults have a faster rate of decline in wealth. Other life course factors, including childhood SES, education, gender, race, working status, and marital status are not related to wealth decline.
Research Question 2 (RQ 2)		
H4	Older adults' health declines over time.	**Fully supported.** Physical mobility limitations and depressive symptoms increase over time, and cognition and self-rated health decrease over time. The joint-health shows that the overall health of older adults declines as they age.
H5	Older adults with higher initial wealth have better initial health and have a slower decline in health over time.	**Partially supported.** Older adults with higher initial levels of wealth have better initial health both individually and jointly, including lower levels of mobility limitations and depressive symptoms and higher levels of cognition and self-rated health. Older adults with higher initial levels of wealth have a slower increase in mobility limitations over time. The initial levels of wealth are not associated with changes in depressive symptoms, cognition, and self-rated health.

Hypothesis	Relationship tested	Findings
H6	Older adults with declines in wealth have a faster rate of decline in health.	**Fully supported.** Older adults with declines in wealth have a faster rate of decline in both individual and joint health. Specifically, wealth declines are associated with more increases in mobility limitations and depressive symptoms as well as more decreases in cognition and self-rated health over time.
Research Question 3 (RQ 3)		
H7	Older adults with wealth patterns that are either maintained at the higher level or increasing over time have health patterns that indicate a maintenance or improving health status.	**Fully supported.** Four wealth patterns (*Low & increasing*, *Stable high*, *Stable low*, and *High & decline*) and five health patterns (*Rapid-decline*, *Slow-decline*, *Stable poor*, *Stable good*, and *Improved*) are identified. Older adults with a wealth pattern that is *Stable high* are more likely to have *Stable good health* or *Improved health*.

Findings from this study suggest that, with some exceptions, life course factors, wealth, and health in later life are intercorrelated and closely connected, as the results indicate that life course factors are associated with wealth, and wealth is significantly related to health in later life. Older adults with cumulative disadvantage characteristics, such as being female, being racial minority, with low childhood and adulthood SES characteristics, are more likely to have low wealth or to be placed into a wealth pattern that has little wealth accumulation, and in turn, have poor physical, mental, and cognitive health. Further, those who have a decline in wealth have an even faster decline in all aspects of health. However, controlling for the effect of life course factors, a virtuous cycle between wealth and health is also found in this study. Those who have a wealth pattern that is either maintained at higher levels or increasing over time showed a better health status. The section below provides detailed theoretical and empirical discussions on the relationships between life course factors, wealth, and health in later life.

5.1.1 Trajectory and Patterns of Wealth in Later Life

Findings in this study provide insights for both trajectory and patterns of wealth in later life. The latent growth curve modeling (LGCM) results showed that wealth trajectory in later life declines over time. Although several models—including the linear function and more complex models such as quadratic function and piece-wise function—were tested in this study, findings from these models generally support that wealth declines at old age. Despite the results of quadratic and piece-wise function of wealth showing a better model fit, this study selects the linear trajectory for wealth as it is a parsimonious model and offers better interpretability.

The trajectory of declining-wealth produced by the LGCM results can be addressed by life-cycle hypothesis (LCH), in that it assumes that all individuals follow a declining trajectory of wealth in later life (Ando & Modigliani, 1963; Deaton, 2005). However, this economic theory may only address part of the wealth trajectory at old age. As suggested by Sherraden (1991), there are heterogeneous developments in wealth across individuals with varied socioeconomic standings, indicating that more than one trajectory of wealth can be identified among older adults. In fact, the significant variance component in the LGCM reveals that heterogeneity occurs in the linear trajectory of wealth, and further investigations should be conducted. The results of latent growth mixture modeling (LGMM) showed that four distinct patterns of wealth are identified. The first trajectory is *Stable high* where the net worth of older adults maintained at high levels, and most older adults (73%) belong to this trajectory pattern. The second trajectory pattern, the *Stable low* (19%), has a wealth pattern with a low and no significant increase in net worth over time. There are about 8% of older adults whose wealth patterns change over time, in that approximately 6% of older adults have a *High & decline* wealth pattern with net worth that start higher at the baseline but gradually decrease over time. The remaining 2% of older adults belong to *Low & increasing* trajectory pattern, with very low net worth observed at the initial level but gradually accumulate their net worth over time. Findings from these results support Sherraden's postulation that multiple trajectories indeed exist in wealth in later life.

5.1.2 Cumulative Disadvantages and Wealth

Cumulative advantage and disadvantage (CAD) model, a theory building on the life course perspective, posits that individuals' wealth in old age are linked to the social advantages and disadvantages they have experienced throughout life, and the disparities in wealth widen over the life course (Carr, 2019). Guided by the CAD model, this study finds that several life course factors are associated with wealth in later life.

Gender and race. The effects of gender and race are evident. Results from this study indicate that females, blacks, and Hispanics have lower initial levels of wealth. There is a large body of work documenting gender and race as important predictors for wealth development. Females (Brown, 2012; Chang, 2010) and people of color (Angel & Mudrazija, 2015; McKernan et al., 2013, 2014a; Oliver & Shapiro, 2006) have been consistently found to have lower levels of wealth compared to their male and white counterparts. For example, Chang (2010) found that the median values of wealth for males ($28,610) are 2.75 times larger than females ($10,400), and Oliver and Shapiro (2006) found that wealth significantly and consistently differs across race even when the results were further stratified by age, occupation status, education levels, and labor market experiences. Using the intersectionality approach, Brown (2012) further found that black women have especially low levels of wealth during middle and late life: they have virtually no net financial assets at age 51, and do not accumulate any wealth as they age.

Possible explanations on why wealth varied by gender and race can be addressed in part by differences in the investment profiles. Although there is not much information by gender, there are a handful of works documenting that investment portfolios significantly differ across race. For example, African Americans and Hispanics (10%) are less likely to have retirement plans compared to older whites (50%) (Angel & Mudrazija, 2015), and they are less likely to possess transformative assets such as homes and inheritance, which are key to economic mobility (Brown, 2012). Another approach uses a structural perspective to explain the wealth disparity. For example, Carr (2019) notes, as community support programs are underdeveloped, women are more likely to experience work discontinuity due to providing care for parents, spouses, or children. Evidence has suggested that caregiving puts females into a vicious cycle of financial instability. Lee, Tang, Kim, and Albert (2014) found that females who provide care are more likely to have lower income, and those with lower income are more likely to be caregivers. Further, Shanks and Leigh (2015) found that employment discriminations are common among people of color: they are more likely to have work that is underpaid and with fewer benefits. These findings suggest that females and people of color are more likely to experience struggles in the process of wealth accumulation, and therefore, have lower levels of wealth when they get old.

Childhood SES factors. The CAD model, adopting the life course perspective, stresses the importance of "linked lives" in the process of accumulating wealth over a lifespan. The linked lives addresses how individuals' experiences can be shaped by a broader network of social relationships, in that it explains how and why childhood and adolescent conditions can affect wealth in later life (Carr, 2019). This study found that childhood SES factors— mothers with low education and fathers with blue-collar jobs—are statistically associated with lower levels of wealth in later life. The bivariate analyses further show that older adults with low childhood SES are more likely to have a *Stable low* wealth pattern. These results can be explained by the intergenerational transmission effect on how parents' characteristics get passed down to their children (Carr, 2019).

Although very few studies directly examine how poor childhood SES relates to wealth in later life, there is a large body of work establishing the pathways from poor childhood SES to poor outcomes in adulthood. For example, Duncan and Brooks-Gunn (1997) discuss the negative consequences of growing up poor, including poor physical and mental health, low school performance, and low educational attainment. These negative experiences have critical impacts on children's life chances, further limiting their future socioeconomic mobility. Wagmiller and Adelman (2009) found that children who grow up poor are more likely to be poor as adults, and those who experience a longer duration of poverty in childhood have even higher odds of being poor when they grow up. The major reason why these children born with early socioeconomic disadvantages stay in poverty is because of a lack of higher levels of education, as education is a power ladder for poor children to escape poverty (Ratcliffe & Kalish, 2017). Ratcliffe and Kalish (2017) find that among children who spend at least half of their childhood in poverty, only 62% of them have a high school education, compared to 90% for those who never experience poverty. In sum, children who experienced socioeconomic disadvantages during childhood, captured by low parental education, family poverty, and parental job insecurity, are less likely to reap economic success (Ratcliffe & Kalish, 2017), which in turn, limit their opportunities of enjoying wealth accumulation in later life.

Income and education. Education and income are both important predictors of wealth in later life. This study found that those without a college degree and with lower income are more likely to have lower levels of wealth. Further, those with lower income are found to have a faster decline in wealth. Evidence has suggested that having a higher education, such as a college degree, is associated with better economic success in the future, including a stable job with better benefits, longer working life, and higher economic independence (Murphy et al., 2013). Further, those with a college degree are more likely to have diverse asset portfolios and more monies in their retirement account. Carasso and McKernan (2008) found that older adults without a college degree have higher chances of being unbanked, whereas those with a college degree are more likely to have savings accounts, stocks, and retirement accounts. The values of these accounts further differ by education levels: the values of retirement accounts for those with a college degree are nearly four times larger than those with a high school education or some college experience. These findings clearly indicate that education has a strong effect in wealth accumulation.

The significant association between income and wealth is corresponded with a large body of economic studies (Alessie, Lusardi, & Aldershof, 1997; Alessie, Lusardi, & Kapteyn, 1995, 1999). For example, Alessie et al. (1995) found that higher income is associated with more bequest motives, whereas income declines are associated with lower levels of saving. They also examine how income is associate with both general saving and motives for precautionary saving (Alessie et al., 1999), and the results indicated that income and savings are highly associated. A recent study also suggests that income has impacts on the trajectory of wealth. For example, Rauscher and Elliott (2016) examine how income trajectory influences net worth trajectory between low- and high-income households. Findings reveal that the effect of income on wealth trajectory is only significant among high-income households. Specifically, those with higher levels of initial income are associated with faster increases in net worth.

The dynamics between income and wealth can be addressed by the virtuous-vicious feedback proposed by Sherraden (1991), in which he argues that initial economic resources are critical in shaping future wealth development and trajectory. For those who have little or no income, they are likely to continue to have little or no assets, and therefore stay trapped in the vicious cycle of income and asset poverty. In contrast, those with higher income puts them into a favorable position, which offers them more opportunities to generate and accumulate even more assets over their life course.

Marriage, work, and cohort. Lastly, this study finds mixed supports for how wealth in later life differs across marriage, work, and cohort. Using the proportion of time to measure engagement in marriage and work, results from this study showed that older adults who spent more time at work have lower levels of wealth, and those who stay married longer have higher levels of wealth. In terms of the effect of cohort on wealth, those born in later cohorts have lower levels of wealth.

First, consistent with the literature, marriage is a protective factor for wealth in later life. Older adults who are married, compared to their non-married counterparts, have higher levels of wealth (Chang, 2010). For example, Denton and Boos (2007) show that non-married respondents, such as those who are divorced, widowed, single, and separated, report significantly lower wealth compared to married respondents, and such effects hold constant across gender. Further, the duration of marriage also matters in the development of wealth. Wilmoth and Koso (2002) find that those who are constantly married, compared to those with marriage disruptions, report having more wealth. The possible explanations on why marriage status has impacts on wealth can be addressed by the differential levels of consumption. Zagorsky (2005) notes that the consumption needs of two adults living together are less than that of two separated single adult households. However, divorce and separation have negative impacts on wealth due to marriage settlement (partner can claim half of wealth) or life-style changes. This evidence suggests that marital status is critical in influencing wealth in later life.

The effect of work on wealth is mixed in this study. Although little research focuses on how working affects wealth in later life, based on the CAD model, this study hypothesizes that older adults with cumulative disadvantages in work—that is, for those who are not working—have lower levels of wealth. However, this study shows that older adults who spent more time at work, or continue to work, have lower levels of wealth. Such a finding is somewhat consistent with Halvorsen (2018), in that he examines how financial well-being varies by working status which include self-employment, wage-and-salary work, and not working. Results showed that, compared to the wage-and-salary work, older adults who are self-employed and not working have *higher* net worth.

The result of working on wealth should be interpreted with caution. This study uses proportion of time to measure work from 2004 to 2014—a duration measure indicates how long older adults keep working, with a score ranging from 0 to 1. The use of such a measure captures a complex picture of working in later life. It may represent older adults who are constantly at work (with a value of 1), or older adults who are not working for a while (with a value of 0). However, for those who are not working constantly, it indeed includes heterogeneous categories such as retirees, the unemployed, or people with disability. For older adults that with a score between 0 and 1, this may represent those who work for certain time points and then stop working due to retirement or other reasons such as being laid-off or having poor health, or represent older adults who enter and leave the labor market multiple times due to involuntary job separation or unexpected retirement. Each category of work has different implications on wealth in later life.

There are several explanations on the effect of work on wealth. If this finding is interpreted as more participation at work leading to lower wealth, the classic pull-push theory can explain such a finding. For instance, older adults with economic disadvantages may feel pushed into the workforce due to financial reasons, such as shortfall of pension income, higher living standard, or having to pay bills (Sewdas et al., 2017), as they need to work due to insufficient savings. If the effect of working is interpreted as older adults working for certain time points—meaning they leave and re-enter the labor market, evidence has suggested that this sporadic work history may negatively influences earnings of older adults, which in turn, resulting in having lower levels of wealth (Johnson & Gosselin, 2018). These results suggest that future research needs to re-examine the longitudinal effect of work on wealth.

Lastly, this study found that cohort is associated with wealth in later life. Older adults born in later cohorts, compared to those born in early cohorts, have lower levels of wealth. This finding is consistent with what McKernan et al. (2014b) and Denton and Boos (2007) found, in which they found that those who are younger (i.e., born in later cohorts) report lower wealth compared to those who are much older (i.e., born in early cohorts). This study further found that those who born in later cohorts, especially for those born between 1942 to 1947 and between 1948 to 1953, have a slower decline in wealth compared to the oldest cohort.

The current evidence does not offer a conclusive answer on why there are differences in wealth across age cohorts, partly because of varied research purposes. For example, McKernan et al. (2014b) found that younger cohorts, compared to older cohorts, have lower levels of wealth due to the fact that they are more likely to hold assets like homes or business equity, which are more likely to be influenced by market fluctuation such as a financial recession. Another recent evidence suggests that Baby Boomers (born between 1946 to 1964) are the fastest growing category of student loan debtors (Guardian Life Insurance, 2019), and 12% of Baby Boomers report that they are still paying student loans either for themselves or for someone else (AARP Research, 2018). It is possible that the issue of student debts makes older adults born between 1942 to 1953 less likely to accumulate assets, and therefore have a slower decline in wealth because they have little wealth to deplete over time. However, the effect of cohort on wealth is still not clear, and we need more research to examine how and why cohort impacts wealth in later life.

5.1.3 Asset-Effect on Health

Wealth is a stock that can be acquired, developed, improved, and transferred across generations (Oliver & Shapiro, 2006). As wealth is a financial cushion for older adults, it can be consumed to generate economic, psychological, social, and health benefits in later life. Using asset-based welfare theory, this study finds that wealth is individually and jointly associated with health in later life. Those with higher initial levels of wealth have higher initial levels of health, including lower mobility limitations and depressive symptoms, and higher cognition and self-rated health. In addition, those with wealth decline are found to have a faster decline in all aspects of health. Further, wealth patterns are associated with health patterns, in that those who have wealth patterns that are either increasing or maintained at higher levels enjoy better health and experience less decline in health or maintain their health at a better level.

These findings support the asset-building framework proposed by Sherraden (1991), where the theory suggests that assets can bring psychological and health benefits for asset owners. This study further extends Sherraden's work by exploring how longitudinal changes in wealth may influence outcomes among older adults, and findings reveal that wealth decline has a deteriorating effect on physical, mental, and cognitive health in later life. This study also supports Sherraden's propositions that heterogeneity exists in the development of wealth accumulation, as this study identifies four wealth trajectories among older adults, and each wealth trajectory demonstrates differential effects on health in later life.

Findings regarding the direct effect of wealth on health are consistent with a large body of studies, in that having more wealth results in better physical (Aittomäki et al., 2010; Deaton & Paxson, 1998; Geyer et al., 2014; Haas, 2008; Hajat et al., 2011; Sloan & Wang, 2005), mental (Bearden & Wilder, 2007; Carter et al., 2009; Chiao et al., 2011; Hamoudi & Dowd, 2014), and cognitive health (Allerhand et al., 2014; Cagney & Lauderdale, 2002; Hamoudi & Dowd, 2014; Lee et al., 2010; Lyu et al., 2014). These longitudinal and direct effects on physical, mental, and cognitive health suggest a virtuous-cycle of wealth-health nexus, in that wealth demonstrates a strengthening or buffer effect on health: people with more wealth are more likely to maintain a higher function of physical, mental, and cognitive health or are more likely to have less decline in health. In addition, a vicious-cycle of wealth-health relationship is also observed in this study. People with very low assets, compared to those with increasing or stable high wealth patterns, are more likely to have poor health patterns that are either rapid-decline or stable low health. In sum, the direct link between wealth and health in later life is largely substantiated in this study.

However, the direct effect of wealth on health should also be interpreted with caution. Although findings from this study indicate that wealth is one of the fundamental ways to improve health, other factors such as social, behavioral, and environment factors (Adler, Glymour, & Fielding, 2016; Marmot, 2005), may also play a role in shaping wealth accumulation during a lifespan. As Pollack, Kaplan, House, & Schoeni (2007, p. 379) note: "*Human health is too multifaceted, its determinants too varied, and the current state of our knowledge is too limited.*" Findings from this study reveal that it is necessary to study how wealth links to health in later life, as we know very little about the connections between wealth and health in later life.

This study urges that, since a direct link between wealth and health has been established, future studies need to explore the possible mediating mechanisms that connect wealth to health. For example, are people with more wealth more likely to engage physically, emotionally, or socially, and are people with fewer assets less likely to purchase better health insurance, healthy foods, or have lack of access to high quality of care? It is well documented that institutional effects such as tax codes or welfare programs have critical impacts on wealth trajectory (Sherraden, 1991), which in turn, may also influence health in later life. There may be other economic, social, and behavioral mechanisms that connect wealth to health. However, very few studies explore these possible mechanisms between wealth and health among older adults. For example, Arber, Fenn, and Meadows (2014) found that subjective financial well-being mediates the relationship between income and self-report health in later life. Results showed that income leads to positive subjective economic well-being, which in turn, leads to better health in later life. Han and Hong (2013) examine how the relationship between wealth and mental health (measured by self-esteem) is mediated by volunteering. Results suggest that volunteering partially mediates the relationship between wealth and self-esteem. Older adults with more wealth are more likely to engage in volunteering, and in turn, have higher self-esteem. In fact, Lerman and McKernan (2008) suggest that dynamics exist in the relationships between wealth and economic, social, psychological and health, and intergenerational outcomes. These possible economic, behavioral, psychological, and social pathways should be seriously addressed in future research.

5.2 Limitations

Although this study employs a longitudinal design and rigorous methods to examine the associations between wealth and health in later life, this study is not free from limitations.

Limitation 1: Investigations for life course effect. Although this study examines how life course factors influence wealth using a series of SES variables in childhood, middle- and late-adulthood, this approach only captures a part of the life course effect as the variables in infancy, early childhood, and young adulthood are not fully investigated. This limitation is caused by using the HRS because this data set only selects respondents aged 50 and older, and most variables measured in childhood are self-reported and they may suffer from recall bias. To get a full picture of how factors in each life stage influence wealth, future studies are encouraged to use certain data sets that include younger respondents, with information on life course factors measured in each life stage.

Limitation 2: Examinations for other asset measures. The use of a single asset measure—net worth—is another limitation in this study. This study uses net worth, a composite measure combining different types of assets, including financial, housing, and other assets. Although net worth is a widely used variable for measuring assets in later life (C. E. Pollack et al., 2007) and is recommended to use when assessing health of individuals using population-based data sets (Cubbin et al., 2011), different types of assets may be associated with different asset effects (Sherraden, 1991). For example, Geyer et al. (2014) find differential effects of debts, owning life insurance, financial assets, and homeownership on self-rated health, Bearden and Wilder (2007) examine how wealth, Social Security income, and life pension income relate to depressive symptoms, and Costa-Font (2008) uses income and housing price to predict physical limitations and self-rated health. Yet, this study does not test what types of assets lead to which types of health outcomes, nor does this study explore this question.

Further, the effects of intangible assets should also be considered. As suggested by Sherraden (1991), assets also have intangible aspects. Intangible assets include (1) access to credit, (2) human capital (e.g., education, knowledge and skills, and working experience), (3) psychological capital (e.g., vision and hope) and subjective aspects of assets, (4) social capital (formal, informal, and organizational), (5) cultural capital, and (6) political capital. Although these capitals may not be directly quantified, individuals with these intangible assets may extend their future opportunities and life chances for further asset development. This study only focuses on the impacts of tangible assets on health without examining the influences of intangible assets, but evidence has suggested that intangible assets, especially the psychological or subjective measure of assets, are important factors in influencing health in later life. For example, measures related to economic strain (Arber et al., 2014; Chiao et al., 2011), needs met by financial resources (Borg, Hallberg, & Blomqvist, 2006), and material deprivations (Arber et al., 2014; Butterworth, Rodgers, & Windsor, 2009) have had been used to examine the effects on self-rated health, satisfaction, and depression. Findings from these studies reveal that the subjective measure of assets are highly associated with health of older adults, and future studies need to test how both tangible and intangible assets influence health in later life.

Limitation 3: Methodological issues in trajectory and patterns of wealth and health. In this study, different functions of wealth and health trajectory (i.e., linear, quadratic, and piece-wise function) using latent growth curve modeling (LGCM) are tested, and results showed that these models demonstrate similar model fits. Despite other models (e.g., quadratic function and piece-wise function) showing a better model fit, the linear trajectory is selected based on parsimonious and interpretability reasons. This pragmatic strategy may oversimplify the wealth and health trajectory in later life, and the use of these models may lose utility in describing the dynamics and changes in wealth and health in a detailed manner.

This study further uses latent growth mixture modeling (LGMM) to explore trajectory patterns for wealth and health. Despite the theoretical perspective being used to guide the selection and identification for both wealth and health patterns, the empirical strategies—including fit index and model interpretability—are also employed in this study. Results using both theoretical and empirical methods show that a total of four classes for wealth and five classes for health are identified. Specifically, this study identifies both "good" and "poor" patterns for wealth and health. Yet, these findings should be interpreted with caution. For example, in terms of good and poor patterns, they are created and labeled based on the individuals' "performance" on wealth and health status in relation to other people. However, how much of what can be classified as having good/poor pattern for wealth and health remains an open question, as it involves an understanding of the "threshold" for defining what can be regarded as good or poor wealth and health. In sum, although these patterns may be theoretically justified, the practical meanings should be further explored. In fact, it should be noted that these patterns are descriptive and exploratory rather than predictive and confirmative, as the use of LGMM is to empirically search for an *optimal* model with an *appropriate* latent class that summarizes the data well (Nylund et al., 2007).

While the use of LGMM has gained increasing attention in the aging field, this method is not without criticism (Infurna & Grimm, 2018). The over-extraction issue in identifying latent trajectory classes is not uncommon in LGMM. Criticisms made by Bauer and Curran (2003) suggest that the extraction may not be true and accurately reflect the population, as the LGMM assumes that the existence of distinct unobserved subgroups can be found in the populational distribution, but their study shows that the trajectory class can be estimated even in the absence of population heterogeneity. Further, LGMM can be tested to constrain or relax the homogeneous variance assumptions in each latent trajectory class, with over-extraction being more common when constraining variance to be equal across latent class (Infurna & Grimm, 2018). In other words, despite these trajectory classes of wealth and health identified in this study, they may not represent true subgroups existing in the population, but the optimal groups that best summarize the data.

Limitation 4: Hidden selection bias and method-effect. Although this study models the effects of life course factors on wealth followed rigorous theoretical frameworks, these factors are mainly *observed* factors, and potential *hidden* factors may not be considered, which means this study is not free from the hidden selection bias. Further, despite this study controls for the mode interview effects due to different data collection methods, it is possible that the rater-effects may remain in the analyses (Guo, 2014). Future studies may need to address the rater-effects in estimating both wealth and health in later life.

5.3 Implications

5.3.1 Policy Implications

Findings from this study reveal that life course factors are associated with wealth, and wealth has a positive impact on health in later life. These findings provide important implications for policy development in the U.S.

Toward an asset-based policy development. Findings from this study suggest that increasing older adults' economic security will promote their health in later life. This is especially important given that Americans are expected to live longer. Life expectancy in the United States increased from 70.8 years in 1970 to 78.9 years in 2015. Yet, research has shown that the average retirement age in the U.S. is 64 for men and 62 for women (Munnell, 2015). This indicates a span of 15 to 17 years for both men and women to support their economic life and maintain economic independence after retirement.

A review made by Huang and Greenfield (2015) suggests that there are several policies and programs operating in different levels that focus on economic security and health issues among older adults. For example, policies related to *retirement income* include Social Security, supplemental security income (SSI), and private-sector defined-contribution pension plans such as 401(k) and individual retirement accounts (IRA). Programs related to *health maintenance and promotion* include Medicare, Medicaid, and health saving accounts (HSA). There are also other programs that operate in other domains but are aimed at promoting income security in later life, including *employment* policies such as Senior Community Service Employment Program (SCSEP) and Senior Environment Employment Program (SEE), *housing* policies such as Housing for the Elderly Program (i.e., Section 202), Housing Choice Voucher Program (i.e., Section 8), and Low Income Housing Tax Credit (LIHTC), and a *community support* policy such as Supplemental Nutrition Assistance Program (SNAP). Details of these programs are presented in Appendix I.

Despite these programs being specifically designed for older adults to strengthen both their income and health, using the criteria (i.e., age eligibility, financial literacy, financial inclusion, asset development strategy, and institutional supports and barriers) developed by Huang and Greenfield (2015), many of these programs are actually income-transferred programs without potential of asset development. For example, *age eligibility* examines whether the programs address cumulative inequality through the lens of life course asset-development. It is found that although many programs are targeted for older adults, most of them are means-test programs and do not adequately balance the cumulative inequalities in assets across older people, as research shows that people of color and women are more likely to be excluded from labor forces due to discrimination and experience employment discontinuity, which in turn, decreases the Social

Security benefits available to these populations (Nam, Lee, Huang, & Kim, 2015). In contrast, people who are male, white, with higher levels of education are more likely to have pension plans (Gonzales, 2015). The criteria of *financial literacy* and *financial inclusion* explore whether programs intend to increase financial literacy and improve opportunities for developing assets, and the evaluation shows that these programs generally do not include these components. In terms of *asset development strategy*, these programs are more likely to encourage asset decumulation rather than accumulation, as older adults need to spend down their assets in order to qualify for certain programs. Lastly, the *institutional supports and barriers* investigates whether programs have institutional features to encourage saving and accumulating wealth, and it is not surprising that most programs don't have such a feature due to the means-test nature. Instead, they create barriers for older persons to further accumulate assets.

The reason why these aging programs have a focus on income consumption rather than asset development is probably because most of policymakers design policies based on the life-cycle hypothesis, as it suggests that older age is the period for individuals to consume their economic resources (Alessie et al., 1997; Browning & Crossley, 2001; Modigliani, 1986), and therefore these programs create disincentives for savings and limit the potential for older persons to accumulate their assets. However, asset development is a broader concept for older persons, and there are several strategies to enhance asset development among older persons, including program outreach for the financial inclusion, emphasizing the role of management and asset accumulation, and providing more financial incentives for older persons (Huang & Greenfield, 2015). These features could be used in future program revisions to support asset-development for older adults.

Further, institutional asset accumulation should also be included in developing policies to strengthen wealth development from a life course perspective. As O'Rand (1996, p. 233) suggests, it is critical to examine "*how institutions allocate value, protection, reward over time in ways that reinforce or ameliorate inequalities*" and how variations in institutional arrangements can be linked to individuals' behaviors. There are several policy features that may influence an individuals' asset accumulation, including: (1) Access (e.g., eligibility, opportunity, and financial inclusion); (2) Information (e.g., general and financial literacy); (3) Incentives (e.g., subsidies such as reduced tax benefits and tax deferent for home purchase or retirement accounts, and rates of return); (4) Facilitations (e.g., automatic features for saving); (5) Expectations (e.g., match caps or saving targets); (6) Restrictions (e.g., purposes and restrictions of using savings); and (7) Security (e.g., protections from risks of lost assets) (see details in Beverly et al., 2008). These policy efforts can be linked to financial capability (Sherraden, 2013), in that it argues that institutional mechanisms can play a role in shaping individuals' ability and opportunity in saving and investment actions, which in turn, can lead to achieving better financial stability, well-being, and development in later life.

Life course asset-building for all. Findings from this study reveals that wealth has a critical impact on health in later life. As both wealth and health need time to development, such findings provide strong evidence for developing assets from a life course perspective. The life course asset-based social policy is characterized by a focus on facilitating saving and accumulation of assets for people in different ages and with varied life course characteristics. The purpose of such a policy is to build a wealth stock for further social development, bringing economic, psychological, and health benefits, and addressing inequality in wealth across gender, race, and other life course disadvantages.

The findings regarding the impacts of wealth in later life can be linked to a broader body of literature on the asset-effect in children and families, in that they examine how asset-building interventions (e.g., Children Development Accounts, CDAs or Individual Development Accounts, IDAs) affect long-term well-being outcomes for children and family members. Findings from these studies largely support that initial assets in childhood could produce positive impacts on multiple outcomes, including better psychological and health outcomes such as lower malnutrition problems, avoiding lack of child health care, better treatment-seeking behaviors and early socio-emotional development (Chowa et al., 2010; Huang, Sherraden, Kim, & Clancy, 2014), better educational outcomes such as higher rates of school enrollment, attendance, and completion (Chowa et al., 2010), and better economic well-being such as more savings for post-secondary education (Huang, Nam, Sherraden, & Clancy, 2015). All of these positive outcomes in childhood can further influence later wealth accumulation.

The positive asset-effect also shows up in early- and late-adulthood. For example, research has shown that assets in childhood lead to more savings in early adulthood (Friedline, Elliott, & Chowa, 2013) and higher education attainment such as higher enrollment and completion rates for college and less burdens when paying for college (Elliott & Sherraden, 2013). Such positive effects may last for decades, seeing that studies have found that assets bring social and economic benefits in late-adulthood, like higher rates of homeownership (Grinstein-Weiss et al., 2013), lower maternal hardships (Wikoff, Huang, Kim, & Sherraden, 2015), and higher tendency of saving for retirement (Grinstein-Weiss et al., 2015).

While a movement that links asset-building with different life stages can be observed in the arena of research, the policy actions about building assets over the life course are still at its nascent stage. The concept of life course asset-building is to create an individual development account that links “from cradle to grave,” that is, a Children’s Development Account (CDA) that enables children and adolescents to save a sizable asset that can be used to further their educational and career development; an Individual Development Account (IDA) that helps families pay for a home, start up a business, or pay for their children's higher education; and a retirement account to ensure older adults achieve greater economic independence in later life (Oliver & Shapiro, 2006). This "linked-lives account" idea sounds ambitious and is difficult to fulfill in the U.S. given the current political turmoil. However, many other international peers have adopted such an innovative idea (Loke & Sherraden, 2009), especially in many Asian societies such as Taiwan, South Korea, and Singapore (Sherraden, Huang, & Zou, 2019). For example, South Korea adopts *Child Development Accounts* targeting institutionalized children in child welfare systems (Han, 2019) and Taiwan implements a universal *Children Future Education and the Development Accounts* for low-income children as a mean to bolster assets accumulation and strengthen human capital (Cheng, 2019). More ambitious efforts in promoting life course asset-building can be seen in Singapore. Beginning at birth to age 6, all children are automatically enrolled in the systems and receive childcare-related benefits from the *Baby Bonus Scheme*, *Child Development Account*, and *Medisave*, with savings contributed from both the parents and initial deposits and matched savings from the government; from age 6 to 20, *Edusave* and *Post-Secondary Education Account (PSEA)* provide funding for educational purposes, and the remaining funds are merged with the *Central Provident Fund (CPF)* that can be used for home purchase, medical expenses, and retirement security (Loke & Sherraden, 2019). Currently in the U.S. several states (e.g., Nevada, Connecticut, Pennsylvania, etc.) have adopted statewide saving policies focused on children (Clancy & Beverly, 2017). It would be desirable that these policy implementations—with features of universal eligibility, automatic enrollment, matched funds, public benefits exclusion, linked lives, and greater potential for social development—in international peers can encourage the U.S. to consider building its universal life course asset-building policy at the national level.

A life course asset-building policy also acknowledges that policy should use a structural approach to address both historically- and institutionally-generated cumulative disadvantages across the life span. This study shows that increasing wealth can improve health in later life. However, it should be noted that both wealth and health are structured by historical and institutional cumulative disadvantages, as disparities in wealth and health can still be observed across race, gender, and socioeconomic conditions. This implies that life course asset-building policy should address the negative impacts of “fundamental causes” in the process of wealth and health development, such as gender discrimination, racism, and disparities in social conditions (Phelan & Link, 2015; Phelan, Link, & Tehranifar, 2010). For example, in order to compensate African Americans and women for their loss in wealth accumulation, the design of life course asset-building policy should foster features from some innovative policies, such as aggressive efforts like anti-discrimination laws that eliminate racial differences in human capitals and the labor market and facilitate asset accumulation for minorities (Brown, 2012), the *Family and Medical Insurance Act* that creates a shared fund to make paid leave affordable for every employer and worker regardless of the size of the firms, or the *Social Security Caregiver Credit* that counts worker’s caregiving hours as part of their work history when calculating the Social Security Benefits (Carr, 2019). In sum, we need more efforts in making the life course asset building policy into a reality, including more scientific and rigorous studies in testing the asset-effect in each life stage, further supports for implementing innovative asset-development demonstrations and experiments, and making the designs of the policy or program inclusive for marginalized groups with cumulative inequality. It is hoped that, through these innovative social investment efforts in each life stage, the life course asset-building policy can gradually close the wealth gaps in later life, which in turn, improve both economic security and health for older adults.

Considering socioeconomic policies as health policy. The most important implications from this study is that, since wealth affects health positively and longitudinally, if translating these research findings into policy level, this implies that any policy aims at increasing economic security can be regarded as a policy to promote health in later life. This means that it is necessary to estimate the "health-benefit" among existing social and economic policies. Yet, such a perspective is not widely recognized in both the academia and government (House, Schoeni, Kaplan, & Pollack, 2007).

There is a common belief that the way to improve population health is to put more efforts in improving the health care system and investing more monies in health policies. Such a phenomenon is partly reflected by the increasing spending in Medicare and Medicaid, as the U.S. spends nearly one-third (28%) of its gross domestic product (GDP) on these programs (Michel & Bogie, 2018). However, findings from this study open up a promising avenue to address population health via the evaluations of current social and economic policies. This echoes what House et al. (2007) have stressed in considering evaluating health impacts of all policies. Research has shown that health care programs and policies only explain 10 to 20 percent of variations in population health (McGinnis, Williams-Russo, & Knickman, 2002), other policy determinants to health—like social and economic policies—are actually major determinants of health in populations (House et al., 2007).

In fact, the U.S. has put largely economic efforts in income policies. Estimates made by Michel and Bogie (2018) show that 41% of the US GDP goes to programs related to Social Security and income security, which provides a greater opportunity to examine how these social and economic policies bring health benefits. However, even though a large body of literature has documented the robust association between income/wealth and health, there is very little research examining the effect of income policies on health (Herd, House, & Schoeni, 2007), probably due to the myth that we assume health care is the only determinant of health, and therefore the policy evaluation—dominated by the biological and medical perspective—has a focus on preventative or remedial medical services.

Findings from this study provide implications for future policy research to examine health impacts of social and economic policies—like the Head Start Program, Earned Income Tax Credit, or Social Security—from a life course perspective. However, several challenges, such as 3Cs (*causality*, *cost-effectiveness*, and *can we do it*) should be addressed in future research (House et al., 2007). As suggested by House et al. (2007), the causality issue should be addressed first, as currently we know very little about the connections between income-related policies and health. To improve this issue, this means that we need more reliable longitudinal data sets that document both income/wealth and health variables of individuals over the life course. Further, we need to develop useful frameworks explaining the mechanisms connecting policy to individuals' health. House (2002) proposes a framework describing the possible pathways from policies to health outcomes, in that the potential pathways include socioeconomic positions, medical care and insurance, psychosocial risk factors (health behavior, social networks, stress, psychological dispositions, and social roles and productive activities), and socio-environmental hazards. The next step requires evaluating the cost-effectiveness and the political, economic, ethical, and technical feasibility of income related programs. Although there is still a long way to go, it is hoped that, by evaluating policies like education, income support, employment, welfare, housing and neighborhood policies, we can learn important implications from these pathways and apply the knowledge to improve health in later life.

5.3.2 Research Implications

This study also offers implications for future research. First, this study highlights the use of proper transformation in studying the effect of wealth on different outcomes. This study uses inverse hyperbolic sine (IHS) transformation (Pence, 2006) to correct the skewness of wealth, and the results showed that the application of IHS demonstrates a better ability in correcting skewness in wealth than the log-transformed method. Further, the use of IHS transformation may also provide an unbiased estimation. For instance, Huang (2011) examines how assets influence education and health outcomes among children with disability. Findings suggest that the asset effects may be overestimated due to the use of log-transformed asset measure, as negative asset values were forced to cluster at the value of zero, which may introduce biases in estimating asset-effect. Friedline et al. (2015) examine the use of IHS and log-transformed wealth on math achievement among adolescents, and the results showed that the estimates of IHS-transformed wealth are highly comparable to the estimates of log-transformed wealth, suggesting that the IHS transformation may be a viable alternative in research that studies wealth.

Second, despite this study modeling how life course factors relate to wealth in later life, only the direct effect—how life course factors in childhood and adulthood influence wealth trajectory—is examined. Such an approach only addresses part of the *process* on how cumulative disadvantage produces inequality on a range of life course outcomes (Dannefer, 2018). Further investigations on the life course process/mechanisms are needed for future research. Current literature indicates that, by using both childhood and adulthood SES, there are four life course models that can be tested: critical period, accumulation model, social mobility, and pathway model (e.g.,Hallqvist, Lynch, Bartley, Lang, & Blane, 2004; Turrell et al., 2002).

The critical period model examines the direct effect of life course factors on outcomes

(Kwon et al., 2018), which is similar to the design in this study on how childhood and adulthood SES affect wealth trajectory in later life. The accumulation model focuses on how risks accumulated in both childhood and adulthood affect outcomes (O'Rand, 1996). The social mobility model tests how patterns of economic mobility across life influence the variables of interest (Hallqvist et al., 2004). The pathway model investigates intergenerational transmission of economic advantages or disadvantages from childhood to adulthood, with a hypothesis that adulthood SES mediates the relationships between childhood SES and outcomes (Luo & Waite, 2005; Pudrovska & Anikputa, 2014). These four models have been widely tested in health outcomes (e.g., Kwon et al., 2018; Lyu & Burr, 2016; Pudrovska & Anikputa, 2014), but their utilities on wealth are not fully examined. Examining these models would better our understanding on how life course factors shape wealth in later life. Although this study does not focus on these life course mechanisms, these issues will be addressed in future publications.

In addition to the investigations on life course mechanisms/processes on wealth in later life, important features, including *human agency* in the cumulative advantage/disadvantage (CAD) model and *institutional arrangement* in the asset-based welfare theory, should also be examined in the process of wealth accumulation across life. Combining both CAD model and asset-based welfare theory, wealth in later life is the product of the interplay between structural environments, institutional arrangement, human agency, and opportunities and constraints over time. Although social structural and early disadvantages are regarded as antecedents to poor wealth accumulation, it is highly possible that poor wealth trajectory and patterns in later life—results from the cumulative life disadvantages—can be altered by effective institutional arrangements and rational choices and selections. Therefore, it is important to examine how interactions across cumulative disadvantages, institutional effect, human agency, and time influence wealth accumulation over the life course.

Third, this study only explores the cohort effect based on birth cohort. To better understand how wealth is shaped in a course of life, it is essential to study how wealth is influenced by age, period, and cohort (APC) (Bell & Jones, 2015). APC effects represent three different models in which wealth can change over time. For example, wealth is associated with *age,* as life cycle hypothesis posits that people accumulate wealth as they get old, with wealth peaking at the time of the retirement. Differences in wealth can also be attributed to *cohort* differences, in that individuals from distinct age, historical, and birth cohort may associate with varied social, economic, and political developments, and such structural arrangements may shape the trajectory of wealth. Wealth can change as a result of *period* effect, as specific time or historical events—such as wars or economic crises—may alter the wealth development over the life course. Understanding the combinations of APC causing change in wealth is important for policymakers and researchers because varied combinations may produce distinct implications for policy development (Bell & Jones, 2015).

Fourth, although this study uses longitudinal panel data from the Health and Retirement Study to examine the wealth trajectory among older adults aged 50 and older in a 10-year span (2004 to 2014), this approach may not fully capture the effect of life course factors on wealth dynamics in a lifespan, especially for explorations on the increasing or accumulating patterns in wealth. In order to build a clearer picture of wealth development in a life course, other data sets—the Panel Study of Income Dynamic (PSID) and the National Longitudinal Survey of Youth 1979 (NLSY79)—with the inclusion of younger respondents may provide more opportunities to track wealth trajectories across the entire life course, and therefore offer a complete context on the longitudinal relationship between life course factors, wealth and health in later life.

Fifth, as Paxton (2001) notes, the asset-effect can be operated through three mechanisms: accumulating assets, possessing assets, and spending assets. Accumulating assets describes the role of financial education and the ways of acquiring assets either by active (e.g., saving) or passive (e.g., received endowment) actions. Possessing assets—the focus of this study—discusses the values and the type of assets. Spending assets examine how consumptions in wealth, such as investment, lead to desired consequences. Future studies need to examine how other asset-effect mechanisms, especially how accumulating assets, spending assets, and owning other types of assets—financial assets, homeownership, or intangible assets—affect outcomes of older adults.

Lastly, as suggested by Sherraden (1991) and Lerman and McKernan (2008), differential asset experiences, either accumulating, possessing, or spending, can lead to varied desirable well-being outcomes in addition to better health. Other outcomes include: *economic* (e.g., more income, more consumption, less material hardships, more assets, and self-sufficiency), *pro-social* (family stability, social capital, and access to resources), *civic engagement* (e.g., volunteering, political participations, and productive engagement), *psychological* (e.g., future orientation, sense of security, less stress, better happiness and satisfaction), and *intergenerational transmission* (e.g., children with better socioemotional development or higher educational attainment). Further, the mediation mechanisms that connect wealth and health are not explored in this study. Potential economic, behavioral, psychological, and social pathways should be addressed in the link between wealth and health. In sum, this study only explores a tiny piece of asset-effect. Future studies are encouraged to test how assets relate to other outcomes, and what the potential pathways in these links are, in order to provide a complete picture of asset-effect in later life.

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Appendix A: Imputation, Weights, and Attrition

Table A.1. Sensitivity Test for the Combinations of Imputation, Sampling Weights, and Attrition in Wealth-Health Estimates

	Joint-Health Patterns			
	Class 1: Rapid-decline health (9.54%)	*Class 2: Slow-decline health (16.80%)*	*Class 3: Stable poor health (10.9%)*	*Class 5: Improved health (10.4%)*
	RRR	*RRR*	*RRR*	*RRR*
Imputation + Sampling Weights				
Wealth patterns (ref: Stable high, Class 2)				
Low & increasing (Class 1)	3.24**	1.81*	3.84***	1.35
Stable low (Class 3)	4.18***	2.06***	6.52***	2.74***
High & decline (Class 4)	2.95***	1.99***	2.62***	1.50*
Imputation + Attrition				
Wealth patterns (ref: Stable high, Class 2)				
Low & increasing (Class 1)	1.86**	1.47*	3.34***	1.70*
Stable low (Class 3)	2.34***	1.66***	4.02***	2.33***
High & decline (Class 4)	2.32***	1.56***	2.60***	1.81*
Imputation + Sampling Weights + Attrition				
Wealth patterns (ref: Stable high, Class 2)				
Low & increasing (Class 1)	3.17**	1.78*	3.85***	1.37
Stable low (Class 3)	4.19***	2.06***	6.53***	2.75***
High & decline (Class 4)	2.92***	1.98***	2.61***	1.51

Note. Imputation is via multivariate imputation by chained equations (MICE). Reference group of health for multinomial model: Class 4 (*Stable good health*). Results were based on 20 imputed data sets, controlling for life course factors.
*p < .05, **p < .01, ***p < .001, two-tailed test.

Appendix B: Influence of Mode of Interview

Table A.2. Effect of Mode of Interview on Wealth and Health

	Face-to-Face Interview vs. Phone Interview
	b (*SE*)
Wealth	
Net worth (IHS transformation)	0.001 (0.007)
Health	
Mobility limitations	0.019 (0.013)
Self-rated health	0.007 (0.005)
Depressive symptoms	0.020 (0.010)*
Cognition	−0.348 (0.021)***

Note. Results were based on regression analysis using long-form (stacked) data.
*p < .05, **p < .01, ***p < .001, two-tailed test.

Appendix C: Skewness of Wealth

Table A.3. Skewness of Wealth Across Different Methods of Transformation

	2004	*2006*	*2008*	*2010*	*2012*	*2014*
Distribution of net worth	*Skew / Kurt*	*Skew / Kurt*	*Skew / Kurt*	*Skew / Kurt*	*Skew / Kurt*	*Skew / Kurt*
Net worth (IHS transformation)	−0.75 / 3.59	−0.75 / 3.45	−0.72 / 3.30	−0.74 / 3.28	−0.64 / 3.07	−0.57 / 2.89
Net worth (logarithm transformation)	−2.33 / 8.28	−2.25 / 7.79	−2.15 / 7.19	−1.87 / 5.51	−1.83 / 5.39	−1.88 / 5.72
Net worth (original metric)	12.86 / 252.27	12.79 / 261.71	11.42 / 235.69	13.51 / 403.35	24.41 / 1014.09	11.58 / 233.10

Note. Skew = skewness. *Kurt* = kurtosis. Values were adjusted to 2014 values.

Appendix D: Industry Types

Table A.4. Father's Occupation Categories

1998–2004 HRS	*2006–2010 HRS*	*2012–2014 HRS*
1. Managerial specialty operation	1. Management Occupations	1. Management Occupations
2. Professional specialty operation and technical support	2. Business Operations Specialists	2. Business and Financial Operations Occupations
3. Sales	3. Financial Specialists	3. Computer and mathematical occupations
4. Clerical, administrative support	4. Computer and Mathematical Occupations	4. Architecture and Engineering Occupations
5. Service: private household, cleaning and building services	5. Architecture and Engineering Occupations	5. Life, Physical, and Social Science Occupations
6. Service: protection	6. Life, Physical, and Social Science Occupations	6. Community and Social Service Occupations
7. Service: food preparation	7. Community and Social Services Occupations	7. Legal Occupations
8. Health services	8. Legal Occupations	8. Education, Training, and Library Occupations
9. Personal services	9. Education, Training, and Library Occupations	9. Arts, Design, Entertainment, Sports, and Media Occupations
10. Farming, forestry, fishing	10. Arts, Design, Entertainment, Sports, and Media Occupations	10. Healthcare Practitioners and Technical Occupations
11. Mechanics and repair	11. Healthcare Practitioners and Technical Occupations	11. Healthcare Support Occupations
12. Construction trade and extractors	12. Healthcare Support Occupations	12. Protective Service Occupations
13. Precision production	13. Protective Service Occupations	13. Food Preparation and Serving Related Occupations
14. Operators: machine	14. Food Preparation and Serving Occupations	14. Building and Grounds Cleaning and Maintenance Occupations

1998–2004 HRS	2006–2010 HRS	2012–2014 HRS
15. Operators: transport, etc	15. Building and Grounds Cleaning and Maintenance Occupations	15. Personal Care and Service Occupations
16. Operators: handlers, etc	16. Personal Care and Service Occupations	16. Sales and Related Occupations
17. Member of Armed Forces	17. Sales Occupations	17. Office and Administrative Support Occupations
	18. Office and Administrative Support Occupations	18. Farming, Fishing, and Forestry Occupations
	19. Farming, Fishing, and Forestry Occupations	19. Construction and Extraction Occupations
	20. Construction Trades	20. Installation, Maintenance, and Repair Occupations
	21. Extraction Workers	21. Production Occupations
	22. Installation, Maintenance, and Repair Workers	22. Transportation and Material Moving Occupations
	23. Production Occupations	23. Military Specific Occupations
	24. Transportation and Material Moving Occupations	
	25. Military Specific Occupations	

Appendix E: Descriptive Statistics

Table A.5. Descriptive Statistics, 2004 to 2014 Wave

	2004	*2006*	*2008*	*2010*	*2012*	*2014*
	M(SD) / N(%)	*M(SD) / N(%)*	*M(SD) / N(%)*	*M(SD) / N(%)*	*M(SD) / N(%)*	*M(SD) / N(%)*
Health status (*time-varying*)						
Self-rated health	3.24 (1.10)	3.21 (1.10)	3.10 (1.10)	3.13 (1.08)	3.10 (1.08)	3.06 (1.05)
Mobility limitations	2.41 (2.72)	2.70 (2.87)	2.85 (2.93)	3.06 (3.06)	3.11 (3.11)	3.28 (3.15)
Depressive symptoms	1.37 (1.92)	1.44 (1.97)	1.39 (3.94)	1.39 (1.94)	1.43 (1.97)	1.41 (1.97)
Cognition	15.74 (4.17)	15.49 (4.43)	15.19 (4.47)	14.81 (4.46)	14.56 (4.51)	14.60 (4.66)
Wealth (*time-varying*)						
Net worth (IHS transformed)	3.54 (1.85)	3.60 (1.90)	3.50 (1.93)	3.24 (2.04)	3.18 (2.02)	3.24 (1.99)
Net worth ($)	$593,643.2 (1,577,548)	$646,184.9 (1,661,333)	$595,664.3 (1,410,620)	$501,084.8 (1,179,207)	$491,698.5 (1,470,925)	$517,578.7 (1,291,953)
Life course factors (*time-invariant / baseline*)						
Childhood SES						
Father's education (low) [a]	3955 (29.00%)					
Mother's education (low) [a]	3446 (23.63%)					
Father's occupation (blue-collar) [a]	8145 (69.31%)					
Family SES (poor)[a]	5094 (31.88%)					
Adulthood SES						
Education level (< college) [a]	12638 (78.23%)					
Income (< median) [a]	7727 (47.73%)					
Life course covariates (*time-invariant / baseline*)						
Age (baseline)	65.45 (9.41)					
Health in childhood (poor or fair) [a]	1035 (6.41%)					
Female [a]	9237 (57.06%)					

	2004	2006	2008	2010	2012	2014
	M(SD) / N(%)	*M(SD) / N(%)*	*M(SD) / N(%)*	*M(SD) / N(%)*	*M(SD) / N(%)*	*M(SD) / N(%)*
Race						
White (*ref*)	11627 (71.85%)					
Black	2713 (16.76%)					
Hispanics	1843 (11.39%)					
Working (proportion of time)	0.33 (0.39)					
Married (proportion of time)	0.64 (0.44)					
Cohort						
Born prior 1923 (AHEAD; *ref*)	1542 (9.52%)					
1924-1930 (CoDA)	1252 (7.73%)					
1931-1941 (HRS)	7981 (49.30%)					
1942-1947 (WB)	2021 (12.48%)					
1948-1953 (EBB)	3393 (20.96%)					
Control variable (*time-invariant / baseline*)						
Living in urban area	7168 (48.08%)					
Mode of interview (face-to-face, proportion of time)	0.58 (0.21)					
Number of chronic diseases	1.74 (1.34)					
Attrition due to death	2786 (17.21%)					
Attrition due to lost contact/drop	2607 (16.10%)					
Attrition (death/lost contact/drop)	5176 (31.97%)					

Note. See section 3.2 for the constructions of these variables. [a] Only present those who report yes. *ref* = reference group.

Appendix F: Generalized Propensity Score Imbalance Check

Table A.6. Covariates Imbalance Check Before and After the Generalized Propensity Score (GPS) Estimation

Wealth Patterns	*Pre-GPS Model*			*Post-GPS Model*		
	Class 1: Low & Increasing	*Class3: Stable low*	*Class 4: High & Declining*	*Class 1: Low & Increasing*	*Class3: Stable low*	*Class 4: High & Declining*
	OR / RRR / b	*OR / RRR / b*	*OR / RRR / b*	*OR / RRR / b*	*OR / RRR / b*	*OR / RRR / b*
Childhood SES						
Father's education (low) [a]	1.49*	2.95***	1.65***	0.82	1.04	0.93
Mother's education (low) [a]	1.47	3.31***	1.66***	0.82	0.99	0.84
Father's occupation (blue-collar) [a]	1.42	1.86***	1.16	0.90	1.19	1.14
Family SES (poor) [a]	1.54**	1.76***	1.30**	1.16	1.18	1.07
Adulthood SES						
Education level (< college) [a]	2.30***	4.42***	2.07***	0.97	1.30	1.09
Income (< median) [a]	2.22***	10.46***	3.03***	0.92	1.21	0.80
Life course/ascribed covariates						
Female [a]	0.77**	1.32***	1.11	0.87	1.15	0.83*
Race (*ref*: White) [b]						
Black	3.29***	6.51***	2.54***	0.85	1.12	0.84
Hispanics	3.29***	6.68***	2.67***	0.88	0.97	0.84
Working (proportion) [c]	0.07*	−0.11***	0.04	−0.003	−0.01	0.08*
Married (proportion) [c]	−0.10**	−0.38***	−0.18***	0.01	−0.002	0.06*
Cohort (*ref*: Born prior 1923, AHEAD) [b]						
1924-1930 (CoDA)	0.83	0.98	0.75	1.19	1.34	0.75
1931-1941 (HRS)	1.09	0.76*	0.56**	0.52	1.36	0.80
1942-1947 (WB)	2.80**	0.8	0.73	0.81	1.48	1.23
1948-1953 (EBB)	3.62**	1.46*	0.96	0.86	1.11	1.16

Note. [a] Odds ratio (OR) produced by logistic regression. [b] Relative risk ratio (RRR) produced by multinomial logistic regression. [c] Unstandardized regression coefficient (*b*) produced by OLS regression. Pre-GPS model uses only sampling weight; post-GPS model uses grand weight combining from sampling weight and propensity score. All the results were based on 20 imputed data sets.
**p* < .05, ***p* < .01, ****p* < .001, two-tailed test.

Appendix G: Growth Factors Interpretations

It is not intuitive to explain the associations between the growth factors, especially for the slopes. The general way to interpret the associations is to focus on the "sign" of the association between two growth factors, and then consider the "direction" for both predictor and outcome to make a proper interpretation (Muthén, personal communication). Consider these three cases:

In Case 1, the correlation between $Slope_A$ and $Slope_B$ is positive, this means when A increases the value of B increases, or when A decreases the values of B decreases; they move in the *same* direction. After this direction has been established, the next step is to identify the directions for both slope A and B. In this case, both slopes are positive (indicating increases in both A trajectory and B trajectory across time), and the correlation between these two slopes is also a positive coefficient, this means that a "compound" or "reinforced" effect is observed in the relationship between $Slope_A$ and $Slope_B$, and the interpretation for this case is: an *increase* in $Slope_A$ results in a *faster increase* in $Slope_B$. Note that this interpretation is based on the facts that the $Slope_A$, $Slope_B$, and the correlation all have a positive sign.

In Case 2, the correlation between $Slope_A$ and $Slope_B$ is negative, this means that when A goes up, B goes down, or when A goes down, B goes up; these two slopes move in an *opposite* direction. In this case, $Slope_A$ has a negative sign (meaning A trajectory decreases across time) but $Slope_B$ has a positive sign (indicating B trajectory increases over time). Because $Slope_A$ has a negative sign, and the correlation between $Slope_A$ and $Slope_B$ is also a negative sign, this means that when *A decreases, B increases*. Further, note that in this case, $Slope_B$ also has a positive sign. Thus, a reinforced effect is observed in this case, and the interpretation is: a *decrease* in the $Slope_A$ results in a *faster increase* in $Slope_B$. Note that this interpretation is based on the facts that $Slope_A$ and the correlation are a negative value but $Slope_B$ is a positive value.

In Case 3, the correlation between $Slope_A$ and $Slope_B$ is positive. $Slope_A$ has a positive sign but $Slope_B$ has a negative sign. Because both the correlation and $Slope_A$ have a positive sign, this means that when A goes up, B also goes up. However, in this case, the B trajectory declines over time, as $Slope_B$ has a negative value. The correlation produces a positive impact on $Slope_B$, but the B trajectory (i.e., $Slope_B$) shows a *decreased* trend. Therefore, a "buffer" or a "reduced" effect on the *declining* trajectory of B is observed in this case, indicating that the decline of $Slope_B$ is *reduced* by the positive correlation. Therefore, the interpretation for this case is: an *increase* in $Slope_A$ results in a *slower decrease* in $Slope_B$.

A quick way to study these associations is to multiply the signs for $Slope_A$, $Slope_B$, and the correlation between $Slope_A$ and $Slope_B$. The sign of this final product can give researchers a sense on the impacts of correlation on the $Slope_B$. If the final product yields a positive sign, it means a reinforced effect can be observed in the $Slope_B$; if it is a negative sign, then a reduced effect can be observed in the $Slope_B$. For example, if $Slope_A$ is negative (−), $Slope_B$ is negative (−), and the correlation between $Slope_A$ and $Slope_B$ is positive (+). By multiplying the sign of these three terms, a final product produces a positive sign (+), and therefore a reinforced effect on $Slope_B$ can be observed. This means: a *decrease* in $Slope_A$ results in a *faster decrease* in $Slope_B$. See Table A.7 for more information on the interpretations for the associations between growth factors.

Table A.7. Scenarios and Interpretations for the Associations between Growth Factors

Scenario	*Sign of Slope$_A$*	*Sign of Slope$_B$*	*Sign of Correlation*	*Interpretation*
A	+	+	+	An increase in A result in *a faster increase* in B
B	+	+	−	An increase in A result in *a slower increase* in B
C	+	−	+	An increase in A result in *a slower decrease* in B.
D	+	−	−	An increase in A result in *a faster decrease* in B
E	−	+	+	A decrease in A result in *a slower increase* in B
F	−	+	−	A decrease in A result in *a faster increase* in B
G	−	−	+	A decrease in A result in *a faster decrease* in B
H	−	−	−	A decrease in A result in *a slower decrease* in B

Note. If the slope is positive, it indicates the change is increasing over time; if the slope is negative, it means the change is decreasing over time.

Appendix H: Changes of Reference Group for Health Patterns

Table A.8. Generalized Propensity Score Analysis for Wealth Patterns on Health Patterns (Reference: Class 1, *Rapid-Decline Health*)

	Joint-Health Patterns			
	Class 2: Slow-decline health (16.80%)	*Class 3: Stable poor health (10.9%)*	*Class 4: Stable good health (52.30%)*	*Class 5: Improved health (10.4%)*
	RRR	*RRR*	*RRR*	*RRR*
Wealth patterns (*ref*: Low & increasing, Class 1)				
Stable high (Class 2)	1.69	0.88	3.01**	2.27*
Stable low (Class 3)	0.90	1.25	0.85	1.51
High & decline (Class 4)	1.26	0.70	1.19	1.19
Wealth patterns (*ref*: Stable high, Class 2)				
Low & increasing (Class 1)	0.59	1.13	0.33**	0.44*
Stable low (Class 3)	0.53**	1.41	0.28***	0.67*
High & decline (Class 4)	0.74	0.79	0.39***	0.52**
Wealth patterns (*ref*: Stable low, Class 3)				
Low & increasing (Class 1)	1.11	0.80	1.18	0.66
Stable high (Class 2)	1.88**	0.71	3.55***	1.50*
High & decline (Class 4)	1.40	0.56	1.40	0.79
Wealth patterns (*ref*: High & decline, Class 4)				
Low & increasing (Class 1)	0.80	1.43	0.84	0.84
Stable high (Class 2)	1.35	1.27	2.53***	1.91**
Stable low (Class 3)	0.72	1.79	0.71	1.27

Note. Reference for health patterns: Class 1 (*Rapid-decline health*). Results were controlled for life course factors, covariates (age, poor childhood health, urban/rural status, numbers of chronic conditions, attrition, and interview method), and were based on 20 imputed data sets and the use of grand weight (propensity score weights × sampling weights). *RRR* = relative risks ratio.
*$p < .05$, **$p < .01$, ***$p < .001$, two-tailed test.

Table A.9. Generalized Propensity Score Analysis for Wealth Patterns on Health Patterns (Reference: Class 2, *Slow-Decline Health*)

	Joint-Health Patterns			
	Class 1: Rapid-decline health (9.54%)	*Class 3: Stable poor health (10.9%)*	*Class 4: Stable good health (52.30%)*	*Class 5: Improved health (10.4%)*
	RRR	*RRR*	*RRR*	*RRR*
Wealth patterns (*ref*: Low & increasing, Class 1)				
Stable high (Class 2)	0.59	0.52*	1.78*	1.34
Stable low (Class 3)	1.11	1.39	0.95	1.68
High & decline (Class 4)	0.80	0.55	0.94	0.94
Wealth patterns (*ref*: Stable high, Class 2)				
Low & increasing (Class 1)	1.70	1.91*	0.56*	0.75
Stable low (Class 3)	1.88	2.65***	0.53***	1.26
High & decline (Class 4)	1.35	1.06	0.53***	0.71
Wealth patterns (*ref*: Stable low, Class 3)				
Low & increasing (Class 1)	0.90	0.72	1.06	0.60
Stable high (Class 2)	0.53**	0.38***	1.88***	0.80
High & decline (Class 4)	0.72	0.40**	1.00	0.56
Wealth patterns (*ref*: High & decline, Class 4)				
Low & increasing (Class 1)	1.26	1.81	1.06	1.06
Stable high (Class 2)	0.74	0.94	1.88***	1.41
Stable low (Class 3)	1.40	2.50**	0.99	1.78*

Note. Reference for health patterns: Class 2 (*Slow-decline health*). Results were controlled for life course factors and covariates (age, poor childhood health, urban/rural status, numbers of chronic conditions, attrition, and interview method), and were based on 20 imputed data sets and the use of grand weight (propensity score weights × sampling weights). *RRR* = relative risks ratio.
*$p < .05$, **$p < .01$, ***$p < .001$, two-tailed test.

Table A.10. Generalized Propensity Score Analysis for Wealth Patterns on Health Patterns (Reference: Class 3, *Stable Poor Health*)

	Joint-Health Patterns			
	Class 1: Rapid-decline health (9.54%)	*Class 2: Slow-decline health (16.80%)*	*Class 4: Stable good health (52.30%)*	*Class 5: Improved health (10.4%)*
	RRR	*RRR*	*RRR*	*RRR*
Wealth patterns (*ref*: Low & increasing, Class 1)				
Stable high (Class 2)	1.13	1.91*	3.40***	2.55**
Stable low (Class 3)	0.80	0.72	0.68	1.21
High & decline (Class 4)	1.44	1.81	1.70	1.71
Wealth patterns (*ref*: Stable high, Class 2)				
Low & increasing (Class 1)	0.89	0.52*	0.29***	0.39**
Stable low (Class 3)	0.71	0.38***	0.20***	0.47***
High & decline (Class 4)	1.27	0.94	0.50**	0.67
Wealth patterns (*ref*: Stable low, Class 3)				
Low & increasing (Class 1)	1.25	1.39	1.47	0.83
Stable high (Class 2)	1.41	2.65***	5.00***	2.11***
High & decline (Class 4)	1.79	2.50**	2.51**	1.41
Wealth patterns (*ref*: High & decline, Class 4)				
Low & increasing (Class 1)	0.70	0.55	0.58	0.59
Stable high (Class 2)	0.78	1.06	1.99**	1.50
Stable low (Class 3)	0.56	0.40**	0.40**	0.71

Note. Reference for health patterns: Class 3 (*Stable poor health*). Results were controlled for life course factors and covariates (age, poor childhood health, urban/rural status, numbers of chronic conditions, attrition, and interview method), and were based on 20 imputed data sets and the use of grand weight (propensity score weights × sampling weights). *RRR* = relative risks ratio.
*$p < .05$, **$p < .01$, ***$p < .001$, two-tailed test.

Table A.11. Generalized Propensity Score Analysis for Wealth Patterns on Health Patterns (Reference: Class 4, *Stable Good Health*)

	Joint-Health Patterns			
	Class 1: Rapid-decline health (9.54%)	*Class 2: Slow-decline health (16.80%)*	*Class 3: Stable poor health (10.9%)*	*Class 5: Improved health (10.4%)*
	RRR	*RRR*	*RRR*	*RRR*
Wealth patterns (*ref*: Low & increasing, Class 1)				
Stable high (Class 2)	0.33**	0.56	0.29***	0.75
Stable low (Class 3)	1.18	1.06	1.47	1.78*
High & decline (Class 4)	0.84	1.06	0.59	1.00
Wealth patterns (*ref*: Stable high, Class 2)				
Low & increasing (Class 1)	3.01**	1.77*	3.40***	1.33
Stable low (Class 3)	3.55***	1.88***	5.00***	2.37***
High & decline (Class 4)	2.54***	1.88***	1.99**	1.33
Wealth patterns (*ref*: Stable low, Class 3)				
Low & increasing (Class 1)	0.85	0.94	0.68	0.56*
Stable high (Class 2)	0.28***	0.53***	0.20***	0.42***
High & decline (Class 4)	0.71	0.99	0.40**	0.56*
Wealth patterns (*ref*: High & decline, Class 4)				
Low & increasing (Class 1)	1.19	0.94	1.70	1.00
Stable high (Class 2)	0.40***	0.53***	0.50**	0.75
Stable low (Class 3)	1.40	1.00	2.51**	1.78*

Note. Reference for health patterns: Class 4 (*Stable good health*). Results were controlled for life course factors and covariates (age, poor childhood health, urban/rural status, numbers of chronic conditions, attrition, and interview method), and were based on 20 imputed data sets and the use of grand weight (propensity score weights × sampling weights). *RRR* = relative risks ratio.
*$p < .05$, **$p < .01$, ***$p < .001$, two-tailed test.

Table A.12. Generalized Propensity Score Analysis for Wealth Patterns on Health Patterns (Reference: Class 5, *Improved Health*)

	Joint-Health Patterns			
	Class 1: Rapid-decline health (9.54%)	*Class 2: Slow-decline health (16.80%)*	*Class 3: Stable poor health (10.9%)*	*Class 4: Stable good health (52.30%)*
	RRR	*RRR*	*RRR*	*RRR*
Wealth patterns (*ref*: Low & increasing, Class 1)				
Stable high (Class 2)	0.44*	0.75	0.39**	1.33
Stable low (Class 3)	0.66	0.60	0.83	0.56*
High & decline (Class 4)	0.84	1.06	0.59	1.00
Wealth patterns (*ref*: Stable high, Class 2)				
Low & increasing (Class 1)	2.27*	1.34	2.55**	0.75
Stable low (Class 3)	1.50*	0.80	2.11***	0.42***
High & decline (Class 4)	1.91**	1.41	1.50	0.75
Wealth patterns (*ref*: Stable low, Class 3)				
Low & increasing (Class 1)	1.51	1.68	1.21	1.78*
Stable high (Class 2)	0.67*	1.26	0.47***	2.37***
High & decline (Class 4)	1.27	1.78*	0.71	1.78*
Wealth patterns (*ref*: High & decline, Class 4)				
Low & increasing (Class 1)	1.18	0.94	1.71	0.99
Stable high (Class 2)	0.52**	0.71	0.67	1.33
Stable low (Class 3)	0.79	0.56*	1.41	0.56*

Note. Reference for health patterns: Class 5 (*Improved health*). Results were controlled for life course factors and covariates (age, poor childhood health, urban/rural status, numbers of chronic conditions, attrition, and interview method), and were based on 20 imputed data sets and the use of grand weight (propensity score weights × sampling weights). *RRR* = relative risks ratio.
*$p < .05$, **$p < .01$, ***$p < .001$, two-tailed test.

Appendix I: Income and Health Programs in Later Life

Table A.13 Programs Related to Asset-Development among Older Persons

Program	*Eligibility*	*Contents of asset-building*	*Asset limit rules*
Retirement income			
Social Security (since 1935)	62+ (full retirement age varies by birth cohort)	None (income support). Individuals will receive a monthly payment. The payment will be based on the age of retirement, with those who are early-retired receiving a fraction-reduction payment.	None.
Private-section Pension Plans (since 1978)	60+	Defined-contribution plans, such as 401(k), 403(b), and IRAs.	Subject to IRS contribution limits.
Supplemental Social Security (SSI, since 1974)	65+, blinded, or disabled	None (income support)	Individuals with no more than $2,000 (or couples with no more than $3,000) in assets may be eligible. Primary home, vehicles, life insurance (less than $1,500), and burial fund (less than $1,500) are not counted as asset limit.
Employment			
Senior Community Services Employment Program (SCSEP, since 2003)	55+, unemployment or low-income. Special consideration for 65+, people with disabilities, limited English proficiency or low literacy skills, live in a rural area, veterans, and homeless or at risk of homelessness	None (income support). Individuals work 20hrs/week, and paid the highest federal/state/local minimum wage	None, but individuals' family income should be less than 125% federal poverty line (FPL).

Program	*Eligibility*	*Contents of asset-building*	*Asset limit rules*
Senior Environmental Employment Program (SEE, since 1984)	55+ with special skills and expertise	None (income support). Individuals choose to work part time or full time, with payments varying by skills and experiences; fringe benefits provided if working over 30 hours/week.	None.
Housing			
Section 202 (Supportive Housing for the Elderly Program, since 1959)	62+, very low-income	None (income support). Provide direct loan or capital advances	None, but only provided to very low-income older persons (less than $10,000). Most recipients are older women living alone.
Section 8 (Housing Choice Voucher Program, since 1974)	For all ages who are low-income, with special rules for older persons	None (income support). Provide cash benefits.	None, but only provided to low-income older persons (income less than 50% of area median income). Around 16% of recipients are older persons.
Low Income Housing Tax Credit (LIHTC, since 1986)	For all ages who are low-income, with special rules for older persons	None (income support). Provide cash benefits.	None, but only provided to low-income older persons (income less than 50% of area median income). Around 30% of recipients are older persons.
Health maintenance and promotion			
Medicare (since 1965)	65+	None (income support). Cover Part A (hospital insurance) and Part B (medical insurance)	None

Program	*Eligibility*	*Contents of asset-building*	*Asset limit rules*
Medicaid (since 1965)	65+, low-income	None (income support)	Have countable assets less than $2,000. Participants are qualified if their income is less than 135% FPL.
Health Savings Accounts (HSA, since 2003)	All (with special rules for 55+)	Tax-exempt saving accounts for those enrolled in the high-deductible health plan (HDHP).	Annual maximum deposit specified by the IRS (for 2015, $3,350 for single and $6,650 for family). If participant is aged 55 or above they can enjoy a catch-up contribution ($1,000 for 2015)
Community support			
Supplemental Nutrition Assistance Program (SNAP, since 1964)	All (with special rules for 60+)	None (income support). Provide in-kind or in-cash support	Have countable assets less than $2,250. If households have at least one person who is either older (60+) or disabled, the countable assets increase to $3,250.

Note. The original source of this table came from Huang and Greenfield (2015), pp. 154–155. Author only selects policies or programs related to older people.